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Original Paper

Combining Big Models and Multimodal Technology to Optimize Learning Path Recommendations in Personalized English Self-learning

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Abstract

With the rapid development of information technology, personalized learning has become an important trend in modern education, especially in the field of English learning. Traditional English teaching methods usually adopt a "one-size-fits-all" approach and fail to fully consider the individual differences of students. This paper aims to solve the problem of insufficient accuracy of path recommendation in personalized English self-learning. To this end, this paper proposes a method to optimize personalized learning path recommendation by combining big models and multimodal technology. Through the analysis and processing of students' learning data by big models, combined with a variety of learning resources such as vision, hearing, and text provided by multimodal technology, the system can dynamically adjust the learning path and provide personalized learning suggestions according to students' learning interests, ability levels, and progress. Specifically, a big model is used to model students' learning history, feedback, and participation, and multimodal technology is combined to generate recommended content that meets students' needs. The experimental results show that the experimental group is superior to the control group in multiple key indicators, including the improvement of learning interest (the average change in the experimental group is 4.3 points, and the control group is 2.5 points), the improvement of task completion (the average learning progress of the experimental group is 93%, and the control group is 75%), and the significant improvement of vocabulary memory retention rate (the experimental group is 88%, and the control group is 73%). In addition, students showed high scores in terms of satisfaction with the recommendation system, relevance of learning content, and adaptability of recommendation difficulty, indicating that the optimization method effectively improved the accuracy and learning effect of personalized learning path recommendations.

Keywords

personalized learning, large model, multimodal technology, learning path recommendation, English autonomous learning

1. Introduction

In the field of English learning, the improvement of vocabulary memory, listening comprehension, oral expression and other abilities is crucial to students' language proficiency. Traditional English learning often relies on the leadership of teachers, but lacks sufficient personalized support, resulting in the inability to maximize students' learning motivation and effectiveness. Therefore, how to optimize personalized learning paths through large models and multimodal technologies and improve students' autonomy and effectiveness in English learning has become the core issue of this study.

This paper aims to combine large models with multimodal technology to propose a new personalized learning path recommendation system, focusing on optimizing students' learning experience and improving learning efficiency. Through experimental verification, we explored the application effect of this system in English learning and compared it with traditional learning methods. The research results show that personalized recommendations combining large models and multimodal technology can significantly improve students' learning interest, learning efficiency and vocabulary memory retention rate, thus providing valuable reference and practical experience for future educational technology applications.

This paper first discusses the background and importance of personalized learning path recommendation system, then introduces the theoretical basis and application of combining large models and multimodal technology, and then elaborates on the experimental design and implementation process, and analyzes the experimental data and results. Finally, the article summarizes the main findings of the study, discusses its significance for the optimization of future personalized learning systems, and proposes possible research directions.

2. Related Works

In recent years, with the continuous development of technology and the innovation of educational concepts, personalized learning systems have made remarkable progress in improving learning outcomes. Zayet et al. proposed a personalized conceptual framework, which includes four stages: student profiling, material collection, material screening, and verification, to optimize the K12 online learning recommendation system (Zayet, Ismail, Almadi et al., 2023). Hwang et al. developed the Smart RoamLingo application, which combines AI-generated example sentences and feedback based on personal writing to improve writing skills. The experimental results showed that the experimental group using the app performed significantly better than the control group in the post-test (Hwang, Nurtantyana, Purba et al., 2023). Charles develops and evaluates a personalized mobile education system based on AI and user-centered design principles. The system will provide customized learning content and recommendations based on individual preferences (Charles, 2023). Bhaskaran and Marappan proposed an enhanced vector space recommender system to optimize personalized e-learning experience. The system automatically recommends learning resources based on learners' interests, needs, and knowledge levels through an improved content filtering method (Bhaskaran & Marappan, 2023). Chiu guided the design of a context-aware ubiquitous language learning system and a fitness English curriculum through needs analysis. They found that learners need to master fitness-related terminology and oral communication skills, and suggested that the CAULL system should adopt hypermedia technology, have a user-friendly interface and learning archive functions (Chiu, Liu, Barrett et al., 2023). Bashori et al. explored the impact of language learning systems based on automatic speech recognition technology on foreign language pronunciation. The data show that both the “I Love Indonesia (ILI)” and “NovoLearning (NOVO)” systems can significantly improve learners’ pronunciation, with NOVO performing better (Bashori, van Hout, Strik et al., 2024). Chiriboga et al. explored the role of artificial intelligence in foreign language teaching. AI tools can improve vocabulary retention, oral fluency, and enhance learning motivation and autonomy (Chiriboga, Burgos, Avila et al., 2025). Lee et al. explored the autonomous learning method based on the Learner Generated Context (LGC) framework and developed and tested an AI-assisted system to improve the English learning experience of Korean students (Lee, Kim, & Sung, 2023). Aslanyan Rad explored the application of personalized WebQuest learning among EFL students in higher education and used literature data mining methods for analysis and description. He found that there is still little research on personalized learning methods (Aslanyan, 2024). Li et al. explored the impact of Self-Directed Learning (SDL) ability on learning behavior and reading outcomes, especially in the school environment. The results showed that students with high SDL ability read more books and read on more days than students with low SDL ability (Li, Majumdar, Chen et al., 2023). Zubanova et al. aimed to explore the relationship between the MCL (Mobile Contextual Learning) system based on GPS (Global Positioning System) and English learning achievement. The results show that students’ self-regulation and self-efficacy significantly affect learning outcomes and can predict future academic performance (Zubanova, Didenko, & Karabulatova, 2023). Existing research still faces bottleneck issues such as data privacy protection, accuracy of personalized recommendations, and system compatibility in the practical application of personalized learning systems.

3. Methods

3.1 Application of Large Models in Personalized Learning Path Recommendation

In personalized learning, the application of big models can effectively improve the accuracy and personalization of learning path recommendations. Big models use deep learning and data analysis techniques to extract effective information from students' learning data and tailor learning plans for students. By analyzing students' learning behaviors, the system can identify students' learning strengths and weaknesses, predict their future learning needs, and make real-time adjustments based on this information.

In English vocabulary learning, the big model can push review content according to the student's memory curve to avoid learning obstacles caused by forgetting. The system continuously tracks the student's learning progress, identifies the student's mastery of certain vocabulary, and pushes personalized review tasks to ensure that students review at the appropriate time to maximize the memory effect. Through this intelligent learning path adjustment, students can master more vocabulary in an efficient time and internalize it into long-term memory.

3.2 Multimodal Technology Improves Learning Experience

In learning English words, students can see the usage scenarios of words through video teaching materials, hear the correct pronunciation of words through audio teaching materials, and understand the meaning of words more intuitively through the combination of images and text. Multimodal learning not only enhances students' learning interest, but also helps students better remember and apply what they have learned. The system can intelligently recommend the most suitable multimodal resources based on students' learning progress and preferences to adapt to students' learning styles.

In addition, using multimodal technology for contextualized learning is also a very effective teaching method. For example, the system can use situational simulation videos to allow students to practice listening and speaking in real contexts, helping students transform language knowledge into practical application skills. By practicing in a simulated real environment, students can not only improve their listening and speaking skills, but also better understand English culture and language background, and enhance their confidence in language use.

3.3 Dynamically Adjust the Adaptability of Learning Paths

English learning is not static, but a dynamic process. Students' learning progress, depth of understanding and mastery will continue to change. Therefore, personalized learning path recommendations need to have the ability to dynamically adjust to meet the needs of students at different learning stages. In this context, the combination of big models and multimodal technology can provide adaptive learning paths to ensure that learning content and learning methods always meet students' actual needs.

For example, in English listening learning, if the student's listening level is low at a certain stage, the system will increase the proportion of listening materials and enhance the student's listening training through multimodal resources (such as video, audio comparison, subtitles, etc.). Through real-time feedback analysis of large models, the system can identify students' learning weaknesses and push targeted practice materials in a timely manner. As students' listening level improves, the system will gradually increase the difficulty and complexity of listening materials to help students gradually overcome learning obstacles.

At the same time, the system can also flexibly adjust the learning content based on students' feedback in different learning links. For example, if students encounter great difficulties in learning grammar, the system will automatically increase the frequency of grammar exercises and recommend relevant grammar video explanations and exercises to help students better master grammar knowledge. The adaptability of the system is not only reflected in the adjustment of learning content, but also in changes in learning methods. For students who prefer visual learning, the system will give priority to recommending learning resources that combine pictures and texts, and for students who like listening exercises, more audio materials will be recommended to ensure that students can achieve the best learning results under different learning methods.

3.4 Feedback-based Adaptive Learning Strategy

Adaptive learning strategies are a critical part of personalized learning. Students will encounter different difficulties and challenges in the learning process. How to dynamically adjust the learning path based on student feedback is the key to improving learning outcomes. Combining big models and multimodal technology, the system can track students' learning progress in real time and dynamically adjust learning strategies based on students' feedback. For example, if a student performs poorly in a certain learning session, the system will automatically push more relevant content and help students overcome difficulties through multimodal learning resources.

In English learning, students usually encounter challenges in grammar, vocabulary, listening, etc. Through the precise analysis of the big model, the system can promptly identify which aspects the students are weak in and recommend corresponding review materials and exercises. The system can dynamically adjust the learning plan based on students' feedback to ensure that the learning content always meets the actual needs of students. For example, the types of errors students make in grammar exercises can be analyzed and fed back by the system, and then the corresponding grammar knowledge points and exercises can be recommended to students.

4. Results and Discussion

4.1 Experimental Design Framework

Participants selected students from different educational backgrounds to conduct the experiment to ensure sample diversity. The experimental group and the control group should have similar learning foundations. The experimental group uses a personalized learning path recommendation system based on large models and multimodal technology, while the control group Use traditional teaching methods.

Experimental group: A personalized learning system supported by large models and multimodal technologies.

Control group: Used traditional offline English learning methods (such as textbooks, paper assignments, online learning platforms without intelligent recommendation systems, etc.).

Students were randomly grouped according to basic factors such as their English proficiency and grade to ensure comparability between the experimental group and the control group.

4.2 Learning Task Design

Design a series of learning tasks based on English listening, speaking, vocabulary, and reading comprehension, and ensure that the task content is the same between the experimental and control groups.

Experimental group tasks: Through the intelligent system, personalized learning content is recommended based on students' personal data and progress. The system will dynamically adjust the difficulty, content and schedule of the tasks, and continuously optimize the recommended path based on students' learning progress and feedback.

Control group tasks: Provide the same tasks, but do not adjust them according to students' learning progress. Students complete the tasks according to the predetermined plan.

4.3 Data Analysis

In this section, the experiment analyzes the experimental data in detail through different indicators to evaluate the effectiveness of the personalized learning path recommendation system. Specifically, several key indicators are analyzed, including changes in students' learning interests, learning efficiency, frequency of learning path recommendation adjustments, feedback satisfaction, and vocabulary learning efficiency.

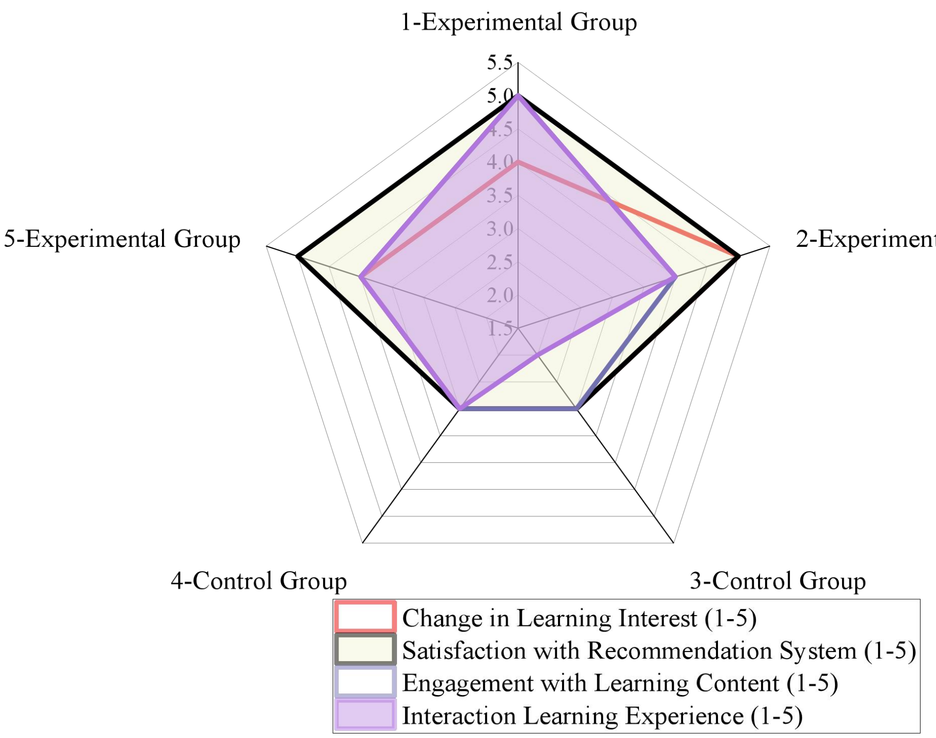

Figure 1. Learning Interest Assessment

From the **perspective of changes in learning interests**, students in the experimental group generally showed higher interest change scores. All students in the experimental group scored 4 points or above, indicating that the personalized recommendation system significantly improved students' interest in learning English. This is closely related to the enhanced learning motivation and improved learning participation of the experimental group. In contrast, the scores of learning interest changes of students in the control group were lower, generally 3 points, which shows that under the traditional teaching model, students' interest changes are relatively limited. Regarding **satisfaction with the recommendation system** , students in the experimental group gave the highest rating (5 points). This result shows that the personalized recommendation system supported by large models and multimodal technology meets students' needs for learning support, and students show high recognition of its functions. The satisfaction scores of students in the control group were generally low (3 points), indicating that traditional teaching methods failed to effectively stimulate students' enthusiasm and meet their personalized needs. In terms of **participation in learning content**, students in the experimental group also scored high (4 points and 5 points), which shows that the personalized recommendation system not only improves students' interest , as shown in Figure 1.

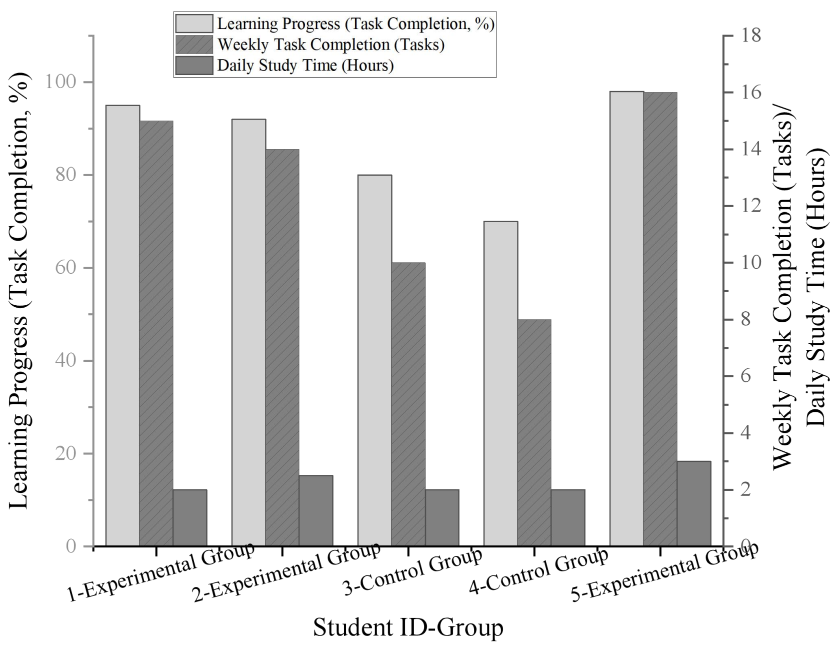

Figure 2. Learning Efficiency Evaluation (Learning Time and Task Completion)

According to the experimental data table in Figure 2 , the analysis results are as follows:

Regarding **daily study time** , students in the experimental group generally spent more time on study, with an average study time of 2 to 3 hours, while students in the control group generally spent 2 hours on study per day. This shows that the experimental group may have stimulated students' learning enthusiasm through the support of the personalized recommendation system, prompting them to spend more time on study, thereby improving learning efficiency. In terms of **weekly task completion** , the experimental group completed significantly more tasks than the control group. The weekly task completion of students in the experimental group was generally 14 or more, while that of students in the control group was lower, generally between 8 and 10. This difference shows that with the help of the personalized recommendation system, the experimental group can complete tasks more efficiently and maintain a higher learning progress. In terms of learning progress (task completion), the experimental group's learning progress was generally high, with a task completion rate of more than 92%, and some students even reached 95% and 98%. In contrast, the task completion rate of students in the control group was low, generally only 70% to 80%, indicating that students' learning progress was slow under the traditional teaching model and it was difficult to achieve the learning efficiency and progress of the experimental group.

Table 1. Frequency of Adjustment of Learning Path Recommendations and Student Feedback

Student ID	Group	Number of Recommendation Path Adjustments	Feedback Satisfaction (1-5)	Relevance of Recommended Content (1-5)	Difficulty Adaptability of Recommendations (1-5)
1	Experimental Group	12	5	5	5
2	Experimental Group	10	4	4	5
3	Control Group	0	3	3	3
4	Control Group	0	3	3	3
5	Experimental Group	15	5	5	5

the number of times the recommended path was adjusted, the number of times the recommended path was adjusted by the students in the experimental group was relatively frequent, with an average of 10 to 15 times, while the number of times the adjustment was 0 for the students in the control group. This shows that the personalized recommendation system of the experimental group can dynamically adjust the learning path according to the students' learning progress and needs, providing students with a more personalized learning experience. The control group did not make any path adjustments, which may be due to the fixed mode of the traditional teaching method, which failed to make flexible adjustments according to the actual needs of the students. In terms of **satisfaction with the adjustment feedback** , the students in the experimental group were generally satisfied, with a score of 4 to 5 points, especially one student gave a full score of 5 points. This shows that the personalized recommendation system of the experimental group was highly recognized by the students after the path was adjusted, and the students were satisfied with the adjustment effect of the system. The feedback satisfaction of the control group was low, generally 3 points, reflecting that the traditional teaching model could not make timely and effective optimization adjustments based on the feedback of students, resulting in low student satisfaction with the teaching content , as shown in Table 1.

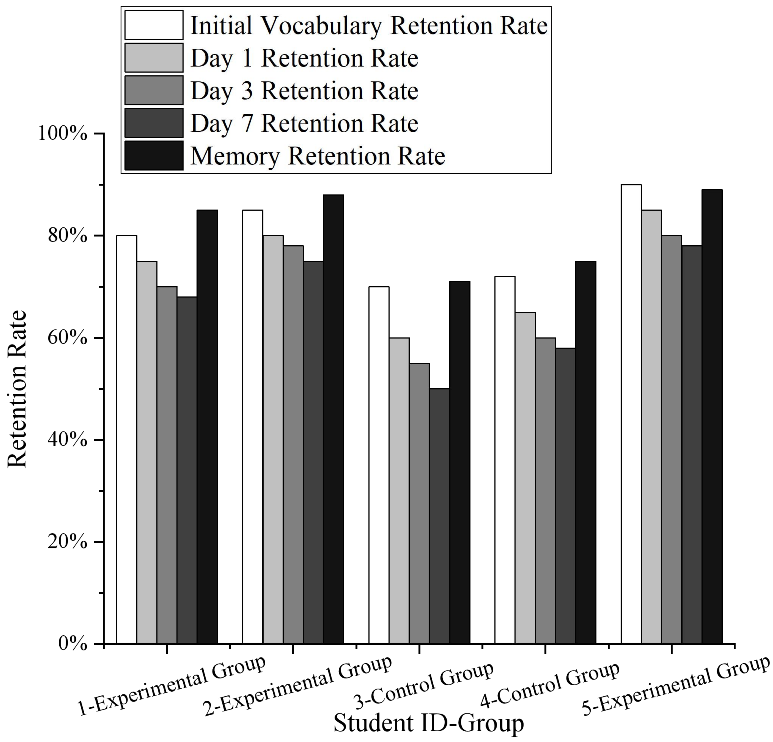

Figure 3. Vocabulary Learning Efficiency (Word Memory Curve Analysis)

In terms of **initial vocabulary memory rate**, the experimental group's initial memory rate was generally higher, averaging 80% to 90%, while the control group's initial memory rate was lower, generally around 70%. This suggests that the students in the experimental group may have acquired relatively solid basic knowledge at the initial stage of vocabulary learning, while the students in the control group started from a lower level. Judging from the change in memory rate from **1 day** to **7 days later** , the memory retention performance of the experimental group was significantly better than that of the control group. The memory rates of the students in the experimental group gradually decreased after 1 day, 3 days and 7 days, but still maintained a high level of memory retention. For example, the first student's memory rate dropped from 80% to 68%, maintaining an 85% memory rate, while the third student's memory rate dropped from 70% to 50%, and the memory retention rate was only 71%. This shows that the learning method of the experimental group may have helped students achieve more significant results in consolidating the memory content through personalized recommendations and optimized learning paths. In terms of the key indicator of **memory retention rate** , the memory retention rate of the experimental group was generally high, ranging from 85% to 89%, which was much higher than the 71% to 75% of the control group (see Figure 3) . This difference suggests that the experimental group can better help students achieve better results in short-term and long-term memory retention through the recommendation and adjustment of personalized learning paths. In contrast, the memory rate of the control group showed a significant decline, indicating that under the traditional teaching model, students' vocabulary memory retention is poor.

5. Conclusion

With the vigorous development of the digital economy, digital technologies such as big data, the Internet, blockchain, artificial intelligence, 5G and the Internet of Things are rapidly integrated into people's production and life, injecting new vitality into the development of China's sports industry. For sports companies, the advent of the digital economy era has not only changed people's sports consumption needs, but also required sports companies to rethink and examine their original operating models. This study combines large models and multimodal technology to propose a learning path recommendation system for optimizing personalized English autonomous learning. Through experimental verification, the results show that the system can significantly improve students' learning interest, sense of participation and vocabulary memory retention, and improve learning efficiency and task completion. The experimental group outperformed the control group in terms of learning task completion, learning progress, and vocabulary memory retention, which proves the effectiveness of large models and multimodal technology in personalized learning path recommendation. The size of the experimental sample was relatively small, which may affect the generalizability of the results. The research process failed to fully consider the differences among students in different learning environments. Future research can expand the sample range and further explore the differences in learning outcomes among students from different backgrounds. Although the recommendation system has improved the accuracy of recommended paths through large models and multimodal technologies, its adaptability and flexibility still need to be further optimized. Future research could be improved in several ways. The system's dynamic adjustment capabilities can be improved by introducing more diversified learning resources and personalized recommendation strategies.

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