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Research Article

Performance Evaluation and Identification of Key Influencing Factors for Student Achievement Based on the Entropy-Weighted TOPSIS Model

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To address the shortcomings of the existing comprehensive evaluation methods, the entropy TOPSIS (Technique for Oder Preference by Similarity to Ideal Solution) method was introduced into the comprehensive evaluation of classes students' grades in college, and the results of year 2019~2020 of 30 classes student's major courses of 2 colleges within 2 semesters were used as an example for analysis. The study shows that the entropy TOPSIS method can not only effectively reflect the course differences but also avoid the subjectivity of weight setting and improve the rationality and objectivity of the comprehensive evaluation and ranking of students' performance in classes, and it can be used as an objective evaluation tool for the external factors affecting students' performance. At the same time, the internal factors affecting students' performance are analyzed. It can be found that reasonable sleep time and the cultivation of good study motivation can help improve students' academic performance. The results of this paper are of great theoretical value and technical reference value for scientific evaluation of student performance in universities.

1. Introduction

The comprehensive evaluation of class students' academic performance of college is an important element of education evaluation. The comprehensive evaluation of students' academic performance is an important element of educational evaluation [1–3]. It is also an important indicator for the evaluation of merit and priority and the awarding of various scholarships. Therefore, a scientific, reasonable, and fair comprehensive evaluation of academic performance is not only conducive to the optimization of teaching and learning management, but also an important indicator for the evaluation and prioritization of educational management and the awarding of various scholarships. The scientific, reasonable, and fair evaluation of academic performance not only helps to improve the management of education, but also can effectively avoid unnecessary conflicts among students in the competition of choosing the best students [4–6].

In the current practice of academic management in classes of college, the main methods of comprehensive evaluation of students' performance are the cumulative method of raw scores, the method of arithmetic averages, the method of average academic performance, and the method of principal component analysis. Some scholars have also developed a factor analysis model based on the GPA model with the modification of factor analysis superimposed on it [7]. The model is based on the factor analysis. In fact, these methods are not fair and reasonable for the comprehensive evaluation and ranking of students' performance [8]. Due to the different status of each course in the teaching system, the difficulty of the course, and the ranking of the course, the students' performance is not fair. In fact, these methods of comprehensive evaluation and ranking of students' grades are not fair and reasonable [9–11].

The original score accumulation method and the arithmetic average method ignore this point and seriously lack the function of simple arithmetic operation. The method of raw score accumulation and the method of arithmetic average ignore this point and seriously lack of science and fairness [12–14]; the method of average credit performance seems to be fair, but in fact, the setting of credits for each course lacks scientific basis and is too subjective [15–17].

The factor analysis method is an obvious improvement over the above methods, but it only provides the main information when extracting the common factors and does not fully reflect all the information [18]. If there are too many indicators and too few samples, the statistical significance of the evaluation results will be directly affected [19–21].

The statistical significance of the evaluation results will be directly affected if there are too many indicators and too few samples [22–25]. In view of the above situation, it is important to explore the scientific and reasonable method of comprehensive evaluation of performance. The authors put the multiobjective comprehensive decision.

The authors introduce the entropy TOPSIS method of multiobjective decision making into the comprehensive performance evaluation and analyze it with examples to show the scientific and objective nature of the method for the comprehensive evaluation and ranking of students' performance of the 2019~2020 from 30 classes student's major courses of 2 colleges. Considering the scientific and objective nature of the method for comprehensive student performance evaluation and ranking, including exogenous factors and internal factors, the analysis process is shown in Figure 1.

The remainder of this paper is arranged as follows. In Section 2, we provide literature review of TOPSIS method and entropy method. Then, in Section 3, entropy-based TOPSIS assessment of class student performance is discussed by of the 2019~2020 from 30 classes student's major courses of 2 colleges. And the results analysis and discussion are provided in Section 4. Finally, the conclusion is in Section 5.

2. TOPSIS Method and Entropy Method

2.1. Basic Principles of the TOPSIS Method. The TOPSIS method (Technique for Oder Preference by Similarity to Ideal Solution) is a multiobjective decision evaluation method that uses a system of indicators for each solution to be evaluated and calculates the closeness of each solution to the ideal solution as the basis for evaluating each solution. It is a multiobjective decision evaluation method. It has been widely used in the fields of enterprise management decision making, comprehensive competitiveness evaluation, etc. [26–29].

The basic principle of the TOPSIS method is to measure the relative distance between the solution to be evaluated and the ideal solution and the negative ideal solution in order to rank and select the best solution in the whole system. In the process of multiobjective evaluation using the TOPSIS method, the determination of weights is a more important aspect.

In order to overcome the subjectivity in the process of determining the weights, this paper adopts the information entropy method to assign the weights. The information entropy weighting method can be profound.

2.2. TOPSIS Method Calculation Process. In this paper, for an evaluation problem, with m evaluated objects, n evaluation indicators, and x_{ij} denoting the $j-th$ indicator corresponding to the $i-th$ evaluated object, the original data form a matrix of m rows and n columns $A=\{x_{ij}\}_{m\times n}$, called the decision matrix [30]. The specific calculation steps are as follows:

(1) Standardize the data and eliminate the dimension. The original data of evaluation indexes are standardized to eliminate the dimension and then the standardized decision matrix $V=\{v_{ij}\}_{m\times n}$[26]. For the larger and better efficiency indexes,

$$v(i,j)=\frac{x(i,j)-x_{\min}(j)}{x_{\max}(j)-x_{\min}(j)}. \quad (1)$$

For smaller and better cost-based metrics:

$$v(i,j)=\frac{x_{\max}-x(i,j)}{x_{\max}(j)-x_{\min}(j)}. \quad (2)$$

(2) Construct the weighted normalized decision matrix. The formed dimensionless normalized decision matrix $V=\{v_{ij}\}_{m\times n}$ is multiplied with the weight vector $W=(w_1,w_2\ldots,w_n)$ determined using the entropy method. So, the weighted normalized decision matrix $R=\{r_{ij}\}_{m\times n}$ is obtained.

(3) Determine the ideal and negative ideal values that constitute the ideal vector S^+ and the negative ideal vector S^-:

$$\begin{aligned} S_j^+ &= \left[\left(\max_i r_{\mathrm{ij}} | j\in I_1\right)\min_i r_{\mathrm{ij}} | j\in I_2\right],\\ S_j^- &= \left\lceil\left(\min_i r_{\mathrm{ij}} | j\in I_1\right)\max_i r_{\mathrm{ij}} | j\in I_2\right\rceil, \end{aligned} \quad (3)$$

where I_1 is a benefit-based indicator and I_2 a cost-based indicator, $i=1,2,\ldots.m$.

(4) Calculate the combined Euclidean distance from the vector of indicators of each evaluation object to the ideal value and the negative ideal value. Let D_i^+ be the distance from the vector of indicator values of evaluation object i to the ideal value S_j^+, and let D_i^- be the distance from the vector of indicator values of evaluation object i to the negative ideal value S_j^+, $i=1,2,\ldots.m$; then,

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{i=1}^{m}\left(r_{\mathrm{ij}}-S_j^+\right)^2},\\ D_i^- &= \sqrt{\sum_{i=1}^{m}\left(r_{\mathrm{ij}}-S_j^-\right)^2}. \end{aligned} \quad (4)$$

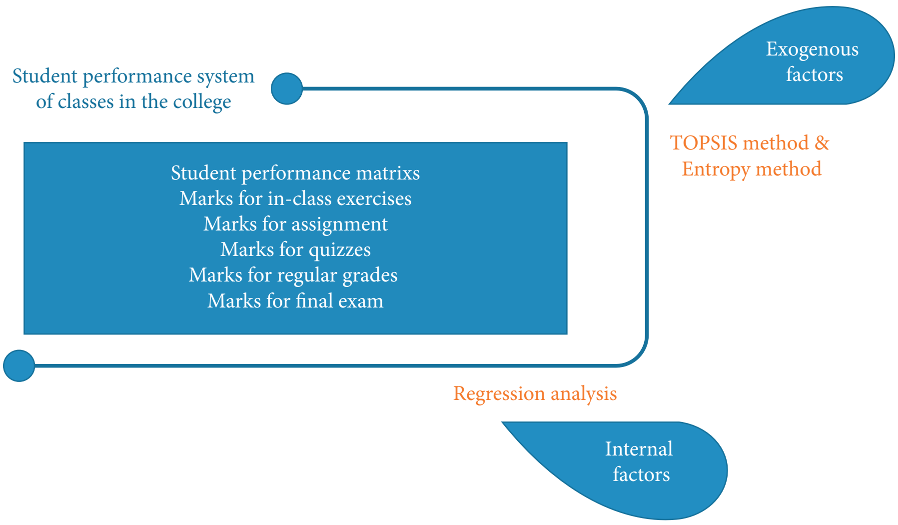

Figure 1: The student performance analysis.

(5) Calculate the relative closeness of each evaluation object to the positive and negative ideal values:

$$\xi_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{5}$$

According to the relative closeness ξ_i, the larger ξ_i is, the closer the evaluation object is to the ideal solution and the better the overall evaluation result is. The closer it is to the ideal solution, the better the overall evaluation result of the evaluation object is.

2.3. The Fundamentals and Value of the Entropy Method. In order to overcome the subjectivity in the process of determining the weights, this paper adopts the information entropy method to assign the weights as mentioned in Section 2.2, which can deeply reflect the utility value of the information entropy value of the indexes.

Entropy is originally a thermodynamic concept introduced by Shannon into information theory to measure the degree of disorder of a system. If the information entropy of a certain index is smaller, it is more reliable. If the information entropy of an indicator is smaller, it means that the degree of variation of the indicator is larger, and the amount of information provided is larger, and the weight of the indicator in the comprehensive evaluation is larger; conversely, if the information entropy of an indicator is larger, the weight of the indicator is smaller.

2.4. The Entropy Method Assigns Objective Weights to Indicators. At present, academic performance evaluation methods are divided into two categories: subjective assignment methods and objective assignment methods. Subjective assignment methods include Delphi method, AHP method, and expert scoring method, while objective assignment methods include entropy method, standard deviation method, factor analysis method, and CRITIC method [31]. In order to avoid the artificiality of subjective assignment, we use the objective entropy method for assignment here. The entropy method is an objective assignment method, the principle of which is to use information entropy to calculate the weight of each indicator and determine the weight coefficient according to the magnitude of the variation of the value of each evaluation indicator. The weighting factor is determined according to the degree of variation of the values of each evaluation indicator [32].

If the information entropy of an evaluation indicator is lower, the greater the variation in the value of the indicator, the greater the amount of information contained, and thus the greater the role of the indicator in the overall evaluation. The calculation process is as follows:

(1) Normalize the original data matrix. As shown in TOPSIS, a standardized decision matrix $V = \{v_{ij}\}_{m\times n}$ is formed.

(2) Calculate the entropy value of each indicator [27]:

$$e_j = -\frac{1}{\ln m_i}\sum_{i=1}^{m} f_{\mathrm{ij}} \ln\left(f_{\mathrm{ij}}\right), \tag{6}$$

where $(f_{\mathrm{ij}}) = v_{\mathrm{ij}}/\sum_{j=1}^{n} v_{\mathrm{ij}}$. Here e_j denotes the entropy value of the $j-th$ indicator; f_{ij} is the weight of the characteristics of the $i-th$ company under the $j-th$ indicator. v_{ij} is the standard value of the $j-th$ indicator data of the $i-th$ company. $\sum_{j=1}^{n} v_{\mathrm{ij}}$ is the sum of the standard data for the $j-th$ indicator of all sample companies. When $f_{ij} = 0$, it is specified that $f_{\mathrm{ij}} \ln(f_{\mathrm{ij}}) = 0$, and then e_j takes values in [0, 1].

(3) Calculate the entropy weighting of each indicator.

$$w_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j}, \tag{7}$$

where w_j is the entropy weighting of the $j-\mathrm{th}$ evaluation indicator and n is the number of evaluation indicators.

3. Entropy-Based TOPSIS Assessment of Class Student Performance

In this paper, the combined results of students' foundation course at the end of the autumn and winter semesters of the 2019~2020 from 30 classes student's major courses of 2 colleges are selected for analysis to illustrate a comprehensive evaluation and ranking of the performance of each class based on student results and models. The 30 classes students of 2 universities at the end of the autumn and winter semesters who took the final exam are selected. The students' scores were divided into marks for in-class exercises (15%), marks for homework (20%), marks for in-class quizzes (5%), marks for regular grades (10%), and marks for the final exam paper (50%), and the final grade is calculated according to the weight of each grade. The final grade will be calculated based on the weighting of each grade.

3.1. Matrix of Averages for Each Student's Performance in Each Class. The results are shown in Table 1 and are referred to as the mean matrix of the students' scores in each class.

3.2. Normalization Process. According to the formula $v_{ij} = x_{\mathrm{ij}}/\sqrt{\sum_{j=1}^{6}(x_{\mathrm{xj}})^2}$, the mean matrices for each of the class students in Table 1 were normalized. The matrix of means for each of the students' grades was normalized, where x_{ij}, $i = 1, 2, \ldots.30$, $j = 1, 2, \ldots.6$, is the average of each class students' grades in Table 1. The average of the students' achievements in each of the categories is shown in Table 1, as well as the normalized matrix of the means of the students' grades in each class. The normalized matrix of the mean of the students' grades in the class is given by $V = [v_{\mathrm{ij}}]$, $i = 1, 2, \ldots.30$, $j = 1, 2, \ldots.6$, and the results are shown in Table 2.

3.3. Calculate the Index Weights of thenEntropy Weight Method. The entropy method index weights are calculated by the formula $w_i = 1 - e_i/6 - \sum_{i=1}^{30} e_i$, $i = 1, 2, \ldots.30$, where $e_i = -1/\ln 6 \sum_{i=1}^{6} b_{\mathrm{ij}} \ln b_{\mathrm{ij}}$ is called information entropy and $b_{\mathrm{ij}} = v_{\mathrm{ij}}/\sum_{j=1}^{6} v_{\mathrm{ij}}$ is called the characteristic weight of the weights; specify $\ln 0 = 0$.

3.4. Calculation of Evaluation Matrix Based on the Weight of Indicators by the Entropy Weighting Method. In order to further improve the objectivity of the comprehensive evaluation and ranking of each class, the entropy weighting matrix calculated above is used to calculate the weight of the indicators, and the normalized matrix of the average values of students' achievements in each class is weighted by the entropy weight indicator weights w_i calculated above. The evaluation matrix R based on the entropy-weighted indicators is shown in Table 3.

$$
\begin{aligned}
R &= \begin{bmatrix} R_{1,1} & R_{1,2} & \cdots & R_{1,6} \\ R_{2,1} & R_{2,2} & \cdots & R_{2,6} \\ \vdots & \vdots & \vdots & \vdots \\ R_{30,1} & R_{30,2} & \cdots & R_{30,6} \end{bmatrix} \\
&= \begin{bmatrix} v_{1,1} * w_1 & v_{1,2} * w_1 & \cdots & v_{1,6} * w_1 \\ v_{2,1} * w_2 & v_{2,2} * w_2 & \cdots & v_{2,6} * w_2 \\ \vdots & \vdots & \cdots & \vdots \\ v_{30,1} * w_{30} & v_{30,2} * w_{30} & \cdots & v_{30,6} * w_{30} \end{bmatrix},
\end{aligned} \tag{8}
$$

where R_{ij} is the evaluation matrix based on the entropy-weighted indicators, v_{ij} is normalized matrix of the mean of the students' grades of each class, and w_i is the characteristic weight of the weights of each class; the results are shown in Table 3.

3.5. Determination of Positive and Negative Ideal Solutions. The maximum and minimum values of each column of the evaluation matrix (Table 3) based on the weights of the indicators of the entropy weighting method were found out separately to constitute the maximum and minimum values of each column, forming a positive and negative ideal solution.

$$
\begin{aligned}
S^+ &= \left\{ \max_{1\le i\le 30} R_{\mathrm{ij}} \mid j = 1, 2, \ldots, 6 \right\} = \{S_1^+, S_2^+, S_3^+, S_4^+, S_5^+, S_6^+\}, \\
S^- &= \left\{ \max_{1\le i\le 30} R_{\mathrm{ij}} \mid j = 1, 2, \ldots, 6 \right\} = \{S_1^-, S_2^-, S_3^-, S_4^-, S_5^-, S_6^-\},
\end{aligned} \tag{9}
$$

where $S^+ = \{0.020104, 0.01583, 7.32\mathrm{E}{-}05, 0.015518, 0.018584, 0.018822\}$ is positive ideal solution and $S^- = \{0.010801, 0.000515, 0, 0.007677, 0.008889, 0.011535\}$ is negative ideal solution.

3.6. Calculate the Comprehensive Evaluation Value. Calculate the Euclidean distance between each index value of each class and the positive ideal solution and negative ideal solution in the evaluation matrix based on the weight of indicators of entropy weight method. Euclidean distance is $D^+ = (D_1^+, D_2^+, \ldots, D_{30}^+)$ and $D^- = (D_1^-, D_2^-, \ldots, D_{30}^-)$, where $D_i^+ = \sqrt{\sum_{i=1}^{m}(r_{\mathrm{ij}} - S_j^+)^2}$ and $D_i^- = \sqrt{\sum_{i=1}^{m}(r_{\mathrm{ij}} - S_j^-)^2}$ is calculated. Finally, the overall evaluation value, which is also called the relative closeness $\xi_, = (\xi_{1,} \xi_{2,}, \ldots \xi_{30,})$, is calculated, where $\xi_i = D_i^-/D_i^+ + D_i^-$ is calculated, $i = 1, 2, \ldots.30$. The classes were ranked according to the overall evaluation value; see Table 4.

4. Results' Analysis and Discussion

By comparing the performance results of thirty classes in two universities, we can effectively determine the correlation between the performance of students in each school and the current situation of real school education, which can help guide the improvement of school education in the future.

Table 1: Matrix of averages for each student's performance in each class.

Classes	Marks for in-class exercises	Marks for assignments	Marks for quizzes	Marks for regular grades	Marks for the final	Final marks
X1	87.8	72.4	0.9	72.7	69.9	74.4
X2	84.4	52.6	0.6	63.8	65.3	71.7
X3	80.7	46.5	0.9	59.8	77	78.7
X4	100.3	96	0.9	88.1	57	72.7
X5	78.6	61.6	0	64.2	53.8	66
X6	93.6	68.2	0.7	74.9	74.2	78.4
X7	79.3	38.4	0.8	55.6	76.7	78.6
X8	43.7	27.3	0.2	33.3	73.1	75.4
X9	51.9	37	0.4	40.6	32.4	36.7
X10	96.6	78.9	0.6	79.2	66.3	74.6
X11	88.8	60.4	0.2	68.8	78.7	80.8
X12	65.2	55.4	0	57.4	61.8	69.3
X13	55.2	21.9	0.2	35.9	28.3	34.6
X14	85.3	64.4	0.4	69.3	68	73.7
X15	77.8	54.1	0.8	63.7	60.7	70.7
X16	44.6	2.4	0.7	23	58.2	60
X17	54.8	28	0.3	38.7	75.2	76.7
X18	97.2	73.6	0.6	77.8	47.6	62.7
X19	66.4	52.1	0.4	55.4	76.7	77.8
X20	70	55.8	0.8	58.5	50	62.3
X21	73.1	60.1	0.7	62.7	71.8	77.3
X22	83.3	67.9	0.2	70.5	69.5	76.4
X23	78.3	72.6	0.9	69.7	74.2	79.6
X24	69	36.9	0.5	48.6	71.8	75.1
X25	90.7	78.6	0.6	77.3	77.5	80.8
X26	63.8	48.1	0.9	52.4	71.2	75.1
X27	66.9	46.1	0.3	53.8	76.8	79.7
X28	76.1	57.1	0.8	63	73.5	78.1
X29	74.1	61.1	1.1	62.3	63.7	72.2
X30	79.9	68.5	0.3	69	67.3	73.9

Table 2: Normalization matrix of averages for each student's performance in each class.

Classes	Marks for in-class exercises	Marks for assignments	Marks for quizzes	Marks for regular grades	Marks for the final	Final marks
X1	0.517	0.425	0.002	0.431	0.414	0.441
X2	0.553	0.346	0.002	0.417	0.426	0.468
X3	0.517	0.296	0.001	0.387	0.494	0.501
X4	0.532	0.508	0.002	0.470	0.301	0.384
X5	0.538	0.422	0.004	0.441	0.367	0.450
X6	0.537	0.390	0.006	0.427	0.421	0.446
X7	0.524	0.253	0.003	0.365	0.508	0.519
X8	0.363	0.226	0.008	0.274	0.598	0.621
X9	0.569	0.415	0.011	0.454	0.360	0.410
X10	0.539	0.440	0.001	0.449	0.370	0.422
X11	0.522	0.359	0.004	0.402	0.462	0.472
X12	0.469	0.397	0.007	0.415	0.445	0.503
X13	0.667	0.261	0.004	0.437	0.346	0.420
X14	0.525	0.400	0.004	0.424	0.419	0.457
X15	0.527	0.367	0.003	0.429	0.413	0.482
X16	0.458	0.021	0.005	0.241	0.593	0.616
X17	0.422	0.219	0.006	0.296	0.583	0.590
X18	0.589	0.446	0.001	0.476	0.288	0.380
X19	0.444	0.352	0.003	0.374	0.512	0.526
X20	0.526	0.421	0.005	0.436	0.372	0.468
X21	0.471	0.388	0.005	0.406	0.465	0.497
X22	0.502	0.410	0.005	0.432	0.422	0.464
X23	0.467	0.431	0.001	0.416	0.444	0.475
X24	0.495	0.268	0.004	0.350	0.524	0.535
X25	0.499	0.431	0.003	0.428	0.427	0.446
X26	0.457	0.341	0.001	0.367	0.505	0.534
X27	0.454	0.314	0.005	0.365	0.518	0.542
X28	0.483	0.366	0.003	0.401	0.473	0.498
X29	0.498	0.404	0.006	0.420	0.427	0.479
X30	0.495	0.425	0.002	0.425	0.424	0.463

Table 3: Evaluation matrix based on the weighting of indicators by the entropy weighting method.

Class	Marks for in-class exercises	Marks for assignments	Marks for quizzes	Marks for regular grades	Marks for the final	Final marks
X1	0.0155	0.0134	0.0000	0.0141	0.0128	0.0134
X2	0.0167	0.0108	0.0000	0.0136	0.0132	0.0143
X3	0.0156	0.0092	0.0000	0.0126	0.0152	0.0153
X4	0.0160	0.0158	0.0000	0.0153	0.0093	0.0117
X5	0.0162	0.0132	0.0000	0.0144	0.0113	0.0137
X6	0.0161	0.0122	0.0000	0.0140	0.0130	0.0136
X7	0.0158	0.0079	0.0000	0.0119	0.0156	0.0157
X8	0.0108	0.0070	0.0000	0.0089	0.0186	0.0188
X9	0.0173	0.0129	0.0000	0.0148	0.0111	0.0124
X10	0.0163	0.0138	0.0000	0.0146	0.0114	0.0127
X11	0.0158	0.0111	0.0000	0.0132	0.0141	0.0144
X12	0.0141	0.0124	0.0000	0.0137	0.0137	0.0152
X13	0.0201	0.0082	0.0000	0.0143	0.0105	0.0128
X14	0.0158	0.0125	0.0000	0.0139	0.0130	0.0138
X15	0.0159	0.0115	0.0001	0.0141	0.0127	0.0145
X16	0.0137	0.0005	0.0000	0.0077	0.0184	0.0187
X17	0.0127	0.0067	0.0000	0.0097	0.0180	0.0180
X18	0.0178	0.0140	0.0000	0.0155	0.0089	0.0115
X19	0.0134	0.0109	0.0001	0.0122	0.0158	0.0160
X20	0.0158	0.0131	0.0000	0.0143	0.0114	0.0142
X21	0.0142	0.0121	0.0000	0.0132	0.0143	0.0151
X22	0.0152	0.0129	0.0000	0.0141	0.0129	0.0141
X23	0.0140	0.0135	0.0000	0.0137	0.0137	0.0144
X24	0.0149	0.0083	0.0000	0.0115	0.0161	0.0164
X25	0.0151	0.0135	0.0000	0.0140	0.0132	0.0135
X26	0.0136	0.0106	0.0000	0.0121	0.0156	0.0163
X27	0.0137	0.0097	0.0000	0.0119	0.0161	0.0165
X28	0.0146	0.0114	0.0000	0.0131	0.0145	0.0152
X29	0.0149	0.0127	0.0000	0.0137	0.0132	0.0146
X30	0.0149	0.0133	0.0000	0.0140	0.0130	0.0140

Table 4: Rank of classes.

Order	Classes	Overall evaluation value	Order	Classes	Overall evaluation value
1	X23	0.6245	16	X15	0.6046
2	X25	0.6242	17	X9	0.5974
3	X30	0.6224	18	X2	0.5969
4	X1	0.6212	19	X19	0.5938
5	X29	0.6195	20	X4	0.5919
6	X22	0.6194	21	X26	0.5894
7	X14	0.6166	22	X18	0.5774
8	X12	0.6160	23	X3	0.5755
9	X21	0.6160	24	X27	0.5724
10	X6	0.6138	25	X24	0.5487
11	X10	0.6100	26	X7	0.5463
12	X20	0.6095	27	X13	0.5238
13	X28	0.6091	28	X17	0.4974
14	X5	0.6081	29	X8	0.4893
15	X11	0.6078	30	X16	0.4011

Therefore, the following specific discussion is made in this chapter.

4.1. Components of a Performance Evaluation System for Student Achievement. Because the real situation of students' academic performance in each class is obtained from Table 1, it is possible to understand the specific composition and percentage of the existing overall performance evaluation system of the classes. Students' performance is mainly composed of two parts: regular grades and final examination results. Students should not neglect to pay attention to the usual grades, and good usual grades can avoid the lowering of the final overall performance ranking caused by the failure of a single final exam to a certain extent. The average of students' regular grades and final exams in 30 classes is shown in Figures 2 and 3, which shows that the average percentage of regular grades in the evaluation system of each class is almost 50%, which indicates that the current evaluation of students' performance in classes has fully considered students' learning situation in the whole semester, instead of evaluating students' academic development through a single exam. System is relatively more scientific.

Based on this, a more detailed analysis of the usual grades shows that the usual grades consist of three main components: class tests, postclass assignments, and class quizzes, as shown in Figure 4. The cumulative percentages of classroom tests, postclass assignments, and classroom quizzes for all 30 classes are shown in the graph. It can be seen that the majority of the classes had more than 50% of the classroom test scores and more than 40% of the postclass assignments. As a direct and rapid assessment indicator, classroom tests can effectively motivate students to participate in the classroom, making classroom lectures and comprehension analysis, in parallel, easy for class teachers to quickly help students to check the gaps. On the other hand, postclass assignments are an effective way to test students' understanding and true performance, but they have a certain degree of potential for students to learn from each other, so they should be lower in proportion than class tests. Finally, some classroom quizzes can be effective in rewarding the performance of some of the more active students, but these quizzes are usually simple and fragmented and do not allow for a comprehensive assessment of students' complete and authentic learning, so the percentage is very low and generally less than 1%.

Averaging the results of classroom tests, postclass assignments, and classroom quizzes across the 30 classes gives the results in Figure 5, which shows that the average percentage of classroom grades is almost 60% across all classes. This indicates that classroom tests are the most important means of evaluating student performance in the current class and that postclass assignments are also an important supplement to student performance.

4.2. Key Influencing Factors of Student Achievement. The main factors affecting students' performance can be divided into external and internal factors. External factors are the teaching and management level of the class itself, and internal factors are the teachers' and students' own factors, such as students' sleep time, teacher-student relationship, learning pressure, and internal learning motivation.

4.2.1. Exogenous Factor. In terms of exogenous factors, as mentioned earlier, the final composite grades of students in the selected classes consist of the scores of the accompanying exercises, the scores of the homework assignments, the scores of the accompanying quizzes, the scores of the regular grades, and the scores of the final exam papers. These scores not only reflect students' learning attitudes, motivation, and knowledge mastery, but also reflect the management level and the strength and capability of learning support services

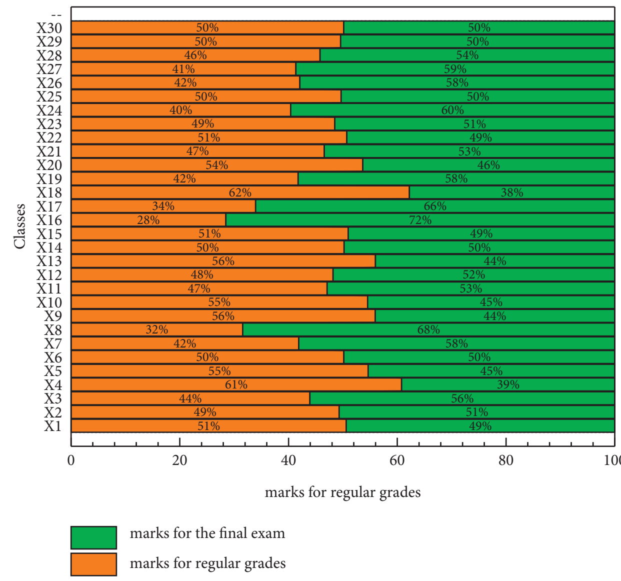

Figure 2: Average of student regular grades and marks of final exam.

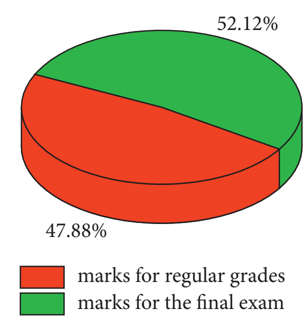

Figure 3: Analysis of the usual grades shows that the usual grades consist of three main components.

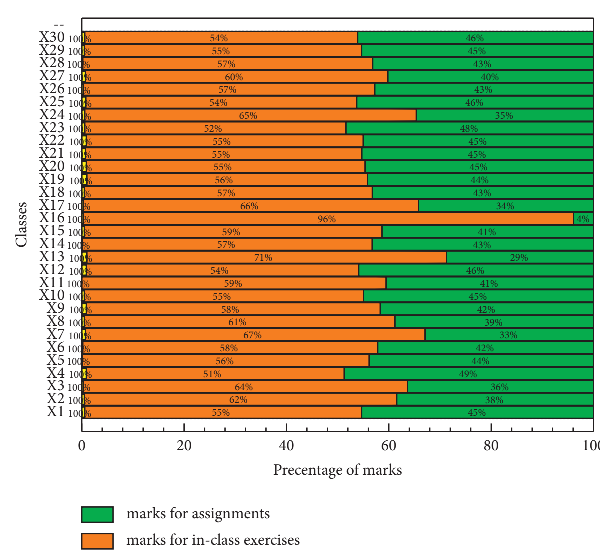

Figure 4: Three main components: class tests, postclass assignments, and class quizzes.

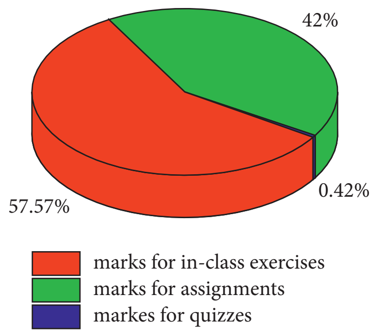

FIGURE 5: Average of percentage of assignment, in-class exercise, and quizzes.

of the classes. For example, students' grades of in-class practice, homework submission, in-class quiz, and regular grades are all related to the management and learning support services of classes. Students' grades in all categories are higher in classes with good management and strong learning support services and are worse in the opposite direction. From the previous analysis, the results of ranking classes based on student achievement and entropy-weighted TOPSIS model and the comparison of Table 1 and 4 show that the top-ranked classes also have higher mean values for all student achievements, while the bottom-ranked classes have worse mean values for all student achievements. The ranking results basically reflect the current situation of the class. This result shows that it not only is feasible but also has some theoretical basis to use students' academic performance as one of the conditions for evaluating classes. Therefore, adding the examination of students' academic performance to the comprehensive evaluation indexes of classes would better reflect the level of management and learning support services of classes in college.

Based on the results in Table 4, we can grade the comprehensive evaluation value $C = (C_1, C_2, \ldots, C_{30})$ and then assign a grade to classes. For example, let $C_i \geq 0.6$, $i \in \{1, 2, \ldots, 30\}$, be excellent, $0.5 \leq C_i \leq 0.6, i \in \{1, 2, \ldots, 30\}$, are normal, and $C_i \leq 0.5, i \in \{1, 2, \ldots, 30\}$, are poor. The grading of classes can make them develop their strengths and overcome their weaknesses, and also provide a theoretical basis for evaluating classes. As can be seen from Table 4, the ranked classes X8, X16, X17 need to be urged to identify their shortcomings in management and support services and to improve them.

4.2.2. External Factors. In contrast to uncontrollable external factors, intrinsic factors are the core and controllable factors that affect student performance in higher education.

In the process of data analysis, we first used the two indicators of regular grades and final exam grades in Table 1 based on the academic quality monitoring data to conduct the analysis, based on which scatter plots and trend lines are drawn, where the vertical axis is the regular grades and final exam grades of each class, respectively, and the horizontal axis is the intrinsic influencing factors to be investigated, according to which the correlation between student performance and each influencing factor is analyzed, and the results of the analysis are as follows.

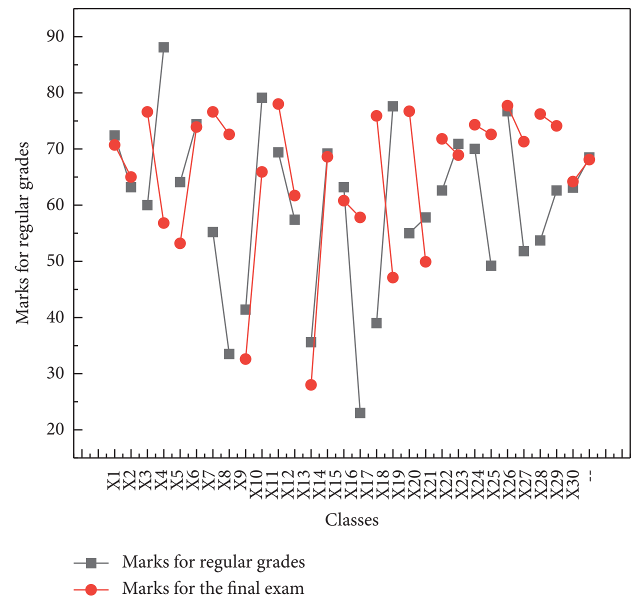

FIGURE 6: Comparison of the regular grade scores and the final exam scores of the 30 classes.

A comparison of the regular grade scores and the final exam scores of the 30 classes in Figure 6 shows that the two trends are basically the same, indicating that active participation in the regular classroom quizzes, as well as careful completion of homework assignments, can improve not only the total regular grade score, but also the final exam score.

In the process of data analysis, the correlation between the average sleep time, the composite student-teacher relationship index, academic stress, intrinsic motivation, and four internal factors with the regular and final grades was analyzed based on the results of the real student performance data of 30 classes based on the regular and final grades, respectively.

Good sleep time is an important factor that affects one's ability to work properly in class. The correlation between sleep time of more than 9 hours and regular grades is low, with R equal to 0.4 in Figure 7. Too much sleep time leads to a decrease in regular grades, which means that sleep is not better for regular grades, but may increase students' tendency to be lazy, which may have a negative impact on long-term regular grades. At the same time, the graph shows a high correlation between the final grade and more than 9 hours of sleep, with R equal to about 0.7. This means that, for the final exam, which is a surprise single academic test, ensuring a longer sleep time is conducive to increasing students' energy and motivation in the final exam, thus improving their final exam performance.

Faculty-student relationship is an important task for student management in classes. From the figure, we can find that, for college students, there is a certain degree of negative correlation between teacher-student relationship and usual grades in Figure 8, where R value is about 0.4. The reason for this is probably because college students and teachers are adults, and the teacher-student relationship is too close,

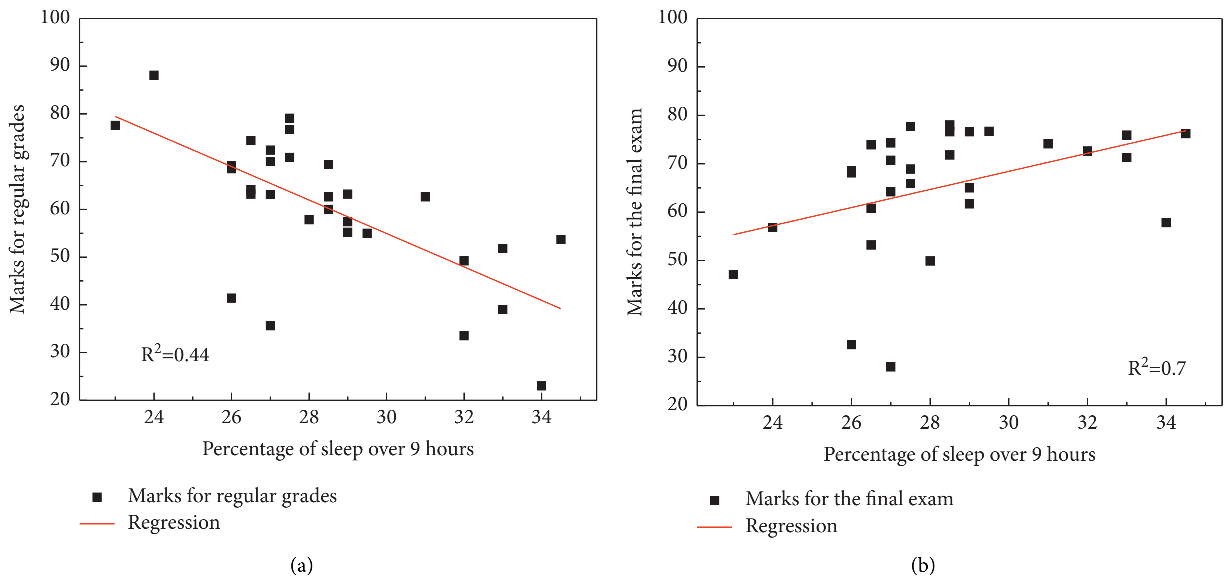

Figure 7: The regression of percentage of sleep over 9 hours related to marks and final exam. (a) Related to marks. (b) Related to final exam.

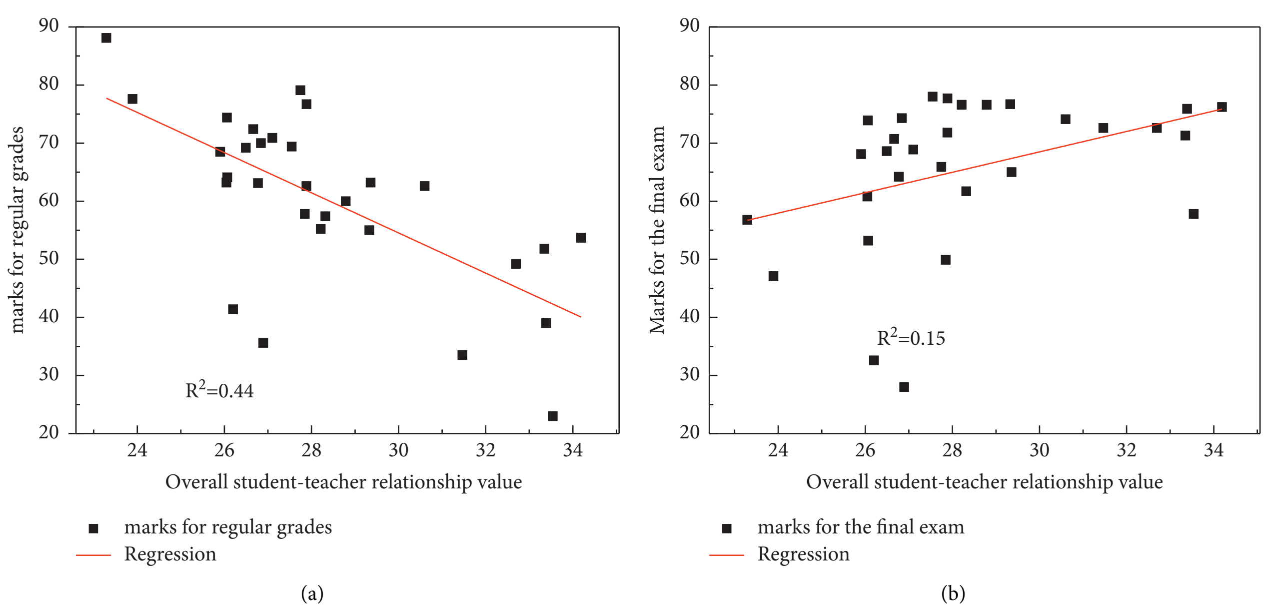

Figure 8: The regression of overall student-teacher related to marks and final exam. (a) Related to marks. (b) Related to final exam.

which easily leads to the lack of proper discipline and restraint of teachers for students, thus lowering the importance of students for their usual academic performance, thus reducing the students' attention to their own academic performance and thus leading to a certain degree of lowering of their academic performance. At the same time, it can be found from Figure 8 that the closeness of the teacher-student relationship hardly affects the students' final examination results, which indicates that the final examination is a relatively independent, fair, and objective academic testing method and is not easily influenced by the subjective preferences of teachers and students in classes.

Academic stress is a widely noted internal factor that affects student performance. Surprisingly, the correlation between academic stress and both regular and final exam scores was almost zero in Figure 9, indicating that academic stress is a relatively subjective internal factor and that there is no strong correlation between the level of academic stress and students' learning ability and performance.

The internal factor that contrasts with the academic pressure is the students' own motivation to learn. As can be seen from the graph, students with higher academic motivation instead show a certain degree of decrease in their usual academic performance, with R correlation coefficient of about 0.45 in Figure 10. This may be due to the fact that such class students are more inclined to expect praise from their teachers as a learning goal, while at the same time trying to avoid negative evaluations from the external

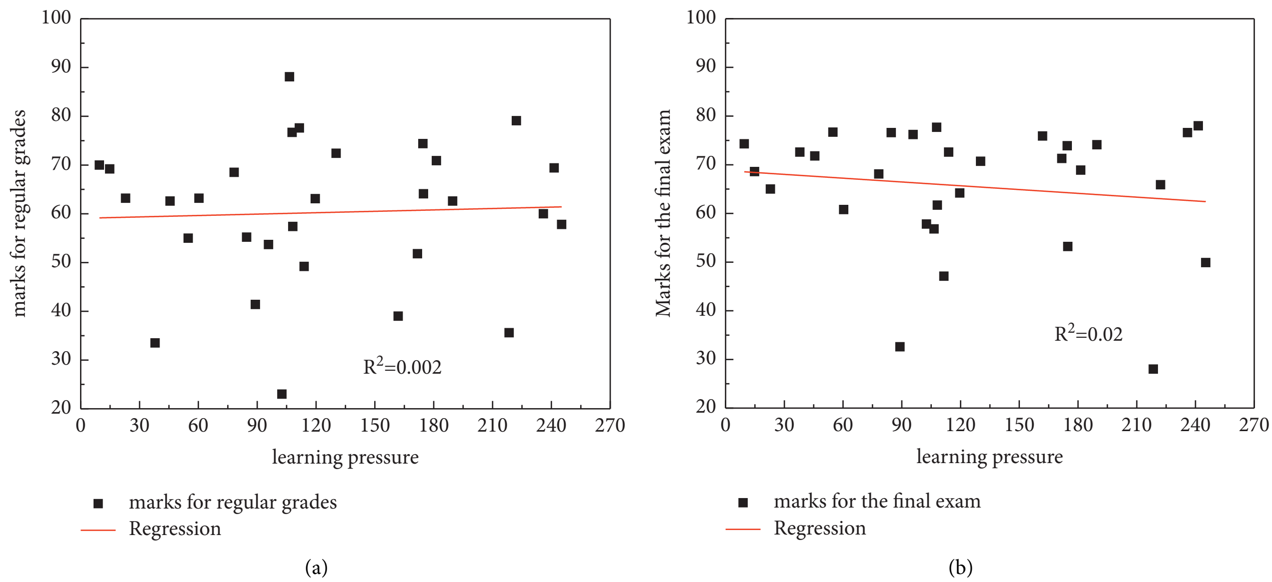

Figure 9: The regression of learning pressure related to marks and final exam. (a) Related to marks. (b) Related to final exam.

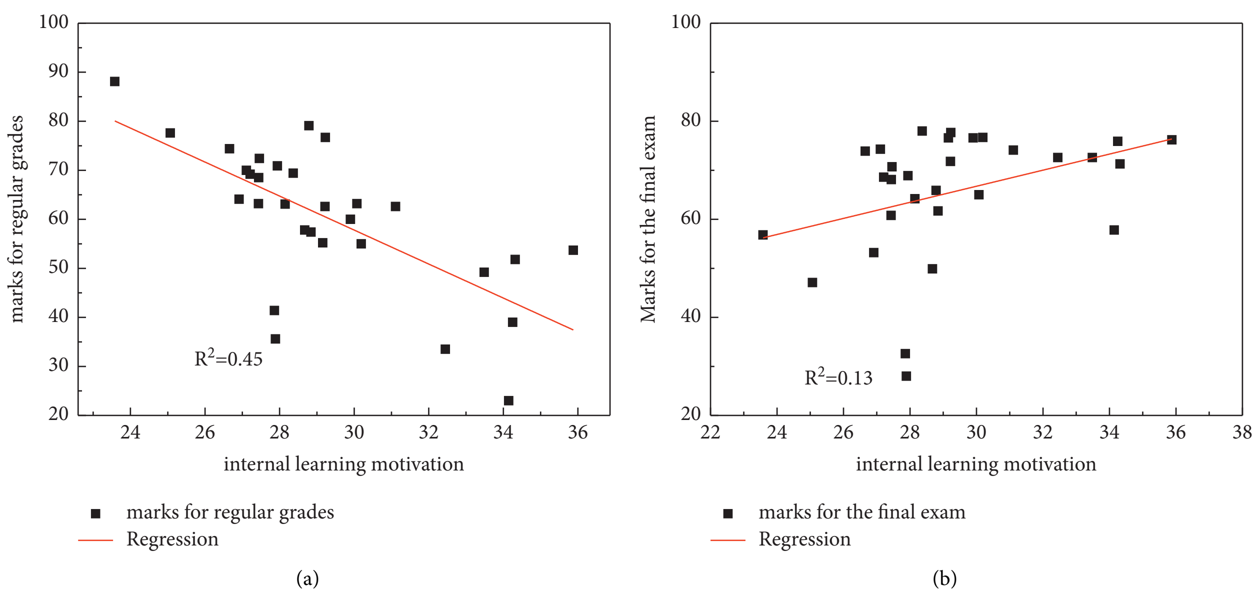

Figure 10: The regression of internal learning motivation and marks. (a) Related to marks. (b) Related to final exam.

environment, and instead, with these two motivations, they produce a certain degree of negative stimulation on the students' usual taking advantage of the opportunity. At the same time, the final exam, as a single objective test, has a small evidential correlation with learning motivation, with –R coefficient of about 0.13. The enhancement of learning motivation can enhance students' concentration to a lesser extent, thus increasing their constant base for the final exam.

5. Conclusion

With the continuous reform and development of higher education in China, it is necessary to evaluate the operation of colleges and classes from multiple perspectives. The comprehensive evaluation and ranking of classes based on students' performance and entropy TOPSIS model provide a certain basis for assessing the teaching management level of classes, ensuring teaching quality and improving teaching level, and provide a feasible method and theoretical basis for using students' academic performance as the evaluation index of classes of colleges. This method can be used for each class to evaluate its own work as well as one of the indicators for each class to assess the overall school operation. The main points of progress are as follows:

(1) The entropy-weighted TOPSIS method is used to comprehensively evaluate and rank students' academic performance, overcoming the drawbacks of

ranking based on the accumulation of raw scores and the average of all students' comprehensive scores in classes of college and reflecting the degree of differences brought about by factors such as the level of teaching management in classes of college, the quality of teachers' teaching, and the composition and calculation methods of comprehensive scores.

(2) The entropy weights of the indexes constructed by the information entropy method are used to rank the average of each student's grades in classes of college. The normalized matrix of student performance in the off-campus learning center avoids the subjectivity of human factors and improves the quality of student performance. The matrix is normalized to avoid the subjectivity of human factors and enhances the scientific, rational, and fair comprehensive evaluation based on students' performance. The matrix is normalized by the entropy weighting method to the average of students' achievements in the off-campus learning center.

(3) The main directions are given for the improvement of educational work in universities. For classes of college, for the differences and similarities between the way of evaluation of regular grades and final exam results of college classes, choose appropriate educational strategies.

(4) The results of this paper can be used as an effective means of evaluating student performance and provide a theoretical basis and technical means for the scientific evaluation of student performance in other institutions in the future.

(5) Future work can revise around the model, establish clearer and more reasonable indicators of student performance evaluation and their percentages, correctly deal with the dominant relationship between regular grades and final grades in the final grade, and establish a universal performance evaluation index applicable to each university.

Abbreviations

TOPSIS: Technique for Oder Preference by Similarity to Ideal Solution,
GPA: Grade point average,
AHP: Analytic hierarchy process,
CRITIC: CRiteria Importance Through Intercriteria Correlation.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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