International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8337-8348

https://doi.org/10.70517/ijhsa463712

Personalized College English Vocabulary Learning Path Design Incorporating Adaptive Algorithms

Li Li[1,*]
[1] Nanyang Medical College, Nanyang, Henan, 473000, China
Corresponding authors: (e-mail: lily5828@163.com).

Abstract College English vocabulary learning faces the problems of blindness, unplannedness and lack of vocabulary learning strategies. The traditional learning system is unable to provide personalized service for students' individual differences. In this paper, to address the problems of blindness and lack of strategies in college English vocabulary learning, we constructed an adaptive learning system with a hybrid recommendation algorithm integrating knowledge graph and collaborative filtering to provide personalized English vocabulary learning paths for college students. The study adopts TransR model and LSTM model combined with Self-Attention attention mechanism for knowledge graph representation learning, and integrates it with collaborative filtering algorithm with improved cosine similarity computation method to achieve personalized learning resources recommendation. To verify the effectiveness of the system, the study recruited 64 college students for a 7-day English vocabulary learning experiment, and divided them into a control group using the traditional learning system and an experimental group using the adaptive learning system. The results show that the adaptive learning system scored 23.07 in the dimension of resource recommendation effectiveness, which is significantly higher than the 15.18 of the traditional learning system; the students in the experimental group scored 20.54 in vocabulary mastery, which is significantly higher than the 15.83 of the control group; and the experimental group's score in vocabulary writing reached 22.86, which is 6.77 higher than that of the control group. The conclusion shows that the adaptive learning system based on the hybrid recommendation algorithm of knowledge graph and collaborative filtering can effectively identify the individual differences of learners, provide targeted learning resources, improve the learning efficiency, significantly enhance the effect of college students' English vocabulary learning, and provide a new way for personalized learning of college English vocabulary.

Index Terms College English Vocabulary Learning, Adaptive Learning System, Knowledge Graph, Collaborative Filtering, Hybrid Recommendation Algorithm, Personalized Learning Paths

I. Introduction

Vocabulary is the foundation of English learning, and the vocabulary and the in-depth mastery of vocabulary knowledge affect the development of the four basic skills of students' listening, speaking, reading and writing to a great extent [1]. Traditional university English vocabulary teaching is usually based on teaching units, with word meaning as the basis and extension to other lexical forms and collocations of the word as the auxiliary means to carry out vocabulary teaching [2]-[4]. Students tend to expand their vocabulary only by mechanically memorizing the form of words or fixed phrases and their corresponding meanings in Chinese, which rarely involves deeper learning by placing the words in context [5]. Learning words in isolation in this way, even if a certain amount of vocabulary has been mastered, comprehension and utilization are often problematic when these words are put into discourse [6], [7]. In order to learn the use of words in discourse contexts, advocating the teaching of words in contextual contexts has been recognized by foreign language teachers, but after all, example sentences are limited in unit texts, and for some examples of key vocabulary words, teachers tend to rely on their own sense of examples, which seriously limits the efficiency of university English vocabulary teaching [8].

Artificial intelligence technology is revolutionizing the field of education, especially in the design of personalized learning paths, through its high level of data analysis and pattern recognition capabilities [9], [10]. The principles of the technology involve machine learning and deep learning algorithms to customize personalized teaching content for students by analyzing their behavioral and performance data [11]. In the specific practice of English vocabulary learning, AI not only has the ability to generate a large number of contextually relevant example sentences, but also provides learning materials and feedback according to the actual level and progress of the learner, thus greatly enhancing the richness and adaptability of the learning process [12]-[14]. Adaptive algorithms, as a cutting-edge artificial intelligence technology, open up a brand new way for language learning with their uniqueness of mimicking human language use and comprehension [15].

The core of language learning lies in the accumulation of vocabulary, and vocabulary ability is the important foundation of language ability. In the current university English vocabulary teaching, students often rely on traditional memorization methods or mobile terminal applications for learning, but lack of systematic planning and targeted guidance. Mobile learning provides students with convenient learning channels, but over-reliance on fragmented learning also brings many problems: students blindly choose vocabulary software, lack of scientific vocabulary memorization plan, lack of independent learning ability, and often difficult to adhere to long-term learning. At the same time, the deepening reform of English teaching in colleges and universities requires vocabulary teaching to reflect the characteristics of the times and cultural connotations, and requires the organic integration of modern information technology and students' in-depth learning. Under the concept of personalized education, it is necessary to fully consider the individual differences of students and provide differentiated learning content and methods. The traditional unified teaching mode is difficult to meet the diverse needs of students with different learning styles, knowledge levels and interest preferences, so it is particularly important to build a system that can intelligently recommend learning resources according to students' individual characteristics.

Under the background of the deep integration of information technology and education, adaptive learning system, as a new type of teaching technology, is gradually being applied to the teaching of various disciplines. Compared with traditional online teaching, adaptive learning system can construct personalized learning paths according to learners' individual characteristics and behavioral tendencies, and effectively improve learning efficiency. Most of the current adaptive learning research focuses on the recommendation algorithm itself, which is not comprehensive enough to explore the user's interests, and there is a lack of research on the application of this technology in specific disciplinary scenarios, especially in the field of English vocabulary learning. Therefore, the development of a personalized university English vocabulary learning system incorporating adaptive algorithms is of great theoretical and practical significance.

In this study, knowledge graph is combined with collaborative filtering algorithm to construct a hybrid recommendation algorithm in order to realize the comprehensive mining of learners' interests and preferences. Rich semantic relations are introduced through knowledge graph, representation learning is carried out by using TransR model and LSTM model combined with Self-Attention attention mechanism, while improved cosine similarity computation method is applied to realize inter-user similarity computation, and finally the two algorithms are fused to form a hybrid recommendation strategy. On this basis, the study designs and develops an adaptive learning online resource system, including functional modules such as learning activity sequence recommendation, learning partner recommendation and similar learning resources recommendation. Through comparative experiments, we verify the application effect of this system in college English vocabulary learning, analyze the impact of different learning systems on students' technology acceptance and English vocabulary learning performance, and provide new ideas and methods for college English vocabulary teaching.

II. Problems and Strategies for Learning English Vocabulary at University level

II. A. The Problems of English Vocabulary Learning in Universities

(1) Blindness and unplannedness

On the one hand, relying on mobile terminals, college students have utilized fragmented time to memorize words and expanded their vocabulary to a certain extent. On the other hand, in the process of learning vocabulary by using mobile terminals, college students also have problems that cannot be ignored.

First, blindly choosing APP vocabulary software. Most college students have downloaded at least no less than two vocabulary memorization software in their mobile terminals, but they don't utilize them reasonably.

Second, there is no scientific vocabulary memorization plan. The vast majority of students admit that they have not made a detailed plan to memorize words.

Third, lack of independent learning ability and mental quality of persistence. English vocabulary learning should follow the learning concept of “one day's perseverance is one day's work, and several days' perseverance is success”, but many students talk about the process of vocabulary memorization, and cannot strictly demand themselves, do not develop good learning habits, and lack of independent learning endurance and staying power.

(2) Lack of vocabulary learning strategies

The Ministry of Education emphasizes that modern information technology should be integrated with students' in-depth learning, and that it should pay attention to the students' subject position and focus on the students' learning effect. As universities continue to promote connotative development, the reform of university English teaching ushers in a new opportunity. Encouraging students to use English to introduce traditional culture, spread cultural wisdom and convey the spirit of outstanding culture is the fundamental direction and important base of university

English teaching reform. In university English courses, both vocabulary learning and vocabulary teaching need to keep pace with the times and reflect cultural characteristics.

In the context of the intelligent era, English vocabulary learning cannot only rely on mobile terminals and students' independent ability. English teachers in colleges and universities should pay attention to vocabulary teaching or English vocabulary research. As we all know, vocabulary level is the foundation of a learner's literacy, listening and listening and translation ability. In the age of intelligence, it is necessary for teachers to study in depth the advantages and disadvantages of vocabulary software on various platforms, analyze scientifically the vocabulary memorization problems of students at this stage, formulate appropriate vocabulary learning plans for students, give students effective guidance about vocabulary strategies and supervise them, so as to help students achieve the goal of efficient vocabulary learning [16]-[18].

II. B.The Path of English Vocabulary Learning for College Students

II. B. 1) Effective vocabulary learning

The Standard requires that "students perceive and understand the meaning of relevant topics through listening, speaking, reading, watching and writing, and use words to express the information and meaning of relevant topics. At the same time, in this series of actions, according to the lexical nature, the customary collocation of words and the content of the theme, to build different vocabulary semantic network, accumulation of words, expanding vocabulary, and in a large number of language learning activities, to strengthen the sense of language, the transfer of the ability to use the words, and ultimately to achieve the internalization of the words". This requirement not only reflects the fundamental rule of vocabulary learning from perception, comprehension to application, but also clarifies the dimension of vocabulary ability development of high school students, i.e. meaningful vocabulary input and meaningful vocabulary output.

(1) Meaningful vocabulary input

Vocabulary input is a prerequisite for vocabulary output. The learning behaviors of vocabulary input mainly include paying attention to vocabulary in time and understanding vocabulary ontology knowledge (pronunciation, spelling, lexical properties, lexical meanings, derivatives, word-chunk collocations, etc.).

Meaningful vocabulary input highlights two aspects:

First, the overarching role of thematic meaning is emphasized. Teachers conduct the vocabulary comprehension stage with thematic leadership. Students are able to understand and accumulate vocabulary independently in contexts containing thematic meaning.

Second, students are able to select and apply appropriate learning strategies, either independently or with the help of teachers, tools, etc., to carry out deep-processing vocabulary comprehension learning activities such as word sense disambiguation and vocabulary semantic network construction. Therefore, there are two criteria to measure whether the vocabulary input is meaningful: the depth of vocabulary knowledge comprehension and the breadth of vocabulary knowledge comprehension.

(2) Meaningful vocabulary output

Vocabulary output is an important measure to test the effectiveness of vocabulary input. Learning behaviors involving vocabulary output mainly refer to vocabulary use. Meaningful vocabulary output emphasizes two aspects:

First, creating a thematic meaning-led vocabulary output field. Teachers need to design and implement output learning activities for students' vocabulary use that are thematically led, which may be the same or similar to the themes that students experienced during the vocabulary input stage, and that lead students to understand the "where" and "how" of the vocabulary that they have previously understood. "Second, students are able to recall the vocabulary in a timely and accurate manner.

Second, students are able to recall vocabulary in a timely and accurate manner. Therefore, two criteria for measuring the meaningfulness of vocabulary output are the precision and richness of vocabulary knowledge utilization and the degree of self-awareness of vocabulary knowledge utilization.

II. B. 2) Personalized Learning of College English Vocabulary

In the process of English teaching, teachers not only need to consolidate students' English knowledge base, but also to improve students' intercultural communication skills and develop students' comprehensive English literacy. The main body of learning is the students, which requires teachers to pay attention to the individual differences of students in the teaching process, and then cultivate and develop students' personality and comprehensive language ability. Personalized learning is the development direction of education in the new era, which focuses more on the development of students' individual characteristics and promotes the development of students' complete personality [19]. Based on this, teachers should promote the deep integration of information technology and the English subject in teaching, combine personalized learning with vocabulary teaching, and effectively help students to carry out personalized learning in English.

(1) Build a platform for independent learning before class

In the teaching of English vocabulary to college students, teachers can use information technology to build a platform for independent pre-study, combining the interests and needs of different students to guide students to personalized learning. Students can use their favorite ways of pre-study in the online platform to study before class, mark their doubts and communicate and interact with each other, so as to build a situation of independent learning in English and let students carry out personalized pre-study before class.

(2) Finding points of interest in vocabulary learning

In college students' English vocabulary learning, in view of the students' character, plus they have mastered certain information technology, so in vocabulary learning, students can make use of information technology to carry out interesting vocabulary learning games, abandoning the tedious and mechanical learning methods in the past. With the advantages of sound, image, picture and text of information technology, students can build links between English vocabulary and actual images. In the actual learning process, they integrate vocabulary learning with the game mode organically, and will find the point of interest in English vocabulary learning.

(3) Utilize the learning platform to carry out hierarchical teaching and tailor the teaching to students' needs

When learning vocabulary, teachers can combine students' learning attitudes, habits and achievements to carry out stratified teaching, combining students' individual differences to teach according to their abilities. In vocabulary teaching, teachers can adopt the mode of “online + offline” to carry out invisible stratification of students, combined with the class learning platform to implement online stratification test.

(4) Checking Learning Progress Anytime, Anywhere with the Help of Interactive Platforms

In English vocabulary teaching for college students, teachers can build an interactive platform with the help of information technology to deepen the communication between teachers and students. At the same time, teachers can check students' learning progress and knowledge mastery with the help of learning analytics, and then reproduce students' learning difficulties and key knowledge in the classroom, thus expanding students' independent learning space and building a personalized English vocabulary learning classroom. Teachers use network platforms to build students' virtual learning situations, provide multiple forms of learning resources with different levels of difficulty to guide students' independent learning, and meet the needs of students' personalized learning.

III. Adaptive learning system design incorporating personalized recommendation algorithms

III. A. Adaptive learning systems

Adaptive Learning System (ALS) can not only provide learners with personalized learning services, but also provide learners with adaptive learning content and adaptive navigation support functions to meet learners' individual needs. Compared with traditional online teaching courses, ALS can make up for the defects such as uniform learning resources, ignoring individual differences of learners, and single teaching strategy [20].

Adaptive learning system can construct a learning path suitable for each learner according to students' personal characteristics and behavioral tendencies. It also combines the characteristics of college English vocabulary learning, supplemented with supporting exercises and real-world projects, to provide learners with personalized learning resources, so as to effectively improve the learning efficiency and motivation of learners.

The adaptive learning recommendation algorithm proposed in this paper is able to conduct a simple examination after the learner logs into the system in order to recommend the knowledge suitable for the learner to study. During the learning process, the algorithm is able to assess the students' mastery of the knowledge points through exercises and comprehensive practical projects, so as to recommend the next learning content that is more suitable for the students' current learning situation.

III. B. Selection of Recommendation Algorithms in Adaptive Learning Systems

Adaptive learning systems can recommend personalized learning resources for different learners according to their interests and preferences. Currently, most of the adaptive learning systems recommend based on user learning behavior, and the mining of user interests is not comprehensive enough. To address the above problems, this paper proposes a hybrid recommendation algorithm based on knowledge graph and collaborative filtering.

III. B. 1) Knowledge graph based recommendation methods

Knowledge Graph (KG) is to describe the relationship between things by modeling the way humans understand the objective world. Knowledge graph-based recommendation algorithms can introduce richer semantic relationships for courses, deeply mine users' interest preferences, and can connect users' historical behaviors and recommendation results to improve the interpretability of recommendation algorithms. The steps of the recommendation algorithm based on knowledge graph are shown in Figure 1.

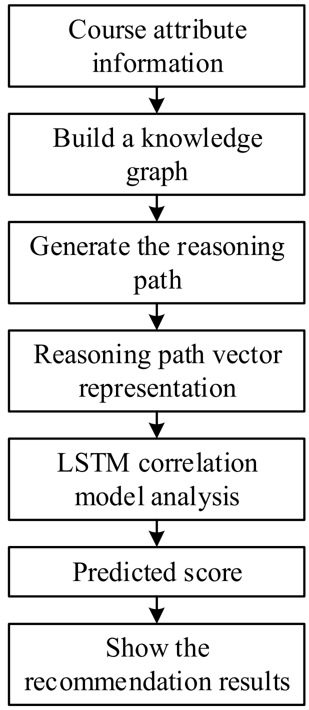

Figure 1: The recommendation algorithm procedure based on the knowledge map

In this paper, we extract the inference paths from the knowledge graph and perform representation learning to transform the inference paths into vector form so that the semantics in the inference paths can be analyzed.

TransE model is the basic representative model of knowledge graph representation learning.TransE model can accurately and figuratively represent knowledge graph triples as space vectors, but there are some shortcomings in this method.TransE model is only effective in one-to-one relationships, and the relationships in the knowledge graph of learning resource domain constructed in this paper are mainly many-to-many. Therefore, the improved TransR model is used in this paper.

The core idea of the TransR model is to project the entities in the original space into the new space where the relation r is located through the relation matrix M_r, after which the representation is learned. The head entity h generates a new vector h_r through the mapping of the relation matrix M_r, and the tail entity t generates a new vector t_r through the mapping of the relation matrix M_r, namely:

$$h_r = hM_r \tag{1}$$

$$t_r = tM_r \tag{2}$$

The vector representation e_c of entity c is generated using the TransR method to obtain the vector representation of the entity for the m th inference path of user-course, which is expressed as the following equation, where e_{ucm} denotes the vector of entity embeddings in the m th path from user u to course c. I.e:

$$p_{ucm} = [e_{ucm1}, e_{ucm2}, e_{ucm3}, \ldots] \tag{3}$$

The vector representation of the inference paths is obtained by the above method, which is input into the LSTM model. The semantic representation of the m th inference path of the entity to user-course is obtained after the LSTM layer, which is represented as the following equation:

$$h_{ucm} = [h_{ucm1}, h_{ucm2}, \ldots, h_{ucmn}, \ldots] \tag{4}$$

Meanwhile, Self-Attention attention mechanism is introduced into the LSTM model. It is able to capture the important content in the semantics of the inference path, when there are l entities in the m th inference path of entity-to-user-course, the attention weight W_{ucmn} of the n th iteration of the LSTM is specified as the following equation:

$$S_{ucmn} = h_{ucml} \cdot h_{ucml} \tag{5}$$

$$W_{ucmn} = \frac{\exp(s_{ucmn})}{\sum_{k=1}^{l} \exp(s_{ucmn})} \tag{6}$$

Introducing the attention weight W_{ucmn}, the final semantic representation of the path is:

$$q_{ucm} = \sum_{n=1}^{l} h_{ucmn} W_{ucmn} \tag{7}$$

The most important features of the vectors are extracted by maximum pooling operation and finally the prediction scores are generated by fully connected layers and Sigmoid function K_{uc}:

$$K_{uc} = \frac{1}{1 + e^{-mpooling\_on([q_{uc1},...,q_{ucn},...])}} \tag{8}$$

III. B. 2) User-based collaborative filtering recommendation methods

For the user's rating data, which can also reflect the user's interest preferences, the collaborative filtering recommendation in this paper adopts the user-based collaborative filtering recommendation algorithm.

The steps of the user-based collaborative filtering recommendation algorithm are shown as follows: first, the preference relationship between users and courses is described by constructing a user-course rating matrix, and the user's rating data for a course is placed in the matrix R_{m*n}. The matrix has m rows and n columns, where m is the number of users, n is the number of courses, and r_{ij} is the rating of user i on course j. In this paper, the evaluation star ratings in the dataset are converted into corresponding scores, with 1-5 stars representing 1-5 points, respectively, and then filled into the user-course rating matrix. The user-course rating matrix is shown in Table 1.

Table 1: User - course scoring matrix

	$Course_1$	……	$Course_j$	……	$Course_n$
$User_1$	r_{11}	……	r_{1j}	……	r_{1n}
$User_2$	r_{21}	……	r_{2j}	……	r_{2n}
……	……	……	……	……	……

The similarity between users is calculated based on the user-course rating matrix, each row of data in the table represents the rating record of a particular user for a course, for user u, its rating record $(r_{u1}, r_{u2}, ..., r_{ui}, ..., r_{un})$ is a rating vector, and the similarity between users can be obtained based on the improved cosine similarity computation method, which is computed in the following way:

$$sim(u,v) = \frac{\sum_{c \in C_{u,x}} (r_{u,c} - \overline{r_u})(r_{v,c} - \overline{r_v})}{\sqrt{\sum_{c \in C_u} (r_{u,c} - \overline{r_u})^2} \sqrt{\sum_{c \in C_v} (r_{v,c} - \overline{r_v})^2}} \tag{9}$$

where $C_{u,v}$ denotes the courses jointly rated by users u, v. C_u, C_v denote courses rated by user u and user v, respectively. $\overline{r_u}, \overline{r_v}$ denote the average rating of user u, v respectively. $r_u, c, r_{v,c}$ denote the ratings of users u, v on course c, respectively.

The similarity $sim(u,v)$ between the target user u and other users v can be obtained by the method in the previous subsection, and the top k users that are most similar to the target user u are selected to form its neighboring user set $V = \{V_1, V_2, ..., V_k\}$, the rating of the course to be evaluated P_{wc} is calculated by the rating prediction formula. Specific calculations:

$$P_{u,c}=\overline{r_u}+\frac{\sum_{v\in V} sim(u,v)(r_{ve}-\overline{r_v})}{\sum_{v\in V}|sim(u,v)|} \tag{10}$$

where $sim(u,v)$ denotes the similarity of interest preferences between user u and v, $\overline{r_u},\overline{r_v}$ denote the average ratings of user u,v, respectively, and r_{vc} denotes the ratings of user v on course c.

The recommendation algorithm in this paper utilizes a hybrid strategy to sum up the predicted ratings obtained from the above two recommendation algorithms according to their weights, and finally generates the predicted ratings of the final hybrid recommendation algorithm through a Sigmoid function.

The specific calculation of the predicted rating values generated by the hybrid recommendation algorithm based on knowledge graph and collaborative filtering is shown in:

$$L_{uc}=\frac{1}{1+e^{-(\beta\cdot K_{uc}+\theta\cdot P_{uc}+b)}} \tag{11}$$

where β,θ denote the fusion scale coefficients of the recommendation algorithm's predictive scores K_{uc},P_{uc} respectively. b is the bias term coefficient. According to the effect of the recommendation algorithm, the model parameters β,θ are set to 0.3, 0.4 respectively.Finally, the relevant courses are recommended for the users according to the level of the predicted ratings.

III. C. Adaptive Learning Online Learning Resource System Design and Development

This paper studies the problem of adaptive recommendation of learning resources in online learning environment. Based on the characteristics of learners, the characteristics of resources and the analysis of behavioral data in the learning process, it determines the needs of learners, carries out the design of adaptive recommendation of learning resources, develops learning services for learners to meet their needs, and pushes the appropriate learning resources to provide the possibility of adaptive pushing of resources in online learning. Therefore, the mini-program mainly includes login and registration, information acquisition, learning activity sequence recommendation, learning partner recommendation, similar learning resources recommendation, learning test and learning process record in terms of function.

In addition to the functional requirements, the system should also have the requirements of security, simple operation and extensibility.

III. C. 1) System feasibility analysis

The feasibility analysis of the system mainly includes:

(1) Operational feasibility: the design system in this paper is able to search for small programs developed with the help of various types of mobile terminals, which are easy to use, strong dissemination, relatively simple to operate, and there is no complex installation and configuration problems.

(2) Economic feasibility:

In terms of development tools, the development environment is built on Windows 10 operating system, using small program developer tools for the development of the front-end interface, Phpstorm for the construction of the back-end, the database uses Navicat MySQL. these development tools can be downloaded for free from the corresponding official website.

In terms of hardware, we need to rent a server to set up a network running environment when the system is being tested. Therefore, a small portion of the cost is needed for this part.

In the middle stage of system development, it is only necessary to make regular backups of the system program. In the later stage of system development, students do not need to download the system, but only need to connect to the network and scan the QR code of the small program to enter the small program for learning. As a result, the system has a certain degree of economic feasibility, and at the same time can bring the corresponding revenue.

(3) Technical feasibility:

Phpstorm is a more practical php integrated development tools, the program background code writing and interface connection provides a stable and convenient compilation environment.Navicat MySQL database using SQL simple and easy to understand the language of data management, security and stability.Apache is a server with high stability and security of the Web server software, which can provide a stable environment for the program's server. Apache is the server with higher stability and security of the Web server software, which can build a more stable operating environment for the server of the program, so that the program can run stably and safely, which shows that the system is feasible in terms of technology.

III. C. 2) Resource Adaptive Recommendation Module

Resource Adaptive Recommendation Module is the main functional module for adaptive recommendation of learning resources in the system. Through comprehensive analysis of learners' basic information, interest preferences, learning styles, knowledge levels and learning behaviors, it recommends personalized resources that meet the needs of learners according to their characteristics.

The adaptive recommendation service of resources in this system mainly includes the recommendation of learning activity sequences, learning partners and similar learning resources.

Learning activity sequence is to recommend learning activities that meet the learner's personality and style according to the learner's style and knowledge level.

Learning partner recommendation is based on the learner's basic information, interest preferences and learning behavior labels, etc. to recommend learning partners and resources recommended by the partners, so as to promote the enhancement of learning effects.

Similar resources recommendation is based on the user's collaborative filtering recommendation algorithm combined with the learner model to analyze the learner's needs and push appropriate learning course resources (learning videos, mind maps, texts) and similar learning resources for them.

The resource adaptive recommendation module is shown in Figure 2.

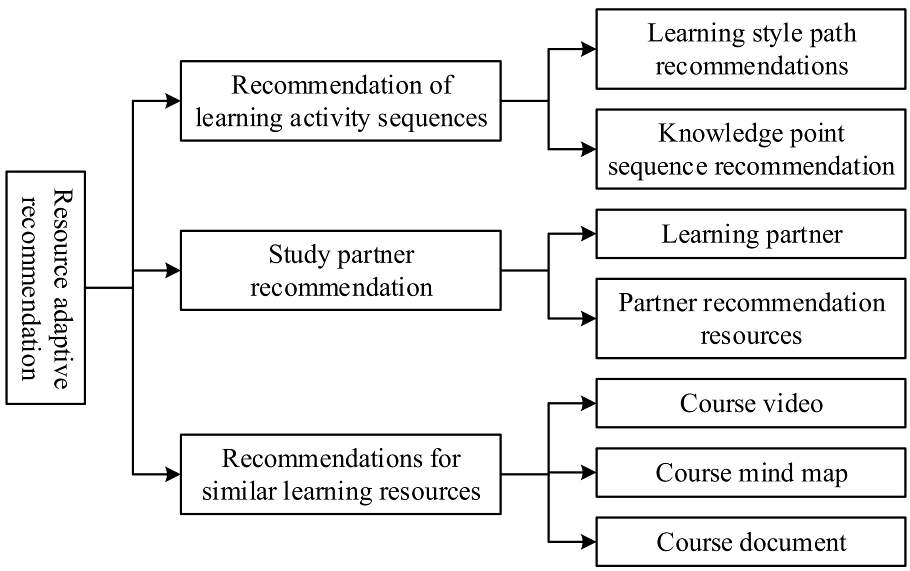

Figure 2: Resource adaptive recommendation module

IV. Adaptive learning systems applied to vocabulary learning

IV. A. Algorithm Analysis of Adaptive Learning System

(1) Evaluation indicators

For each user in the dataset, the items that the user has ever interacted with are considered as positive samples and the rest are considered as negative samples. The recommendation task in this paper is to select the highest rated items to form a recommendation list for Top K recommendation.

The most common metrics are chosen to measure the performance of the model in the experiments, Recall@K (R@K) and NDCG@K (N@K) are two metrics where the larger the value, the better the recommendation performance.

Recall@K and NDCG@K are two common recommendation performance measures. Among them, Recall@K is mainly used to measure the recall rate of the recommender system, i.e., how many of all the items of interest to the user are successfully recommended. E.g.:

$$Recall@K = \frac{TP@K}{TP@K + FN} \tag{12}$$

where TP@K denotes the number of relevant items correctly identified in the first K recommended items and FN denotes the number of relevant items not identified.

The Recall@K metric focuses on the system's ability to capture items of interest to users, but it does not take into account the ranking order of recommended items and the intensity of users' preferences for different items. In contrast, NDCG@K considers not only whether the recommended items are clicked or adopted by users, but also the ranking position of the items. Namely:

$$DCG@K=\sum_{i=1}^{k}\frac{2^{rel_i}-1}{\log_2(i+l)} \tag{13}$$

DCG@K denotes the DCG (Cumulative Discount Gain) calculated for the first K recommended items, and rel_i denotes the relevance score of the i th recommended item. I.e.:

$$NDCG@K=\frac{DCG@K}{IDCG@K} \tag{14}$$

IDCG (Ideal Cumulative Discount Gain) is achieved by ranking the truly relevant items based on relevance scores.NDCG@K is the ratio of DCG@K to IDCG@K.

(2) Datasets

In this paper, experiments are conducted on two publicly available datasets: ML-1M is a movie recommendation dataset that contains user rating data for different movies.Last-FM is constructed from an online music platform. This dataset collects records of users listening to various music artists.

(3) Baseline Model

The proposed model is compared with the following baseline models which include DMF, NNCF and knowledge graph based recommendation models RippleNet, KTUP and KGIN and MCCLK.

DMF is a matrix factorization (MF) model optimized in a neural network framework that maps users and items into a common low-dimensional space with nonlinear projections.

NNCF is a neighborhood-based collaborative filtering method for neural networks, in which the input part introduces the respective neighborhood information of users and items in addition to the information of users and items respectively, compared to the traditional collaborative filtering model.

The RippleNet model iteratively discovers users' potential hierarchical interests by propagating preferences in the knowledge graph.

KTUP utilizes a single relational information to represent user interests in the knowledge graph in order to understand why users prefer an item.

KGIN combines different relationships in the knowledge graph to form the intention behind the user's interaction with an item in order to understand the user's needs at a deeper level.

(4) Parameterization

The implementation of this experiment is based on the Pytorch framework. For a fair comparison, the embedding size is fixed to 32 and the Adam optimizer is used with a batch size of 512 and a learning rate of 0.01.

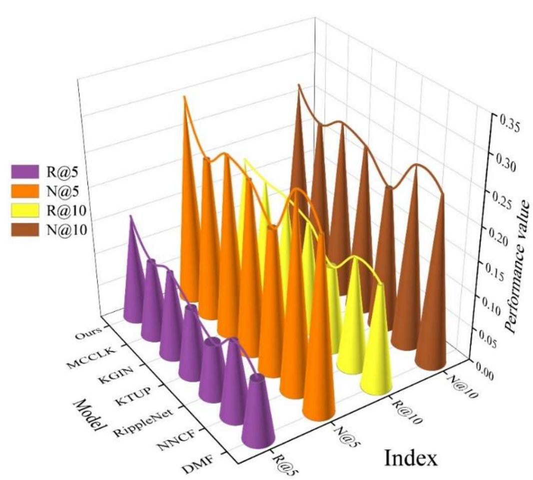

Figure 3: The performance comparison of this model with the baseline model

(5) Performance Comparison

The length K of the recommendation list is set to {5, 10, 20} for the experiments. The performance comparison between the model in this paper and the baseline model is shown in Fig. 3.

The index scores of the model (a hybrid recommendation algorithm based on knowledge graph and collaborative filtering) in this paper are R@5=0.1563, N@5=0.3015, R@10=0.1858, and N@10=0.2719, respectively. The proposed model is better than the baseline model, and the R@5 index is improved by 0.0427 compared with the MCCLK model.

The performance of this paper's model and the baseline model on the Last-FM dataset is shown in Figure 4, and both of this paper's models outperform the competitors on the Last-FM dataset.

Especially on the Last-FM dataset, the proposed model is 0.19% and 0.35% higher than the KGIN model in R@5 and R@10, respectively.

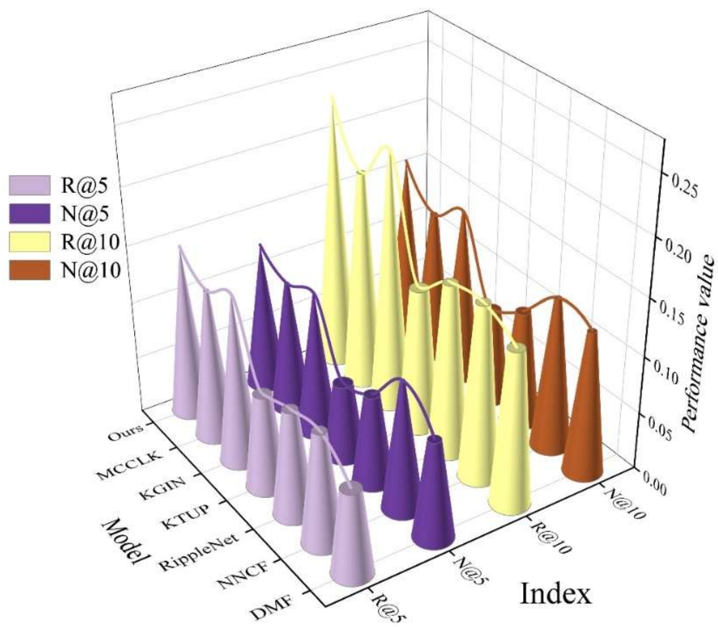

Figure 4: The performance of each model in the data set of the data set

IV. B. Adaptive Learning System Application Analysis

The main purpose of this experiment is to apply the constructed adaptive learning system to college English vocabulary learning, and to verify the usefulness of the adaptive content learning system based on hybrid recommendation algorithm of knowledge graph and collaborative filtering to the learners and the impact on their English vocabulary learning.

(1) Experimental Subjects

A total of 70 people were recruited through the summer public welfare training, these students come from the neighborhood of a university, and the student samples with the building of the adaptive learning system based on adaptive learning system come from the region and do not accept duplicate enrollment. The student samples participating in the model building will not be able to participate in the teaching experiment, and students are required to have no other English platform learning experience.

Seventy students reported a final number of 64, which were cross-assigned to the experimental and control groups through pre-test score ranking to ensure that both groups had the same level of English vocabulary. Thirty-two students in the experimental group used the traditional English learning platform for learning, while 32 students in the control group learned vocabulary under the adaptive learning system.

(2) Experimental Implementation

A total of 64 college students were recruited and divided into the experimental group and the control group for a one-week English vocabulary learning experiment.

Before the learning activity, students were first allowed to register and sign in, and then led to familiarize themselves with the operation of the platform. Then, the students were given a pre-test of their English vocabulary level. Since there were only 80 vocabulary questions and the questions were simple concepts, the students were given 25 minutes to take the pre-test. Students were allowed to hand in their papers in advance, and the papers were scored, and students were divided into two groups according to their rankings, with odd and even numbered students in each group.

Students learned vocabulary through the regular English learning platform throughout the learning process, and there was no difference in the length of study, teacher level, learning environment, or platform used, except for the different content of study.

For the control group, the lexicon used for the learning content during the 7 days was the University English Advanced Thesaurus (UEAT), and the initial lexicon of the experimental group on the first day was also the University English Advanced Thesaurus (UEAT).

Unlike the control group, background data statistics on the four variables of the experimental group's English vocabulary familiarization rate, vocabulary review correctness rate, the number of newly learned words, and the average length of word learning will be conducted at the end of each day's session. And the data were imported into the trained adaptive learning system. On the second day, students with different learning conditions were pushed English vocabulary of different difficulty levels according to the adaptive pushing mechanism. The whole teaching activity lasted for 7 days, with 4 lessons per day and 30 minutes per lesson.

At the end of the experiment on the 7th day, the teacher conducted a vocabulary level post-test for both groups of students, and the students also received measures of technology acceptance and system satisfaction.

(3) Data Analysis

The t-test analysis of technology acceptance in the posttest of students of different learning systems is shown in Table 2, with cognitive usefulness, cognitive ease of use, technology acceptance, and effectiveness of resource recommendation set at 0~25 points, respectively.

There are significant differences between the traditional learning system and the adaptive learning system in the four dimensions of cognitive usefulness, cognitive ease of use, technology acceptance, and resource recommendation effectiveness, respectively. The p-value of all four dimensions is less than 0.05. The adaptive learning system scored 23.07 points in the dimension of resource recommendation effectiveness, which is highly recognized by college students.

Table 2: Test analysis of the technology acceptance t of different learning systems

	Mean(SD)		df	t	P	d
	Traditional learning system	Adaptive learning system				
Cognitive usefulness	16.31(4.85)	22.59(4.61)	70	-0.15	0.001*	0.025
Cognitive use	14.07(3.49)	20.85(5.77)	70	2.36	0.001*	-0.518
Technical acceptance	17.66(7.43)	18.66(6.53)	70	1.87	0.001*	-0.401
Resource recommendation validity	15.18(6.21)	23.07(5.12)	70	1.04	0.001*	-0.335

The effects of different learning systems on students' English vocabulary learning achievement are shown in Table 3. English vocabulary learning achievement includes four dimensions: vocabulary learning, vocabulary cognition, vocabulary writing, and vocabulary mastery. The vocabulary writing scores of students using the adaptive learning system are 6.77 points higher than the writing scores of students using the traditional learning system.

The study shows that there is a significant difference between the posttest English vocabulary learning scores of the control group and the experimental group under different learning systems. The academic performance of the students under the traditional learning system is lower than that of the students using the adaptive learning system and there is a significant difference. Therefore, the students with the learning system obtained better academic performance. This study proves that students using adaptive learning system have better academic performance than students using traditional learning system.

Table 3: The influence of different systems on students' English vocabulary

	Mean(SD)		df	t	P	d
	Traditional learning system	Adaptive learning system				
Lexical acquisition	19.56(4.18)	22.71(5.60)	70	-2.61	0.001*	-0.023
Vocabulary cognition	17.42(5.29)	20.15(4.24)	70	-2.14	0.005*	0.654
Vocabulary writing	16.09(5.11)	22.86(6.17)	70	0.74	0.004*	0.507
Vocabulary mastery	15.83(6.07)	20.54(5.02)	70	-2.55	0.012*	0.168

V. Conclusion

The hybrid recommendation algorithm based on knowledge graph and collaborative filtering performed well on the experimental dataset, with the R@5 index reaching 0.1563 and the N@5 index reaching 0.3015 on the ML-1M dataset, which was 0.0427 higher than that of the best baseline model MCCLK on the R@5 index. Compared with the KGIN model on the Last-FM dataset, the R@5 and R@10 were improved by 0.19% and 0.35%, respectively. The experiment proved that the algorithm has strong recommendation accuracy and generalization ability. Applying the algorithm to an adaptive learning system for university English vocabulary learning, through a 7-day teaching experiment, it was found that students using the adaptive learning system were significantly higher than those using the traditional learning system in all dimensions of technology acceptance, especially in the dimension of effectiveness of resource recommendation with a score of 23.07 (out of a possible 25 points). More importantly, the adaptive learning system had a significant positive impact on students' English vocabulary learning performance, and the scores of the students using the system in the four dimensions of vocabulary learning, vocabulary cognition, vocabulary writing and vocabulary mastery were 22.71, 20.15, 22.86, and 20.54, which were significantly higher than those of the group using the traditional learning system. Especially in vocabulary writing, the adaptive learning system group scored 6.77 points higher than the traditional learning system group, indicating that the personalized learning path has a significant effect on improving students' vocabulary application ability. By accurately recognizing learners' individual differences and providing targeted learning resources, the adaptive learning system effectively improves college students' English vocabulary learning efficiency and learning outcomes, and provides a new technical support and practice mode for promoting the reform of college English teaching.

References

[1] Farjami, F., & Aidinlou, N. A. (2013). Analysis of the impediments to English vocabulary learning and teaching. International Journal of Language and Linguistics, 1(4-1), 1-5.

[2] Siddiq, M., Arif, I. M. Q., Shafi, S. C., & Masood, M. H. (2021). A survey research analysis of effectiveness of vocabulary learning through English vocabulary corpus. International Journal of Education and Pedagogy, 3(2), 1-13.

[3] Bates, J., & Son, J. B. (2020). English Vocabulary Learning with Simplified Pictures. TESL-EJ, 24(3), n3.

[4] Afzal, N. (2019). A study on vocabulary-learning problems encountered by BA English majors at the university level of education. Arab World English Journal (AWEJ) Volume, 10.

[5] Wahyudin, A. Y., Pustika, R., & Simamora, M. W. (2021). Vocabulary learning strategies of EFL students at tertiary level. J. English Lit. Educ. Teach. Learn. English as a Foreign Lang, 8(2), 101-112.

[6] Zhang, Y., Lin, C. H., Zhang, D., & Choi, Y. (2017). Motivation, strategy, and English as a foreign language vocabulary learning: A structural equation modelling study. British Journal of Educational Psychology, 87(1), 57-74.

[7] Gao, C., & Xu, B. (2013). The Application of Semantic Field Theory to English Vocabulary Learning. Theory & Practice in Language Studies (TPLS), 3(11).

[8] Salawazo, I. S., Simbolon, M., Hutabarat, V. E., Veronika, A. N., & Saragih, E. (2020). Analysis of students' vocabulary in learning English. Linguistic, English Education and Art (LEEA) Journal, 3(2), 469-475.

[9] Somasundaram, M. J. K. M. S., Junaid, K. M., & Mangadu, S. (2020). Artificial intelligence (AI) enabled intelligent quality management system (IQMS) for personalized learning path. Procedia Computer Science, 172, 438-442.

[10] Deng, W., Wang, L., & Deng, X. (2024). Strategies for Optimizing Personalized Learning Pathways with Artificial Intelligence Assistance. International Journal of Advanced Computer Science & Applications, 15(6).

[11] Chen, C. M., & Chung, C. J. (2008). Personalized mobile English vocabulary learning system based on item response theory and learning memory cycle. Computers & Education, 51(2), 624-645.

[12] Liu, P. L., & Chen, C. J. (2023). Using an AI-based object detection translation application for English vocabulary learning. Educational Technology & Society, 26(3), 5-20.

[13] Kazu, I. Y., & Kuvvetli, M. (2023). The Influence of Pronunciation Education via Artificial Intelligence Technology on Vocabulary Acquisition in Learning English. International Journal of Psychology and Educational Studies, 10(2), 480-493.

[14] Son, J. B., Ružić, N. K., & Philpott, A. (2023). Artificial intelligence technologies and applications for language learning and teaching. Journal of China Computer-Assisted Language Learning, (0).

[15] Huang, X., Zou, D., Cheng, G., Chen, X., & Xie, H. (2023). Trends, research issues and applications of artificial intelligence in language education. Educational Technology & Society, 26(1), 112-131.

[16] Hengyu Li. (2024). EFL Learners' Preferences for English Vocabulary Learning Strategies: A Case Study of Chinese Students in Malaysia. Lecture Notes on Language and Literature,7(6).

[17] HuangDaoyu,ZhangXiaoqing & GuanYuanyuan. (2024). English Vocabulary Learning Strategies between High-achievers and Low-achievers. English Linguistics Research,13(1),26-26.

[18] Jose Belda Medina & Max Benjamin Goddard. (2024). The Effect of Digital Storytelling on English Vocabulary Learning in Inclusive and Diverse Education. International Journal of English Language Studies,6(1),110-118.

[19] Sujata Moharana. (2025). Prospects of Artificial Intelligence (AI) and Personalized Learning in Inclusive Education Integrated to NEP-2020. Asian Journal of Education and Social Studies,51(4),109-116.

[20] Xiaoman Wang,Rui "Tammy" Huang,Max Sommer,Bo Pei,Poorya Shidfar,Muhammad Shahroze Rehman... & Florence Martin. (2024). The Efficacy of Artificial Intelligence-Enabled Adaptive Learning Systems From 2010 to 2022 on Learner Outcomes: A Meta-Analysis. Journal of Educational Computing Research,62(6),1568-1603.