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A Study on the Economic Linkage of Greater Sanya Tourism Highway and the Synergistic Path of Double Leaders in Universities Based on Big Data Computational Optimization

Qiong Liu[1,✉], Dan Han[1]

[1] *Sanya Institute of Technology, Sanya, Hainan, 572000, China*

ABSTRACT

Based on the status quo of Sanya Digital Intelligence Tourism Economy, this paper puts forward the strategy of intelligent teaching change under the dual-leader cultivation mode of colleges and universities. Relying on clustering analysis technology to achieve the mining processing of the whole process data of the wisdom teaching platform, to promote the optimization of the process of wisdom teaching change. The catechism data of the basic course of tourism management of a smart teaching platform is collected, and z-score and PCA principal component analysis are utilized to eliminate the quantitative influence of the data. The best cluster values were determined by hierarchical cluster analysis, and the learners were divided into three cluster groups with the help of K-Means clustering algorithm. One-way ANOVA was introduced to compare the achievement data before and after smart teaching of the three groups of students to explore the effect of smart teaching. The results showed that among the paper grades, category 2 students had the greatest change in the mean value of their grades. In practical grades, the mean value of category 2 students' practical grades was 95.63, which was 20.18 and 26.75 points higher than those of category 0 and category 1 students, respectively. p-value of 1.56951E-17 was less than 0.05, which indicated that the grades of the three categories of students showed significant differences.

Keywords: smart teaching, hierarchical clustering, K-Means clustering, one-way ANOVA, tourism talent cultivation

1. Introduction

After the rapid development in recent years, China's social and economic landscape has undergone great changes, the national standard of living has been greatly improved, and gradually began to enter the era of leisure tourism for all [1-2]. With the announcement of the State Council that Hainan Province has become an international tourist island, Hainan has once again become a hotspot for

✉ Corresponding author.
E-mail address: lq15501979218@163.com (Q. Liu).
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domestic and international tourism [3-4]. As the only tropical island in China, Hainan has rich tourism resources, which are scarce, unique and irreplaceable in the whole country, and even in the international arena [5-6]. And tourism has become a pillar industry of Hainan's national economy, vigorously develop tourism, is Hainan Province to maintain, enhance and play the ecological advantages, to create huge economic and social benefits of the inevitable choice, but also to cope with the global financial crisis, change the mode of economic development of the best decision [7-10]. However, Hainan Province was founded late, the level of economic development is low, and the overall infrastructure is incomplete. For example, the low level of highway, low road network coverage, poor road quality, tourism highway, scenic spot highway mismatch, no comprehensive transportation station hub, the traffic network structure of hierarchical contradictions and other problems [11-14].

The construction and implementation of a number of major regional transportation infrastructure projects within Sanya, such as the West Ring High Speed Railway, the East Intercity Railway, the separation of the three ports, and the expressway around the city, will have a significant impact on the Sanya urban structure, land use layout, and the network of the urban transportation system, and at the same time, it will also bring a new historical opportunity for the optimization and adjustment of the urban system in Sanya [15-17]. However, Sanya has not yet established the transportation development idea with tourism service support as the core, and the construction of urban comprehensive transportation system belongs to the traditional development mode of small and medium-sized cities, which is mainly manifested in the low technical indexes, poor accessibility, lack of coordination between highway and landscape, relatively single landscape setting, and relative backwardness of transportation infrastructure, which is difficult to satisfy the needs of rapid development of tourism industry [18-20].

Based on the background of digital wisdom tourism, this paper sorted out the implementation conditions of the dual-leader talent cultivation model for tourism management majors in colleges and universities. By analyzing the status quo of digital intelligence tourism in Sanya, Hainan, it puts forward a smart teaching change strategy that combines the tourism highway economy and the dual-leader model in colleges and universities. The hierarchical aggregation algorithm and K-Means clustering algorithm are used as the educational data mining clustering algorithm of the smart classroom teaching platform to explore the hidden educational laws behind the learner behavior data. Take a smart teaching platform as an example to analyze the behavioral characteristics of tourism management students. The z-score and PCA principal component analysis are used to standardize the data, and the hierarchical clustering is completed based on Euclidean distance and Ward's method. K-Means clustering algorithm was used to cluster the data, relying on the descriptive statistical results of the behavioral performance of different categories of learners to obtain their behavioral characteristics. SPSS26 software was used to analyze the data of theoretical and practical classes before and after the wisdom education of the three categories of students to evaluate the effect of wisdom teaching.

2. Tourism highway economic linkage and university dual-leader synergy path design

The development of digital technology and intelligent technology has changed the pattern of development of some industries, prompting the development of industry gradually oriented industrial upgrading and industrial transformation reform. In order to keep up with the trend of intelligent and digital education, colleges and universities should strengthen the adaptability of education. For the cultivation of tourism talents in Sanya, this chapter combines the talent cultivation mode of tourism management majors and the status quo of digital and intelligent tourism development in Sanya, and puts forward the strategy of intelligent teaching change for tourism management majors.

2.1. Conditions for the implementation of the dual-leader training model for tourism management majors

1) School-enterprise “double-head professional leader” teacher team. The mode of “double professional leaders” of university and enterprise means that universities select and employ two leaders in one major at the same time, one is “professional leader on campus”, who is a backbone teacher with high moral integrity, good teaching effect, outstanding scientific research ability, and strong team organization, coordination and management ability; the other is “professional leader in enterprise”, who is a backbone teacher in an enterprise that maintains stable and close cooperation with the university. The other one is the “enterprise professional leader”, who is selected from the enterprises that have maintained stable and close cooperation with the university, and is an expert managerial talent or technical expert with high moral integrity, love for education and strong influence in the industry. The two leaders with different advantages will implement agreement management, clarify their respective roles and positioning, rights and responsibilities, and strict selection and assessment, use and cultivation, so that they will perform their respective duties, jointly build and enhance the overall quality of the team, and jointly organize and lead the team or members to do a good job in professional teaching and professional connotation construction.

2) Establishment of on- and off-campus practical training bases. The “practice” of higher education is not only a ladder for learning “theory” or a process of making skills more skillful, but the main purpose is to learn to work. Therefore, the design of on-campus and off-campus training bases should be based on the analysis of work tasks, and the layout of the teaching place should be designed according to the principle that the spatial structure coincides with the work site. The practical training room is not only a place for skill training, but should be able to build a context for the integration of occupation and learning, so that the teaching process is closely integrated with the work (or simulated work) process.

3) Establish digital learning resources. In order to accelerate the pace of curriculum construction and reform of tourism management, promote the sharing of high-quality teaching resources, create a digital learning environment for “anytime, anywhere” learning, and improve the effectiveness of school running and the quality of talent training, according to the actual requirements of the construction of model colleges and universities and assessment, based on the principle of school-enterprise alliance and joint construction and sharing, and based on the specialty Based on the principle of joint construction and sharing between schools and enterprises, and according to the professional cultivation objectives and professional courses, the teaching resource library of tourism management will be established.

4) Actively promote the reform of teaching methods and teaching tools. Reform the teacher-oriented teaching methods in the past, and actively adopt various teaching methods such as inspirational, guided inquiry, and teacher-student interaction. Make full use of the college multimedia classroom, campus network and other modern teaching means, so that the use of multimedia teaching courses and hours to reach 100% of the ratio.

2.2. Status of Economic Development of the Greater Sanya Digital Intelligence Tourist Highway

The development status of digital intelligence tourism in Sanya, Hainan is mainly reflected in the following aspects: First, information infrastructure construction. As of March 2022, more than 13,000 5G base stations have been built in Hainan, realizing continuous outdoor coverage in cities and counties, and building a “full optical network province”, realizing the coverage of optical fiber, 4G and WiFi in key public places. The construction of “4G + optical communication” network in urban and rural areas has made it possible to extend the network coverage to the countryside and narrow the digital divide between urban and rural areas. At present, Hainan has built 6 submarine cables, 11T out of the province broadband, network communication speed increased several times. At the same time, Hainan has realized the province's government information integration, is the only province in the country, the construction of “data, personnel, funds, management, technology” big data “five centralized" system, co-ordinate the construction of the province's e-government infrastructure. Second, the construction of digital tourism platform. Hainan Province actively promote the construction of digital tourism platform, in 2020, the Hainan Provincial Culture and Tourism Department launched the "Smart Tourism Hainan APP", through the cell phone application for tourists to provide comprehensive tourism services, including tourism information query, personalized services and safe and standardized tourism environment, so that tourists can experience a cell phone can travel all over the convenience of Hainan.

2.3. Wisdom Teaching and Learning Change Strategies for Tourism Management Majors

1) Build an intelligent teaching environment. Colleges and universities need to increase financial investment, actively update technology, and build a teaching environment that integrates intelligent classrooms, advanced laboratories and practical training bases. At the same time, the implementation of regular technical equipment assessment mechanism to ensure the timely elimination of backward equipment, and the introduction of cutting-edge digital teaching tools and equipment, such as intelligent blackboards, interactive multimedia systems, etc., in order to fully support the in-depth implementation of intelligent teaching. Strengthening the updating and maintenance of software systems is also key to ensuring the stable operation of digital teaching. Utilizing cloud computing, big data and other technical means, integrating high-quality teaching resources inside and outside the university, and constructing a shared teaching resource library, including online courses, teaching videos, industry cases, etc., to provide teachers and students with rich and diverse learning materials.

The construction of intelligent teaching environment can have a positive impact on students. The richer and more vivid teaching content and learning methods provided by the intelligent teaching environment can stimulate students' interest and enthusiasm in learning. At the same time, with the help of intelligent teaching means and practical activities, students can better combine theoretical knowledge with practice and improve their practical ability. In addition, the intelligent education platform provides convenient interaction and communication channels for teachers and students, which makes the communication and cooperation between teachers and students closer and more efficient.

2) Integration of quality teaching resources. Colleges and universities can establish on-campus or inter-campus teaching resource sharing platforms, digitize and upload high-quality teaching resources to the platform, so that teachers and students can access the platform at any time and any place to obtain the required teaching resources. At the same time, colleges and universities can establish cooperative relationships with tourism enterprises and industry associations to introduce high-quality teaching resources in the industry, including enterprise cases, industry reports and practical experience sharing, etc., so as to provide students with a more realistic and vivid learning experience. Colleges and universities can also make use of school-enterprise cooperation projects to jointly develop teaching resources with some enterprises to realize resource sharing and complementary advantages and provide students with more practice opportunities, which can promote the in-depth cooperation between schools and enterprises and promote the integrated development of industry-university-research.

Integrating and optimizing teaching resources not only enriches the teaching content, but also makes the teaching form more diversified, which greatly stimulates students' learning interest and enthusiasm. At the same time, the reference and application of quality teaching resources by teachers in the process of integrating quality teaching resources also helps to innovate teaching methods and approaches and improve teaching effectiveness. In addition, quality teaching resources often pay more attention to practice and application, which can provide students with more practice opportunities and practice scenes, so that students' practical ability, innovation ability and comprehensive quality can be cultivated and improved, laying a solid foundation for their future career development.

3. Analysis of Educational Data Mining Related Technologies for Smart Teaching Platforms

As an important part of smart teaching in tourism management, the smart teaching platform mines its teaching behavior data, which is of great significance in promoting the reform of the evaluation process of smart classroom teaching. However, the big data of teaching behavior in the smart teaching platform is usually not directly equivalent to educational information, and it is necessary to rely on data mining technology to explore the hidden potential value behind the data. Educational data mining usually adopts automated processing methods, such as classification, clustering, regression, etc., to explore the values and patterns embedded in large amounts of educational data. This chapter describes the relevant techniques that need to be used to mine the learner characteristics of smart teaching platforms from the current needs of smart teaching evaluation reform.

3.1. *Hierarchical Cluster Analysis*

In order to reduce the negative impact of randomly determining the number of clusters on the clustering effect, this paper first adopts the hierarchical cluster analysis algorithm that can adaptively obtain the optimal or near-optimal number k of clusters, and then uses the number of clusters as the initial specified number K of values for the K-Means cluster analysis, in order to reduce the error caused by manually selecting the K values.

In this paper, the hierarchical aggregation algorithm in hierarchical clustering algorithm is used, and the Euclidean distance is used as the similarity measure. The linkage rules mainly include:

Single join aggregation rule:

$$d\left(o_i,o_k\right)=\min_{x\in o_i,y\in o_k}\|x-y\| \tag{1}$$

Full link aggregation rules:

$$d\left(o_i,o_k\right)=\max_{x\in o_i,y\in o_k}\|x-y\| \tag{2}$$

Interclass average join aggregation rules:

$$d\left(o_i,o_k\right)=\left(1/n_in_k\right)\sum_{x\in o_i}\left(\sum_{y\in o_k}\|x-y\|\right) \tag{3}$$

Average join aggregation rules within a class:

$$d\left(o_i,o_k\right)=\left(1/C\left(n_i+n_k,2\right)\right)\sum_{x,y\in\left(o_i,o_k\right)}\|x-y\| \tag{4}$$

Ward Law:

$$d\left(o_i,o_k\right)=\left(1/\left(n_i+n_k\right)\right)\sum_{x\in\left(o_i,o_k\right))}\|x-n\|^2 \tag{5}$$

Ward's method was used in this study. Next, using SPSS26 software, hierarchical clustering was completed based on Euclidean distance and Ward's method for z-score normalized information.

3.2. K-Means Cluster Analysis

The basic procedure of the K-Means clustering algorithm is as follows: first, k objects are selected as the initial grouping centers from the n objects in the data, and then, based on their similarities (distances) to these grouping centers, the remaining objects are assigned to the most similar classes, respectively. The formula for calculating the similarity is as follows, assuming that the class center of the j rd class is c_j. Then, the distance between x_i and c_j is:

$$d\left(x_i, c_j\right)=\sqrt{\left(x_i^1-c_j^1\right)^2+\cdots+\left(x_i^k-c_i^k\right)^2+\cdots+\left(x_i^d-c_j^d\right)^2} \tag{6}$$

The similarity is:

$$s\left(x_i, c_j\right)=1/d\left(x_i, c_j\right) \tag{7}$$

Next, the cluster center is calculated for each updated class, if $\left\{x_{j1}, x_{j2}, \cdots, x_{jn}\right\}$ is a sample among the j nd class, indicating that the number of samples is n_j, then the cluster center is $c_j=\left(c_j^1, c_j^2, \cdots, c_j^k, \cdots c_j^d\right)$, where c is the class center and the k th attribute of c_j is:

$$c_j^k=\frac{x_{j1}^k+x_{j2}^k+\cdots+x_{jn_i}^k}{n_j} \tag{8}$$

Subsequently, keep looping the above process and stop looping when the standard measure function converges. The standard clustering measure function is usually in the form of mean square deviation, which takes the following form:

$$J=\sqrt{\frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(x_i-c_i\right)^2}{n-1}} \tag{9}$$

The flow of the K-Means clustering algorithm is shown in Figure 1.

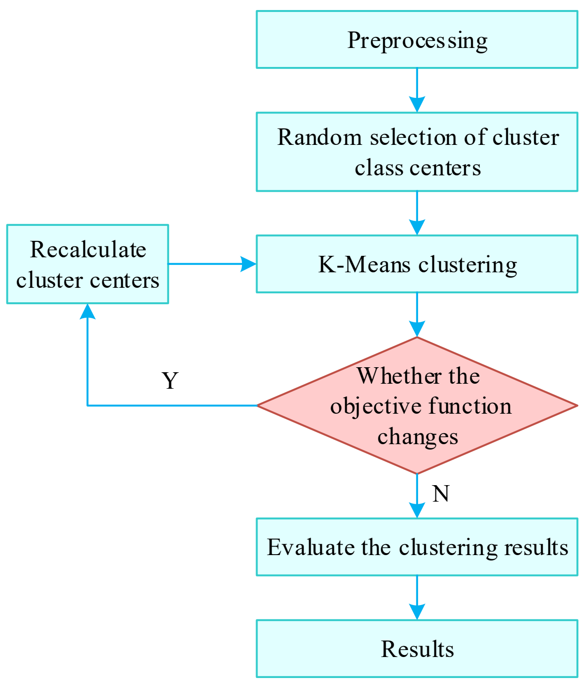


Fig. 1. K-Means clustering algorithm flow

4. Research on the effect of wisdom teaching in tourism management based on cluster analysis

The research data in this chapter comes from a catechism course of the basic course of tourism management on a smart teaching platform, which is well represented as a high-quality teaching resource for tourism management majors. In this paper, the learning and performance data of the course during the start of the course in March-April 2024 were collected, including information on quiz students' completion, homework students' completion, exam students' completion, students' final grades, and so on. The total number of student behavior data is 15,246, and 14,745 items are retained after removing the noise data, and the data validity rate is 96.71%.

The functional modules provided by the smart teaching platform in this study include four parts: the resource module, the teaching activity module, the test module and the assignment module. Combined with the log data of student behaviors recorded in this platform, seven dimensions of resource downloading, watching microclasses, logging into the platform, participating in discussions, actively answering questions, submitting assignments, and participating in online tests were selected for cluster analysis of student behavioral characteristics.

4.1. *Cluster Analysis of Student Behavioral Characteristics*

Before clustering the data, the first step is to standardize the collected data, which aims at eliminating the variability between the data. In this study, z-score is used to convert data of different magnitudes to the same magnitude in order to improve the comparability of the data. Meanwhile, in order to improve the efficiency of data processing and reduce the complexity of data, PCA principal component analysis was used to downscale the data in seven dimensions.

In this study, the hierarchical aggregation algorithm in hierarchical clustering algorithm was used to determine the optimal cluster value (K) with the following rules:

$$SSE = \sum_{i-1}^{K} \sum_{p \in C_i} \left| p - m_i \right|^2 \tag{10}$$

SSE represents the sum of squares of errors within the clusters, C_i represents the i nd cluster, p is the sample points in Ci, and m_i is the mean value of all samples in Ci, which represents the clustering effect. The process of determining the K-value of the clustered clusters is shown in Fig. 2, from which it can be seen that as the K-value increases, the SSE value decreases at a gradual rate of leveling off. When the K value increases to the inflection point position, the contribution of adding more clustering clusters to the SSE is not obvious, therefore, the inflection point value is usually chosen as the best clustering cluster value. When $K = 3$, the inflection point is produced, the decrease of SSE slows down significantly from $K = 3$ to $K = 4$, so the optimal clustering cluster value is 3.

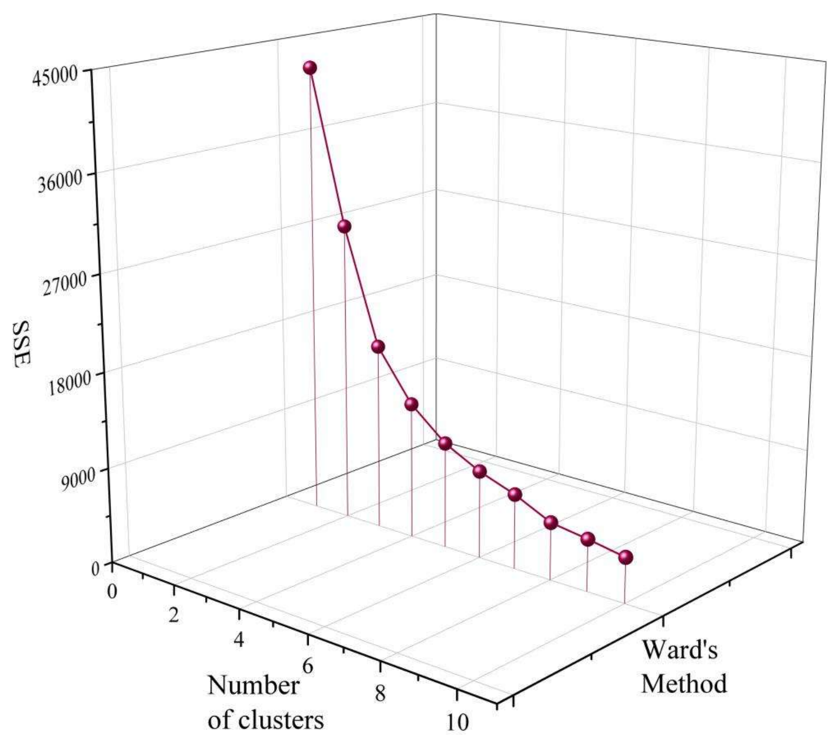


Fig. 2. Determination process of K value of cluster

After obtaining the best cluster clusters the data is clustered and analyzed using K-Means clustering algorithm with the following rules:

$$P(x) = \frac{D(x)^2}{\sum_{x \in X} D(x)^2} \tag{11}$$

The shortest distance between each sample and the currently existing cluster center is denoted by $D(x)$. The probability $P(x)$ that each sample point is selected as the next cluster center is calculated, and then the sample point corresponding to the maximum probability value (or probability distribution) is selected as the next cluster center, and the results of the sample clustering visualization are shown in Figure 3. Different colors are used to represent different categories, and the number of students included in the 3 clusters can be judged according to the size of the clustering points. The more the clustering points are distributed, the bigger the bubbles are, and the more the number of students included, and vice versa, the less. The analysis shows that cluster 2 has the largest size and the densest distribution of cluster points, representing the highest number of students, followed by cluster 1 and cluster 0.

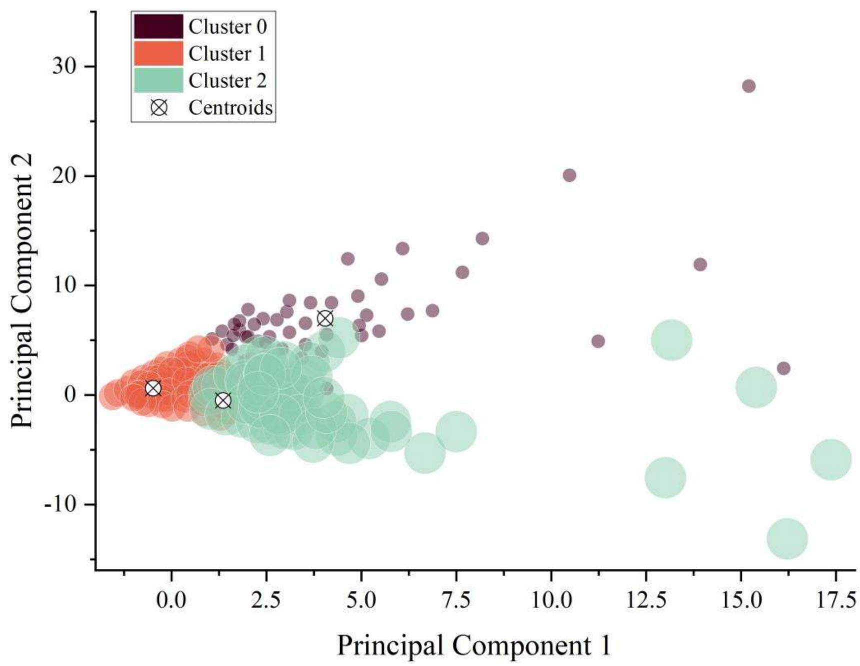


Fig. 3. Cluster visualization results

4.2. Descriptive statistics

In order to present more clearly the differences in the learning behaviors of students of the three clustered groups in the smart teaching platform, this study further calculated the mean and standard deviation of the behavioral performance of different categories of students in the seven data dimensions, and the descriptive statistical results are shown in Table 1. It can be seen that students' use of resources can reflect their learning engagement in the smart teaching platform, the teaching activity module and homework module can reflect students' learning initiative, and the testing module is a necessary part for students to test their learning effect after completing the stage of learning. Through the results of descriptive statistics, the final characteristics of the three types of learner behavior are as follows:

Cluster 0 contains 1082 students, which is approximately 7.34% of the total sample. As can be seen from Table 1, the mean value of students in this category is significantly higher in the dimension of submitting assignments (AVG=7.28, SD=1.04), while the mean value of students in category 0 is significantly lower in the three dimensions of downloading resources, participating in discussions, and actively answering questions, and the difference with the group of students in category 1 in the dimensions of participating in online tests and logging in to the platform is relatively small. The basic characteristics of this group of students are: the motivation for learning comes from the teacher's supervision, the initiative for learning is average, the purpose of their learning is mainly to complete the relevant tasks in the Smart Teaching Platform, and the sense of active participation in classroom teaching activities is not high. Therefore, this type of students is named as medium-involved passive learners.

Cluster 1 contains 5077 students, which is approximately 34.43% of the total sample. The means of this group of students in terms of logging into the platform (AVG=1.39, SD=0.98) and actively answering questions (AVG=0.63, SD=0.39) are significantly lower than the overall mean of the student sample, indicating that this group of students is not highly motivated to use the smart teaching platform to carry out learning. In terms of submitting assignments, although lower than the sample mean, the difference is not significant, indicating that the purpose of using the platform for this group of students mainly lies in attending classes and handing in assignments. The basic characteristics of this category of students are: low utilization of the teaching resources of the Smart Teaching Platform, low initiative in learning, and negative learning attitude. Therefore, students in this category are named as low-involvement negative learners.

Cluster 2 contains 8586 students, which is approximately 58.23% of the overall sample. This group of students performs better in terms of downloading resources (AVG=9.39, SD=0.97), participating in discussions (AVG=4.17, SD=1.03), and actively answering questions (AVG=5.26, SD=2.64) compared with the medium-input passive learners. The basic characteristics of this group of students are: they are able to utilize the resources provided by the platform to complete the learning tasks better, have higher classroom participation, and are capable of independent learning. Therefore, this category of students is named as highly engaged active learners.

Table 1. Descriptive statistics of cluster group performance in 7 dimensions

Dimension	Cluster0 (N=1082)		Cluster1 (N=5077)		Cluster2 (N=8586)		Mean of sample
	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation	
Resource Download	7.25	4.16	2.08	2.09	9.39	0.97	6.24
Watch micro-lecture	8.37	2.98	3.08	1.12	9.07	4.28	6.84
Landing platform	5.38	2.44	1.39	0.98	6.28	3.27	4.35
Participate in the discussion	3.04	2.53	1.82	0.53	4.17	1.03	3.01
Proactively answer questions	3.25	1.19	0.63	0.39	5.26	2.64	3.05
Submit homework	7.28	1.04	3.98	3.53	6.42	2.97	5.89
Take the online quiz	7.63	3.18	5.67	1.49	8.37	1.87	7.22

4.3. *Evaluation of the effectiveness of smart teaching*

Considering that different student characteristic behaviors will have different impacts on the effect of smart teaching, this study launched a controlled analysis of the achievement data of the three categories of students. In order to make the analysis results more reliable, the paper grade data of the three types of students before using the smart teaching platform were obtained and compared with the paper grade data of the three types of students after using the smart teaching platform. SPSS26 software was used to analyze the results, and the mean and standard deviation of the pre-test scores and post-test scores are shown in Figure 4. As can be seen in Figure 4, the mean value of Category 2 students' grades changed the most, and the post-test grades were 16.54 points higher than the pre-test grades.

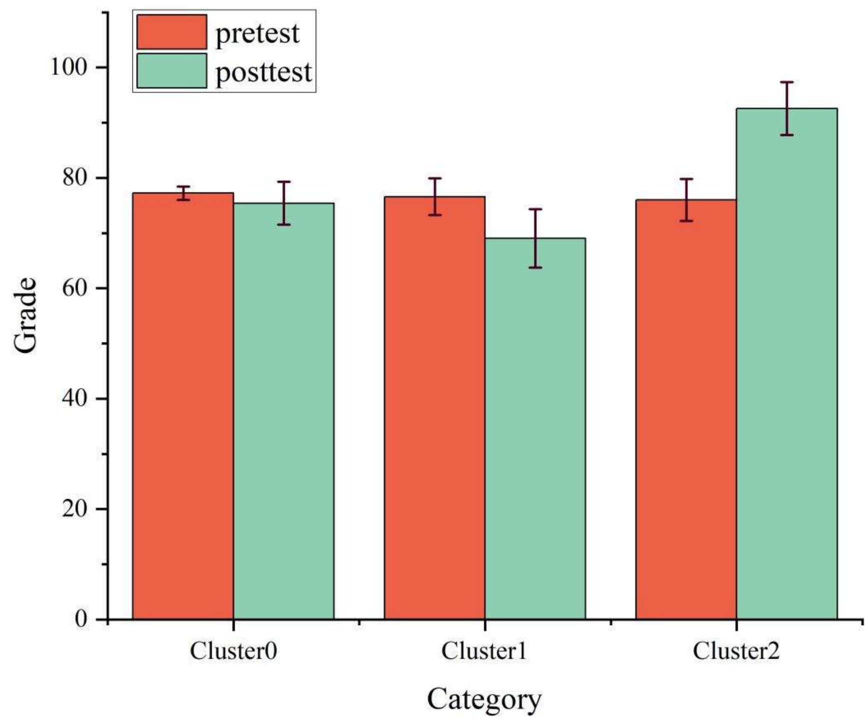
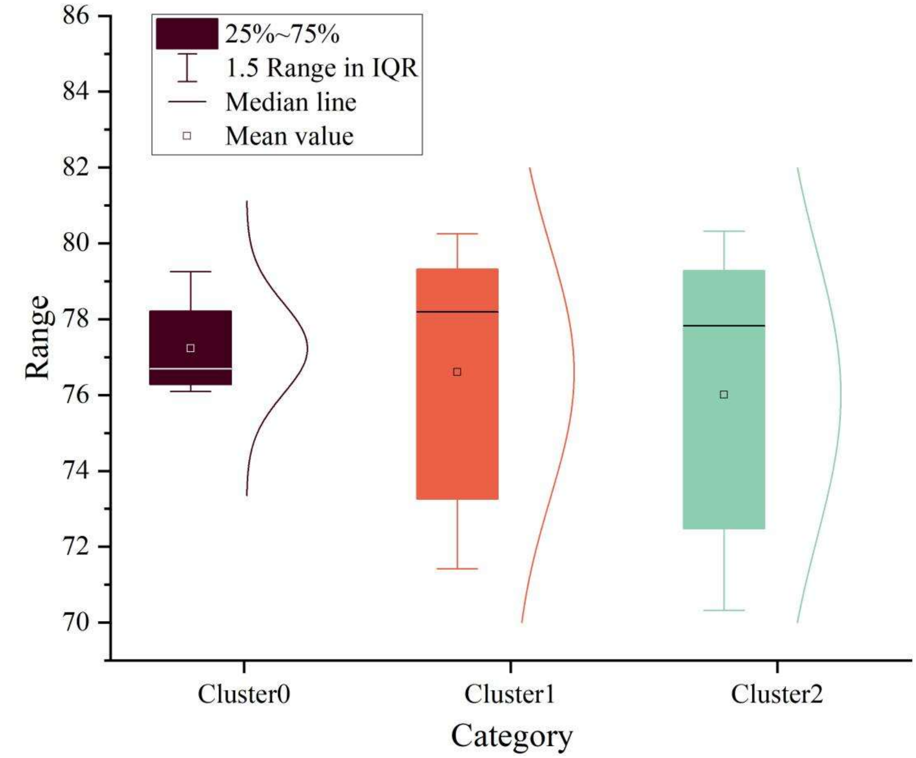
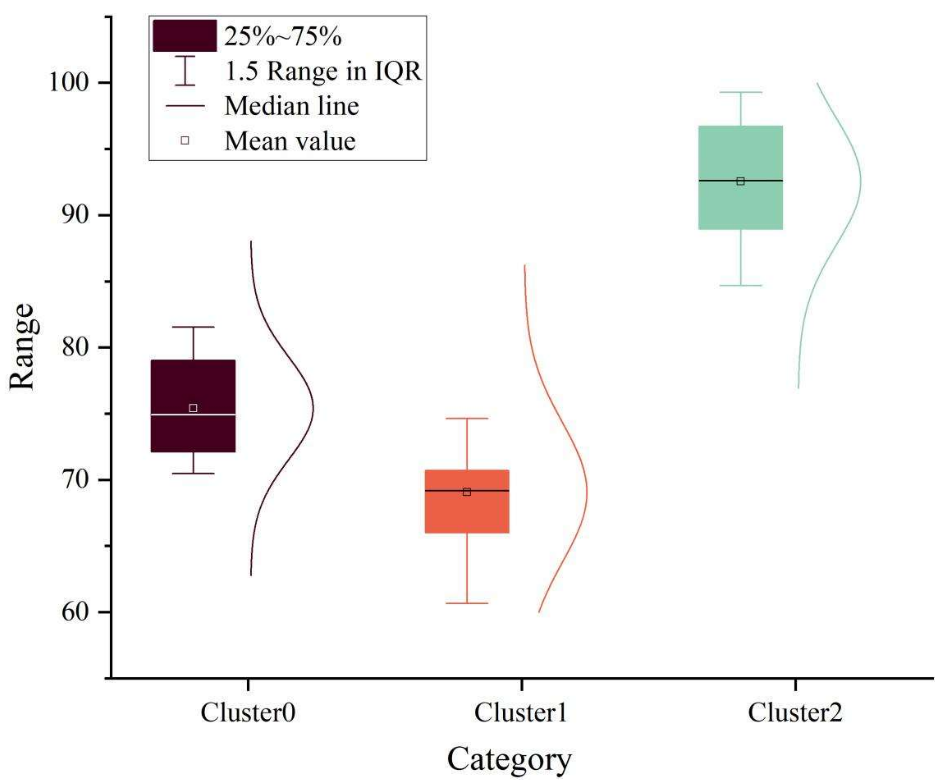


Fig. 4. Mean score and standard deviation

One-way ANOVA was conducted on the pretest students' paper scores, and the test results were visualized as shown in Figure 5(a)(b). From the figure, it can be seen that the pre-test and post-test scores are normally distributed and meet the conditions of one-way ANOVA. The pre-test scores have a p-value of 0.61097 greater than 0.05 in the one-way ANOVA, indicating that the three types of students are basically the same and not significantly different. Posttest scores in one-way ANOVA, p-value of 2.04093E-13 is less than 0.05, indicating that the three types of students show significant differences in performance. According to the results of data analysis, statistically, it can be observed that category 2, i.e., high-involvement active learners, had the best performance, category 0, i.e., medium-involvement passive learners, had the second best performance, and category 1, i.e., low-involvement passive learners, had the worst performance, which indicates that smart teaching has a positive effect on the improvement of the theory course performance of tourism management students.



(a)Pretest



(b)Posttest

Fig. 5. Visualization of one-way ANOVA

In terms of practical skills, the "Tour Guide Service Skills Competition" was held to assess the mastery of practical skills of the three types of students after intelligent teaching (see Table 2). The means and standard deviations of the practical scores of the three types of students are shown in Table 2, and the results of one-way ANOVA are visualized in Figure 6. From Figure 6, it can be seen that the practice scores conform to normal distribution and meet the conditions of one-way ANOVA. The p-value of 1.56951E-17 is less than 0.05 in one-way ANOVA for the practice scores, indicating that the scores of the three categories of students show significant differences. The mean value of practical achievement of category 2 students was 95.63, which was 20.18 and 26.75 points higher than category 0 and category 1 students respectively. It also had the lowest standard deviation, indicating that Category 2 students' performance was the most stable. Based on the results of data analysis, statistically, it can be observed that smart teaching has the same positive effect on improving the performance of tourism management students in practical courses.

Table 2. Mean score and standard deviation

Category	Quantity	Mean value	Standard deviation	Mean SE
Cluster0	1082	75.45	3.92	1.13
Cluster1	5077	68.88	4.93	1.42
Cluster2	8586	95.63	2.31	0.67

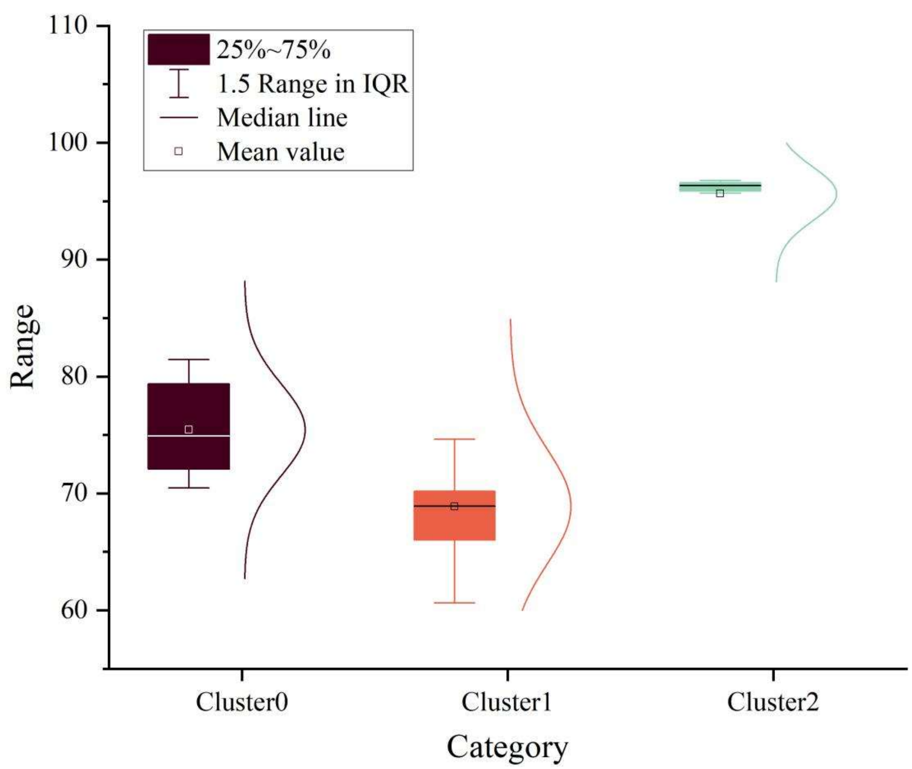


Fig. 6. Visualization of one-way ANOVA

5. Conclusion

In this paper, hierarchical clustering and K-Means clustering were used to categorize the learners and one-way ANOVA was used to explore the change in their performance after smart teaching.

The results showed the best clustering cluster value of 3. Based on the behavioral characteristics, the students were classified as medium-involved passive learners, low-involved passive learners, and high-involved active learners. Among the paper scores, category 2 students had the greatest change in the mean value of their scores, with the post-test scores being 16.54 points higher than the pre-test scores. In practical scores, the mean value of category 2 students' practical scores was 95.63, which was 20.18 and 26.75 points higher than category 0 and category 1 students, respectively. It also had the lowest standard deviation, indicating that category 2 students' performance was the most stable. p-value was less than 0.05, indicating that the performance of the three categories of students showed significant differences.

The results showed that the academic performance of the students who were good at utilizing the smart teaching platform was significantly improved, while the performance of the students who were less adaptive to the smart teaching method did not change much, which verified the effectiveness of the smart teaching model.

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