J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5981--6002

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Optimization and Selection of English Teaching Paths in Colleges and Universities Based on the Combination of Dynamic Planning Algorithm and Traditional Teaching Methods

Lin Lin[1, ✉]

[1] *Department of Public Education, Changchun Technical University of Automobile, Changchun, Jilin, 130013, China*

ABSTRACT

In the era of artificial intelligence, online learning of English courses in colleges and universities has gradually become one of the mainstream learning modes. Based on the traditional teaching methods, this paper carries out the research on the optimization of English teaching path in colleges and universities. A micro-learning unit clustering model is constructed with four modules: data preprocessing, learning pattern mining, learning path diagram construction and micro-learning unit clustering. The model analyzes the learning state of learners through sequence pattern mining technology, and conducts orderly planning of learning resources based on learners' characteristics. On this basis, this paper defines the online learning path planning problem and online learning path planning according to the continuity characteristics of learning knowledge points, and constructs the online learning path planning model. At the same time, the dynamic planning algorithm is selected to carry out the optimization of path planning. Based on the learning status of different learners, the optimal online learning path is planned to realize the optimization of English teaching path. Compared with similar classical algorithms, the online learning path planning model has the highest matching degree of 0.8 between the planned paths and the learning states of users under different learning resources conditions, which verifies the superiority of this paper's model in the optimization of English teaching paths in colleges and universities.

Keywords: sequence model; dynamic programming algorithm; learning path planning; college English teaching

✉ Corresponding author.
E-mail address: 13944927250@163.com (L. Lin).
Received 05 March 2024; Revised 25 May 2024; Accepted 05 December 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-328

1. Introduction

With the rapid development of the society, the education system pays more and more attention to and advocates education informatization and teaching informatization, and educational units at all levels actively respond to the call of social demand, scientifically integrate the existing teaching resources, research and development of new teaching technologies, and promote the construction of the education informatization system with all efforts to improve the overall standard of informatization teaching and cultivate all-round talents [1-4]. At the same time, with the development of globalization and the increasing frequency of cross-cultural exchanges, English, as an international common language, has entered into various fields of daily life [5]. It has become an important tool for people's communication, which puts forward a new requirement for the training of talents in institutions of higher education, that is, they must have strong English application ability. In today's comprehensive promotion of quality education, the English curriculum emphasizes the cultivation of various abilities of students, which requires intercultural competence, critical thinking, independent learning, and level exams in addition to the basic skills of listening, speaking, reading, writing and translating in English [6-9]. However, there are some obvious deficiencies in English teaching to be solved. For example, teachers' teaching concepts and teaching modes are outdated, teaching materials lack innovation, the gap between the levels of the student population widens, and the differences in students' English learning ability increases, the value of teaching tools is emphasized on this point, the tendency of teaching to the test seriously exists, etc [10-13]. Among them, the most typical is the consistency of the teaching path is not conducive to students' independent learning and individualized needs, such as leading to the low pass rate of the fourth and sixth grade exams [14]. Therefore, it is necessary to incorporate new teaching techniques in English teaching in order to combine the advantages of existing teaching and to jointly develop new English teaching paths.

Dynamic programming algorithm is a method for solving optimization problems, which is based on the ideas of partitioning and recursion, Dynamic programming algorithm usually uses a recursive formula to solve the problem, which can be decomposed into sub-problems, and together with the optimal solution of the original problem by solving the optimal solution of the sub-problems [15]. The algorithm solves a decision problem in such a way that decisions after the current state do not affect previous decisions [16]. Therefore, only the current state and previous states need to be considered when state transfer is involved. At present, dynamic programming algorithms have been applied in course scheduling, teaching management optimization, assisted e-learning, etc., starting from solving the optimal strategy, the decision-making is well adapted in terms of personalization and dynamics, which paves the way for the optimization of English teaching paths [17-19].

For the optimization of English teaching path in colleges and universities, this paper starts from the learner's perspective. Firstly, it establishes a micro-learning unit clustering model, analyzes the model structure and the corresponding functions as the mining of learners' learning state and the combination method of learning resources. Then we explore the online learning path planning problem and the definition of learning path planning, describe in detail the core principle of dynamic planning algorithm and its mathematical architecture, so as to construct the online learning path planning model. Finally, the performance analysis of the model is carried out in the form of dataset testing and visualization operation, and simulation experiments are designed to evaluate the application effect of the model in various dimensions.

2. Microlearning unit clustering model

This paper proposes a microlearning unit clustering model, which intends to analyze the learning history of learners with different learning statuses, and cluster the microlearning units of learners with different learning statuses in English courses in colleges and universities according to their learning cycles. The main content of this chapter is to detail the definition of learners, and the structure of the microlearning unit clustering model.

2.1. Learners

The learner occupies the main position in the learning process, so the key to realizing the microlearning system lies in analyzing the target student model and analyzing the learner's data from different perspectives, so as to find out the learner's learning mode and ultimately provide personalized services for the learner in order to improve his/her learning efficiency. In order to reflect the real situation of learners and pave the way for subsequent research, on the basis of the past learner model, the learner's basic information, cognitive level, and the learning path formed by that learner learning a certain course are synthesized and constructed into a learner characteristic model, i.e., learner = {basic information, cognitive level, learning path}, which is structured as in equation (1):

$$LA = \{BF, CL, LP\} \tag{1}$$

Where BF indicates the learner's personal information, such as student number, gender, age, and academic background. CL indicates the learner's mastery of knowledge for a course, this paper mainly uses the final grade, whether or not the course has been retaken to indicate the learner's knowledge level achieved on the learning domain. LP indicates the learning path formed by the learner learning the course. The representation of BF is shown in equation (2):

$$BF = \{U_{id}, U_{sex}, U_{age}, U_{aca}\} \tag{2}$$

where U_{id} denotes a unique identifier that identifies the learner, usually the learner's school number. U_{sex} denotes the gender of the learner. U_{age} denotes the age of the learner. U_{reg} indicates the learner's location. U_{aca} denotes the learner's highest level of education, such as master's degree and above, bachelor's degree, high school, middle school and below. And CL is represented as in equation (3):

$$CL = \{U_{dis}, U_{res}\} \tag{3}$$

Where U_{dis} indicates whether the learner has retaken the course. U_{res} indicates the final score level of the learner when he/she finishes the course.

2.2. Model structure

The microlearning unit clustering model designed in this paper is divided into the following four modules. The first is the microlearning data preprocessing module, which preprocesses the input learner and learning history information and models the data in order to transform the data into a format that can be recognized and processed by the model. Next is the learning pattern mining module, which uses a sequence pattern mining algorithm to mine the learning history of a particular learner to obtain the frequent learning patterns preferred by the learner, and to further process the learning patterns. The second is the learning path graph construction module, which builds a learning path graph according to the learning sequence between microlearning units in the learning pattern, which can reflect the personalized learning preferences of a particular learner, including learning unit information and learning sequence information. Finally, there is the microlearning unit clustering module, which will cluster the microlearning units on the learning path diagram, and finally get the clustered microlearning unit data. The model structure is shown in Fig. 1.

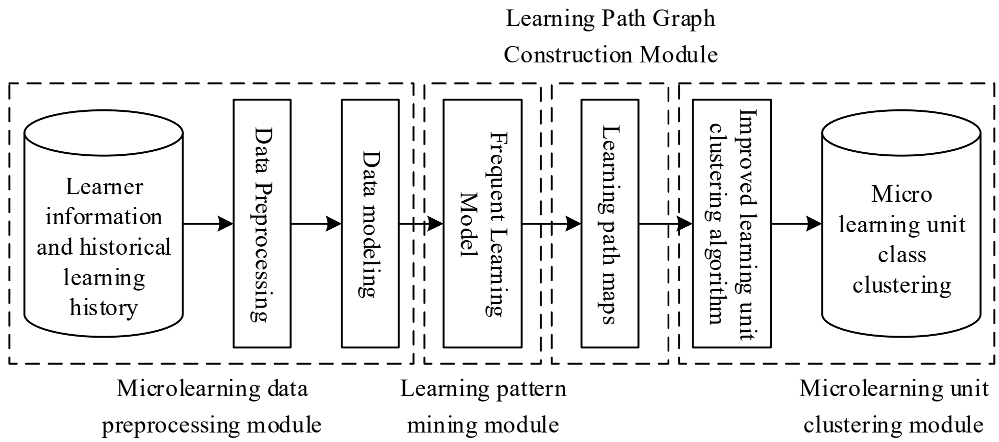


Fig. 1. Model of Micro-learning unit clustering

3. Construction of an online learning path planning model

By using the micro-learning unit clustering model proposed above, the correlations existing between learners of different learning states and their compatible learning units are obtained, and different learning resources suitable for learners are clustered, so as to mine multiple learning paths suitable for learners. For the optimization and selection of optimal learning paths, this chapter describes the online learning path planning problem and discusses the mathematical definition of learning path planning. Combining the dynamic programming algorithm and the traditional teaching methods of English in colleges and universities, the online learning path planning model is constructed.

3.1. Definition of the online learning path planning problem

With the continuous popularization of "Internet +" educational applications, online learning has become an important channel for many learners to acquire knowledge or carry out related course content learning, and a huge amount of learning resources are also presented on the Internet. At this time, learners are not able to obtain suitable learning resources in a relatively short period of time and carry out orderly combination, the problem has become an important research content of many scholars in the field of intelligent e-learning applications, and the key issue in the study of intelligent e-learning system is how to plan the learning path.

In general, learning path planning is to enable intelligent e-learning systems to reorganize and order the recommended learning resources according to the knowledge level and learning goals of the learners, forming a learning path suitable for the learners to complete their learning goals quickly and effectively. The online learning path planning problem can be described as follows: on the basis of the completion of the learning resources recommendation, according to the learning resources difficulty and the ability of the learner, the learning cost between the learning resources and the correlation between the knowledge and the learning resources, etc., the learning resources will be sorted according to the adaptability function value in order, and the learner will start learning from the designated learning resources until the completion of the learning of all the resources. The solution to the online learning path planning problem is a set of ordered sequences composed of online learning resources, which is the result of comprehensive matching and optimization of learner attribute characteristics and learning resource attribute characteristics.

3.2. Definitions related to online learning path planning

In this chapter, the online learning resources learning path planning (optimization) problem is regarded as a single-objective optimization problem transformed from a multi-objective one, i.e., solving for the minimum of four objective functions simultaneously. According to the value of the required function, a complete learning path can be obtained by sorting from smallest to largest. Assuming that a learner needs to learn an online course, this course consists of N learning resources that need to be recommended to the learner: $r_1, r_2, \ldots, r_i, \ldots r_N$. In order to be able to recommend these learning resources to the learner in a reasonable order according to the learner's characteristics, this section defines and analyzes the model from the three aspects of the difficulty of the learning resources and the difference in the ability of the learner, the learning expenditure, and the relevance of the learning resources to the learning knowledge points.

Definition 1 An e-learning system should consider whether the difficulty of learning resources matches the learner's ability when recommending learning paths for learners. Let the online learning system be represented by RAS, the difficulty of learning resources be represented by D, and the learner's ability be represented by A, then the expression is shown in equation (4):

$$\{D \ match\ A\} \in RAS \tag{4}$$

The learning difficulty here refers to the overall difficulty of the conversion process from one learning resource to another.

The relationship between the difficulty of learning resources in the learning path is shown in Fig. 2. In the learning path line, the overall difficulty level from the current learning resource to the next learning resource should show an overall increasing trend, if learning resources 1, 2, 3, and 4 are recommended to the learner sequentially, the overall difficulty level from learning resource 1 to learning resource 2 should be $D1$ less than the overall difficulty level from learning resource 2 to learning resource 3. $D2$. 2 to Learning Resource 3 should be less than the overall difficulty level $D2$ from Learning Resource 3 to Learning Resource 4 $D3$.

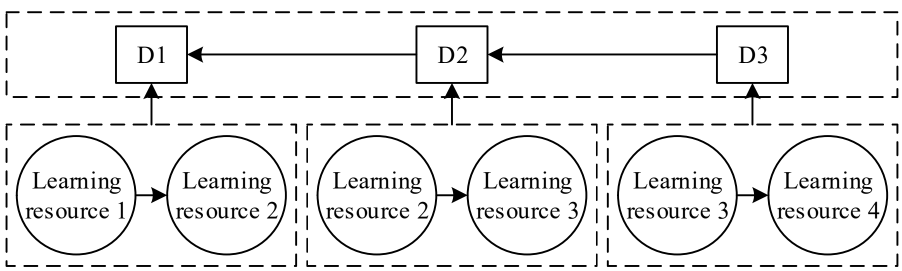


Fig. 2. Relationship of learning resource difficulty in learning path

Definition 2 An e-learning system should also consider the size of the learning expense of the learning resource when recommending learning paths for learners. The size of a resource's learning expenses is a comprehensive reflection of the difficulty of the learning resource, the time spent, and the energy invested by the learner. Therefore, when the learner is a beginner, the e-learning system should recommend learning resources with lower learning expenses. When the learner reaches a certain level, it is recommended that the learning resources with higher learning expenses. Let the learning path be represented by LP, and the learning expenditure be represented by S, then there is an expression such as equation (5):

$$\{S1 < S2 < \cdots < Sn\} \in LP \tag{5}$$

The relationship between learning expenditures in the learning path is shown in Fig. 3. In the learning path line diagram, the learning expenditures from the current learning resource to the next learning resource should show an overall incremental trend, $S1$, $S2$, $S3$ are the learning expenditures from learning resource 1 to learning resource 2, learning resource 2 to learning resource 3, and learning resource 3 to learning resource 4, respectively, which satisfy $S1 < S2 < S3$.

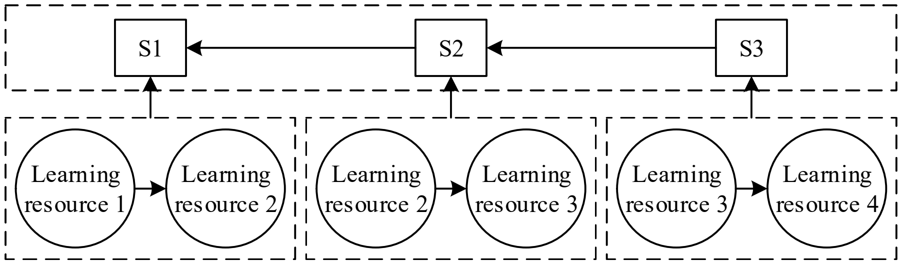


Fig. 3. Learning the spending relationship in the learning path

Definition 3 When recommending a learning path for a learner, an e-learning system should also consider the matching degree between the learning resource and the target knowledge point expected by the learner. Let the matching degree between the learning resource and the knowledge point be represented by R, then there is an expression as in equation (6):

$$\{R1 < R2 < \cdots < Rn\} \in LP \tag{6}$$

The relationship between the matching degree of learning resources and knowledge points in the learning path is shown in Fig. 4. In the learning path line diagram, the matching degree of learning resources and knowledge points should show a decreasing trend on the whole. Taking the three learning resources as an example, the match R1 between learning resource 1 and the knowledge point should be greater than the match $R2$ between learning resource 2 and the knowledge point. The match $R2$ between learning resource 2 and the knowledge point should be greater than the match $R3$ between learning resource 3 and the knowledge point.

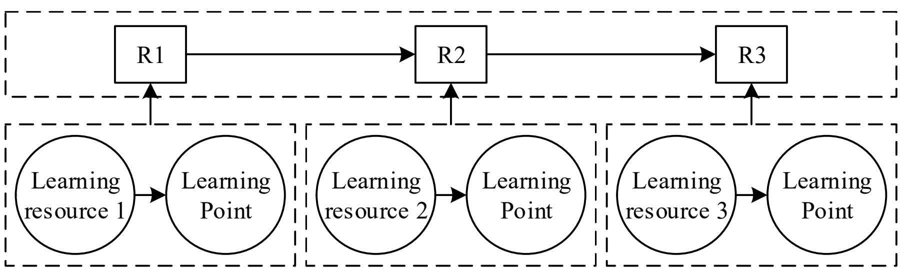


Fig. 4. The matching degree of learning resources and knowledge points

For the matching degree, it can be presented by matching degree matrix. Assuming that there is N learning resource with M knowledge points, the matching degree matrix of M knowledge points with N learning resources is R as in equation (7):

$$R = \begin{bmatrix} R_{11} & R_{12} & R_{13} & \dots & R_{1N} \\ R_{21} & R_{22} & R_{23} & \dots & R_{2N} \\ \dots & \dots & \dots & \dots & \dots \\ R_{M1} & R_{M2} & R_{M3} & \dots & R_{MN} \end{bmatrix} \tag{7}$$

Definition 4 The sequence of learning resources that will be recommended to the learner after the current learning resource recommendation is completed can be determined by the computation of the learning resource's repugnancy. The repugnance of learning resources is obtained from the values of three aspects: the difference between the difficulty of the learning resources and the learner's ability, the learning expenditure, and the match between the learning resources and the knowledge points. The size of the repulsion is a measure of the degree of relevance of the two learning resources, the smaller the repulsion, the higher the degree of relevance of the two learning resources, the higher the possibility of recommending the two learning resources to the learner in the previous and subsequent order. Conversely, the smaller it is. Based on the size of the repulsion, it is possible to determine the next learning resource to be recommended to the learner after the current learning resource is recommended.

Definition 5 After the generation of online learning paths, the merit of each learning path requires an evaluation index. In the online learning path, the evaluation index is used to evaluate the matching degree between the learning path generated by each algorithm and the learner, i.e., to evaluate the advantages and disadvantages of the learning path, and the value of the evaluation index of the learning path is denoted by E. The evaluation index value is the total value of the repugnancy of all the current learning resources and the learning resources to be recommended on the learning path. For example: there is a learning path $2 \to 3 \to 5 \to 1 \to 4 \to 6$, learning resources 2 and learning resources 3 repugnance of 0.2, learning resources 3 and 5 repugnance of 0.5, learning resources 5 and 1 repugnance of 0.4, learning resources 1 and 4 repugnance of 0.6, learning resources 4 and 6 repugnance of 0.3, then the overall learning path of the evaluation of the index value of E for the above repugnance of the sum of the indicator value of 2. The range of the indicator value. 2. The range of the indicator value is between 0 and 5.

3.3. Dynamic Planning Algorithm

Dynamic programming (DP) is an optimization algorithm for solving multi-stage decision-making problems, proposed by scholars in the 1950s and elaborating the well-known Bellman optimality principle. According to Bellman's optimality principle, the optimal policy has the property that regardless of the initial state and the initial decision, the remaining decisions must form an optimal decision about the state resulting from the first decision. Dynamic programming, based on Bellman's principle, obtains an optimal solution to the entire problem by decomposing the complex problem into a series of smaller problems with overlapping properties and solving them individually, ultimately combining the solutions of these subproblems to obtain an optimal solution to the entire problem. It is this ingenious idea of cutting and synthesizing the optimization stages that not only makes Dynamic Programming play a crucial role in decision-making optimization in many fields, but also makes it able to give the optimal English learning paths for students with different English learning abilities and learning states.

Figure 5 illustrates the optimality principle.

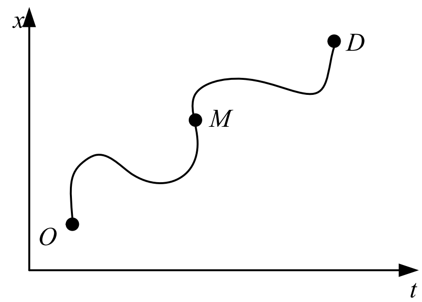


Fig. 5. Optimality principle schematic

Bellman's optimality principle defines the optimal path from O to D and introduces a new point M in Figure 5. The main use of the optimality principle is that if all optimal paths for any initial state x at moment $n+1$ are known, then every optimal path from moment n must use one of these optimal paths starting and continuing from moment $n+1$, i.e., the optimal solution to the original problem contains the optimal solution to the subproblem.

3.3.1. Mathematical models. In order to give a mathematical model of the dynamic programming algorithm mathematical equations can be introduced, first defining the notation used in this section: the state of the system is denoted by x, which is usually a real vector of finite dimensions, and for simplicity its dimension is defined as 1, (i.e. x is a number). The multiple decision paths from O to D are shown in Figure 6.

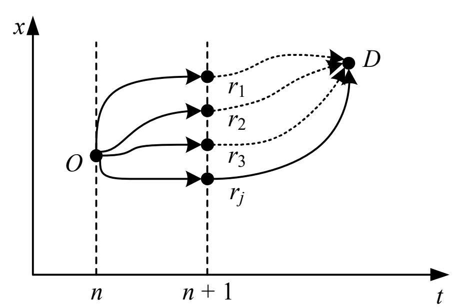


Fig. 6. Multiple paths from O to D

According to Eq. (8), at the n moment when the state is $x(n)$, the controller has to choose a decision-making strategy $r(n)$ so that the system reaches state $x(n+1)$ at the $n+1$ moment.Eq. (8) is also known as the state transfer equation.

$$x(n+1) = f(x(n), r(n)) \tag{8}$$

If the optimality of certain paths and control strategies is to be discussed, the concept of cost must be introduced. The optimal path is the path that minimizes the cost J from the initial state $x(n)$. In dynamic programming, the cumulative cost is used, which consists of the sum of the step costs $c(x,r)$ as in equation (9):

$$J(x(.), r(.)) = \sum_{n=0}^{N} c(x(n), r(n)) \tag{9}$$

where $r(n) = r(x,n)$ is the decision variable at any moment n and at any state x. When it is applied to the system, Equation (10) is obtained:

$$x(n+1) = f(x(n), r(x,n)) \tag{10}$$

3.3.2. Optimal control strategy. After determining the optimal decision variable, the discussion needs to focus on how to find it. If for any learning state x the optimal decision quantity at moment $n+1$ is known, then the controller at moment n has to decide which path to choose for the first step, using the optimal control strategy state x at moment $n+1$ the total cost can be defined as $V^*(x,n+1)$, this function is called the optimal value function.

At moment n, the role of the controller is to choose a strategy r that minimizes the sum of the cost of the steps from n to $n+1$ and the remaining cost from $n+1$ to the end of the whole state, which is the principle of Bellman's equation. Its expression is shown in equation (11):

$$V^*(x,n) = \min_{r(n)} \left\{ V^*(f(x(n), r(n)), n+1) + c(x(n), r(n)) \right\} \tag{11}$$

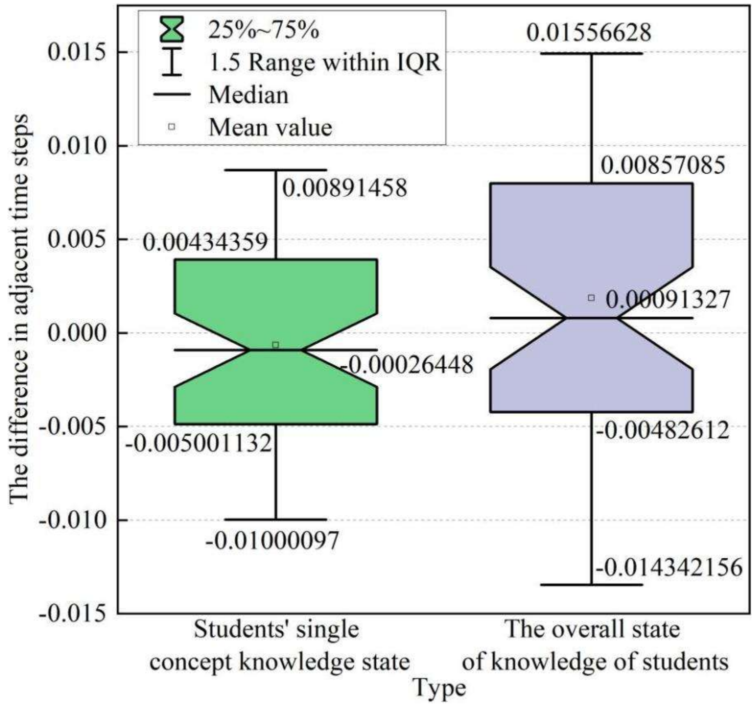
Given the value function $V^*(x,n+1)$, it is possible to calculate the value function $V^*(x,n)$ and the value of the control variable $r(n,x)$ at moment n. Therefore, starting from the last step, the optimal control variables can be found by recursive iteration to determine the optimal English learning path planning decision.

4. Model performance analysis and application evaluation

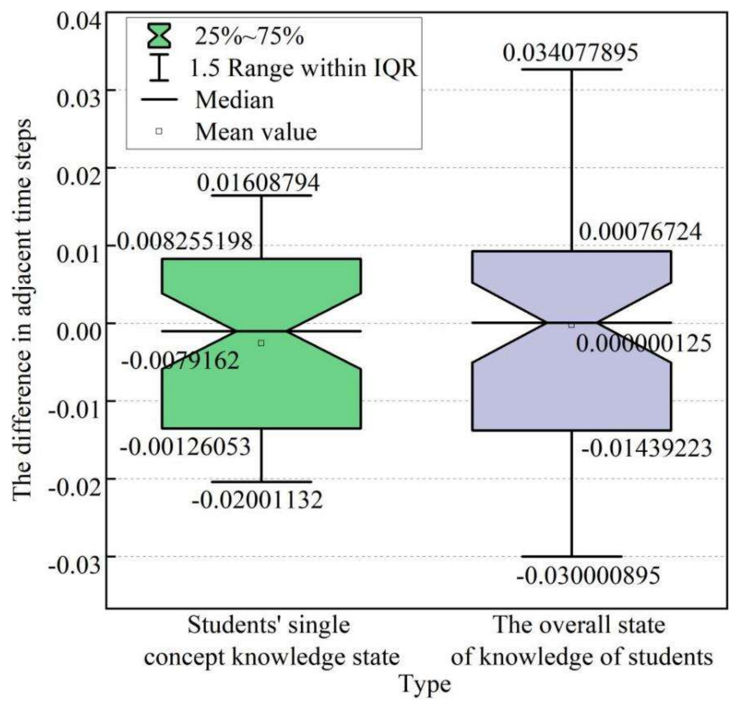
In order to verify whether the online learning path planning model proposed above can effectively assist the teaching of English in colleges and universities, this chapter firstly develops the performance analysis of the model itself, and then designs simulation experiments to compare the learning path planning results as well as the feasibility and effectiveness of the planning paths of this paper's model with those of the similar models, Genetic Algorithm Model (GA) and Original Ant Colony Algorithm Model (ACO).

4.1. Performance analysis of the model

4.1.1. Stability analysis. This subsection analyzes the online learning path planning model with respect to the stability of knowledge tracking: first, the model is used to obtain the knowledge state of each student at each time step in different test sets. Second, the difference between the students' individual conceptual knowledge states and the difference between their overall knowledge states at neighboring time steps is calculated. Finally, a box-and-line plot is drawn based on the obtained differences as shown in Figure 7. The data for the ASSIST15 test set and the ASSIST09 test set were collected from the online English tutoring platform ASSISTments, which contains records of students' interactions on the platform in 2015 and 2009, respectively.



(a) ASSIST15



(b) ASSIST09

Fig. 7. Stable analysis of knowledge tracing

As can be seen in Figure 7:

1) the absolute values of the median (-0.00026448), upper quartile (0.00434359), and lower quartile (-0.005001132) of the difference in the students' knowledge states of individual concepts in adjacent time steps in the ASSIST15 dataset are all in the order of magnitude of 10-3 (or even smaller), which indicates that the students' knowledge states of individual concepts in adjacent

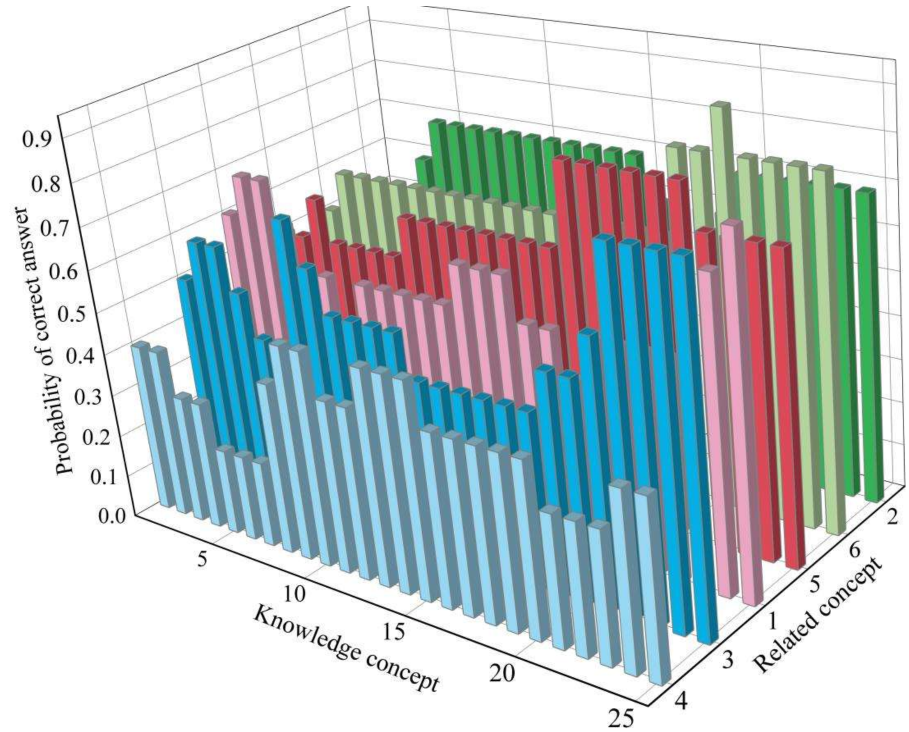
ASSIST15 dataset in adjacent time steps of a single concept in the ASSIST15 data set have small changes in the state of knowledge and show good stability.

2) The median (0.000091327), upper quartile (0.00857085), and lower quartile (-0.004482612) of the difference in the students' overall knowledge states at adjacent time steps in the ASSIST15 dataset are also in the order of 10-3 (or even smaller), indicating that the students' change in overall knowledge status is also smaller. The experimental results on the ASSIST09 dataset are similar to those on the ASSIST15 dataset.

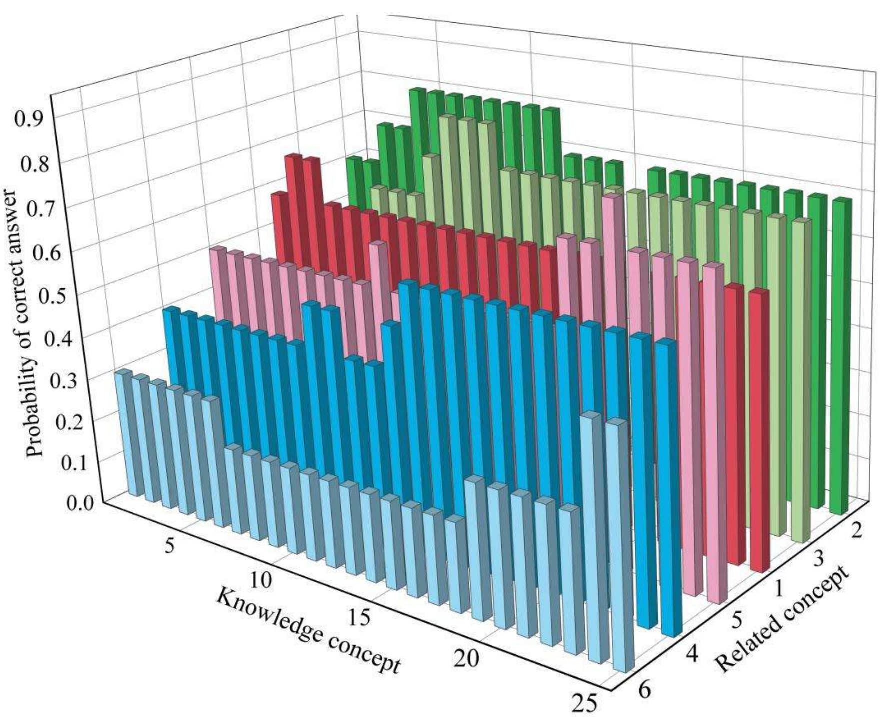
In summary, it can be seen that the online learning path planning model is able to track the steadily evolving knowledge state, and thus more accurately determine the students' learning state.

4.1.2. Visualization analysis. Based on the results of the stability analysis of the model above, the evolution of the students' knowledge states was visualized:

First, 2 students' English question answering interaction sequences were selected from the ASSIST15 dataset. Subsequently, knowledge tracing was performed for each of these 2 sequences using the online learning path planning model. Finally, the knowledge states are visualized in Fig. 8. The X-axis coordinates 1-25 in Fig. 8 correspond to a total of the following 3 scenarios in turn: (1) English knowledge point concepts C1-C20; (2) 1-25 time steps; and (3) knowledge concept exercises ex1-ex20.



(a) The change of the knowledge state of the first student



(b) The change of the knowledge state of the second student

Fig. 8. Visualization of knowledge state change of two students

From Figure 8:

1) When a student completes the exercise about concept c20, there is a change in the student's knowledge state about concept c1, and a change in the knowledge state about other knowledge concepts that have a learning transfer relationship with concept c1, such as concept c19 and concept c17.

2) The student's knowledge state does not undergo a sudden change due to a momentary correct or incorrect response, but is updated smoothly. For example, after the student answered three exercises about concept c6 correctly consecutively from time step 4 to time step 6, the student's mastery of concept c6 only increased from 0.5 to 0.7. After the student answered the exercises about concept c9 incorrectly at time steps 10 and 11, the change in the student's mastery of concept c9 was less than 0.1. The change in the state of knowledge of the second student was similar to the change in the state of knowledge of the first student's change in state of knowledge was similar.

4.2. Simulation Experiments

The online learning path planning model proposed in this paper aims to plan efficient learning paths for students that are both suitable for students' learning states and in line with the actual learning process, to help students effectively achieve their own learning goals in English courses, so as to improve student satisfaction and to solve the problems of high dropout rates and low course pass rates in online learning. Therefore, the validation of the online learning path planning model in this section consists of two main parts: the degree of conformity between the learning path and the students' learning state and the students' satisfaction.

4.2.1. Experimental design. The experimental data in this paper comes from the Y College English Online Education website. Four students with large differences in learning status were simulated as experimental subjects to illustrate the objectivity of the experiment. The learning status of the four test students is shown in Table 1.

Table 1. Four test the user's learning state

User number	Learning state
User 1	(1,-1,-3,7)
User 2	(-3,1,-3,7)
User 3	(7,9,-7,-9)
User 4	(-11,-3,3,7)

4.2.2. Learning path planning results. Randomly select the learners from Y college English online education website, add the English courses in their history logs into the solution space, and artificially set the target English courses for them, and use the online learning path planning model to unfold the solution of the optimal path. The number of model solving iterations is shown in Fig. 9, which shows that the model of this paper finds the optimal solution of the problem in about 100 iterations.

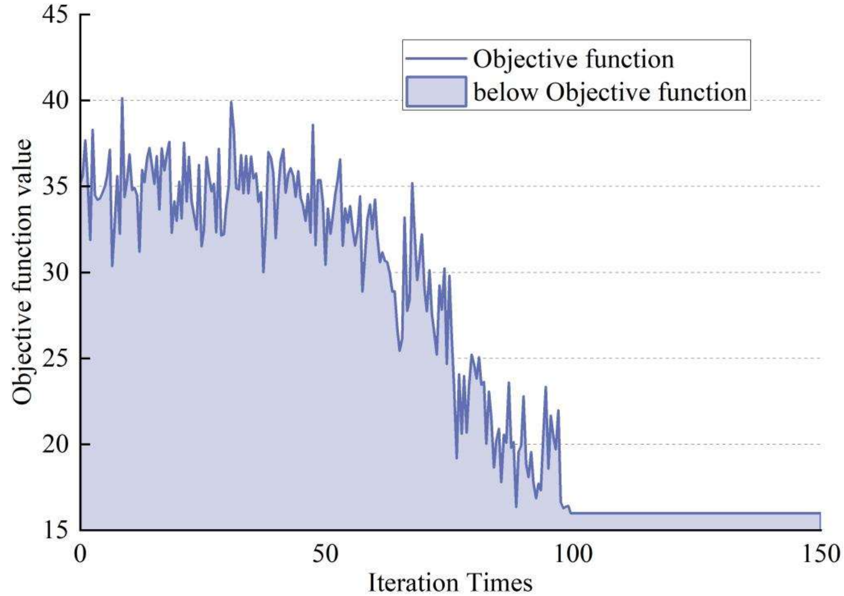
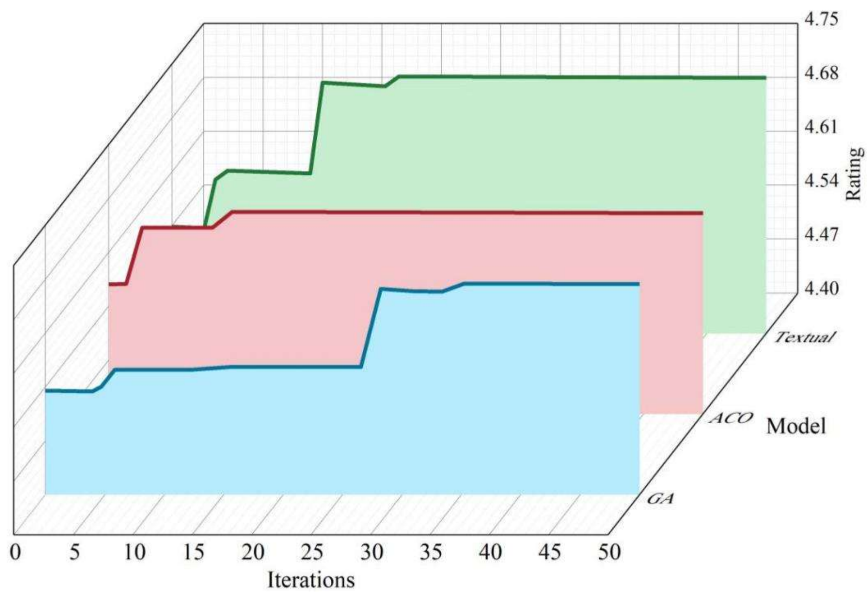
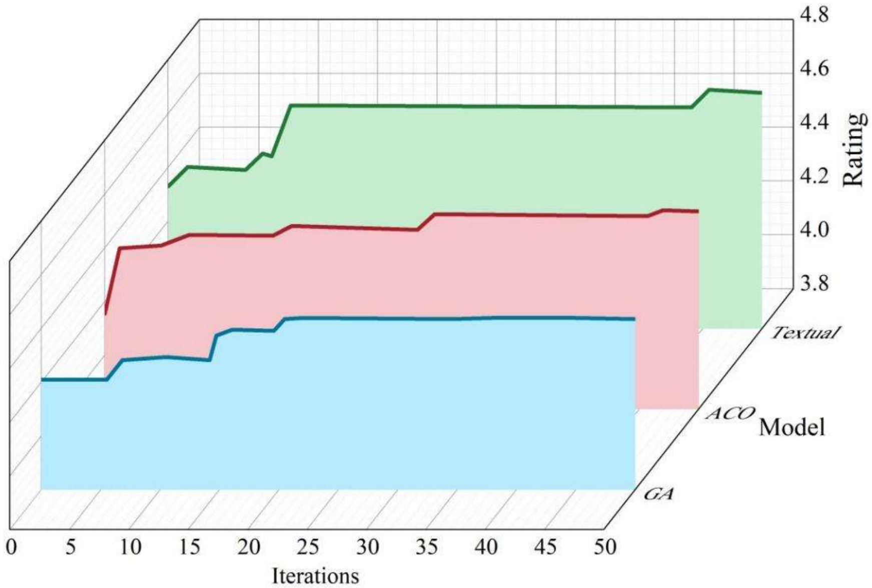


Fig. 9. Iteration Times

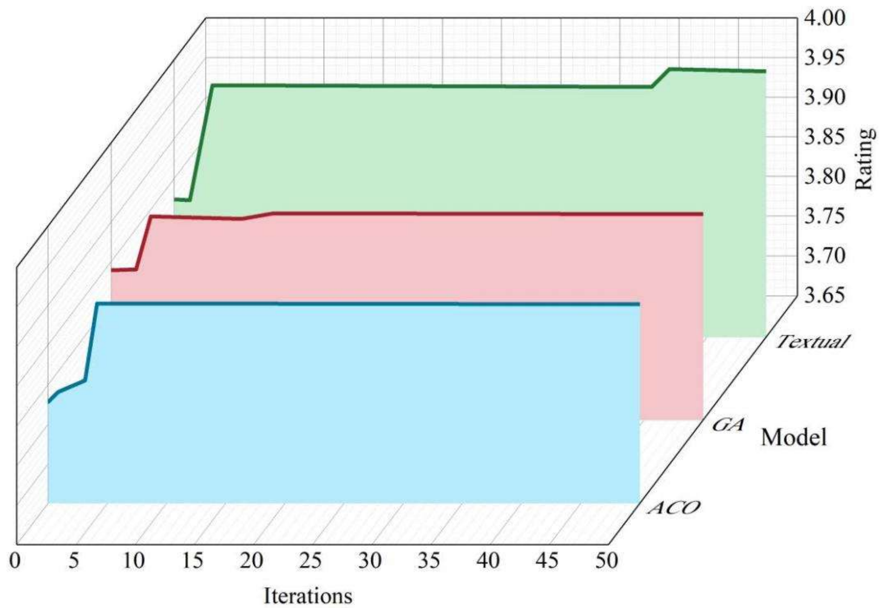
4.2.3. Feasibility of planning pathways. In order to verify the superiority of this paper's model, this paper compares the results of this paper's model with the planned path given by GA and ACO methods for four students with different statuses in terms of student satisfaction and the degree of matching between the path and the students' learning status. The comparison results of the three models are shown in Fig. 10.



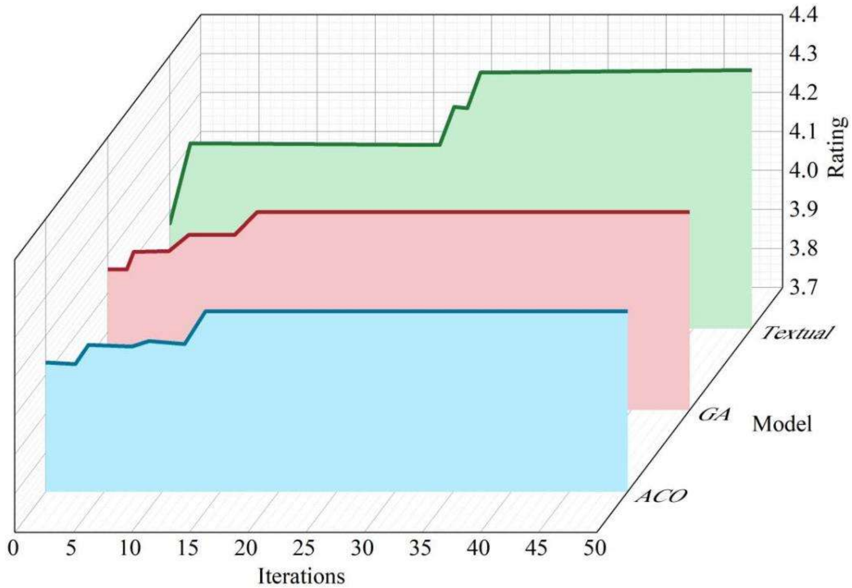
(a) User1: (1,-1,-3,7)



(b) User2: (-3,1,-3,7)



(c) User3: (7,9,-7,-9)



(d) User4: (-11,-3,3,7)

Fig. 10. Experimental results of three methods for four types of users

This experiment was tested on all four experimental users, and it can be clearly seen that all three methods continue to produce learning paths with higher user satisfaction as the number of iterations increases, and gradually stabilize after reaching a certain height. It can be seen that all three methods are able to plan online learning paths for users in different learning states. However, from the experimental results of all four users, it can be seen that through 50 iterations, the results iterated by this paper's model are better than the other two, that is to say, the learning path planning method proposed in this paper is able to obtain a higher degree of user satisfaction.

Secondly, the results derived from this paper's model are compared with the learning paths calculated by the models GA and ACO.Taking user 2 as an example, the degree of matching between the learning path and the user's learning state is evaluated in Table 2.The similarity between the learning path and the user's learning state is the mean of the similarity of the 10 nodes.

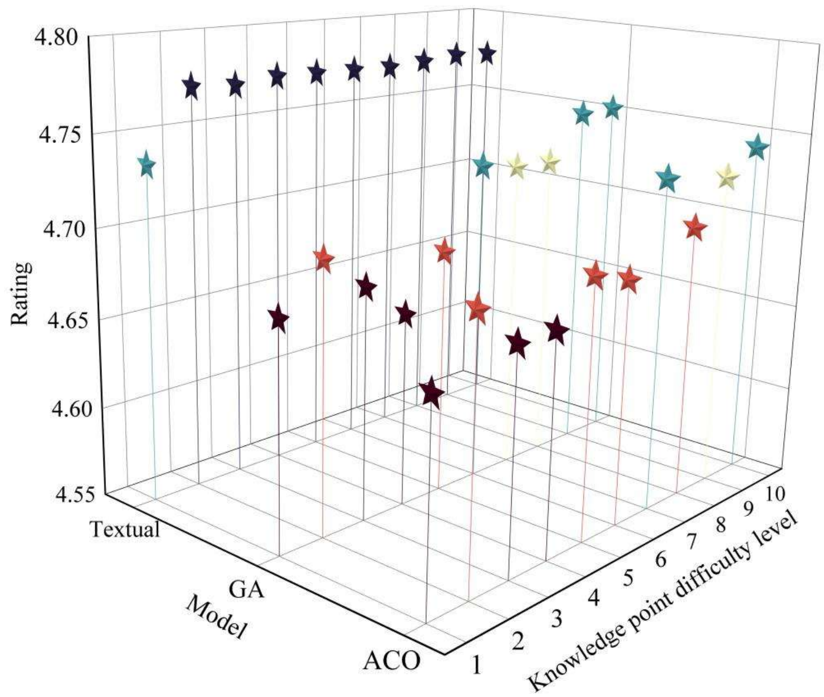
Table 2. The similarity between the learning path and user 2's learning style

Method		Textual model	GA	ACO
Learning path	Node 1	0.73	0.79	0.69
	Node 2	0.73	0.63	0.60
	Node 3	0.79	0.65	0.73
	Node 4	0.84	0.56	0.84
	Node 5	0.81	0.71	0.78
	Node 6	0.88	0.71	0.72
	Node 7	0.69	0.77	0.63
	Node 8	0.72	0.82	0.65
	Node 9	0.75	0.79	0.56
	Node 10	0.61	0.60	0.63
Matched-degree		0.76	0.72	0.68

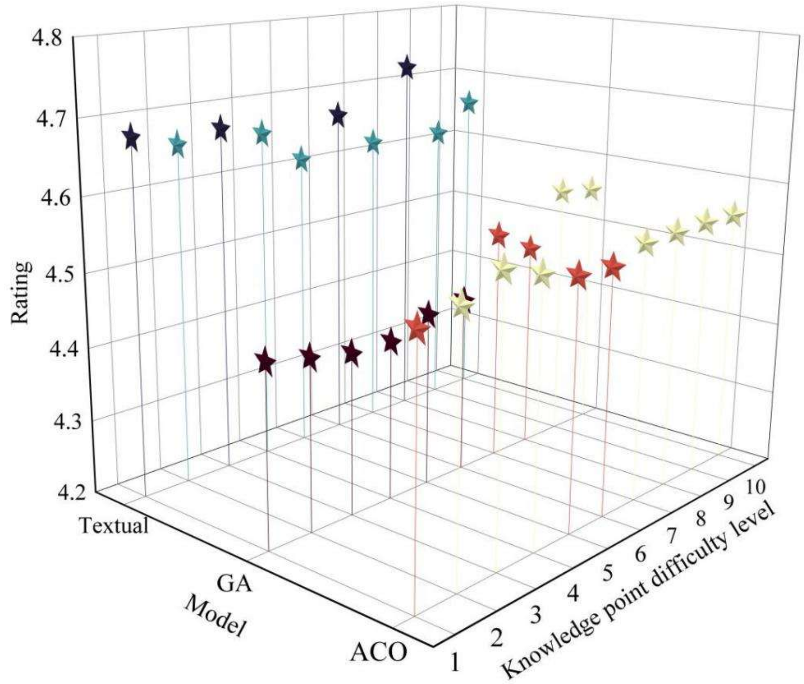
It can be seen that the overall matching degree of the learning path planned by the model in this paper is 0.76, that of the GA model is 0.72, and that of the ACO model is 0.68. In contrast, the learning path at the planning place of this paper's model matches the learning state of user 2 the most, and is more in line with user 2's learning state.

4.2.4. Effectiveness of planning pathways. In order to further verify the effectiveness of this paper's model in solving the online learning path planning problem, this paper changes the values of the variables English Knowledge Point Difficulty and Learning Resources, respectively, and compares the experimental results with those obtained by the GA and ACO algorithms. For the objectivity of the experiment, this experiment still takes the four experimental users in Table 1 as the test subjects while testing the effectiveness of the method. All the experimental results are obtained after 50 iterations.

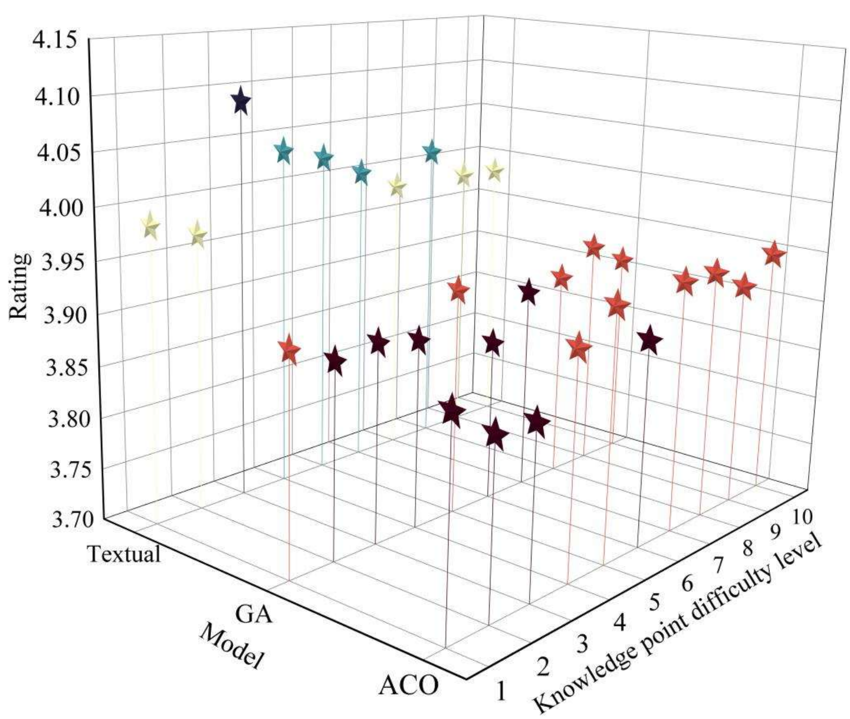
In this experiment, the number of nodes is set to 10, and the difficulty of English knowledge points gradually increases from 1 to 10. The experimental results of the three methods for the four users under different English knowledge point difficulties are shown in Figure 11.



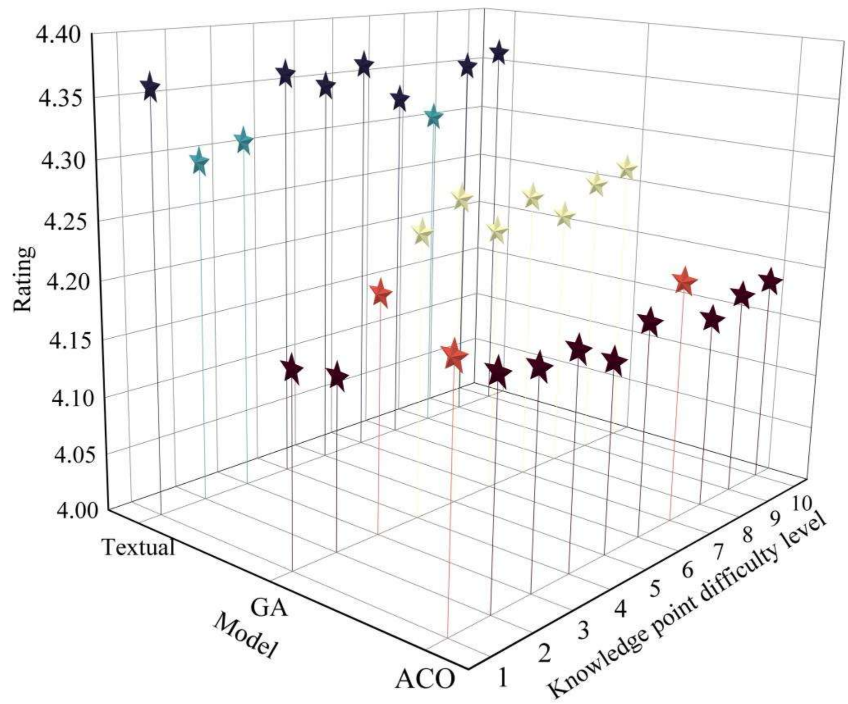
(a) User1: (1,-1,-3,7)



(b) User2: (-3,1,-3,7)



(c) User3: (7,9,-7,-9)



(d) User4: (-11,-3,3,7)

Fig. 11. Experimental results of different knowledge point difficulty

With the increasing difficulty of the English knowledge points, the user satisfaction obtained from the optimal learning paths iterated by all three methods fluctuates. However, in the test results of the four experimental users, this paper's model yields better learning paths, i.e., higher user satisfaction, than the genetic algorithm GA and the original ant colony algorithm ACO in most cases.

In order to further verify that the learning paths planned by this paper's model are more suitable for the users' learning state than those of GA and ACO algorithms, this paper adopts the Euclidean-based similarity calculation method to calculate the similarity between the optimal learning paths obtained by the three methods and the users' learning state under different learning resources. Taking user 2 as an example, the experimental conditions of 123 learning resources and 508 learning resources are set respectively. The results of the matching degree between the learning path and the user's learning state given by the model under different numbers of learning resources are shown in Table 3.

Table 3. Matching degree between paths and users in different learning resources

Number of learning resources		123			508		
Method		Textual	GA	ACO	Textual	GA	ACO
Learning path	Node 1	0.87	0.88	0.67	0.76	0.62	0.64
	Node 2	0.87	0.55	0.65	0.83	0.64	0.67
	Node 3	0.90	0.73	0.64	0.73	0.71	0.77
	Node 4	0.90	0.74	0.79	0.87	0.81	0.62
	Node 5	0.89	0.67	0.70	0.83	0.74	0.77
	Node 6	0.87	0.79	0.77	0.58	0.57	0.59
	Node 7	0.73	0.67	0.70	0.59	0.60	0.70
	Node 8	0.62	0.66	0.65	0.76	0.63	0.74
	Node 9	0.56	0.67	0.85	0.87	0.74	0.67
	Node 10	0.84	0.48	0.51	0.65	0.69	0.63
Matched-degree		0.81	0.68	0.69	0.75	0.67	0.68

Under the condition of 123 learning resources, the matching degree between the learning path and the user's learning state given by this paper's model is 0.81, which exceeds the matching degree of GA and ACO models by 0.13 and 0.12, respectively. Under the condition of 508 learning resources, the matching degree between the learning path given by this paper's model and the learning state used for the learning exceeds the matching degree of GA and ACO models by 0.08 and 0.07, respectively. Compared to the other two similar models, this paper's model achieves a higher matching degree between the online learning path and the user's learning state. Compared with the other two similar models, this paper's model gives a higher match between the online learning path and the user's learning state.

Based on the above experimental results, it can be seen that this paper's model for online learning path optimization and selection of English courses in colleges and universities, compared with the models GA and ACO, can bring greater satisfaction to users with different learning states, and the optimal learning paths planned are not only more suitable for the user's learning state, but also in line with the actual learning sequence, so it can help users efficiently achieve their learning goals.

5. Conclusion

In this paper, we use the micro-learning unit clustering model to explore the learning status of different learners and rationally combine learning resources based on the learning status. Then the online learning path planning model based on dynamic programming algorithm is used to find the optimal online learning path, so as to provide the optimization and selection of teaching paths for English teachers in colleges and universities. The online learning path planning model not only has high stability in operation, but also can accurately identify students' learning status and plan the most suitable learning path. The model finds the optimal learning path only after about 100 iterations, and in comparison with similar models, the matching degree with students' learning state is the highest, 0.76 and 0.81, respectively, both in terms of the difficulty of different knowledge points and in terms of different learning resources.

Funding

This research was supported by the Vocational education of machinery industry in Jilin Province “Synergistic innovation of production, science and education” project: Research on the reform of "professional" foreign language teaching at the undergraduate level and the path of international talent training in the machinery industry (JXHYZX2024092).

References

[1] Yan, S., & Yang, Y. (2021). Education informatization 2.0 in China: Motivation, framework, and vision. ECNU Review of Education, 4(2), 410-428.

[2] Kalaman, O., Bondarenko, S., Telovata, M., Petrenko, N., Yershova, O., & Sagan, O. (2023). Management of digital and intellectual technologies integration in education informatization. TEM Journal, 12(3), 1645.

[3] Akram, H., Abdelrady, A. H., Al-Adwan, A. S., & Ramzan, M. (2022). Teachers' perceptions of technology integration in teaching-learning practices: A systematic review. Frontiers in psychology, 13, 920317.

[4] Zhang, H., & Fang, M. (2021). Research on the integration of heterogeneous information resources in university management informatization based on data mining algorithms. Computational Intelligence, 37(3), 1254-1267.

[5] Atasheva, G. (2024). The importance of English language in the formation of cross-cultural relations. American Journal of Philological Sciences, 4(02), 58-62.

[6] Menggo, S., Ndiung, S., & Midun, H. (2022). Integrating 21st-century skills in English material development: What do college students really need?. Englisia: Journal of Language, Education, and Humanities, 9(2), 165-186.

[7] Weda, S., & Atmowardoyo, H. (2018). Cross-Cultural Competence (CCC) and Cross-Cultural Understanding (CCU) in multicultural education in the EFL classroom. The Journal of English as an International Language, 13(2.2), 9-31.

[8] Zhang, L., & Kim, S. (2018). Critical Thinking Cultivation in Chinese College English Classes. English Language Teaching, 11(8), 1-6.

[9] Zhang, X., & Jiang, R. (2024). A Study on the Cultivation of Autonomous Learning Ability in College English Teaching. Journal of Social Science Humanities and Literature, 7(5), 84-87.

[10] Nurhamsih, Y., & Syahrial, S. (2018). Evaluation of English teaching materials used at a vocational high school based on Cunningsworth's checklist. JOALL (Journal of Applied Linguistics and Literature), 3(2), 33-46.

[11] Rasskazova, T., Guzikova, M., & Green, A. (2017). English language teacher development in a Russian university: Context, problems and implications. Ampersand, 4, 1-9.

[12] Hasanah, N., & Utami, P. T. (2019). Emerging Challenges of Teaching English in Non-Native English-Speaking Countries: Teachers' View. English Language Teaching Educational Journal, 2(3), 112-120.

[13] Zhang, J., & Lin, H. (2018). The new developments of constructivism theory and its reflection on college English teaching in the era of new media–A case study of international textile trade English. Theory and Practice in Language Studies, 8(6), 649-655.

[14] Lin, C., Shaozu, C., & Hui, G. (2023). Research and Analysis of Factors Influencing the Passing Rate of CET-4 in Local Universities. Lavai-International Journal of Education, 19(29), 30-41.

[15] Alzubi, O. A., Alzubi, J. A., Alweshah, M., Qiqieh, I., Al-Shami, S., & Ramachandran, M. (2020). An optimal pruning algorithm of classifier ensembles: dynamic programming approach. Neural Computing and Applications, 32, 16091-16107.

[16] Pan, X., Wang, Y., He, S., & Chin, K. S. (2020). A dynamic programming algorithm based clustering model and its application to interval type-2 fuzzy large-scale group decision-making problem. IEEE Transactions on Fuzzy Systems, 30(1), 108-120.

[17] Han, X., & Wang, D. (2025). Gradual Optimization of University Course Scheduling Problem Using

Genetic Algorithm and Dynamic Programming. Algorithms, 18(3), 158.

[18] Wang, H., Wang, Z., & Ding, S. (2019). Optimization of teaching management in colleges and universities based on dynamic programming. Cluster computing, 22, 13731-13738.

[19] Alqahtani, N., & Nadeem, F. (2021). Improving the effectiveness of e-learning processes through dynamic programming: A survey. International Journal of Advanced Computer Science and Applications, 12(5), 818-825.