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Application of Fuzzy Clustering Algorithm in the Analysis of Students' Learning Styles on International Education Platforms

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This paper discusses the analysis and application of middle school students' learning styles in a cross-border education platform, facilitated by a fuzzy clustering algorithm. With the increasing popularity of online education, it has become important to personalize the course content and teaching approach according to students' individual learning styles. How to do so in order to improve learning outcomes has become a core issue in the education field. For this study, student learning data from multiple cross-border education platforms was collected, and a fuzzy clustering algorithm was applied to classify students' learning behaviors. "Five main learning styles were identified: visual, auditory, kinesthetic, reading/writing, and multimodal , in which learners flexibly combine multiple strategies rather than relying on a single mode. These learning styles reflect the differences in students' preferences during the learning process, demonstrating the importance of designing personalized learning paths. The research results show that the fuzzy clustering algorithm can cope with the diversity and complexity of students' learning behavior, accurately identify each student's learning style by calculating the degree of membership, and provide a basis for a personalized teaching strategy design for the platform. The evaluation results demonstrate that the proposed fuzzy clustering algorithm enhances not only the classification accuracy but also the robustness of learning style identification, ensuring consistent and reliable outcomes under varying data conditions. This study provides new ideas and methods whereby cross-border education platforms can analyze students' personalized learning, and provides theoretical basis and practical guidance for educators and platform developers wishing to implement personalized teaching.

Keywords: fuzzy clustering algorithm; cross-border education; learning style; personalized teaching; data analysis

1. INTRODUCTION

With increasing globalization and the rapid development of information technology, cross-border education platforms are faced with the challenge of finding ways to optimize teaching according to students' individual needs while providing global learning resources and cross-cultural communication. In the field of online education, the difference of students' learning style has become an important factor affecting the learning outcomes. Analyzing and understanding students' learning style and formulating corresponding teaching strategies can improve the effect of online education platforms. Learning style theory holds that there are individual differences in the learning process, and different students have different preferences, habits and cognitive methods [1]. The traditional education model usually adopts a unified teaching scheme, which cannot be easily adjusted to meet the specific needs of each individual student. With the advancement of data analysis and artificial intelligence technology, the education field has gradually adopted more accurate and personalized education methods. The fuzzy clustering algorithm, an important unsupervised learning method, has advantages in dealing with fuzzy and uncertain student learning data. Through fuzzy clustering, students' learning styles can be identified and

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analyzed effectively, and more scientific and personalized teaching support can be provided for the education platform.

Current research on learning styles and educational practices presents a diversified development trend. In the study on learning styles, Clinton-Lisell and Litzinger explored the validity of the hypothesis of learning styles-matching through meta-analysis, and the results showed that, although the theory of learning styles is widely used in education, there is no substantial evidence to support that matching learners' learning styles with teaching methods can significantly improve learning outcomes [2]. Kumar et al. reviewed the application of fsQCA (Qualitative comparative Analysis of Fuzzy Sets) in tourism and hospitality management, finding that this method can reveal the complex relationship between different factors, and has potential in the field of education, especially in the interdisciplinary study of learning styles [3]. Muijsenberg summarized the factors influencing adult learning styles and emphasized the importance of adopting different methods to assess learning styles in health education, especially taking into account individual differences in adult education [4, 5]. In a cross-cultural context, Zhai et al. studied the satisfaction of mobile health application users and examined the correlation between topic analysis and user feedback, which provided a new perspective for understanding how learners interact on different platforms [6]. Transnational education is also an important topic in current research. Carvalho et al. conducted a systematic review of the research on transnational higher education and quality assurance, and pointed out that in the context of transnational education, the mechanism of education quality assurance still needs to be further strengthened, especially the adaptability of learning styles in a multicultural environment [7]. Sonnenschein et al. explored the influence of different cultural backgrounds on learning styles through the study of cultural readjust of international students and returning students, emphasizing the potential impact of cultural distance on learning outcomes [8, 9]. In the field of decision analysis, Saiz et al. proposed a project portfolio optimization method based on cluster analysis and discussed the applicability of different decision methods in different educational environments, which is in line with the study on the adaptability of learning styles [10]. Khamparia and Pandey discussed the relationship between learning styles and e-learning problems, pointing out that individuals with different learning styles may face different learning challenges in e-learning environments - a finding that provides an important reference for future online education design [11]. Stander et al. systematically reviewed the learning styles of physical therapists and emphasized the importance of evaluating learning styles in professional education, especially in the field of medical education, where understanding the learning styles of different students can help improve educational outcomes [12].

This study explores the application of the fuzzy clustering algorithm in the analysis of students' learning styles in cross-border education platforms, examines in depth the characteristics of students' learning styles through data analysis, and proposes personalized teaching strategies based on these characteristics. By analyzing the student behavior data on a cross-border education platform, we can identify different learning style groups, provide a scientific basis for the education platform, optimize the course design and improve the learning effect. After data collection and sample selection, the fuzzy clustering algorithm is adopted as the main technical means of training and verifying the model [13]. Through multi-dimensional analysis of student behavior data, the group characteristics of different learning styles are identified to provide support for personalized teaching on education platforms. Online behavioral data and questionnaires were collected, noisy data was removed, and the retained data were standardized. Through experiments and comparative analysis, the effectiveness and accuracy of the fuzzy clustering algorithm in analyzing students' learning style were verified [14]. The significance of this study is to fill the gap in the analysis of students' learning styles on a current cross-border education platform and provide more accurate and personalized teaching strategies for the field of online education. Through the application of the fuzzy clustering algorithm, students' learning habits and preferences within a multi-cultural environment can be better understood, providing a theoretical basis for the personalized customization of teaching content and services of education platform. The research results will help promote the development of education informatization and improve the education quality of cross-border education platforms.

2. MATERIALS AND METHODS

2.1 Data Collection and Sample Selection

2.1.1 Sample Sources and Characteristics

The sample comprised registered student data from multiple cross-border education platforms, involving students in China as well as international students. The online learning data obtained from the cross-border education platform constituted the basic sample. By taking into consideration the multicultural backgrounds of students engaging in online cross-border education, the sample selection ensured the diversity of cultural backgrounds and education systems [15]. As shown in Table 1 below, the student sample covered a range of ages from middle school to college, accounting for the different stages of education. The sample data also included students from different countries and regions, ensuring that the findings reflected differences in learning styles across cultural contexts. In terms of sample characteristics, key indicators were extracted from the anonymous student behavior data provided by the platform, such as each student's learning frequency, online learning duration, types of learning modules undertaken, completion of homework and tests, and after-class feedback. [16]. In order to analyze students' learning styles, self-assessment questionnaire data were collected, including students' self-reported learning preferences, learning environment requirements, information acquisition methods and problem-solving methods. The total sample size was 200, ensuring the statistical representation and wide applicability of the research results.

Table 1 Sample characteristics and data statistics.

Item	Statistic Value
Total Sample Size	200 people
Grade Level of Students	Secondary School, University
Gender Distribution of Students	Male 48%, Female 52%
Regional Distribution of Students	China (60%), Overseas (40%)
Study Duration (hours/week)	Average 15 hours
Participation in Learning Modules	High (80%), Medium (15%), Low (5%)

2.1.2 Data Collection Methods

In order to ensure the comprehensiveness and representativeness of the data, online behavioral data collection and questionnaire survey were used. Online behavioral data was obtained from the Learning Management System (LMS) of the education platform, including student login information, participation in online learning activities, study duration, and test results after the completion of each unit. This data can accurately reflect the participation degree and learning behavior of students when engaged in online learning. Through the API interface of the platform, the students' behavior data can be obtained in real time to ensure the timeliness and integrity of the data. In order to understand students' learning styles, self-assessment questionnaires were also designed and distributed to all participants. In order to collect data on students' subjective evaluation of their own learning habits, the questionnaire included students' self-reported learning preferences, information processing methods, and social interaction needs. The students responded to items on a five-point Likert scale; the items were related to students' cognitive style, learning environment needs, and technology usage habits so as to provide data support for the subsequent fuzzy cluster analysis.

2.1.3 Data Preprocessing

To ensure the accuracy and consistency of the data, the collected data were de-noised to remove incomplete and invalid data. For online behavioral data, the samples with many missing values were deleted and the extreme values were corrected to ensure the representativeness and analyzability of the data. In the questionnaire data, incomplete or repeated questionnaires were eliminated to ensure the integrity of the data of each sample. The behavioral data of students were standardized to eliminate the influence of differences in learning time and activity frequency of different students on the analysis results. The standardized data allows different indexes to be compared on the same scale, which is convenient for the subsequent fuzzy cluster analysis. For the questionnaire data, factor analysis was used to reduce the number of questionnaire items, extract the most representative learning style factors, and remove redundant data so as to improve the efficiency of analysis. The result of data preprocessing yield a clear feature matrix of student behavior, which provides a reliable data basis for the application of the fuzzy clustering algorithm.

2.2 Model Construction

2.2.1 Model Selection

For this study, a fuzzy clustering algorithm was chosen as the main tool to analyze students' learning style. Unlike the traditional hard clustering method, the fuzzy clustering algorithm allows each sample to belong to multiple clusters, assigns a membership value to each sample, and can deal with fuzziness and uncertainty in learning data. Due to the diversity of students' learning styles, each student has multiple learning preferences at the same time; the fuzzy clustering algorithm provides a more flexible way to identify and divide students' learning patterns. The basic idea of fuzzy clustering is to divide the data set into multiple clusters, where each data point belongs to different clusters with different degrees of membership. By calculating the degree of membership of each sample, fuzzy clustering can indicate the transition state of students in multiple learning styles and avoid the bias that may be caused by strict division. The analysis of educational data indicates that students' learning behavior is multi-dimensional and dynamic. The application of the fuzzy clustering algorithm can help to accurately identify those students who have similar learning styles, and provide support for personalized education and teaching strategies.

2.2.2 Model Architecture Design

The architecture design of the model follows the requirements of data orientation and learning style division, and includes the fuzzy clustering algorithm for multi-stage data processing. In the data preprocessing stage, the data were standardized to ensure that the learning data for different dimensions can participate in the cluster analysis fairly. Through the feature extraction stage, key indicators such as students' learning time, participation and homework completion were extracted from the original data. These features were used as input data for the clustering.

In the clustering stage, the Fuzzy C-Means (FCM) algorithm was used to minimize the weighted distance between samples and cluster centers, and calculate the degree to which each sample belonged to a particular cluster. Through the iterative process, the algorithm constantly adjusts the cluster center until the preset stopping condition is reached, and finally forms multiple learning style clusters. In the final analysis stage, based on the clustering results, different learning styles can be identified, such as independent learning, cooperative learning, mixed learning and so on.

Table 2 Distribution of model training data set and test data set.

Dataset	Sample Size	Grade Level Distribution	Regional Distribution	Average Study Duration (hours)
Training Set	140	Secondary School: 45%, University: 55%	China: 60%, Overseas: 40%	15
Test Set	60	Secondary School: 50%, University: 50%	China: 58%, Overseas: 42%	14

2.2.3 Division of Training and Test Data Sets

In order to ensure the validity and reliability of the model, the data set was divided into a training set and a test set. The model was trained and optimized on the training set, and the test set was used to evaluate the generalization ability of the model. As shown in Table 2 below, 70% of the samples were used as the training set and 30% were the test set. The data of the training set was used for the iterative learning of the fuzzy clustering algorithm to adjust the model parameters to get the optimal clustering results. The data from the test set was used to verify the accuracy of the model and its ability to predict new data.

2.2.4 Model Optimization and Implementation Steps

The optimization of the model focuses on the membership calculation and cluster center updating process of fuzzy clustering algorithm. In practical applications, the diversity of students' learning behaviors, noise and data outliers may affect the clustering results. The optimization steps include data denoising, feature selection and adjustment of cluster numbers. A weighting function is included to give greater weights to important features in the calculation of membership degree, so as to improve the accuracy and stability of the model. The specific steps are as follows:

(1) Standardize the original data so that all data dimensions have the same scale;

(2) Extract key characteristics of students' learning behavior, such as study duration, homework completion and online interaction;

(3) Apply the fuzzy C-means algorithm for clustering; membership degree of each data point is calculated iteratively, and the cluster center is updated;

(4) Optimize cluster number and membership threshold through cross-validation and model evaluation;

(5) Forecast the new data according to the optimized model, and analyze the results.

The objective function of the fuzzy C-means algorithm is as follows (1):

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{C} u_{ik}^{m}\|x_i - c_k^2\| \tag{1}$$

where, u_{ik} is the membership degree of sample i belonging to the cluster k, x_i is the sample point, c_k is the center of the cluster k, m is the ambiguity index, and C is the number of clusters. Membership degree $u_{ik}$is calculated as follows (2):

$$u_{ik} = \frac{1}{\sum_{j=1}^{C}\left(\frac{\|x_i - c_k\|}{\|x_i - c_j\|}\right)^{\frac{2}{m-1}}} \tag{2}$$

2.3 Data Analysis and Result Verification

2.3.1 Data Analysis Methods

Data analysis is the core part of this study, which analyzes students' behavior data and extracts representative characteristics to provide a basis for the classification of learning styles. After applying the fuzzy clustering algorithm, the membership value of each student in different learning style clusters is obtained, and the membership value indicates the degree of students' belonging to each learning style. A multi-dimensional data analysis method was used in order to ensure the accuracy of the analysis results. The main dimensions of the data are: learning time, engagement, homework and test scores, and interaction frequency. The comprehensive analysis of these dimensions reveals the different learning styles of students. For the clustering outcome analysis, students are divided into groups, each representing one or more learning styles. Based on the results of fuzzy clustering, the learning characteristics of each type of student group are analyzed and described in detail. The degree of membership of each student in each group can be calculated to determine the main learning preferences of each group of students, such as visual, auditory, kinesthetic. In order to better demonstrate the results of these analyses, Table 3 presents the number, percentage and main characteristics of students in each learning style group. The statistical data provide a reliable basis for the subsequent design of teaching strategies.

2.3.2 Result Verification Method and Evaluation Index

In order to verify the effectiveness of the fuzzy clustering algorithm in analyzing students' learning styles, a variety of evaluation indexes were adopted. The contour coefficient was used to evaluate the clustering effect. The contour coefficient can measure the tightness and separation of clustering results, and a higher value of the contour coefficient indicates a better clustering effect, as shown in (3) below:

$$S = \frac{b - a}{\max(a, b)} \tag{3}$$

Table 3 Distribution statistics for students with different learning styles.

Learning Style	Number of Students	Percentage of Students	Main Learning Characteristics
Visual	80	40%	Prefers visual materials such as images and videos
Auditory	60	30%	Prefers learning through lectures and audio materials
Kinesthetic	40	20%	Prefers hands-on practice and experiments
Multimodal	20	10%	Exhibits a combination of various learning preferences

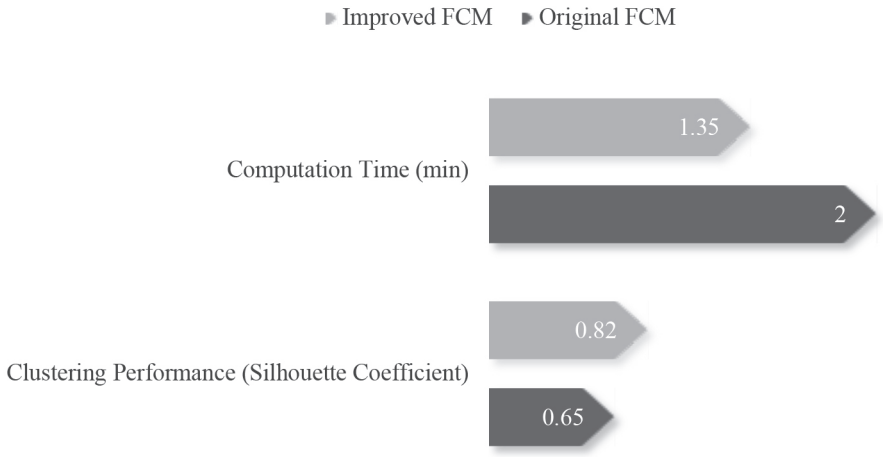

Figure 1 Comparison of optimization algorithm results.

where a represents the average distance between the sample and other samples in the same cluster, and b represents the average distance between the sample and the nearest cluster. The value range of the contour coefficient is $[-1,\ 1]$; the larger the value, the better the clustering effect. Another important evaluation index is the error measure, which is generally used to measure the degree of error of the model's prediction results. The error measure is as follows (4):

$$E = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{4}$$

where x_i represents the actual value, $\hat{x}_i$ represents the predicted value, and n represents the number of samples. By calculating the error measure, the degree of deviation between the clustering results and the real data is obtained. A small error in the model indicates that the clustering algorithm can accurately determine students' learning styles.

2.4 Model Application and Optimization Path

2.4.1 Selection and Improvement of Optimization Algorithm

During the preliminary construction and verification process of the model, the fuzzy clustering algorithm showed a good clustering effect. In order to improve the accuracy and practicability of the model, the algorithm was optimized according to the characteristics of the data set. The core objective of optimization is to improve the accuracy and stability of the clustering results and reduce the influence of noisy data on the analysis results. An improved fuzzy C-means (FCM) algorithm was chosen for this study. Unlike the traditional FCM algorithm, the improved algorithm has a weighting factor to dynamically adjust the membership degree of each sample. Based on the intensity and importance of student behavior data, the clustering results can better reflect the real differences in learning styles. For the purpose of optimization, in addition to improving the membership degree calculation method, the convergence speed and computing efficiency of the algorithm are optimized. The distributed computing method is adopted to divide the data into multiple subsets for parallel processing, which accelerates the processing of large-scale data. The stability and accuracy of clustering results are improved by introducing the error term and fitness function. These improvements effectively solve the overfitting problem that may occur in the traditional clustering algorithm when processing large-scale education data. The results of the optimization algorithm are shown in Figure 1.

2.4.2 Learning Style Analysis Path Design

The learning style analysis path of the system is designed based on the improved fuzzy clustering algorithm, Combined with multi-dimensional information such as students' behavior data, questionnaire results and academic performance, it provides a personalized learning style analysis scheme for cross-border education platforms. The process includes data preprocessing, feature extraction, cluster analysis, learning style identification, and evaluation. The platform collects online behavior data of students who are engaged in learning, uses data cleaning and standardized processing, and converts it into characteristic values that can be used for analysis. Combined with the results of students' self-assessment questionnaire, the data dimension is enriched,

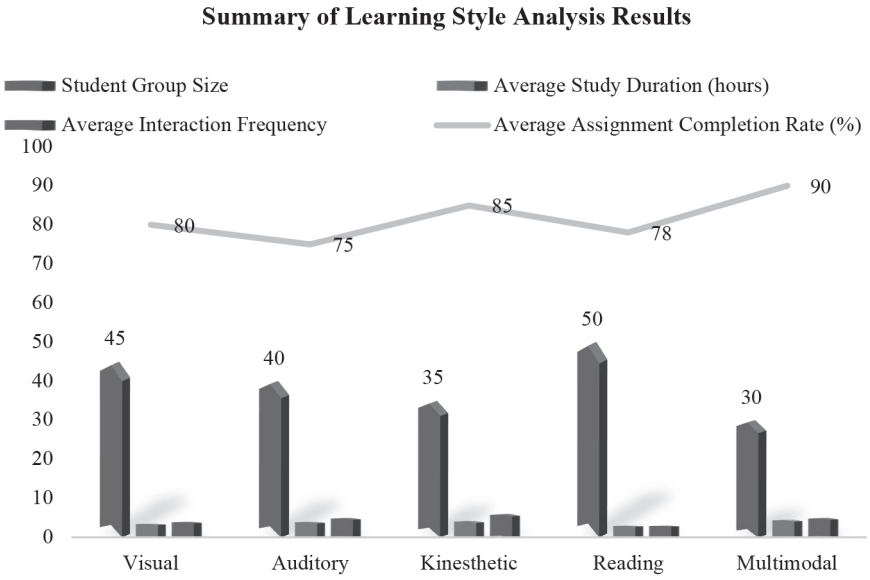

Figure 2 Summary of learning style analysis results.

and more accurate input is provided for cluster analysis. After the clustering is completed, the system can generate a personalized learning style report for each student based on the student's membership of various learning style groups. The report includes the main types of students' learning styles, covering students' learning preferences, weaknesses, and suggestions for the optimization of each dimension. The education platform can adjust the teaching content according to the analysis results, recommend suitable learning resources, and constantly adjust the personalized learning path according to the students' feedback. Through path design, the platform can effectively enhance student learning efficiency and engagement, ensuring that each student can learn in a way that suits them. When learning style prediction is realized, the probability formula of learning style prediction is proposed to quantify the degree of students' belonging to a particular learning style, as shown in (5).

$$P(C_k|X) = \frac{P(X|C_k)P(C_k)}{P(X)} \tag{5}$$

Where $P(C_k|X)$ represents the probability that student X belongs to a certain learning style category C_k, $P(X|C_k)$ is the conditional probability that student X's behavior data is observed under the learning style C_k, and $P(C_k)$ is the prior probability of learning style C_k. $P(X)$ is the total probability of student X's behavioral data. The formula can accurately predict the type of students' learning style and provide data support for subsequent personalized education programs.

3. RESULTS AND DISCUSSION

3.1 Result Display

3.1.1 Learning Style Analysis Results

Based on fuzzy clustering algorithm, this paper analyzes the learning behavior data of students in cross-border education platform. By analyzing the characteristics of students' learning time, homework completion, interaction frequency, and the types of learning modules they participate in, five main learning styles are identified: visual, auditory, kinesthetic, reading, and comprehensive. These learning styles represent students' preferences and behavior patterns in different learning activities. For each learning style, there are differences in the performance of the respective students, and these differences provide a strong basis for the development of personalized teaching programs. As shown in Figure 2 below, visual students learn mainly through visual materials such as images, charts and videos, showing high learning efficiency and participation, especially in tasks requiring graphics and video assistance. Auditory students understand and absorb information better by listening to lectures, discussions and explanations. They perform better in tasks that require listening skills. Kinesthetic students prefer to learn through hands-on operation, experiment and practice, and they usually receive higher grades for practical tasks. Reading students tend to acquire knowledge through a lot of reading and writing materials; comprehensive students switch between various learning styles and choose the most appropriate learning style according to different learning situations.

3.1.2 Proportion of Students With Different Styles

Based on the results of cluster analysis, the proportion of students with different learning styles is statistically analyzed. Visual, auditory and kinesthetic students are the main learning groups, while the number of reading and comprehensive students is relatively small. As shown in Figure 3 below, visual students account for the highest proportion, reaching 22.5%, followed by reading students, accounting for 25%. The proportion of kinesthetic and auditory students is similar, 17.5% and 20% respectively, while the comprehensive students account for 15%. It reflects the diversity of students' learning styles and the balanced distribution of different learning style groups in the education platform. Through

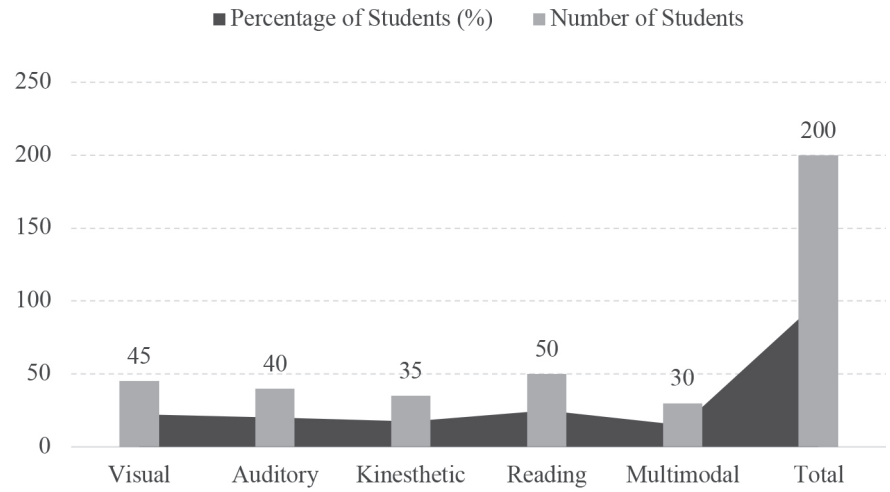

Figure 3 Number of students exhibiting different learning styles.

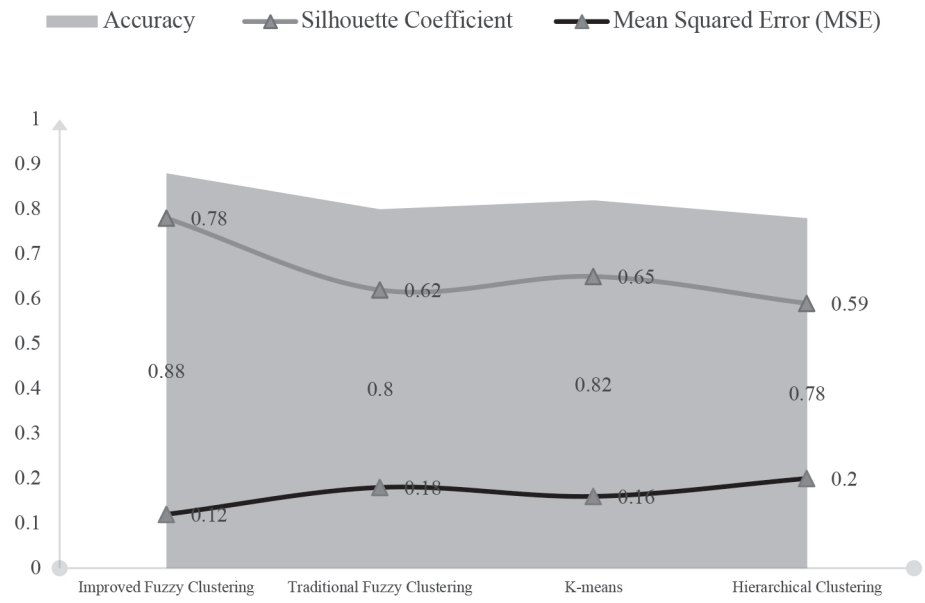

Figure 4 Model accuracy and effect.

the analysis of the proportion, the education platform can be designed according to the needs of the student group, ensuring that each type of student group can find their own learning materials and ways on the platform. According to the characteristics of different groups, the platform can choose more flexible teaching strategies, such as providing more images and video resources for visual students, and designing more interactive tasks for kinesthetic students, to improve the teaching effect of the education platform.

3.1.3 Model Accuracy and Effect Analysis

In order to verify the accuracy and effect of the fuzzy clustering model, the performance of the model is analyzed comprehensively by using several evaluation indexes. It utilizes a contour coefficient and an error measure, which can effectively measure the quality of clustering results and the accuracy of classification. By comparing the traditional hard clustering algorithm with other common classification algorithms, it was found that the improved fuzzy clustering algorithm has obvious advantages in terms of clustering effect. The Silhouette Coefficient is an important indicator of cluster quality. A higher value indicates that data points are closer together in clusters and the separation between clusters is better. As shown in Figure 4 below, after several experiments and model tuning, the contour coefficient of the improved fuzzy clustering algorithm is 0.78, higher than that of the traditional algorithm (0.62), indicating that the proposed model can better classify students' learning styles. In order to verify the effect of the model, an error measure (mean square error) was also used to evaluate the clustering results. As shown in Figure 4 below, the mean square error of the model is 0.12, lower than that of other algorithms (0.18), indicating that the model has fewer errors and greater clustering accuracy. The accuracy of the model is calculated as follows (6):

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \times 100 \tag{6}$$

3.2 Discussion

3.2.1 Summary of Research Results

By means of the fuzzy clustering algorithm, it was found that students in cross-border education platforms show obvious differences in learning styles. There are five major learning styles: visual, auditory, kinesthetic, reading/writing and multimodal. The classification of learning styles is consistent with the existing theories of learning styles, and confirms that different students have different behavior patterns and preferences when engaged in learning. For example, visual students tend to learn through visual materials such as images, videos and diagrams, while auditory students prefer to acquire information by auditory means such as lectures and discussions. Kinesthetic students prefer practical operation and hands-on tasks, while reading/writing students are more inclined to learn through a large number of text materials. Integrated students demonstrate the flexibility to switch between multiple learning styles and are able to choose the most appropriate learning method according to the learning context. These results validate the general applicability of learning style theory and provide a new perspective for the design of personalized learning paths in cross-border education. Students' learning needs and behavior patterns in multicultural environments can be more clearly understood by means of the fuzzy clustering algorithm. The differences in learning preferences of students from different cultural backgrounds should encourage educators to consider ways to effectively meet diverse learning needs. Given the extent of globalization, this has become a challenge for online education platforms.

3.2.2 Research Significance and Impact

The results of this study contribute to both educational theory and practice. From a theoretical point of view, the study validates the applicability of learning style theory in the digital education environment. The fuzzy clustering algorithm can identify students' individual learning style, support the theoretical framework of personalized learning, and strengthen the value of personalized education. Learning is a highly personal process, and different students show different needs and preferences when learning, so the design of personalized learning paths is the key to improving learning efficiency and outcomes. From the practical perspective, the results of the research provide a practical reference for the design of online education platforms. By identifying students' learning styles, the platform can provide personalized learning content and teaching strategies for different groups of students. For visual students, more illustrated learning materials can be provided; for auditory students, audio- and video-based learning resources can be designed. For kinesthetic students, the design of interactive and practical tasks can be strengthened. This personalized teaching approach not only increases students' engagement and motivation to learn; it also improves their learning outcomes. The study also found that there are differences in students' learning styles depending on cross-cultural backgrounds, which suggests higher requirements for the development of cross-border education platforms. When designing a global online education platform, the diverse learning needs of students in different regions and from different cultural backgrounds must be fully taken into account. The platform should have a flexible teaching mode and be able to provide customized learning content according to the specific needs of students to achieve better teaching and learning outcomes. This study provides a theoretical basis for personalized teaching via online education platforms and promotes the progress of educational technology. Future research could explore how technology, such as big data analytics and artificial intelligence, can automatically identify students' learning styles, adjust learning paths and course content in real time, and provide more precise personalized education services to learners worldwide.

4. CONCLUSION

In this study, by applying a fuzzy clustering algorithm, the learning styles of students in a cross-border education platform are comprehensively analyzed. Through the cluster analysis of students' learning behavior data, five main learning styles were identified: visual, auditory, kinesthetic, reading/writing and multimodal. Each learning style represents the different preferences and behavioral patterns that students exhibit during the learning process. The research results show that the diversity and individuation of learning styles are factors that cannot be ignored. In the cross-border education platform, students' different cultural backgrounds and educational environments add to the complexity of learning styles. The fuzzy clustering algorithm can effectively deal with the uncertainty and diversity of learning data, and accurately reflect the transition of students between different learning styles through the calculation of membership degree, offering a new approach in terms of the design of personalized learning paths. By identifying the different learning styles of students, educators can design more accurate course contents and teaching methods according to students' learning preferences, so as to improve the learning outcomes and learners' participation. From a practical point of view, the results of this study are of great significance to the teaching design of cross-border education platforms. Given the globalization trend, educational platforms are faced with the challenge of meetiing the needs of students from different cultural backgrounds. By identifying students' learning styles, the education platform can provide a more personalized learning experience and improve students' satisfaction and learning outcomes. The fuzzy clustering method used in this study is not only applicable to cross-border education platforms, but can also be extended to other types of online learning systems, providing strong support for personalized learning research in the field of education. This study verifies the application value of learning style theory in modern online education and provides a theoretical basis for the optimization of teaching strategies in cross-border education platforms. On this basis, future research could explore ways to combine artificial intelligence and big data analysis technology in order to more finely mine students' learning characteristics and achieve more accurate personalized education.

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