

Analysis of College Students' Second Classroom Ability Evaluation Based on Principal Component and Clustering Methods

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Abstract

For better cultivating the comprehensive quality of students, this paper takes the perspective of the second classroom and combines various data of students' indicators, to explore and analyze, so as to better promote the development of higher education in our country. In this paper, a data set of second classroom from college students is studied using principal component analysis and hierarchical clustering. Based on the definition of second classroom, this paper constructs evaluation indexes which include competition, research and innovation, foreign language, cadre, public interest, and physical test for college students. Firstly, this paper uses principal components to analyze the second classroom situation of individual students, and selects the top four principal components as the main evaluation indexes of the second classes based on the cumulative contribution rate. Secondly, this paper uses hierarchical clustering method to cluster the samples. The model is evaluated and analyzed Silhouette Coefficient, Calinski-Harabasz Index, and Davies-Bouldin Index. The results show that the clustering model is optimal when the category is 3 and the cluster distance is 'single'. The model is reliable, scientific and reasonable. By identifying the categories of students and providing appropriate recommendations, we can better promote the development of higher education in our country.

Keywords: *The Comprehensive Quality of Students, Hierarchical Clustering, Clustering Evaluation Index, Data Visualization*

1. INTRODUCTION

1.1. Background

At present, college teachers mainly evaluate college students based on their performance in the first classroom, and pay less attention to the second classroom of college students.

In order for college teachers to better understand students' performance in the second classroom, cultivate students' second classroom ability and quality in a targeted manner, and promote the development of the second classroom in colleges and universities, this paper therefore conducts a more in-depth study on the evaluation of the second classroom.

The second classroom is an educational activity that allows students to improve themselves through organized

extracurricular group activities outside of regular teaching time, under the guidance of teachers and arrangements made by the schools [6].

In June 2018, The Communist Youth League of China and Ministry of Education of the People's Republic of China jointly issued "Opinions of the Ministry of Education on the Implementation of the Second Class Transcripts System of the Communist Youth League in Universities", which makes clear requirements for the future development of the second classroom. This opinion emphasizes that the implementation of "The Second Class Transcripts" system should focus on the balanced development of Classroom activities and the second classroom, and pay attention to the combination of learning and practice [13].

Therefore, this research can help universities nationwide to explore a scientific and efficient system

and practice system of "The Second Class Transcripts", which can provide important institutional guarantee and practical experience for higher education institutions to better perform their educational functions [2].

1.2. Contribution

At present, the academia is expanding the breadth and depth of research on the direction of the second classroom for college students. In this paper, a new evaluation system is proposed, and the main contributions of this paper are as follows:

- Data perspective. This paper explores several aspects of the student situation by collecting data from a domestic university with representative and unique data;
- Model building perspective. In this paper, on the basis of cluster analysis, multiple distance parameters are used to cluster the samples, and the optimal model is selected from them to evaluate the samples, and the established model has a certain degree of rationality;
- Model evaluation perspective. In this paper, in order to compensate for the chance of evaluation of one indicator, multiple indicators are used to evaluate the clustering effect and the model results are more reliable.

2. RELATED WORK

At present, China takes the evaluation of the second classroom of college students as an important direction in the evaluation of quality education of college students [3].

In terms of data collection, scholars at home and abroad mainly use questionnaires and interviews to collect data related to the second classroom of college students and study the second classroom of college students based on the collected data. Mouzhi Yu et al [12] used a questionnaire to investigate the performance of the second classroom of college students in a university since the implementation of the second classroom report card, analyzed the problems from the questionnaire results, and proposed a series of improvement measures to bring the second classroom report card into play. In order to improve the overall quality of college students, we propose a series of improvement measures to bring into play the positive role of the second classroom report card in nurturing college students. Zeng Jianxiong et al [11] adopted the interview method to conduct interviews with college students participating in the second classroom in the university to explore the situation of the second classroom of college students in the university, examine some of its failures and causes, and explore how to comprehensively promote the construction of the second classroom in the university, make the education mechanism of the second classroom in the university

systematic, scientific and effective, so as to carry out the second classroom more solidly and effectively. In order to carry out the second classroom education more solidly and effectively and better promote the overall growth and success of college students.

In terms of research methods, scholars at home and abroad are currently conducting in-depth studies on the evaluation of the second classroom of college students from operational research methods and traditional statistical methods, respectively. Huang Lijin et al [5] used Analytic Hierarchy Process to assign scores to the indicators at all levels of the second classroom of college students, and realized the evaluation analysis of the second classroom of college students by constructing a judgment matrix, performing hierarchical single ranking and hierarchical total ranking, and conducting consistency tests, and then calculating the weight values of indicators at each level of the second classroom of college students. Sun Na [8] used Analytic Hierarchy Process to construct an index system for the process of organizing activities in the second classroom of English, to evaluate the process of organizing activities in the second classroom of English, to find out the problems in the process of creating an extracurricular practice center of English in college, and to provide guidance for better organizing the second classroom. Wei Lei et al [9] used Analytic Hierarchy Process to make an objective evaluation of the second classroom performance and test the results of students' participation in the second classroom in order to guide students toward an excellent second classroom system for college students. Qiankun Yang et al [10] conducted a correlation analysis based on Linear Regression Theory between a certain influencing factor of the second classroom of all college students in the college and their average performance in the second classroom, and obtained that the influencing factor was significantly and positively correlated with the average performance in the second classroom, and the influencing factor was interpretable.

In summary, the above scholars mainly focus on questionnaire method and interview method in terms of data collection, and mainly focus on Operation Research Methods and Traditional statistical methods in terms of research method. In this paper, we improve the above data collection and research methods. In terms of data collection, we used the second classroom data set of a major in a university to study the second classroom situation of college students. In terms of research methods, we use PCA and hierarchical clustering to model and analyze the second classroom data of college students, which makes up for the subjectivity of the analysis hierarchy process in the operations research method and the applicability of the data distribution of linear regression theory in the traditional statistical method.

3. RESEARCH METHODOLOGY

3.1. Overall Research Idea

This paper is based on principal component analysis and hierarchical cluster analysis to analyze the second classroom of college students in a university. The research process can be divided into four steps: data collection, principal component analysis, multi-distance clustering analysis, and evaluation of clustering effects.

Step1: This paper establishes six indicators: competition score, research and innovation score, foreign language score, student leader score, public interests score and total sports score, and then collects data on the second classroom of college students in a university.

Step2: Performing principal component analysis on the data to map the principal component scores between 0 and 100.

Step3: In this paper, the scores of the four new indicators obtained from the principal component analysis were clustered based on $k=3, 4$, and 5 classes with four different distances of 'ward', 'complete', 'average', and 'single', respectively.

Step4: Using the contour coefficient, Calinski-Harabasz index, Davies-Bouldin index for the four distances of clustering effects were evaluated. The most suitable clustering distance and number of classes are selected according to the principle of majority rule. Accordingly, the data are clustered, and then a three-dimensional plot is drawn to show the data distribution of the clusters.

The flow chart is shown in Figure 1:

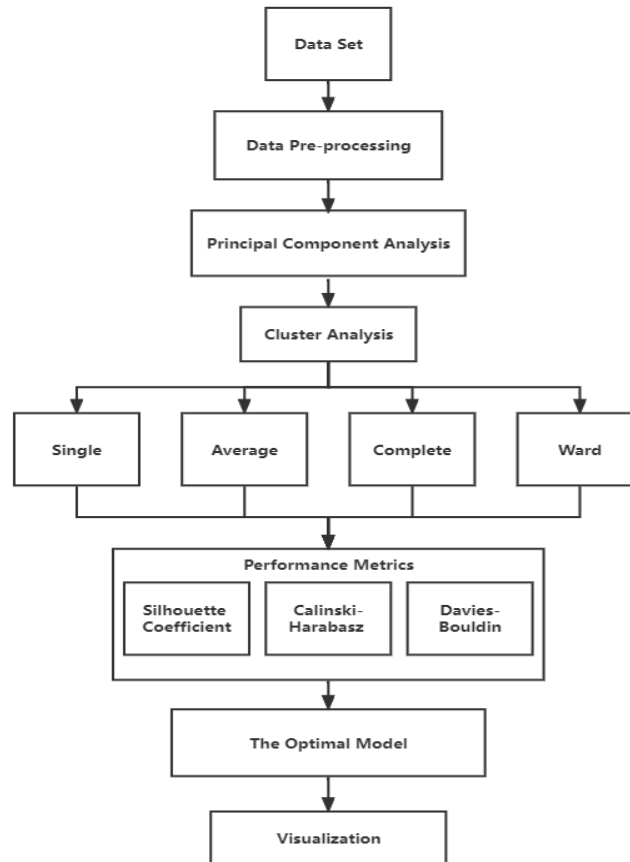


Figure 1. Flow chart.

3.2. Data Sources and Processing

This paper collects a dataset of the second classroom in a college of a university based on the six indicators established. This dataset has six variables, which are competition score, research and innovation score, foreign language score, student leader score, public interests score and total sports score. These variables are denoted

as $x_1, x_2, x_3, x_4, x_5, x_6$ in this paper. The relevant variables are described in the following table.

Table 1. Variable descriptions.

Variable	Explanation
x_1	Subject knowledge competitions in which students participated and won awards while at university.

x_2	Papers published by students participating in subject research projects.
x_3	Additional points for other foreign language certificates such as CET4 and CET6 certificates and IELTS TOEFL certificates obtained by university students during their studies.
x_4	The score of this item includes the extra points earned by students who have served as student club officers, professional class management officers, teacher assistants and other student officer positions during the semester.
x_5	Quantitative points are awarded based on the number of hours of charity work done by students during their studies.
x_6	The total score of each sport of college students' physical quality in an academic year aggregated by the university.

Because of the inconsistency in the scale of inter-indicator scores in the data set of this paper, they are standardized. Its function expression is as in Equation (1).

$$\tilde{a}_i = \frac{x_{ij} - \bar{x}_i}{s_i} \quad (1)$$

where x_{ij} is the value of the j -th sample of the i -th indicator in the data set, \bar{x}_i is the mean of the i -th indicator, and s_i is the standard deviation of the i -th indicator, and \tilde{a}_i is the standardized value of x_i .

After de-quantizing the dataset, a normalized dataset was obtained. As shown in Table 2 below.

Table 2. Standardized data.

Name	x_1	x_2	x_3	x_4	x_5	x_6
xxxx	2.584	2.117	3.393	3.053	2.077	0.935
xxxx	1.126	2.117	3.393	0.468	0.677	1.174
xxxx	-	-	-	-	-	-
xxxx	0.331	0.898	5.268	5.268	2.077	0.365
xxxx	4.041	6.993	0.358	0.640	0.640	0.918
...
xxxx	-	-	-	-	-	-
xxxx	1.126	2.117	0.385	0.640	0.723	0.166
xxxx	1.126	2.117	0.358	0.640	0.723	0.773
xxxx	-	-	-	-	-	-
xxxx	2.584	2.584	0.358	0.468	0.163	0.198
xxxx	-	-	-	-	-	-
xxxx	0.331	-0.32	0.321	1.576	1.576	1.016

3.3. Building a Principal Component Analysis Model

Firstly, the correlation coefficient matrix R between the six indicators in the dataset is calculated. The formula for calculating the correlation coefficient between two variables is given in Equation (2).

$$r_{ij} = \frac{1}{m-1} \sum_{k=1}^m \tilde{a}_{ik} \tilde{a}_{kj}, (i, j = 1, 2, \dots, 6) \quad (2)$$

where m is the sample size, r_{ij} is the value of the i -th row and j -th column of the correlation coefficient matrix R , and \tilde{a}_{ik} is the data in the i -th row and k -th column of the data set. of row i and column k in the data set.

In this paper, the strength of the correlation coefficient is defined in Table 3.

Table 3. Definition of the strength of the correlation coefficient.

Correlation coefficient interval (Absolute value)	Level
[0.8,1]	Extremely strong correlation
[0.6,0.8]	Strong correlation
[0.4,0.6]	Moderate correlation
[0,0.4]	Weak or no correlation

Then, the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_6$ (Ranking the characteristic roots from smallest to largest Order $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_6$) and the corresponding eigen roots: u_1, u_2, \dots, u_6 are calculated based on the correlation coefficient matrix R .

Finally, by calculating the variance contribution of the six principal components, the cumulative variance contribution of the top k principal components is obtained α_k . The variance contribution of the principal components α_k is given in Equation (3).

$$\alpha_k = \frac{\lambda_k}{\sum_{i=1}^6 \lambda_i} \quad (3)$$

In this model, the variance contribution ratio represents the percentage of variation in the original data set that can be explained by the new indicator. Based on the principle that the cumulative Based on the principle that the cumulative contribution is greater than or equal to 80%, the first four principal components are extracted in this paper.

In this paper, the scores of the four principal components are used as inputs to the hierarchical clustering model. To facilitate the subsequent work, a mapping function is used with a mapping interval of [0,100]. The mapping function as in Equation (4).

$$y_{ij} = \frac{100}{\tilde{a}_{max} - \tilde{a}_{min}} \times (\tilde{a}_{max} - \tilde{a}_{min}) \quad (4)$$

where y_{ij} is the mapped value of a_{ij} , a_{max} is the largest value in a_{ij} , and a_{min} is the smallest value in a_{ij} .

3.4. Building a Cluster Analysis Model

In this paper, we use hierarchical clustering method to cluster the samples. In order to make the clustering better, we choose four different cluster distances, such as ward, complete, average and single:

- Ward: Refers to the shortest distance of samples between clusters as the cluster distance.
- Complete: Refers to the longest distance of samples between clusters is the cluster distance.
- Average: Refers to the average of the sample distances between classes is used as the cluster distance.
- Single: Refers to the distance between the sample centers between clusters as the cluster distance.

3.5. Clustering Effect Evaluation

After clustering, they were divided into 3, 4, 5 classes in order, and then their clustering effects were evaluated. In this paper, we used the following three evaluation methods: Silhouette Coefficient [7], Calinski-Harabasz Index [1], Davies-Bouldin Index [4].

- Silhouette Coefficient is the comparison of the similarity of the sample for its own class and other classes, and the larger the Silhouette Coefficient, the better the clustering effect.
- Calinski-Harabasz is an analysis of the degree of intra-class closeness, and the degree of class. The degree of dispersion between classes, so as to evaluate how well the clustering works. In general, the larger the Calinski-Harabasz number, the means its clustering effect is more excellent.
- Davies-Bouldin also compares the clustering effect by calculating the sum of intra-class distance and inter-class distance. The smaller the value of Davies-Bouldin, the better the clustering effect.

Therefore, this paper uses these three methods to evaluate the clustering results of each type, and by comparing the magnitude of the values of three metrics for evaluation, as a way to determine which type of clustering to choose under. Since the three evaluation clustering effect indicators may inconsistent judgments, for example, if the Silhouette Coefficient thinks that a certain classification effect is good. However, it is Calinski-Harabasz which shows that the other category works better, thus leading to an ambiguous choice of results. Therefore, this paper using a minority-majority

approach and a holistic analysis. For example, if there are two methods that think that type A clustering works well A method considers that type B clustering works well, so A scenario clustering is chosen.

4. EXPERIMENTS AND RESULTS

4.1. Results of Principal Component Analysis

4.1.1. KMO and Bartlett's Test

Before using the principal component analysis, the results of the principal component analysis used in this paper were tested considering the feasibility of the method, and the results were obtained as shown in Table 4.

Table 4. KMO and Bartlett.

Kaiser-Meyer-Orlkin	Metrics	0.640
Bartlett's spherical test	Approximate cardinality	163.642
	df	15
	Sig	0.000

For Bartlett's test of sphericity, the null hypothesis is that the correlation coefficient matrix is a unit array, i.e., all elements on the diagonal of the correlation coefficient matrix are 1 and all elements on the non-diagonal are zero. The results show that the value of KMO was $0.640 > 0.6$, indicating a strong correlation between the variables. (The closer the KMO statistic is to 1, the stronger the correlation between the variables stronger, the weaker the bias correlation.) And the significance level of Bartlett's sphericity test is less than 0.05, so the null hypothesis is rejected. indicates that principal component analysis can be performed.

4.1.2. Analysis of Results

Firstly, calculate the correlation coefficients of the six indicators. As shown in Table 5 below.

Table 5. Correlation coefficients among the 6 indicators.

	x_1	x_2	x_3	x_4	x_5	x_6
x_1	1.000	0.773	0.282	0.310	0.384	0.062
x_2	0.773	1.000	0.303	0.216	0.284	0.045
x_3	0.282	0.303	1.000	0.382	0.264	0.003
x_4	0.310	0.216	0.382	1.000	0.413	0.086
x_5	0.384	0.248	0.264	0.413	1.000	0.122
x_6	0.062	0.045	0.003	0.086	0.122	1.000

From Table 5, we can see that the correlation coefficient between x_1 and x_2 is 0.773, and the correlation coefficients between x_1 and x_3 , x_4 , x_5 , and x_6 are 0.282, 0.310, 0.384, and 0.062, respectively. 0.282, 0.310, 0.384, and 0.062, respectively, so x_1 has the strongest linear correlation with x_2 . x_3 and x_6 with the

remaining variables the correlation coefficients between all of them are less than 0.4. The correlation between x_4 and x_5 is stronger than all other variables, with a correlation coefficient of 0.413. Based on Table 3, we conclude that x_1 and x_2 are strongly correlated, and x_4 and x_5 are moderately correlated.

Then, the six indicators were subjected to principal component analysis and six principal component loadings were obtained. As shown in Table 6 below

Table 6. Principal component loadings.

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
x_1	0.526	0.375	0.217	0.104		0.719
x_2	0.488	0.487	0.234	-0.104		-0.674
x_3	0.381	-0.159	-0.422	-0.695	-0.402	
x_4	0.403	-0.444	-0.303		0.734	
x_5	0.41	-0.354		0.632	-0.537	-0.129
x_6		-0.524	0.791	-0.3		

In Table 6, *Comp1*, *Comp2*, ..., *Comp6*, respectively represent the first, second, ..., sixth principal components. From Table 6: *Comp1* and x_1 and x_2 loadings are 0.526 and 0.488, respectively, they are larger than all other loadings, so *Comp1* contains mainly the information content of x_1 and x_2 (the principal components are more correlated with the variables with larger loadings). *Comp3* with the load of x_6 is larger than the load of *Comp2* and x_6 , so *Comp3* contains mainly the amount of information of x_6 . Then, *Comp2* contains mainly the amount of information of x_4 , x_5 . Since x_1 , x_2 , x_6 are already included in *Comp1* and *Comp3*, the remaining primitive variables with large loadings in *Comp2* are x_4 , x_2 . *Comp4* has the largest load with x_3 , so *Comp4* contains mainly the amount of information of x_3 . To determine how many principal components need to be taken in this paper to reflect the information of the original data set, draw a gravel map of these six principal components.

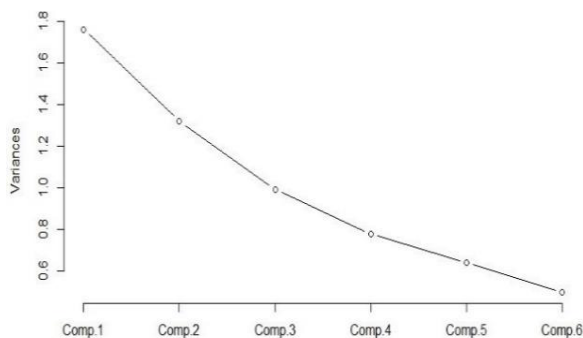


Figure 2. Gravel map of six principal components.

As can be seen from the Figure 2: the first four principal components already contain a large amount of information about the original data set, and the fourth principal component followed by the other principal components has a small decline, indicating that they

contain little information about the variation of the data and have no important impact on this paper's analysis. Therefore, this paper decided to discard these principal components with small information content. In order to verify that the four principal components can reflect the variance of the original data, we calculate the cumulative contribution of the variance of the first four principal components in the original data set, and we can get 87% of the variance of them in the original data set. That is, the Using these four principal components can explain 87% of the information in the original data, and they are linearly independent of each other and can be used independently as an evaluation index.

Based on Table 6, a description of the principal components is given as shown in Table 7.

Table 7. Explanation of principal component analysis.

Cluster	Explanation	Main contained raw variables
<i>Comp1</i>	Innovation	x_1 , x_2
<i>Comp2</i>	Practice	x_4 , x_5
<i>Comp3</i>	Physique	x_6
<i>Comp4</i>	Foreign Language	x_3

In this paper, the four principal component scores are used as new variables to measure the overall performance of the second classroom. A college student A was randomly selected and a radar map of his ability in the second classroom was drawn for him. As shown in Figure 3.

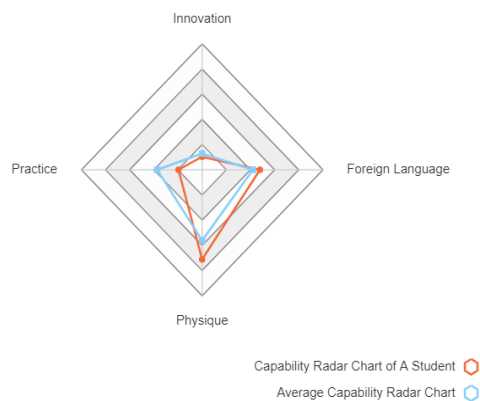


Figure 3. College student a capability radar chart.

The red line in the graph represents the ability value of college student A. The blue line represents the average ability value of all students in this study. From Figure3, we can see that A is lacking in practice and needs to be further strengthened. However, A had higher proficiency values in innovation, sports, and foreign languages than all students in this study.

The calculations showed that A scored 5.54 higher in innovation than the average ability value of all students studied; in practice, A scored 29.37 lower than the

average ability value of all students studied; in physical fitness, A scored 5.60 higher than the average ability value of all students studied; in innovation, A scored 6.22 higher than the average ability value of all students studied.

In summary, although the scores of College Student A in sports and innovation are higher than the average ability value, they are not very different from the average ability value, which means that A still has more room for development in these aspects. From the aspect of innovation of A, his ability value is much higher than the average ability value, which indicates that he has innovative thinking and can discover, dig and create new things better.

4.2. Results of Cluster Analysis

4.2.1. Selection of Cluster Distance

Before using the principal component analysis, the results of the principal component analysis used in this paper were tested considering the feasibility of the method, and the results were obtained as shown in Figure 4.

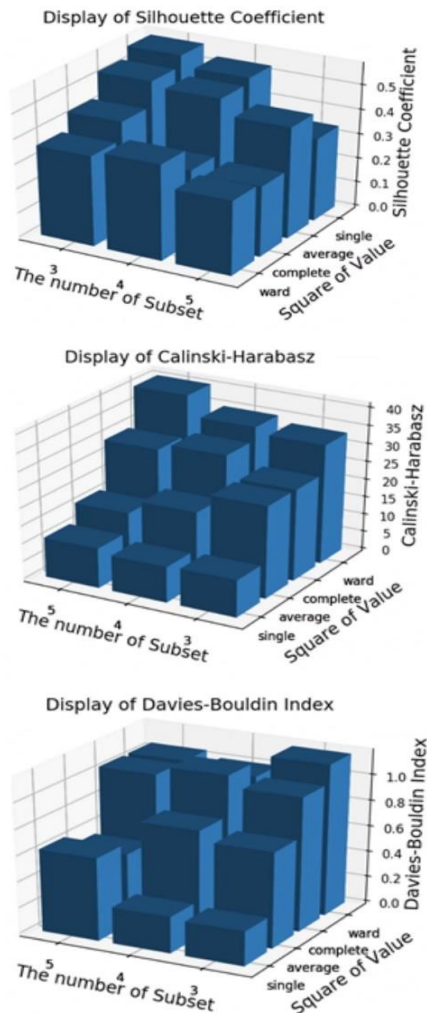


Figure 4. 3D effects of different evaluation indicators.

From Figure 4, the Silhouette Coefficient of the clustering result is the largest when the number of classes is 3 and the Cluster distance is single. According to the nature of Silhouette Coefficient, the larger the value, the better the clustering effect, so it is considered that the number of classes is 3 and the Cluster distance single clustering effect is the best. The Calinski-Harabasz Index of the clustering result is the largest when the number of classes is 5 and the Cluster distance is ward. According to the nature of Calinski-Harabasz Index, the larger the value, the better the clustering effect, so it is considered that the number of classes is 5 and the Cluster distance ward clustering effect is the best.

The Davies-Bouldin Index x of the clustering result is the smallest when the number of classes is 3 and the Cluster distance is single. According to the nature of Calinski-Harabasz Index, the smaller the value, the better the clustering effect, so it is considered that the number of classes is 3 and the Cluster distance single clustering effect is the best.

4.2.2. Analysis of Results

In this paper, the analysis is based on the clustering results, which show that the samples are divided into three classes, namely Class *I*, Class *II* and Class *III*.

The mean values of the indicators for each category are shown in Table 8 below.

Table 8. Average value of indicators for each category.

Class	Innovation	Practice	Physique	Foreign Language
I	12.8718	36.35144	63.7328	58.5662
II	95.6245	72.84833	88.1915	72.5870
III	46.2969	33.25271	45.9172	25.2663

From Table 8, it can be seen that students in category A are much higher than students in the other two categories in all indicator values. Between category *I* and category *III* students, category *III* students scored significantly higher than category *I* students on innovation indicators. The scores for practical, physical, and foreign language were all lower than those for category *I* students, especially in foreign language, where category *III* students scored 33 points lower than category *I* students.

The variance values for each category of indicators are shown in the following table.

Table 9. Variance values of indicators for each category.

Class	Innovation	Practice	Physique	Foreign Language
I	135.024	119.316	291.017	188.701
II	38.2898	1474.425	278.877	59.108
III	869.166	155.126	340.813	170.337

From Table 9, it can be seen that among the three categories of students, the largest variance value is found

in the practical aspect for category *II* students, the smallest in the innovation and foreign language aspect, and the largest variance is found in the innovation aspect for category *III* students. In summary, category *II* students have greater advantages in innovation, practice, physical fitness, and foreign languages. However, there are large differences among students in terms of practice. Category *III* students are at an intermediate level in innovation, but students differed significantly in this area, while occupying the lowest values in all the remaining areas. Category *I* students are at the lowest level of innovation and the rest are at the middle level.

5.CONCLUSION

This paper establishes six indicators, namely, competition score, research and innovation score, foreign language score, student leader score, public welfare score, and total physical test score, corresponding to the collection of second classroom data of college students in a university.

Firstly, four principal components (innovation, practice, physical fitness, and foreign language) were extracted from six indicators (competition score, research and innovation score, foreign language score, cadre score, public service score, and total sports score) using principal component analysis, and their cumulative variance contribution rate reached 87%. Using the four principal component scores as indicators for evaluating the second classroom, a radar chart was drawn, and a college student was randomly selected and analyzed for the second classroom about him. The analysis shows that the student is lacking in practice and needs to be further strengthened. However, the student is better in innovation and is at an average level in physical fitness and foreign language.

After obtaining the results of principal component analysis, the four principal component scores were clustered according to different cluster distances and number of clusters using hierarchical clustering, and then the clustering effect was evaluated by applying the Silhouette Coefficient, Calinski-Harabasz Index, Davies-Bouldin Index. Based on the evaluation results, the clustering method of clustering into 3 classes and cluster distance of single was selected for clustering. The student population was divided into 3 categories, *I*, *II* and *III*. Category *II* students have greater advantages in innovation, practice, physical fitness, and foreign language, but there are significant differences between students in practice. Category *I* students are at the lowest level of innovation and at an intermediate level in all other areas.

The results allow teachers to understand the current status of their students' development in the second classroom. For the individual student, teachers can develop students' abilities more comprehensively based

on the Capability Radar Chart; for all types of students, teachers can provide guidance to students in category *II* who are weak in Practice, give help to students in category *I* in Innovation, and guide students in category *III* to strengthen their learning in Practice, Physique and Foreign Language; for students as a whole, teachers can target to increase the proportion of Innovation in the second classroom due to the large number of students in category *I*.

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REFERENCES

- [1] Caliński T, Harabasz J 1974 "A Dendrite Method for Cluster Analysis" *COMMUN STAT-THEOR M* 3:1-27.
- [2] CCYL Central Committee 2018 Opinions of the Ministry of Education on the Implementation of the "Second Class Report Card" System of the Communist Youth League in Universities *All-China Youth Federation* 5.
- [3] Cheng Y 2010 Research on the Second Classroom Talent Cultivation Model in Colleges and Universities.
- [4] Davies D L, Bouldin D W 1979 "A Cluster Separation Measure" *TPAMI PAMI*-1(2):224-227.
- [5] Huang L J, Pang H B, Shi Y J 2022 The evaluation system of second class report card in higher education institutions based on CIPP model and AHP *China-Arab States Science and Technology* 2022(01):150-154.
- [6] Liu Q 2014 Research on the construction of the second classroom in colleges and universities *Education and Vocation* 2014(06):41-42.
- [7] Shutaywi M, Kachouie N N 2021 Silhouette Analysis for Performance Evaluation in Machine Learning with Applications to Clustering *Entropy* 23(6):759.
- [8] Sun N 2015 The establishment of the process evaluation index system of English second classroom organization activities *Computer Technology and Development* 2015 25(05):157-160.
- [9] Wei L, Duan W C The construction of comprehensive quality assessment system for college students based on AHP-Fuzzy Comprehensive Judgment Method *China Market* 2010(48):222-225.

- [10] Yang Q K, Zhao S P, Liang C Y Building a 'big data + ideological and political education' quality evaluation system based on 'the second class report card' *Heilongjiang Researches on Higher Education* 2020 38(2):133-138.
- [11] Yu M Z 2020 Analysis and reflection on the effect of the implementation of the second class transcript system for university students: an example from Huabei Normal University for example *Science & Technology Vision* 2020(34):46-47.
- [12] Zeng J X, Song D, Liu Y R 2019 Second classroom for college students: realistic dilemmas and ways to dissolve them *Higher Education of Sciences* 2019(03):81-88.
- [13] Zeng J X 2018 A study on the influence of second classroom on developing core competitiveness of college students.

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