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Personalized learning of college English using knowledge graphs combined with user portraits

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In this study, user portraits were combined with knowledge graphs to develop a personalized recommendation algorithm for English exercises and applied it to the teaching of English. A case analysis was conducted using sophomore students from the School of Foreign Languages at Ningxia Medical University. The optimal parameters of the long short-term memory (LSTM) algorithm for classifying exercise knowledge points were tested first, and a knowledge graph of English exercises was then constructed. The students were divided into a control group and an experimental group. The control group received traditional multimedia teaching, while the experimental group utilized the personalized recommendation algorithm for English exercises to facilitate their learning. English tests were conducted before and after a four-week teaching period. Moreover, a questionnaire was administered to the experimental group to gather feedback on the new teaching method. The results showed that the LSTM algorithm performed best in classifying exercise knowledge points when the number of nodes in the hidden layer was 128, and the activation function was sigmoid. The teaching mode, assisted by the personalized recommendation algorithm based on the user portrait and knowledge graph, effectively improved students' English scores and increased their interest in learning English.

Keywords: user portrait, knowledge graph, English, personalized recommendation

1. INTRODUCTION

With the rapid advancement of information technology, the field of education is undergoing unprecedented changes. Particularly in regard to the teaching of English in the higher education sector, providing accurate and efficient personalized learning solutions based on individual student differences has become crucial in enhancing teaching quality and learning outcomes (Yulia & Amirudin, 2021). A user portrait is a significant tool for understanding learners' characteristics, and its combination with a knowledge graph, a useful tool for organizing and representing knowledge, can offer new research perspectives and practical pathways for the personalized learning of college students (Davis et al., 2015; Wang et al., 2022). In English teaching, a user portrait comprises basic information about a student, including interests and a set of learning behaviors that can indicate the student's knowledge mastery (Ren & Wang, 2019; Xie, 2023). The knowledge graph in English teaching illustrates the structural connections between knowledge points. Personalized English learning can be achieved by integrating learning behaviors from user portraits with the knowledge graph.

Wang (2022) combined the knowledge graph-embedded scoring algorithm with the link-scoring algorithm to effectively address the issue of missing answers in the current knowledge graph-embedded question and answer method. Yuan et al. (2023) introduced the graph convolutional network (GCN) and attention mechanism to establish an attention-guided GCN-based relationship extraction model and a GCN-based text categorization model to automatically extract knowledge of advanced mathematics and construct knowledge graphs for this subject. Yue et al. (2022) designed an open-knowledge-point model based on the knowledge graph to bridge the gap between theory and practice in the knowledge point setting for courses on artificial intelligence.

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Figure 1 Basic hierarchies of a college English student's portrait.

In this current study, user portraits were integrated with knowledge graphs to develop a personalized recommendation algorithm for English exercises that was subsequently applied to the teaching of English. This was followed by a case analysis involving sophomore students from the School of Foreign Languages at Ningxia Medical University.

2. ENGLISH LEARNING RESOURCE RECOMMENDATION BASED ON THE USER PORTRAIT AND KNOWLEDGE GRAPH

2.1 User Portrait

A user portrait is created by gathering and analyzing multidimensional data such as basic information about the user, and his or her learning behaviors and main interests, yielding a comprehensive and detailed understanding and description of the user (Deng et al., 2022). The construction of a user portrait typically involves data collection, data processing, and portrait development. In this study, the English learning portrait of college students was established; the fundamental hierarchical structure of the portrait is illustrated in Figure 1. The portraits of college English students has a hierarchical structure comprising four dimensions: basic information, psychological characteristics, knowledge point mastery, and learning outcomes (Kar, 2016). Basic information is contained within the student's profile; psychological characteristics include learning styles and English learning anxiety. Knowledge point mastery involves a morphology knowledge point, a syntax knowledge point, and integrated application. Knowledge point mastery is determined through the analysis of daily exercises and test results. Learning outcomes demonstrate a students' English learning performance, indicated by test scores (Zeng et al., 2016).

In the portrait model of the college English student, "knowledge point mastery" is a crucial foundation for the planning of personalized learning, particularly when combined with the knowledge graph of English learning resources. The portrait data related to this dimension is derived from analyzing students' performance on daily exercises and tests. The approach involves analyzing the exercises or test questions to identify the specific knowledge points being assessed, and subsequently evaluating students' mastery of these points based on their scores on the questions (Lavitt & Boothe, 2015).

One of the most straightforward methods used to identify the type of knowledge points assessed by a question is to have a professional, such as a teacher, determine the type of knowledge points. However, this manual approach is inefficient and not conducive to computer recognition (Khobragade et al., 2016). The advent of intelligent algorithms offers a new method of addressing this challenge. In this study, the long short-term memory (LSTM) algorithm is employed to assess the knowledge points examined in the questions, with the following basic steps: ① input the questions, their answers, and analyses; ② utilize word-to-vector (Word2vec) to convert the input text into vectors; ③ feed the vectorized text into LSTM for forward computation; and ④ generate the judgment results.

2.2 Knowledge Graph

This study leverages knowledge graphs (Baran & Sozbilir, 2017) and user portraits to provide personalized exercise recommendations for students. The node hierarchy within the constructed knowledge graph of college English teaching resources can be categorized into subject, knowledge points, exercises related to knowledge points, and answers and analysis of the exercises from high to low. Following the division of node hierarchies, the knowledge graph of English exercise resources can be developed, the basic steps of which are: ① utilize a web crawler program to extract English exercise resources; ② preprocess the exercise resources by removing exercises lacking answers or analyses; ③ apply the LSTM algorithm to classify the knowledge points assessed in the exercises; ④ based on the outcomes of the knowledge point classification, allocate the exercise resources to the appropriate end node according to the classification of the node hierarchy (Han, 2022).

2.3 Personalized English Learning Resource Recommendation

A knowledge graph can summarize the English exercise resources according to the knowledge points involved. The knowledge point mastery status reflected in the user portrait can be used to recommend targeted exercise resources for students' weak knowledge points to improve the teaching effect. The steps for recommending personalized English exercise resources by combining user portraits and knowledge graphs are:

① Information about a student is collected to form a user portrait when the student is learning English.

② The knowledge point mastery status reflected in the student portrait is analyzed. The corresponding exercises that address the student's weak knowledge points are selected according to the preset threshold.

③ According to the knowledge points corresponding to the selected exercises, the collection of exercises with the same knowledge points is retrieved by a path in the knowledge graph (Li & Xie, 2021).

④ Although it is possible to recommend the retrieved collection of exercises to students directly, this approach is suitable only for recommending small collections. Once the number of exercises in the collection is too large, it will increase the burden on students. Moreover, the resources in the collection belong to the same knowledge points, but the forms and focus of the exercises are different; thus, the students need to search them for suitable exercises. Therefore, this study uses the cosine similarity (Guo & Gao, 2022) to further screen and recommend suitable exercises for student. The formula is:

$$sim = \frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i1}^{n} B_i^2}}, \tag{1}$$

where sim is the cosine similarity, A_i and B_i are the value of test question text vectors A and B in the i-th dimension. The test question text vectors are calculated by the Word2vec model. Equation (1) can be used to compare the cosine similarity between the exercises involving weak knowledge points within the student portrait and the collection of exercises with the same knowledge points in the knowledge graph.

3. CASE STUDY

3.1 Subjects

An analysis was conducted using sophomore students from the School of Foreign Languages at Ningxia Medical University. Two hundred students were recruited and randomly assigned to two groups: a control group and an experimental group. The control group received traditional multimedia teaching, while the experimental group utilized personalized recommendations based on a knowledge graph combined with a user portrait to facilitate their learning.

3.2 Testing Items

(1) Performance test of exercise knowledge point classification algorithm

Before implementing the personalized recommendation algorithm to support teaching, a performance test was conducted on the LSTM algorithm that is used to classify the knowledge points of the exercises. The English exercise data needed for the test was gathered from the Massive Open Online Courses (MOOC) platform through a crawler program. Specifically, 4,250 exercises examined morphology knowledge points, 3,520 exercises examined syntax knowledge points, and 3,410 exercises examined integrated application knowledge points.

The parameters of the LSTM algorithm were configured as follows. The dimension of the Word2vec vector was set to 300; the number of nodes in the input layer were set to 300; the number of nodes in the hidden layer was set at 32, 64, 128, 256, and 512, and the activation function was relu, tanh, and sigmoid. The algorithm's performance was evaluated across different numbers of nodes in the hidden layer and activation functions. Subsequently, the LSTM algorithm with the most optimal parameters was employed to build the knowledge graph of English exercises by integrating the node hierarchy of knowledge points.

(2) The impact of personalized recommendation algorithms on college students' English learning

Initially, the control and experimental groups undertook an English test before the commencement of teaching. The test comprised five questions for each knowledge point. Subsequently, both groups of students received English instruction for four weeks. The control group followed the traditional multimedia teaching approach, and teachers assigned homework after classes. In contrast, the experimental group utilized the personalized recommendation algorithm to support teaching and learning. Specifically, the personalized recommendation algorithm was employed to select exercises as homework following the conventional multimedia teaching in the classroom. After the four-week English teaching period, an English test was administered once more to students in both groups to assess their progress.

An independent samples t-test was conducted to compare the English scores of the two groups of students before and after teaching. A p value less than 0.05 in the t-test indicates a significant difference between the two groups.

(3) A survey of students' satisfaction with the teaching mode based on the personalized recommendation algorithm

To acquire a deeper understanding of the effectiveness of the teaching mode supported by the personalized recommendation algorithm, a questionnaire was administered to the experimental group. The questionnaire comprised four questions: 1. Do you believe that the teaching mode assisted by the personalized recommendation algorithm is a novel approach? 2. Did you experience enjoyment and freedom during the course? 3. Did the learning materials in the new teaching mode meet your learning requirements? 4. Do you feel that your proficiency in using English has improved following the course?

These answers were categorized into five levels according to the degree of agreement: 1 for total disagreement and 5 for total agreement.

3.3 Test Results

The classification performance of the LSTM algorithm for English exercise knowledge points was initially tested under

Table 1 Classification accuracy of the LSTM algorithm with different activation functions and number of nodes in the hidden layer.

Number of hidden layer nodes	32	64	128	256	512
Relu	0.664	0.716	0.813	0.814	0.815
Tahn	0.675	0.759	0.857	0.858	0.859
Sigmoid	0.736	0.874	0.983	0.984	0.985

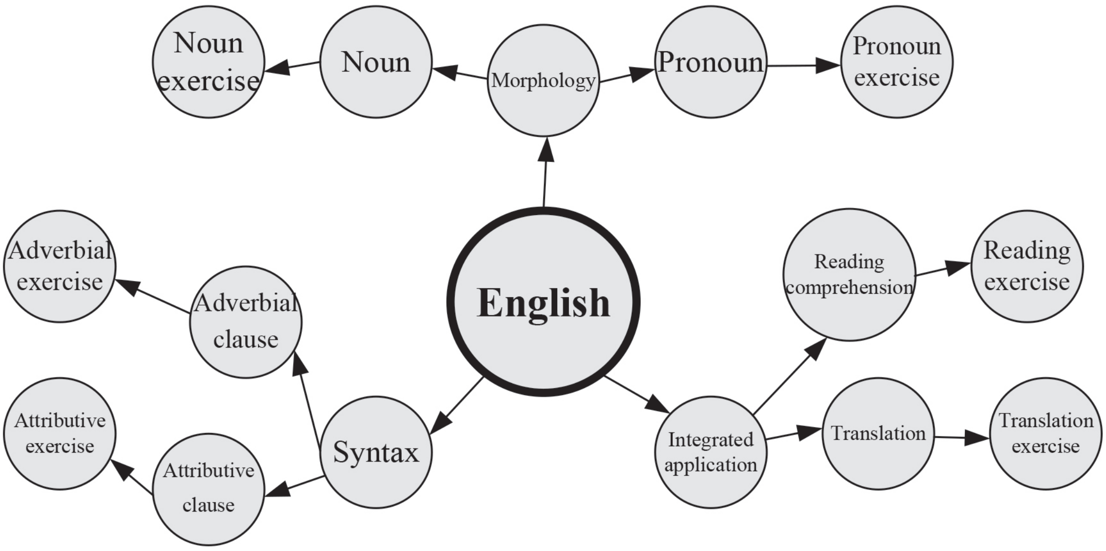

Figure 2 Partial knowledge graph of English exercises.

Table 2 Comparison of English scores of the two groups.

	Before teaching	After teaching	P value
Control group	65.3 ± 1.1	69.4 ± 2.3	0.167
Experimental group	64.6 ± 1.2	97.4 ± 1.3	0.011
P value	0.125	0.021	

various configurations of hidden layer nodes and activation functions. The results are presented in Table 1. The table reveals that the algorithm's classification performance was optimal when the number of hidden layer nodes in the LSTM algorithm was set to 128, and the activation function was configured as sigmoid.

Then, a knowledge graph was constructed for the exercise resources gathered by the crawler program using the LSTM algorithm and the node hierarchical division of knowledge point. Due to space constraints, only a portion of the English exercise knowledge graph is displayed in Figure 2. In the figure, the primary node represents the subject (English), and secondary nodes denote the three general knowledge points: "morphology", "syntax", and "integrated application". Subsequently, detailed knowledge points were listed under each general knowledge point as third-level nodes. Each detailed knowledge point includes a collection of exercise resources specific to that knowledge point.

Subsequently, the impact of the personalized recommendation algorithm based on user portraits and knowledge graphs on English learning was evaluated. The results of this assessment are presented in Table 2. The table demonstrates that the English scores of students in the experimental group exhibited significant improvement following the teaching intervention, with their scores being notably higher than those of the control group.

The outcomes of the questionnaire survey conducted with students in the experimental group after teaching are depicted in Figure 3. The figure indicates that most students in the experimental group had a positive attitude toward the new teaching mode, viewing it as a novel approach. They highlighted that this new teaching mode facilitated enjoyment and a sense of freedom and improved learning outcomes through independent information retrieval. Importantly, students believed that their English proficiency had improved upon course completion. The survey findings suggested that the teaching mode supported by the personalized recommendation algorithm based on user profiles and knowledge graphs effectively stimulated students' interest in their learning of English.

4. CONCLUSION

In this study, user portraits were integrated with knowledge graphs to develop a personalized recommendation algorithm for English exercises and applied it to the teaching of English. A case analysis was conducted with sophomore students from the School of Foreign Languages at Ningxia Medical University. During the analysis, the parameters of the LSTM algorithm used to classify exercise knowledge points were tested, and a knowledge graph of English exercises was

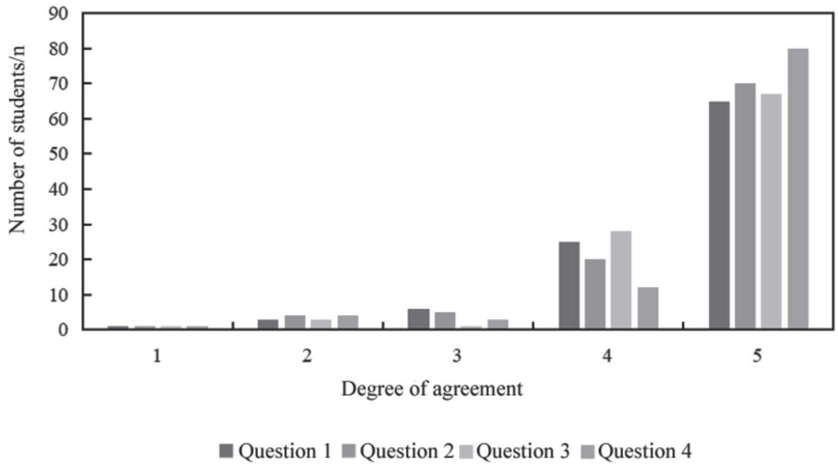

Figure 3 Results of questionnaire survey on the new teaching mode of the experimental group students after teaching.

constructed. The students were divided into a control group and an experimental group. The control group received conventional multimedia teaching, while the experimental group utilized the personalized recommendation algorithm for English exercises to assist their learning. English tests were conducted before and after a four-week teaching period. A questionnaire was used to gather feedback from the experimental group regarding the new teaching method. The optimal performance for classifying knowledge points was achieved when the number of nodes in the hidden layer of the LSTM algorithm was 128, and the activation function was sigmoid. A knowledge graph for English exercises was constructed based on this. Following the teaching period, the English scores of students in the experimental group significantly improved and were higher than those of the control group. The teaching mode supported by the personalized recommendation algorithm based on user portraits and knowledge graphs effectively increased students' interest in learning English.

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