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PAPER

Improving English Listening and Speaking Abilities in Online Interactive Platforms

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ABSTRACT

In the globalized and digitized modern society, the cultivation of English listening and speaking ability has attracted more and more attention. With the development of information technology, the application of classroom online interactive platforms in English listening and speaking teaching is becoming increasingly widespread. However, existing studies focus on the technical performance and functionality of online interactive platforms, lacking a deep understanding of students' actual learning behaviors and teachers' using behaviors. Moreover, most of the studies analyze the platform effect at the macro level and neglect the impact of the student-teacher interactive mode at the micro level. Therefore, this research focused on studying the hierarchical clustering of students' online learning behaviors and the typical student-teacher interactive mode of "resource-platform-need," aiming to fill this gap. A data-driven research method was used, which was expected to provide new understanding and perspectives, bringing new theoretical and practical values to the educational technology field. The research results helped design and optimize the online interactive platform and better met the needs of students and teachers, thus promoting the development of English listening and speaking teaching.

KEYWORDS

classroom online interactive platform, English listening and speaking teaching, hierarchical clustering of learning behaviors, resource-platform-need interactive mode, educational technology, data-driven research method

1 INTRODUCTION

In the modern society of globalization and digitization, the cultivation of English listening and speaking ability is becoming increasingly important. This cross-cultural communication ability has become one of the most important universal skills in the 21st century [1–3]. English listening and speaking ability plays an irreplaceable role, from academic research and business communication to communication

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in daily life. As the world becomes more interconnected, the demand for such a communication skill is also increasing. Therefore, as a key teaching subject, English listening and speaking teaching has been undergoing changes in order to meet this constantly changing demand [4–7].

It is particularly noteworthy that English listening and speaking teaching has also begun to adopt classroom online interactive platforms along with the rapid development of information technology, making teaching more in line with modern requirements and significantly improving the teaching effect [8–13]. This change not only corresponds to the demand for English listening and speaking ability in today's society but also helps improve teaching efficiency and quality, thus bringing enormous value to the improvement of educational quality and social progress [14–16].

Therefore, it is necessary and important to discuss the application of classroom online interactive platforms in English listening and speaking teaching. Deep understanding and optimization of the platform application not only further improves teaching methods and enhances students' learning effect but also promotes the development of educational technology and makes possible more comprehensive preparation for the future educational environment. Although studies of this field have been gradually increasing, there are still many shortcomings in existing studies.

Most existing research methods focus on the technical performance and functionality of the online interactive platform, but the research on students' actual learning behaviors and teachers' using behaviors is insufficient. However, these behaviors are crucial when understanding how to more effectively use an online platform to improve the effect of English listening and speaking teaching [17–19]. In addition, existing studies focus more on understanding the role of online interactive platform at the macro level, while neglecting the impact of the student-teacher interactive mode on teaching effect at the micro level. These deficiencies limit the comprehensive understanding and further improvement of classroom online interactive platforms in English listening and speaking teaching application.

Therefore, this research aimed to fill these gaps by studying two main aspects: first, research on the hierarchical clustering of students' online learning behaviors, which expects to reveal the internal laws and patterns of the behaviors by deeply mining and analyzing a large amount of learning behavior data; second, research on the typical student-teacher interactive mode of "resource-platform-need," which explores how online interaction platforms meet the needs of students and teachers, and how this interactive mode affects the teaching effect. It is expected that the in-depth research on these two aspects can provide a new perspective of understanding the application of online interaction platforms in English listening and speaking teaching.

This study not only makes up for deficiencies of existing studies but also brings new theoretical and practical values to the educational technology field. Furthermore, this study may help design and optimize online interactive platforms to better meet the needs of students and teachers, and promote the sustained development of English listening and speaking teaching, thus ultimately achieving the goal of improving the teaching quality.

2 HIERARCHICAL CLUSTERING OF STUDENTS' ONLINE LEARNING BEHAVIORS

Hierarchical clustering of students' online learning behaviors helps explain more deeply how students learn English listening and speaking in an online environment and the behavior patterns they exhibit during this process, which helps improve teaching methods and better meet students' learning needs.

2.1 First-hierarchy clustering

The raw data sources for the hierarchical clustering research on students' online learning behaviors include records of login, learning resources accessed and used, assignment submission, interaction, academic performance, students' feedback, and teacher evaluation, as shown in Figure 1, which provide rich information for hierarchical clustering research, helping deeply explain students' online learning behaviors and patterns.

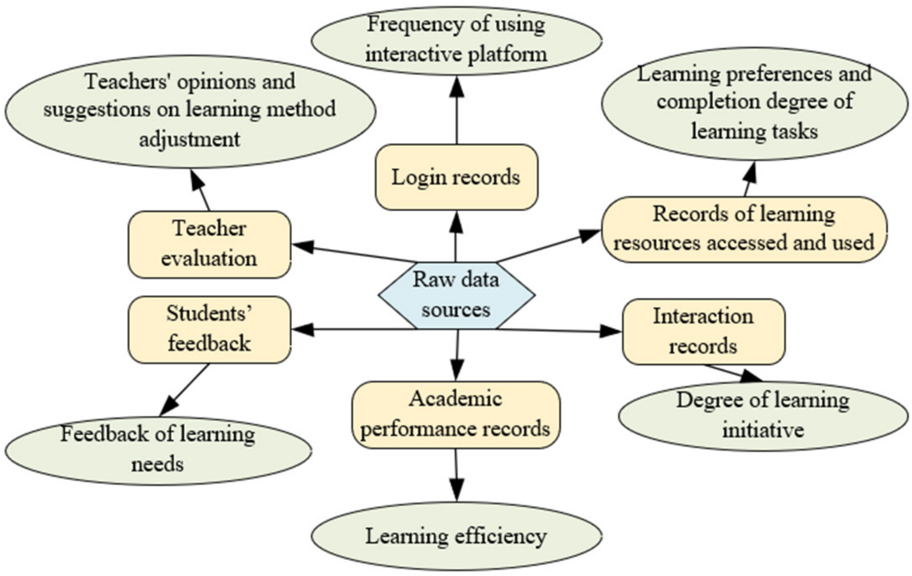

Fig. 1. Raw data sources of hierarchical clustering research on students' online learning behaviors

For hierarchical clustering of students' online learning behaviors, data were preprocessed first, including normalization processing, which aimed to eliminate the dimensional and scale effects of the data, allowing different features to be compared on the same scale. This processing made the dynamic changes in students' online learning behaviors more apparent and filtered out the noise impact on basic learning needs, laying the foundation for recognizing and classifying the subsequent online learning behaviors of students. Then, symbolic aggregate approximation was made, which converted the continuous-learning-need curves of students into discrete strings, aiming to reduce the complexity of data, the amount of calculation, and the storage space occupied. Markov models were used to extract the dynamic learning behavior characteristics of students, because the learning behaviors of each student were considered as the transfer process of a series of states. Then K-L distance was used to measure the differences of the Markov models between students, which generated the K-L distance matrix between students or between teachers and students. Calculation of the K-L distance between students quantified their learning behavior differences. Finally, the adaptive K-medoids algorithm was used for the first-hierarchy clustering.

This series of operations essentially extracted meaningful information from the raw online learning behavior data of students through a bottom-up approach and hierarchically classified it, which revealed not only their learning behavior patterns but also the hierarchical relationship between these patterns.

The traditional K-medoids algorithm used absolute difference and sum of absolute differences (SAD) to determine the clustering effect. Let f_{uk} be the dynamic learning behavior characteristics of student k belonging to the u-th class students, p_u be the dynamic learning behavior characteristics of the cluster center of the u-th class students, and bv_u be the total number of students belonging to the u-th class students. Calculation of SAD was completed using the following equation:

$$ASF = \sum_{l=1}^{j} \sum_{f_u \in V_u} DI\left(f_u, p_u\right) = \sum_{l=1}^{j} \sum_{f_u \in V_u} \sqrt{\sum_{k=1}^{bV_u} \left(f_{uk} - p_{uk}\right)^2} \tag{1}$$

An improved adaptive K-medoids algorithm was proposed in this study, because the traditional algorithm was not applicable to the scenario, where the number of clustering categories was determined in advance. After each K-medoids clustering was completed, the improved algorithm verified whether all data samples in each category met the requirements. If there were data samples that did not meet the requirements, the 2-medoids method was used to reclassify all data samples into the category where the data samples belonged. If all data samples met the requirements, clustering continued for the remaining samples. Let V_{juk}^{y} be the j-th cluster center, and φ be the distortion value, then there were:

$$R_j = \sum_{u=1}^{Y} \sum_{k=1}^{B} \sum_{u=1}^{B} \left(f_{uk}^{y} - V_{juk}^{y}\right)^2 \leq \varphi \sum_{u=1}^{Y} \sum_{k=1}^{B} \sum_{u=1}^{B} V_{juk}^{y\,2} \tag{2}$$

2.2 Second-hierarchy clustering

In the context of blending learning reform, this study analyzed students' online learning behaviors in the application scenario, where students participating in classroom online interactive learning were recommended suitable learning plans. The existing learning plans were divided into two categories: ladder and time-sharing learning plans. Therefore, all student categories generated based on the adaptive K-medoids algorithm merged. Finally, all learning behaviors of students were divided into two types: regular and variable.

Furthermore, differentiated feature extraction was performed for the merged two types of students. For students with variable learning behaviors, the total amount of learning behaviors was used as their classification features. For students with regular learning behaviors, the total amount and dense period distribution of their learning behaviors were used as their classification features, because their learning behaviors were dense with concentrated distribution periods. Based on the extracted characteristic quantity of students, their learning behaviors were classified in the second hierarchy.

For students with variable learning behaviors, the monthly cumulative amount of their learning behaviors was extracted as the characteristic attribute of the second-hierarchy clustering. Let DA be the number of days in a month for students participating in classroom online interaction. W_{MO}, the total monthly learning behaviors of each student, was calculated using the following equation:

$$W_{MO} = \sum_{u=1}^{DA} \sum_{k=1}^{TI} W_{uk} \tag{3}$$

In the learning-need data of students, the time when the learning behaviors were greater than the daily average learning behaviors was selected as a time of dense learning behaviors. Let TI be the total amount of sampling time of students' learning-need data in a day and W_u be the amount of learning behaviors corresponding to the sampling point at time u, then β_d, the density threshold of students, was calculated using the following equation:

$$\beta_d = \frac{1}{TI}\sum_{u=1}^{TI} W_u \tag{4}$$

Let bd_u^y be the number of days for dense learning behaviors of student u at sampling time y, then bd_u, the time-frequency vector of dense behaviors, shown in the following equation, was constructed for students based on β_d:

$$bd_u = \left[bd_u^1, bd_u^2, \ldots, bd_u^{48} \right] \tag{5}$$

After using W_{MO} and bd_u as the characteristic quantity of learning behaviors, the adaptive K-medoids algorithm was used to further divide students with regular behaviors, which obtained student types with different distribution patterns of dense behaviors.

3 TYPICAL STUDENT-TEACHER INTERACTIVE MODE OF "RESOURCE-PLATFORM-NEED"

This research studied the typical student-teacher interactive mode of "resource-platform-need," which aimed to better understand how students used and interacted with teaching resources, as well as how these resources met or did not meet their learning needs. Figure 2 shows the research framework. Students and teachers are the main users of online interactive platform, and their interaction behaviors and needs should be important references for platform design. By observing and analyzing how they interact on the platform, the advantages and disadvantages of platform design can be identified to make improvements. Moreover, the study of "resource-platform-need" interactive mode can help understand students' learning needs more deeply. Each student has his/her own unique learning needs, which may be affected by his/her learning objectives, knowledge background, learning style, and other factors. By observing how students use resources and the platform to meet these needs, more information about these needs can be obtained, thus providing more personalized and effective teaching support.

For students with the ability to participate in interactive learning and propose learning needs—that is, for students either submitting learning needs to the classroom online interactive platform or participating in interactive learning on the platform—this section constructed a hierarchical model of "resource-platform-need" information and interaction between classroom online interaction platform and students, and proposed a strategy that game competition of students' learning needs ultimately determined the selection plan of teaching resources and classroom online interaction form. Based on the method of "centralized regulation, distributed autonomy, and remote collaboration," multi-level control was introduced into the platform, which managed students participating in classroom online interaction.

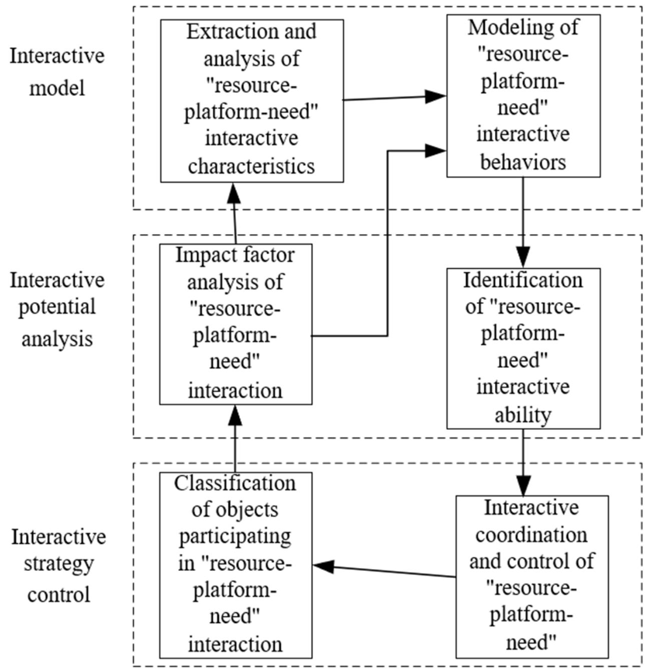

Fig. 2. Research framework of the "resource-platform-need" interactive mode

In order to encourage more students to participate in interactive learning on the platform and enhance their interest in learning, a game strategy of learning needs was proposed based on the fairness of the polling vickrey strategy, which not only met the most learning needs of the student cluster and maximized the collective learning efficiency but also enabled more students to obtain balanced benefits.

For the *b*-th opportunity to meet learning needs of student *j*, let c_j^b and n_j^b be the estimated and true values of the number of classmates with the same needs. The core idea of this strategy is represented by the following equation:

$$c_j^b = n_j^b \tag{6}$$

The game strategy of learning needs, which was proposed based on the fairness of the polling vickrey strategy, was a complex process and included five steps; namely, defining the estimation vector, submitting the learning-need vector, calculating the cumulative vector and weight vector of the number of opportunities, calculating the game vector with most of the needs being met, and completing allocating opportunities of meeting learning needs.

Step 1: Each student estimated the number of classmates with the same needs, and used this estimated value as a vector. This estimation vector not only reflected the similarity between students with a certain need but also was an important factor in determining the opportunities of meeting students' needs. Let $c_j = [c_j^1, c_j^2, \ldots, c_j^R]$ be the estimation vector, and $c_j^b (b = 1,2,\ldots,R)$ be the learning efficiency expected to achieve after student *j* obtained the *b*-th opportunity to meet the learning needs. If totally *B* students participated, then there were:

$$c_j^1 \geq c_j^2 \geq \cdots \geq c_j^R,\ j = 1,2,\ldots,\hat{J}_y \tag{7}$$

Step 2: Based on his/her own learning needs, each student submitted a need vector, which contained all the learning needs, such as understanding knowledge points and mastering skills. The vector was used to compare with the needs of other students to identify common needs. Let $n_j^b(b = 1,2,...,R)$ be the submitted R needs, and N be the subspace of the R-dimensional real vector space E_+^R, then there were:

$$N := \left\{ n_j \in E_+^R \middle| n_j^1 \geq n_j^2 \geq \cdots \geq n_j^R, \forall j = 1,2,...,B \right\} \tag{8}$$

Step 3: The cumulative vector and corresponding weight vector of the number of opportunities, which each student obtained to meet his/her learning needs, were calculated based on the learning-need vector and estimation vector submitted by students. Calculation of the weight vector usually took into account factors such as the intensity and difficulty of students' needs, thus determining the weight of each student obtaining the opportunities to meet his/her needs. Let e be the cumulative vector, and Q^b be the weight vector; that is, $Q^b = [Q_1^b, Q_2^b, ..., Q_{B1}^b]$ $(b = 1,2,...,R)$, with elements in the vector being 0 or 1. The initial values of the elements in $e = [e_1, e_2, ..., e_{B1}]$ were all 0. As the number of opportunities for students to meet their learning needs increased, 1 was added to the value of the corresponding element.

Step 4: For each opportunity proposing learning needs, the game vector with most of the needs being met was calculated. This vector reflected which needs were or were not met when each opportunity of needs was proposed. Let $V_b = [n_1^b, n_2^b, ..., n_{B1}^b]$ $(b = 1,2,...,R)$ be the game vector, then it was solved by arranging the game vector of each student in rows to construct a $B_1 \times R$ game matrix N.

$$N_{B_1 \times R} = [N_1 \quad N_2 \quad N_3 J \quad N_{B_1}]^Y = \begin{bmatrix} n_1^1 & n_1^2 & n_1^3 & \cdots & n_1^R \\ n_2^1 & n_2^2 & n_2^3 & \cdots & n_2^R \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ n_{B_1}^1 & n_{B_1}^2 & n_{B_1}^3 & \cdots & n_{1B_1}^R \end{bmatrix} \tag{9}$$

The Hadamard product was used to obtain the game vector V_b for each opportunity of meeting learning needs. Let $*$ be the Hadamard product, then there were:

$$(S * N)_{uk} = s_{uk} n_{uk} \tag{10}$$

Let $Q^{\%}$ be the inverse operation of the elements 0 and 1 in Q^y, and η_u be the student whose opportunities of meeting learning needs were obtained for the u-th time, then the game vector with the opportunity of meeting learning needs each time was as follows:

$$v_1 = Q_1 * N_1 \tag{11}$$

$$v_1 = Q^1 * v_{u-1} + Q^{\%} * N_{e_{u-1}+1} \tag{12}$$

The weight value of the u-th opportunity of meeting learning needs was calculated using the following equation, with $u = 2,3,...,R$:

$$Q^y = \left[Q_{\eta_u}^y = 0, Q_j^y = 1 \middle| \forall j \neq \eta_u \right] \tag{13}$$

Step 5: Finally the game vector was used to complete allocating opportunities of meeting learning needs. Each student determined the order of his/her needs based on his/her own weight and game vectors, which maximized the opportunities of meeting the needs. If the learning needs of student *j* were met for b_j times, then the total learning efficiency obtained by the student on the classroom online interactive platform during the current period arising from proposal of learning needs was:

$$C_j = \sum_{k=1}^{b_j} c_j^k \tag{14}$$

Step 6: By following the above steps, R allocation results $\eta = [\eta_1, \eta_2, ..., \eta_r]$ with opportunities of meeting learning needs and e_j (the number of opportunities that each student ultimately obtained to meet their learning needs) were obtained. The optimal allocation model of opportunities to meet learning needs, which was obtained from the game strategy of students' learning needs, was as follows:

$$MAX\ O = \sum_{j=1}^{B_1} O_j = \sum_{j}^{B_1} \sum_{b=1}^{b_j} c_j^b - v_b' \tag{15}$$

$$c_j^1 \geq j_j^2 \geq \cdots \geq_j^{bj} \tag{16}$$

$$n_j^1 \geq n_j^2 \geq J \geq n_j^R \tag{17}$$

$$b_j \in [0, R] \tag{18}$$

$$\begin{cases} v_{u+1,j} = v_{u,j}, j \neq \eta_u \\ v_{u+1,j} = n_j^{e_j+1}, j = \eta_u \end{cases} \quad \forall u \in [1, R] \tag{19}$$

where O_j is the learning efficiency obtained by student *j* when proposing learning needs on the classroom online interactive platform, and O is the total learning efficiency benefits of the student group, which are obtained after the platform meets the learning needs.

4 EXPERIMENTAL RESULTS AND ANALYSIS

It can be observed from Figure 3 that the performance of the method proposed in this study, traditional K-medoids method, and traditional K-means clustering method changes in the maximum information assurance (MIA) index, as the number of students increases. When the number of students changes from 600 to 700, the MIA index of the method proposed in this study significantly increases from 0.18 to 0.34, because the hierarchical clustering method proposed in this study better handles a larger amount of data as the number of students increases. In contrast, changes of the traditional K-medoids method and K-means clustering method are relatively small in the MIA index, because their performance improvement in processing large amounts of data is not as significant as the method proposed in this study. Then, as the number of students continues to increase to 1,000, the MIA index of the method proposed in this study slightly decreases but is still significantly higher than that of the K-means clustering method. Moreover, compared with the K-medoids method, the performance of the method proposed in this study is relatively stable when the number of students ranges from 800 to 1,000, indicating that the proposed method has good stability and efficiency for datasets of different scales. Overall, the hierarchical clustering method proposed in this study performs better than traditional K-medoids method and K-means clustering method in MIA index, especially when dealing with large amounts of student data.

It can be observed from Figure 4 that the traditional K-medoids method, the method proposed in this study, and the traditional K-means clustering method perform differently in inter-class distance (representing the degree of difference between different classes) as the number of students increases. The inter-class distance of the traditional K-medoids method increases slightly, from 0.19 to 0.206, with the increase in the number of students, indicating that the classification effect of the method does not significantly improve when dealing with larger datasets. The inter-class distance of the method proposed in this study significantly reduces from 0.025 to 0.02 when dealing with datasets of 700 to 900 students, indicating that the classification effect of the method within this range is significantly better than that of the other two methods. However, the data for this method are not provided when the number of students is 600 and 1,000. The inter-class distance of the traditional K-means clustering method slightly fluctuates as the number of students increases but is relatively stable on the whole, indicating that the method has the same processing effect for datasets of different scales. Overall, the method proposed in this study has the smallest inter-class distance when dealing with datasets of 700 to 900 students, indicating that its classification effect is the best. However, traditional K-medoids method and K-means clustering method do not have significant advantages in inter-class distance, especially when dealing with large-scale data. Therefore, the method proposed in this study has more advantages in improving the precision of student behavior classification on online teaching platforms.

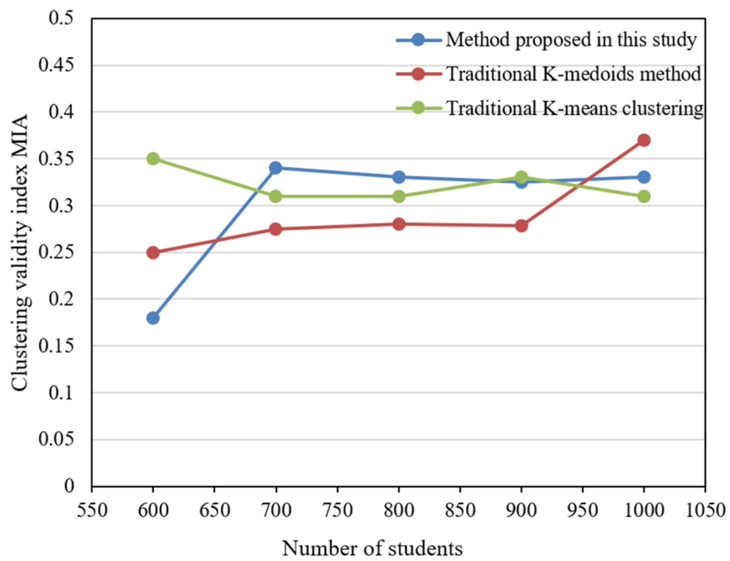

Fig. 3. Comparison of MIA index of different clustering methods when the number of students changes

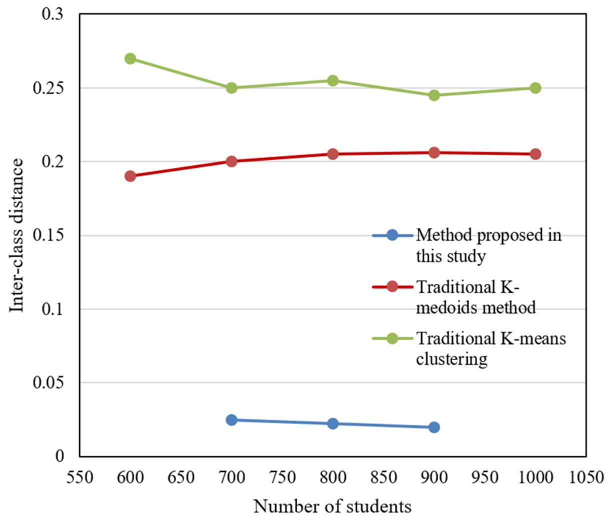

Fig. 4. Comparison of inter-class distances of different clustering methods when the number of students changes

It can be seen from Figure 5 that different allocation methods have different impacts on the MIA index of students. When the random allocation method is used, the MIA index of most students is 1, indicating that the information gap between students is not large, because the random allocation does not consider the specific needs and characteristics of students. The MIA index of the method proposed in this study ranges from 1 and 5, which obviously has a larger distribution range than the other two allocation methods, showing that this method better captures the differences between students and allocates effectively correspondingly, which is an important reason why it is superior to other methods. When the fixed allocation method is used, the MIA index ranges from 0 and 3. Although its difference is not as good as the method proposed in this study, the fixed allocation at least considers certain rules compared with random allocation, thus increasing the allocation difference to a certain extent. Therefore, the method proposed in this study outperforms random and fixed allocation in the distribution range of the MIA index and in capturing the differences of students, which further verifies that the method proposed in this study allocates students in a personalized manner more effectively in practical online teaching scenarios, thus improving the potential of teaching effect.

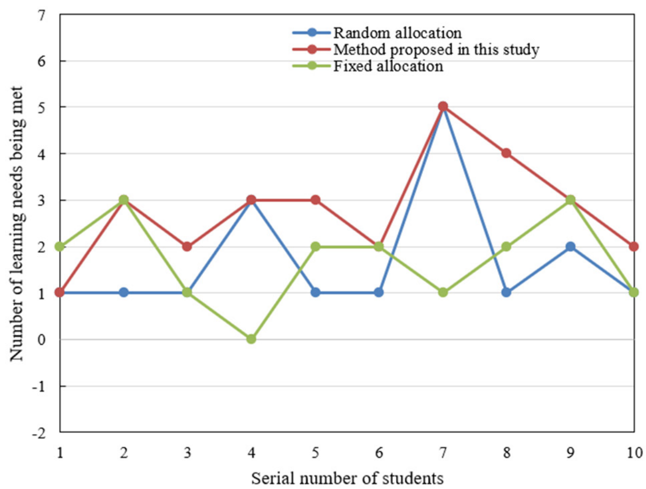

Fig. 5. Comparison of allocation results of opportunities of meeting three learning needs

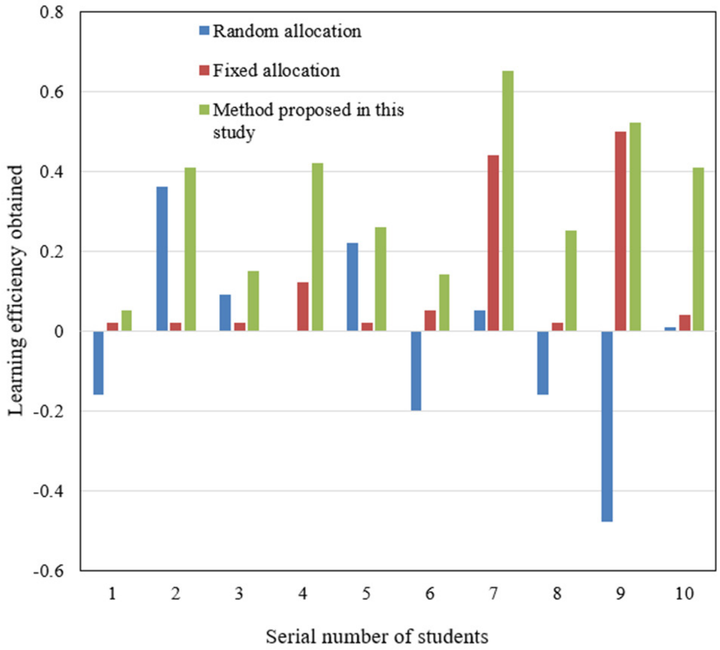

Fig. 6. Comparison of learning efficiency results finally obtained by students under the allocation strategy of opportunities meeting three learning needs

According to Figure 6, which compares and analyzes the allocation strategy of opportunities of meeting three learning needs, it can be seen that the impacts of random allocation, fixed allocation, and the method proposed in this study on the learning efficiency results obtained by students are significantly different. When the random allocation strategy is used, students' learning efficiency exhibits significant fluctuations, and the learning efficiency of some students is even negative, meaning that random allocation does not effectively meet students' learning needs and cannot guarantee the learning efficiency of all students. When the fixed allocation is used, the learning efficiency of all students is positive. However, it is relatively low on the whole, with the highest learning efficiency reaching only 0.5, because fixed allocation cannot differentially deal with needs of individual students, which limits the improvement of learning efficiency. In contrast, when the method proposed in this study is used, the learning efficiency of all students is significantly higher than that of the other two strategies, with the lowest learning efficiency also reaching 0.05, indicating that the method more effectively meets students' learning needs and significantly improves their learning efficiency.

Table 1. Comparison of test data before and after mode application

Test Number	Totally Consistent		Quite Consistent		Consistent		Not Quite Consistent		Not Consistent	
	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest
1	19	18	24	24	24	28	15	14	11	5
2	14	15	28	30	20	25	20	13	11	11
3	16	12	16	13	33	28	15	26	13	15
4	11	20	13	25	31	29	28	5	11	6

(Continued)

Table 1. Comparison of test data before and after mode application *(Continued)*

Test Number	Totally Consistent		Quite Consistent		Consistent		Not Quite Consistent		Not Consistent	
	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest
5	11	18	11	22	18	27	41	17	13	4
6	13	20	11	21	24	28	35	15	13	14
7	11	18	13	28	19	19	38	15	13	14
8	11	21	15	20	26	20	31	21	14	12
9	11	11	15	20	14	22	40	28	14	13
10	11	12	13	16	19	29	38	25	13	12

It can be observed from the data in Table 1 that students' acceptance of "resource-platform-need" interactive mode significantly changes before and after the mode is applied. In the two options of "quite consistent" and "consistent," it can be seen that data increase in most cases after the interactive mode is applied (posttest), indicating that more students better accept and understand this interactive mode after the application. However, data in "not quite consistent" and "not consistent" in some test numbers increase after the mode application, because the application has caused some students to feel troubled or uncomfortable, and these students need more guidance and assistance to adapt to the new mode. Comparative analysis shows that most students better accept and understand the "resource-platform-need" interactive mode after the mode is applied, indicating that this mode has good application value and potential in practical teaching. However, it should also be noted that some students do not like this mode. Therefore, it is necessary to combine feedback of various kinds of students and flexibly adjust teaching strategies in the practical application process, thus maximizing the advantages of this mode.

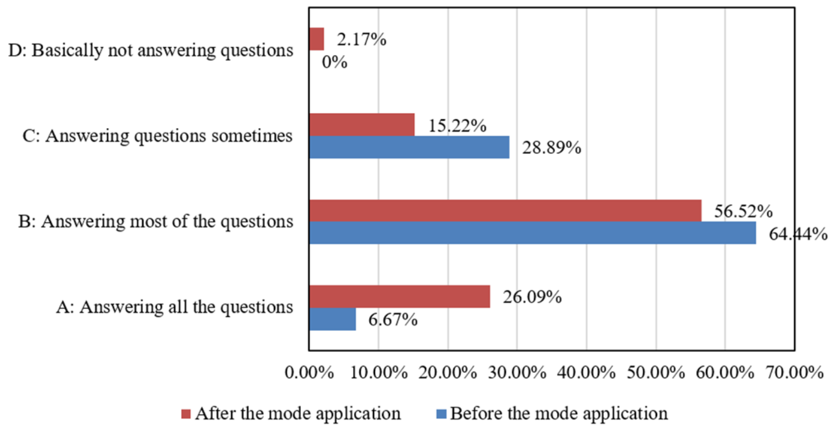

Fig. 7. Answering test questions before and after the mode application

Figure 7 shows the changes in students' ability to answer test questions before and after the "resource-platform-need" interactive mode is applied. For "A: Answering all the questions," the proportion after mode application (26.09%) is significantly higher than that before (6.67%), indicating that more students fully answer the test questions after the interactive mode is applied, which means that they have made significant improvements in their learning. For "B: Answering most of the questions," the proportion before and after the mode application does not change significantly, but the proportion after the mode application (56.52%) is slightly lower than that before (64.44%), because some students have increased from "Answering most of the questions" to "Answering all the questions" after the mode application. The proportion of "C: Answering questions sometimes" after the mode application (15.22%) is also significantly lower than that before (28.89%), also reflecting that students have improved their learning effect and can better answer test questions after the mode application. Although the proportion of "D: Basically not answering questions" after the mode application (2.17%) slightly increases, it is very low on the whole, and the proportion before the mode application is 0, indicating that the vast majority of students still answer some or all of the test questions after the mode application. In summary, after the "resource-platform-need" interactive mode is applied, students have significantly improved their learning effect, with more students fully or partially answering test questions, which fully proves the effectiveness and superiority of this interactive mode in practical teaching.

5 CONCLUSION

After deeply discussing the application of online interactive platform in English listening and speaking teaching, this study revealed the importance of clustering analysis of students' online learning behaviors and application of the "resource-platform-need" interactive mode in improving the teaching effect. Experimental results were summarized as follows:

1. Hierarchical clustering of students' online learning behaviors obtained a deeper understanding of their learning needs and behavior patterns. The clustering method proposed in this study has a higher precision than traditional K-medoids and K-means methods in MIA index. Moreover, when the method was used to deal with large datasets, the inter-class distance of clustering was also better than that of traditional methods, which proved higher efficiency of the method while ensuring the clustering quality.
2. Application of the "resource-platform-need" interactive mode also proved its significance in improving students' learning effect. The game strategy of learning needs was proposed based on the fairness of the polling vickrey strategy, which enabled more students to obtain the opportunities to meet their learning needs, thus maximizing the collective learning efficiency.
3. The results showed that both students' ability to answer test questions and their satisfaction with the classroom significantly improved after the interactive mode was applied, which fully proved the effectiveness of the interactive model in practical teaching.

Overall, the effectiveness and superiority of the method and mode proposed in this study have been verified in theory and practice, which have important reference value for promoting online English listening and speaking teaching and improving students' learning effect. However, many areas in this study can still be improved and deepened, such as further optimizing the clustering algorithm, improving the ability to process large datasets, and exploring more interactive modes. It is expected that other researchers will continue to deepen their research in this field in the future based on this study and make more contributions to the development of online teaching.

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7 REFERENCES

[1] Ji, L. (2023). Analysis of the improvement path of English listening and speaking ability based on big data technology. Applied Mathematics and Nonlinear Sciences, 8(2): 335–345. https://doi.org/10.2478/amns.2023.1.00190

[2] Ilyas, M., Hermawati, S., Refnaldi. R. (2023). The sse of English language learning videos designed through Canva app: Students' perceptions. International Journal of Interactive Mobile Technologies, 17(8): 100–112. https://doi.org/10.3991/ijim.v17i08.39215

[3] Gao, M., Song, W., Zhang, C., Zhou, Q., Su, P. (2022). Situational teaching based evaluation of college students' English reading, listening, and speaking ability. International Journal of Emerging Technologies in Learning (Online), 17(8): 140–154. https://doi.org/10.3991/ijet.v17i08.30561

[4] Ma, Y. (2022). QA learning system-based English listening and speaking ability improvement strategy. Mobile Information Systems, 2022: 7560714. https://doi.org/10.1155/2022/7560714

[5] Pham, A.T. (2022). Engineering students' perception of using Webcams in virtual English classes. International Journal of Engineering Pedagogy, 12(6): 115–127. https://doi.org/10.3991/ijep.v12i6.33317

[6] Liu, Z. (2015). Factors affecting English listening and speaking abilities of non-English major students: Taking engineering students as an example. World Transactions on Engineering and Technology Education, 13(4): 593–597.

[7] Wu, Z., Li, H., Zhang, X., Wu, Z., Cao, S. (2021). Teaching quality assessment of college English department based on factor analysis. International Journal of Emerging Technologies in Learning, 16(23): 158–170. https://doi.org/10.3991/ijet.v16i23.27827

[8] Song, W., Zhang, C., Gao, M. (2022). Analysis method for teacher-student interaction in online English courses. International Journal of Emerging Technologies in Learning, 17(9): 170–183. https://doi.org/10.3991/ijet.v17i09.31371

[9] Liu, X., Abu Samah, N., Md Salleh, S. (2022). The impact of using a mobile app on improving students' creative thinking in business English writing with self-regulated learning. International Journal of Interactive Mobile Technologies, 16(15): 46–61. https://doi.org/10.3991/ijim.v16i15.31477

[10] Luo, Y. (2021). Statistical characteristics of the application of English human-computer interaction mathematical algorithm in online courses. In Journal of Physics: Conference Series, 1952(4): 042046. https://doi.org/10.1088/1742-6596/1952/4/042046

[11] Cao, M. (2021). Design and implementation of multidimensional interaction in online English course under the assistance of omnimedia. Scientific Programming, 2021: 1–10. https://doi.org/10.1155/2021/3713161

[12] Wang, S. (2023). Interactive design method of English online learning interface based on visual perception. International Journal of Continuing Engineering Education and Life Long Learning, 33(2–3): 282–298. https://doi.org/10.1504/IJCEELL.2023.129220

[13] Wilang, J.D. (2022). Specific anxiety situations and coping strategies in full English medium instruction engineering programs. International Journal of Engineering Pedagogy, 12(6): 70–84. https://doi.org/10.3991/ijep.v12i6.33453

[14] Telagam, N., Somanaidu, U., Arun Kumar, M., Sabarimuthu, M., Kandasamy, N. (2021). IoT based secure lock/unlock system using Google Assistant based English and French languages. International Journal of Online and Biomedical Engineering, 17(10): 34–47. https://doi.org/10.3991/ijoe.v17i10.24279

[15] Tao, J., Wei, W. (2022). Application of intelligent flipped classroom technology and HCI interactive mode in English online course design from smart data mining perspectives. In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, pp. 1394–1397. https://doi.org/10.1109/ICESC54411.2022.9885563

[16] Cao, S., Li, H., Wu, Z., Liu, H., Yang, M. (2021). Application of project-driven teaching in college English class. International Journal of Emerging Technologies in Learning, 16(21): 149–162. https://doi.org/10.3991/ijet.v16i21.26869

[17] Zhdanova, D., Korneeva, L. (2019). The use of the interactive platform VIMBOX in English language teaching: A comparison of traditional, blended (flipped classroom), and online models of learning. CEUR. Innovative Approaches in Computer Science within Higher Education, 2562: 25–35.

[18] Yu, W. (2022). Research on interactive practice system of mathematics online classroom under computer artificial intelligence technology. In 2022 International Conference on Computers, Information Processing and Advanced Education (CIPAE), Ottawa, ON, Canada, pp. 150–154. https://doi.org/10.1109/CIPAE55637.2022.00039

[19] Monalisa, L.A., Fatahillah, A., Prihandini, R.M., Hussen, S., Fajri, E.D.R. (2021). The development of online interactive learning media by using Google Classroom assisted by GeoGebra software on the quadratic function material. In Journal of Physics: Conference Series, 1832(1): 012059. https://doi.org/10.1088/1742-6596/1832/1/012059

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