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Research on Optimization of English Vocabulary Learning Path for Undergraduate College Students Based on Ant Colony Algorithm

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Abstract The construction of personalized vocabulary learning paths is the key to improving the effectiveness of English vocabulary teaching for undergraduate college students, which can increase students' engagement and motivation, and thus enhance learning effectiveness. In this paper, the Felder-Silverman Learning Style Scale and K-Means clustering algorithm are used to represent the English vocabulary learning styles of undergraduate college students, and the learner model and learning knowledge point model are constructed based on the CELTS-11 learner model specification. Then the decision variables and objective functions of personalized learning paths were constructed from the learner characteristics and combined with English vocabulary learning resources. Considering that the Ant Colony algorithm may fall into local optimality when solving the optimization results, this paper improves the A-ACO algorithm through the heuristic function and pheromone reward and punishment mechanism, and uses it to solve the English vocabulary personalized learning path optimization model. It is found that the A-ACO algorithm has high stability and accuracy in solving the model, and the optimized learning path is used in English vocabulary practice teaching, the students' English vocabulary scores are improved by 16.51 points as a whole, and the vocabulary richness of the students is also improved significantly. The optimization results of English vocabulary learning paths for undergraduate college students solved by Ant Colony algorithm help students to systematically and comprehensively master the lexical properties, meanings and collocations of common words, and lay a solid foundation of vocabulary for students' English learning.

Index Terms Ant Colony algorithm, K-Means, A-ACO algorithm, learning path optimization, English vocabulary

I. Introduction

With the further development of economic globalization, the requirements for English learning are getting higher and higher, and colleges and universities should pay more attention to the cultivation of students' basic English ability [1], [2]. Vocabulary is the foundation and key of English learning [3]. Words can form phrases, sentences and articles, leaving words, we can't express our thoughts, without enough vocabulary, we can't effectively train listening, speaking, reading and writing, and we can't use English for effective communication and exchange. Therefore, in the process of learning English, the learning and memorization of words are essential [4]. However, learning itself is a complex process, and the process of learning English vocabulary is affected by many factors, such as learners' learning environment, learning ability and cognitive level, and other external or internal factors, which directly or indirectly affect the efficiency and quality of learning, and the level of learning is ultimately determined by their interaction [5]-[9]. Different students face different learning difficulties, in order to solve this problem, different learning paths and learning strategies need to be developed for different students, which is the adaptive learning approach in the field of education [10]-[13]. By optimizing the learning path, it enables students to adjust their learning pace according to their own learning situation, so that learners can get a better learning experience [14], [15]. It can solve the problem that learners are unable to obtain the optimal learning mode due to the complex and changing learning factors that lead to academic difficulties [16], [17].

With the development of intelligent science and technology, adaptive learning methods are transformed from traditional computer-assisted support for learning to big data and artificial intelligence technology support, making education and learning more scientific and achievable [18]-[20]. Intelligent algorithms of computers analyze and learn from students' and teachers' behavioral data, making students' learning diagnosis and learning path planning more objective [21]-[23]. It has changed the traditional computer technology in accordance with the script to assist learning, the real learning counseling personalized so that the adaptive education platform is truly intelligent [24], [25].

At home and abroad, + In recent years, there are some studies on the optimization of college students' English vocabulary learning path. Literature [26] developed an adaptive learning model of English vocabulary based on blockchain and deep learning, and the English vocabulary learning strategy supported by the model effectively stimulates students' learning initiative and expands their vocabulary learning scope, and enhances learners' memory level of English vocabulary. Literature [27] created a dialogic educational chatbot learning system, QuizBot, which can help students deepen their knowledge of English vocabulary in a more immersive and sustained way than the traditional vocabulary learning method of a flashcard application. Literature [28] introduces ULearnEnglish, an open-source learning system with context-aware ubiquitous learning features, which shows higher acceptance of contextualized English vocabulary learning tasks by students, and has a greater potential for application in the field of language learning. Literature [29] proposes the use of target visual detection technology to improve the efficiency of English vocabulary teaching in online education, and vocabulary feature extraction and analysis through convolutional neural network detection model to provide guidance and reference for online English vocabulary teaching. Literature [30] constructed a deep learning system of English vocabulary for mobile platforms, which can provide learners with accurate English vocabulary evaluation results to deepen their understanding of English vocabulary and thus improve learning efficiency.

In addition, machine learning, as the most popular topic in the field of artificial intelligence, has also achieved fruitful results in the field of English vocabulary assisted teaching. Literature [31] utilizes the AdaBoost algorithm to calculate the conditional probability of key parameters in order to assess the cognitive adaptability of learners to vocabulary learning content, and builds an adaptive learning system for English vocabulary based on this to significantly improve learners' enthusiasm and learning efficiency. Literature [32] designed an English vocabulary learning recommendation system based on decision tree algorithm and plain Bayesian algorithm, which helps learners learn and memorize words more effectively by recommending learning content that meets their learning needs and cognitive situation. Literature [33] establishes a deep learning architecture for English vocabulary learning, introduces tuned LSTM neural network and EHGS algorithm to construct a hybrid learning model, and provides learners with personalized, adaptive, and immersive English vocabulary learning experience.

Personalized vocabulary learning paths allow students to choose learning materials and methods according to their cognitive styles, learning speeds, and points of interest so as to achieve efficient English vocabulary learning. The article takes the learning style representation of English vocabulary learners as the entry point, and classifies students' learning styles into eight types through the Felder-Silverman Learning Style Scale, and then combines it with the K-Means clustering algorithm for clustering learner characteristics. Relying on the CELTS-11 learner model specification, the learner model and the learning knowledge point model were established respectively, and the objective function was established from four dimensions, namely, the learner's cognitive ability, the learning resource information, the learner's expected target knowledge point information, and the learner's effective learning time, so as to establish the personalized learning path model for undergraduate college students' English vocabulary. In order to obtain the optimal English vocabulary learning path, this paper introduces the heuristic function and the pheromone reward and punishment mechanism to improve the Ant Colony algorithm, and simulates and verifies the application effect of the A-ACO algorithm. Finally, the optimized learning path is applied to English vocabulary teaching to demonstrate the effect of learning path optimization on English vocabulary teaching.

II. Personalized Learning Path Model for English Vocabulary

Without grammar, people cannot express many things, while without vocabulary, they cannot express anything. Vocabulary is the foundation of language expression, just like the foundation of a house, without a certain amount of vocabulary, it is difficult to listen, speak, read, write and translate. Therefore, if college students want to be the talents who have mastered English and professional knowledge and skills in the new era, they must expand their vocabulary and strengthen the input of English words. At the same time, it is also necessary to ensure the effective output of English vocabulary, make use of a variety of tools and multimedia resources, do a good job of adequate vocabulary reserves, and lay a solid foundation for the generation of personalized learning paths for English vocabulary.

II. A.Learner Learning Style Representation

II. A. 1) Felder-Silverman learning style

Learning style refers to the different learning tendencies shown by each learner in the learning process. In order to provide learners with more suitable and attractive learning content, learners' learning styles can be modeled so that all learners can learn according to the learning style that meets their preferences, thus realizing the personalization of online learning [34]. According to the Felder-Silverman learning style scale, the learning style is summarized into four dimensions and eight different types to quantify it, and its specific content is shown in Table 1, according to which the quantitative rules applicable to the English vocabulary learning path optimization problem in this paper are designed.

Table 1: The learning style quantification table

Learning style	Behavior pattern	Threshold value	
		L<->M	M<->H
Active type /reflective type	Posting	<2	>5
	Reply quantity	<10	>30
	BBS time	<5%	>15%
	Discussion number	<2	>5
	Test frequency	<2	>5
Feeling type/intuitive type	Document browsing times	<50%	>75%
	Document browsing duration	<75%	>100%
	Download number	<50%	>75%
	Test duration	<70%	>90%
Visual type /Verbal type	Video browsing	<75%	>100%
	Video playback times	<75%	>100%
	Map browsing	<50%	>75%
	Map length	<75%	>100%
Sequence type /Complex type	Click the chapter button number	<30%	>70%
	Click on the knowledge point button number	<30%	>70%
	Number of searches	<30%	>70%

For each learner's learning style c is influenced by a variety of behavioral patterns $P_1, P_2, ..., P_n$, so it is stipulated that the threshold for quantifying a learner's behavioral pattern is classified in the range of L-M, then $P_i \in \{H\}$, if in the range of M-H, then $P_i \in \{L\}$, and if in the other ranges, then $P_i \in \{M\}$. To sum up, a certain behavioral pattern P_i for learner j can be denoted as P_i^j. According to the description, the definition of P_i^j is as follows:

$$P_i^j = \begin{cases} 1 & P_i^j = H \\ 0 & P_i^j = M \\ -1 & P_i^j = L \end{cases} \tag{1}$$

Then the learning style C for learner j on the number of n behavioral patterns can be expressed as:

$$V_j(C) = \frac{\sum_{i=1}^{n} P_i^j}{n} \tag{2}$$

This paper collects the learning log data in the MOOC platform, extracts learners' learning behaviors and processes them before calculating the learning styles according to the quantitative rules. Assuming that the learning style of learner j is $C \in$ {sensory, intuitive} and $V_j(C) = 1/2$, the learning style of learner j can be judged to be the left-side sensory type, and by the same token, we can get the specific styles of the other three groups, and ultimately get the learning style of the learner.

II. A. 2) Learner feature clustering

Aiming at the learning characteristics of learners, this paper mainly adopts K-Means clustering algorithm for learner feature clustering. The problems that need to be solved lie in three points, the first is the selection of feature vectors for students' learning styles, i.e., which variables are used to characterize students' learning styles. The second is the measurement and similarity calculation of the feature vectors, which is reflected in the criteria used to assign the samples to the corresponding clusters in the process of cluster analysis. The third is the establishment of the evaluation function [35]. The details are as follows:

(1) The establishment of feature vectors. This paper mainly focuses on the cluster analysis of students' learning styles, so the feature vectors are based on the students' learning styles measurement table as the basis for the establishment of their feature vectors. It mainly includes active, contemplative, perceptive, intuitive, visual, verbal,

sequential and comprehensive, totaling eight aspects of measurement. The representation of the eigenvector of students' learning styles after accounting for this information is:

$$S = \{Vis, Hea, Kin, Res, Exp, Com, Ext, Inn\} \tag{3}$$

where Vis, Hea, Kin, Res, Exp, Com, Ext, and Inn represent students' learning style measurements on eight different types, respectively.

(2) Measurement of feature vectors and similarity calculation. Since the Likert 5 scale is used in this paper to measure students' learning styles, the corresponding learning style measurements are all represented by discrete numbers of “1-5”. The cosine of angle formula is used to calculate the similarity. The formula is:

$$d(S_i, S_j) = \cos(\overline{S_i}, \overline{S_j}) = \frac{\overline{S_i} \cdot \overline{S_j}}{\left|\overline{S_i}\right| \cdot \left|\overline{S_j}\right|} \tag{4}$$

where S_i, S_j is the eigenvector of sample student i and sample student j respectively, $d(S_i, S_j)$ is the similarity between student i and student j, the size of which is calculated by the cosine formula of the angle of the two vectors, $\overline{S_i}\overline{S_j}$ is the dot product between vectors S_i, S_j, and $\left|\overline{S_i}\right|, \left|\overline{S_j}\right|$ is the mode of vector S_i, S_j respectively.

(3) Selection of evaluation function. The purpose of cluster analysis of students is to cluster students of different types, so there should be a more obvious difference between different types, this paper will be any sample and the cluster (i.e., each classification) of the sum of the mean square deviation between the eigenvectors as the evaluation function. Its calculation formula is:

$$J = \sum_{k=1}^{K} \sum_{n=1}^{Z_k} (d(\overline{x_k}, x_n))^2 \tag{5}$$

where J is the evaluation function, $\overline{x_k}$ is the feature vector of the k rd cluster, x_n is the feature vector of the n th sample. K is the number of initial clusters, and Z is the number of all samples. The classification model is continuously trained by adding new samples (i.e., updating the feature vectors of the clusters) until the sum of the mean squared deviations of the newly added samples and the feature vectors of the clusters remains constant.

II. B.Personalized Learning Path Model

II. B. 1) Learner Modeling

The learner model specification focuses on describing direct static information about the learner, including academic information, management information, relationship information, preference information, performance information, etc. In the whole learning process of the learner, the learner's indirect dynamic information often contains a greater amount of information, such as cognitive level, interest preferences, etc., and the above specification does not adequately describe the dynamic information, which, to a certain extent, results in a waste of information resources [36]. Therefore, this paper further designs and constructs the learner model on the basis of the CELTS-11 learner model specification, integrating all kinds of static and dynamic data information in order to extract learners' personalized characteristics, and its layered architecture is shown in Figure 1. The model contains a data layer, an analysis layer, a representation layer, and an application layer. The static and dynamic data information of learners is collected, pre-processed and classified in the data layer, while the analysis layer organizes the information obtained in the data layer and further mines and analyzes it to provide a data basis for the construction of personalized features in the representation layer, and finally, the personalized features can be applied to applications such as learning resource recommendation and information retrieval.

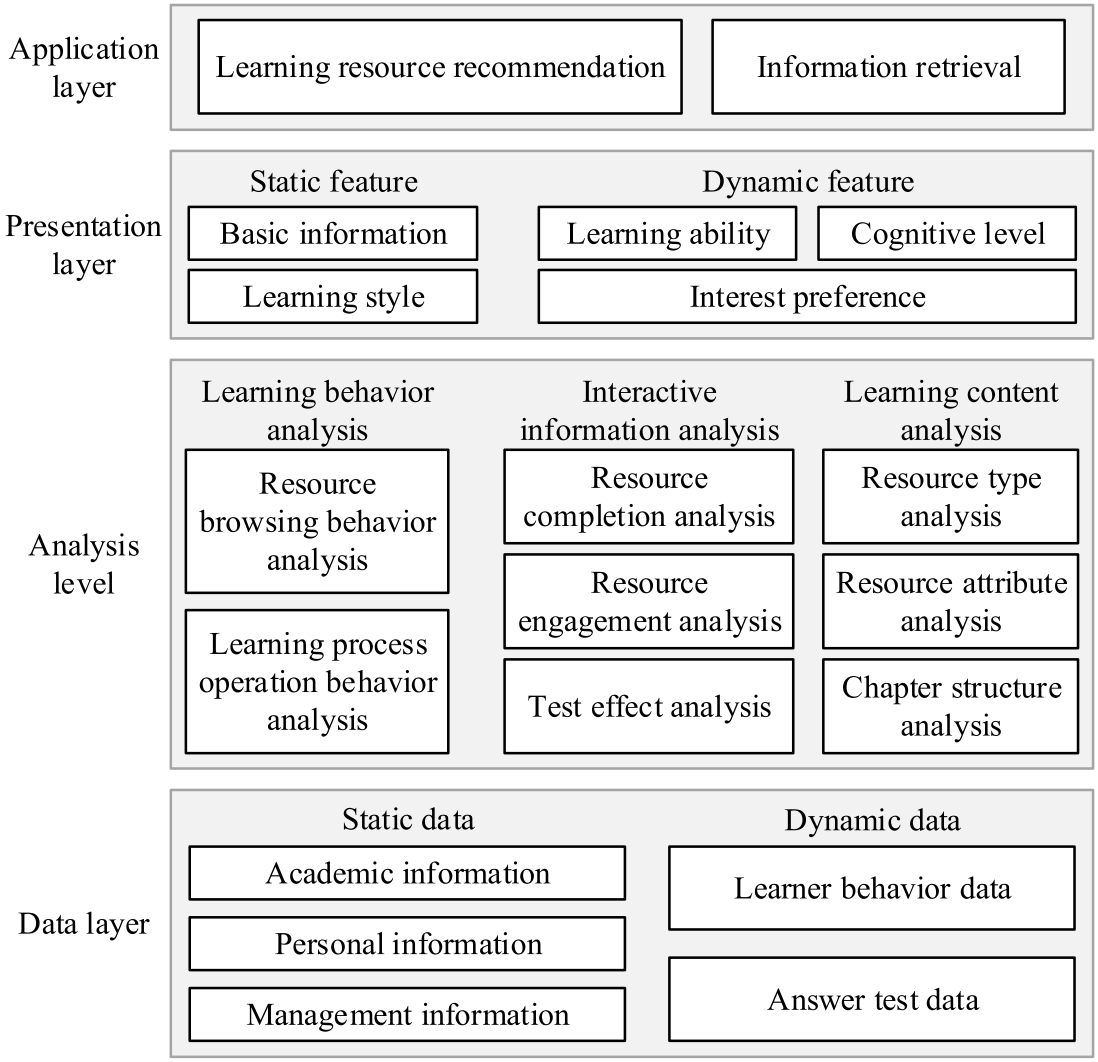


Figure 1: The layered architecture of the learner model

The data layer is the cornerstone of the learner model, while the analysis layer and the representation layer are the main part of the learner model, which are responsible for using various feature extraction means to deeply understand the potential information of the learners. The application layer is the embodiment of the value of the data layer, analysis layer, and representation layer, which are indispensable, interrelated, and inseparable. Relying on this learner model, it serves the design of the algorithm for personalized learning path optimization of English vocabulary for undergraduate college students carried out later.

II. B. 2) Learning Knowledge Point Modeling

The generation of personalized English vocabulary learning paths for undergraduate college students requires not only the construction of a suitable and standardized learner model, but also the consideration of the correlation between knowledge, so as to ensure the scientificity and rationality of the construction of personalized learning paths. Based on the design of the knowledge mapping schema layer of the English vocabulary course, according to the metadata standards such as Dublin Core, IEEE LOM and CELTS-3, and referring to the existing researches to take the learning objects as the various attribute mapping entities describing the knowledge points, the appropriate model of the students' knowledge points of English vocabulary is designed as shown in Fig. 2.

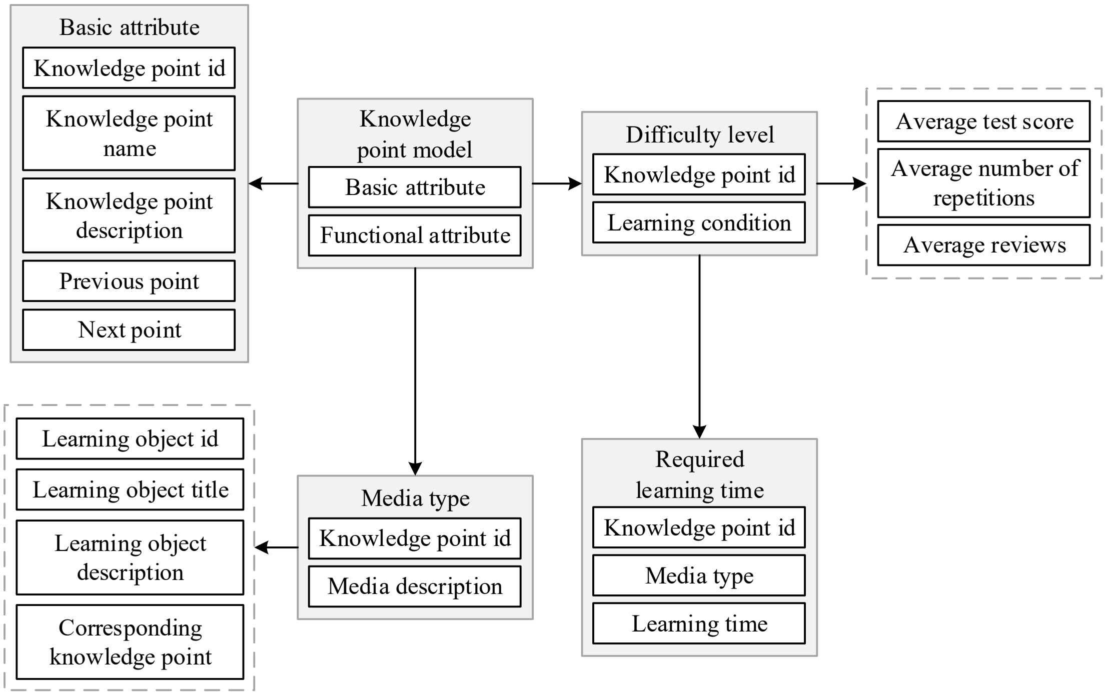


Figure 2: English vocabulary knowledge point model

Let n knowledge point be presented in the form of $(KP_1, KP_2, KP_3, ..., KP_n)$ and KP_j denote the j th knowledge point. Each knowledge point KP_f has basic attributes such as ID and name, as well as functional attributes such as media type, difficulty level, and required learning time.

Let the learning object cover the set of knowledge points $MC_n = (MC_{1n}, MC_{2n}, MC_{3n}, \ldots, MC_{kn})$ and MS_{jn} denote the knowledge points contained in the j rd learning object. The learning objects designed in this study correspond to generic learning paths consisting of knowledge points, and each learning object contains one knowledge point.

Let media type $MS_n = (MS_{ln}, MS_{2n}, MS_{3n}, MS_{4n})$, MS_{jn} denote the learning object representation of KP_j, and MS_j = (1 = forum/notes, 2 = videos/blogs, 3 = formulas/cases, and 4 = lesson plans/lesson plans). Visual learning objects, such as pictures or videos, match well with visual-based learning styles, while reading learning objects match better with verbal-based learning styles. Intuitive learning styles favor learning objects presented in symbols and formulas, while perceptual learners prefer factual and data-based learning objects. Sequential learners prefer step-by-step learning objects, while synthesizing learners prefer summary-type learning objects. Active learners prefer interactive learning scenarios Reflective learners usually prefer to record and think.

Let difficulty level $DL_n = (DL_1, DL_2, DL_3, ..., DL_k)$, DL_j denote the difficulty level of KP_j, DL_i = (1=knowledge, 2=understanding, 3=mastery, 4=application).

Let the learning time required $MT_n = (MT_1, MT_2, MT_3, ..., MT_k)$, ML_j denote the learning time required for the j th learning object, and the learning time is measured in minutes.

The learner model plays a fundamental and central role in the study of personalized learning path construction. Through the multi-dimensional features in the personalized learning parameters, the learner model is constructed from the basic attributes and functional attributes to ensure the scientific and comprehensive model construction. The construction of the knowledge point model requires a good knowledge system structure, which can provide a data source for learners' personalized learning, and its modeling method directly affects the effect of personalized construction of learning path.

II. B. 3) Decision variables and objective functions

Based on the learner model and the learning knowledge point model of undergraduate college students' English vocabulary, the English vocabulary learning resource path variable is set to X_{aribrj}, and the value of variable X_{aribrj} is encoded in binary, where $1 \le i \le N, 1 \le j \le N$ the learning path is from the i th learning resource to the j th learning resource, then $X_{aribrj} = 1$, otherwise $X_{aribrj} = 0$.

In the personalized learning path model of English vocabulary for undergraduate college students, the learner characteristics include four characteristics: the cognitive ability of the learner, the information of the learning resources being studied, the information of the learner's desired target knowledge points and the effective learning time of the learner, and the learning resource characteristics include four characteristics: the difficulty of the learning resources, the information of the learning resources to be studied by the learners, the information of the learning resources containing knowledge points and the learning time of the learning resources. Learning resource features include four features of learning resource difficulty, learning resource information that learners will learn, learning resource containing knowledge point information and learning time of learning resource. The learning path optimization function set contains four different objective functions, which are represented by $F1, F2, F3, F4$ as follows:

Objective function $F1$ (learner's cognitive level objective) indicates the difference between the learner's cognitive level and the difficulty level of the learning resources, the smaller the difference, the more the difficulty of the learning resources in the recommended learning path meets the learner's cognitive level. That is:

$$F1 = \sqrt{\sum_{j=1}^{N} \left| \frac{\sum_{i=1}^{N} \left[X_{ar_i br_j} (d_{ar_i} - c_h) + X_{ij} (d_{br_j} - c_h) \right]}{2\sum_{i=1}^{N} ar_i br_j} \right|^2}, 1 \le h \le H \tag{6}$$

The objective function $F2$ (Learner Expectation Objective) represents the difference between the knowledge contained in the learning resource and the knowledge that the learner expects to acquire; the smaller the difference, the more the knowledge contained in the learning resource matches the knowledge that the learner expects to acquire. Namely:

$$F2 = \frac{\sum_{q=1}^{Q} \sum_{n=1}^{N} x_{nh} \left| Y_{nq} - W_{hq} \right|}{\sum_{n=1}^{N} X_{nh}}, 1 \le h \le H \tag{7}$$

The objective function $F3$ (Objective of Expenditure between Learning Resources) represents the information about the expenditure between learning resources, i.e:

$$F3 = \sum_{j=1}^{N} \sum_{i=1}^{N} x_{ar_i br_j} s_{ar_i br_j} \tag{8}$$

The objective function $F4$ (learning time objective) represents the difference between the learning time to complete the learning resource and the range of learning time that the learner can afford, i.e:

$$F4 = \begin{cases} \sum_{n=1}^{N} T_n X_{nh} - T_{l_{hn}} > 0 \\ \sum_{n=1}^{N} T_n X_{nh} - T_{u_{hn}} < 0 \end{cases} \tag{9}$$

d_{ar_i} and d_{br_j} in the function represent the difficulty level of the i rd learning resource that the learner is learning and the difficulty level of the j th learning resource that the learner is going to learn, $1 \le i \le N, 1 \le j \le N$; c_h represents the cognitive ability level of the learner h, and the cognitive ability level of the learner h is different for different learning resources: Y_{nq} represents the q th knowledge point of the n th learning resource, $l \le n \le N, l \le q \le Q$; W_{bq} represents the h th knowledge point that the learner expects to learn. q , $l \le h \le H, l \le q \le Q$; $sar_t br$ represents the learning expenditure between the i th learning resource that is being learned and the j th learning resource that is going to be learned: $T_{l_{hn}}$ represents the lower limit of the learning time of the h st learner for the n nd learning resource, $T_{u_{hn}}$ represents the upper limit of the learning time of the h th learner for the n th learning resource, $1 \le h \le H, 1 \le n \le N$.

These are the four sub-functions representing the characteristic parameters of learners and learning resources, which together construct a personalized learning path recommendation model for undergraduate college students' English vocabulary. The smaller values of the four objective functions determine that the generated personalized learning paths for English vocabulary are more in line with the requirements of undergraduate college students.

The related research utilizes the four weights to combine the sub-functions into a total objective function, so undergraduate college students with English vocabulary learning paths always have a conversation function constructed from the sub-mapping functions by weighting coefficients, i.e:

$$\min F(x) = \sum_{i=1}^{4} w_i f_i \tag{10}$$

where w_i denotes the weighting factor.

III. Improvement of Ant Colony algorithm for learning path optimization

In the English teaching of undergraduate college students, vocabulary is an important foundation of English learning, and it is also recognized by teachers and students as a more difficult part to overcome, and the highly time-consuming and inefficient vocabulary problem is a stumbling block that hinders the smooth implementation of English vocabulary teaching activities. Applying optimization algorithms to the optimization of English vocabulary learning paths of undergraduate college students can more conveniently and efficiently help students construct the horizontal connection and vertical extension of vocabulary sound, form, meaning and usage, and form an effective vocabulary knowledge system. It can also mobilize students' multi-sensory abilities, help them deeply understand the context and connotation of vocabulary, and promote vocabulary transfer and use.

III. A. Improvement of Ant Colony Algorithm Optimization

III. A. 1) Improvement of the Ant Colony algorithm

In the computational model that simulates the food-seeking behavior of ants in nature, each ant k decides its next move based on the density of pheromones on its path as it explores. Compared to ants in nature, the artificial ants in the algorithm have memory capabilities, which allow them to use historical information to guide future decisions.

Ant k memory is represented through the taboo table $tabu_k (k = 1, 2, ..., m)$, a mechanism that records the order of all the nodes that ant k has passed so far. In the search for the optimal solution, the ant will evaluate both the pheromone strength and the heuristic cues on the path to determine the probability of moving from location i to location j. The pheromone strength and the heuristic cues on the path will be evaluated at the same time. $p_{ij}^k(t)$ at time t reflects the transfer probability of ant k moving from location i to location j, i.e:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^k \left[\eta_{ik}(t)\right]^\beta}{\sum\limits_{z \in allowed_i} \left[\tau_{is}(t)\right]^k \left[\eta_{is}(t)\right]^\beta} & j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where η_{is} denotes the inverse of the distance between locations i and s. $allowed_k = \{1, 2, \ldots n\} - tabu_k$, and when $allowed_k$ is empty, it indicates that the ants completed a roving task. α reflects the importance of the pheromone, and the larger the value, the more ants previously choosing location j at location i, and the greater the probability that ants k tend to choose location j. β, on the other hand, reflects the importance of the distance between location i and location j, and the larger this value is, the more ants tend to choose destinations closer to them.

When all the ants have completed the location visiting task, the algorithm updates the pheromone concentration of all the paths passed by the ants according to Eq. (12) and Eq. (13) at the moment $(t+n)$. In order to simulate the volatilization characteristics of ant pheromone in nature, the algorithm designs a pheromone decay mechanism so that it gradually decreases over time.

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{12}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}(t) \tag{13}$$

where $p(0 < p < 1)$ is the pheromone evaporation coefficient and $\Delta\tau_{ij}^k(t)$ is the concentration of pheromone left by ant k during this iteration. i.e:

$$\Delta\tau_{ij}^k(t) = \begin{cases} \dfrac{Q}{L} & \text{If the k mosquito passes through } (i, j) \text{ in this cycle} \\ 0 & \text{other} \end{cases} \tag{14}$$

where Q denotes the total amount of pheromone released by the ants in this search process, and L is the total length of the path passed by the k rd ant in this search process.

For the personalized learning path optimization of English vocabulary for undergraduate college students in this paper, if the traditional ant colony (ACO) algorithm is used for the optimization and solution, there are some shortcomings, such as slow convergence and easy to fall into the local optimal solution. If the parameters are not set properly, it will affect the effect of ACO algorithm, with high computational complexity and poor dynamic adaptability, therefore, the improvement strategy is introduced for optimization [37].

(1) Improvement of heuristic function

In the traditional ACO, the heuristic function only considers the distance between the next node and the end point, which is easy to fall into the local optimal solution. To overcome this problem, the Euclidean distance between the current position and the position of the next node is added to the heuristic function, which improves the search ability of the path, and the formula is:

$$\eta_{ij} = \frac{1}{(\varepsilon \times d_{is} + \mu \times d_{jE})^{\frac{3}{2}}} \tag{15}$$

where d_{is} is the Euclidean distance from the current node to the next node, d_{jE} is the Euclidean distance from the next node to the end point, ε is the current position factor, and μ is the end point position factor.

(2) Pheromone reward and punishment mechanism

In the ACO algorithm, the pheromone update strategy is performed at the end of each iteration [38]. Specifically, the path traveled by each ant is evaluated and pheromone is added to the path traveled by the ants that successfully reach the destination. However, some ants will choose a more distant path to reach the goal and add pheromone to the redundant paths, but such paths do not meet the requirements of path optimization, which will affect the choice of paths by subsequent ants and thus affect the quality of iteration.

To cope with this, this paper adopts a reward and punishment mechanism to regulate the pheromone concentration to improve the efficiency and accuracy of the algorithm. Specifically, for the optimal path, the pheromone concentration is increased by incentives to promote more ants to choose that path. Conversely, for the worst-performing path, the pheromone concentration is reduced by punitive measures to avoid its frequent selection in subsequent iterations. Such a reward and punishment mechanism can effectively guide ants to choose better paths, accelerate the convergence of the algorithm, and improve the solution efficiency. The formula for the pheromone update strategy is:

$$\tau_{ij}(k+1) = (1-\rho)\tau_{ij}(k) + \sum_{m=1}^{M} \tau_{ij}^{m}(k) \tag{16}$$

$$\tau_{ij}^{m}(k) = \begin{cases} \dfrac{5Q}{L_m} + \alpha \dfrac{L_y - L_m}{L_{mean} - L_y}, L_m \le L_y \\ \dfrac{Q}{L_m} - \beta \dfrac{L_m - L_c}{L_c - L_{mean}}, L_m \ge L_c \\ \dfrac{Q}{L_m}, \text{otherwise} \end{cases} \tag{17}$$

where ρ is the pheromone evaporation factor, Q is the pheromone intensity, $\tau_{ij}(k)$ is the pheromone from node i to node j in iteration k, M is the total number of ants in iteration k, $\tau_{ij}^{m}(k)$ is the pheromone increment from node i to node j by ant m in iteration k, L_y is the length of the optimal path in the current iteration. L_c is the length of the worst path in the current iteration, L_m is the total length of the paths completed by ants m in this iteration, L_{mean} is the average path length in the current iteration, α and β are the weight coefficients of the optimal and worst paths.

III. A. 2) Learning path optimization model solving

Based on the learner model and learning knowledge point model established in the previous section, the feature mapping relationship between the two is extracted, and the optimization of English vocabulary learning paths for undergraduate college students is transformed into a multi-objective optimization problem, which can be better solved using the Improved Ant Colony algorithm (A-ACO). Therefore, in this section, the learner's personalized characteristics and the English vocabulary knowledge point system are parametrically represented, and the fitness value corresponding to each learning path is used as the criterion of whether the learning path is effective or not. The model is solved by the A-ACO algorithm, which makes the solved English vocabulary personalized learning paths match undergraduate college students better, and Fig. 3 shows the solving steps of the optimization model of English vocabulary personalized learning paths for undergraduate college students.

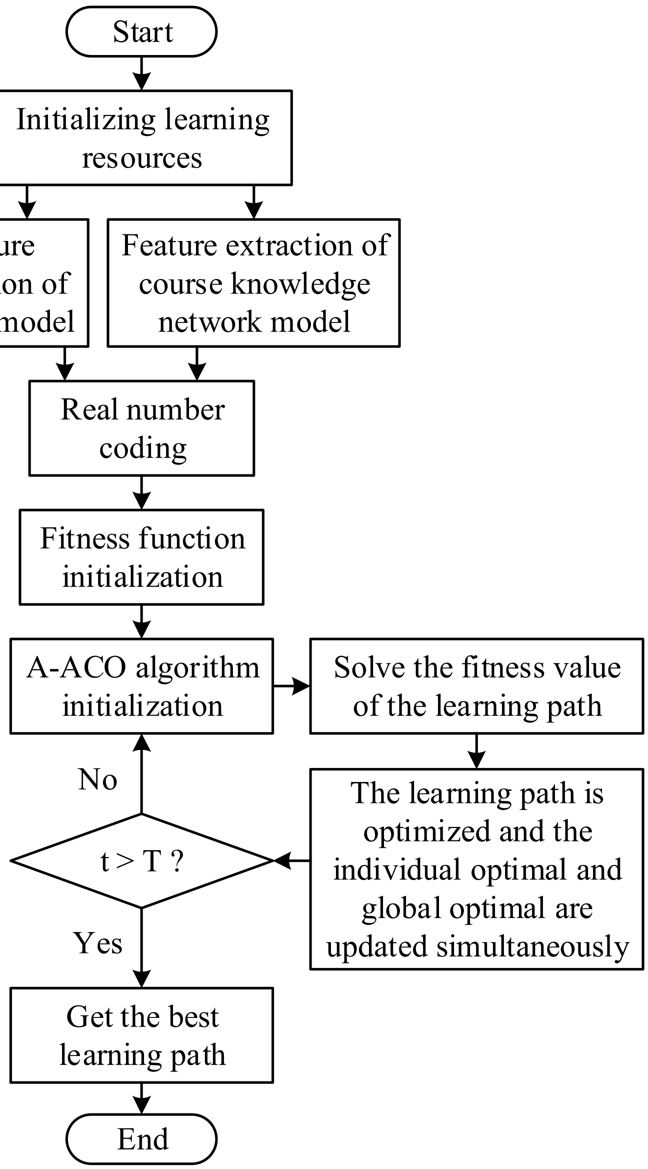


Figure 3: Solving steps of learning path optimization model

(1) Feature parameter setting. The feature parameters of the learner model and the learning knowledge point model should be defined before initializing the fitness function.

(2) Calculate the fitness value of the learning path representation function. Through the total function of learning path optimization, the fitness value of the learning path is centralized to determine whether the learning path meets the requirements of the learner.

(3) Generate learning path optimization. Relying on the A-ACO algorithm designed in this paper to optimize the generated English vocabulary learning paths, the learning path optimization aggregate function is used in the A-ACO algorithm to calculate the fitness value of the learning path. The best fitness value after each calculation is retained, and after many iterations, the English vocabulary learning path with the best fitness value is selected and recommended to learners.

III. B. Experimental results and analysis

III. B. 1) Experimental Environment and Parameter Settings

The selection of parameter values of the A-ACO algorithm has a very important impact on the experimental results. Adopting A-ACO algorithm to realize the learning path recommendation of English vocabulary for undergraduate college students, how to set the values of each parameter and determine the reasonable number of learning units as well as learners to better realize the learning path recommendation is the first work to be carried out. Under the MALTAB environment, the program is used to simulate the learning process of the learners, and the effects of the parameters such as the inspiring information factor, the pheromone concentration factor, the pheromone concentration volatilization factor, the number of iterations, the number of learning units, and the number of learners on the results are investigated.

The basic parameters of the algorithm were finally determined by analyzing and studying the pheromone concentration distribution change process through several experiments and considering the time complexity of the algorithm. Among them, the heuristic information factor takes the value of 1.35, the factor of pheromone concentration takes the value of 1.15, the volatile pheromone concentration takes the value of 0.85, and the number of iterations takes the value of 300 times.

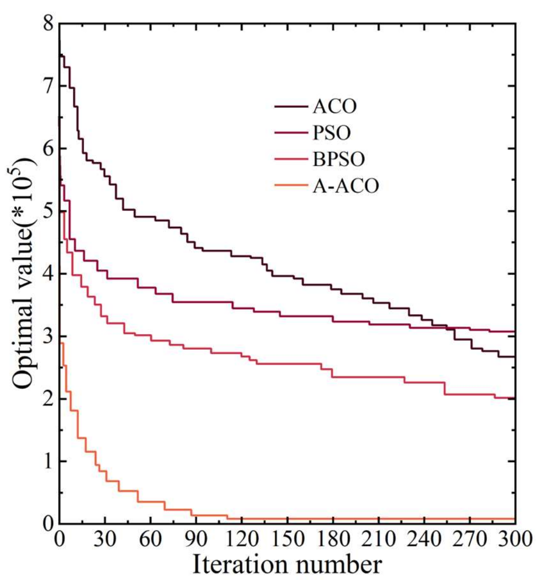
III. B. 2) Simulation experiment results and analysis

(1) Algorithm convergence curve comparison

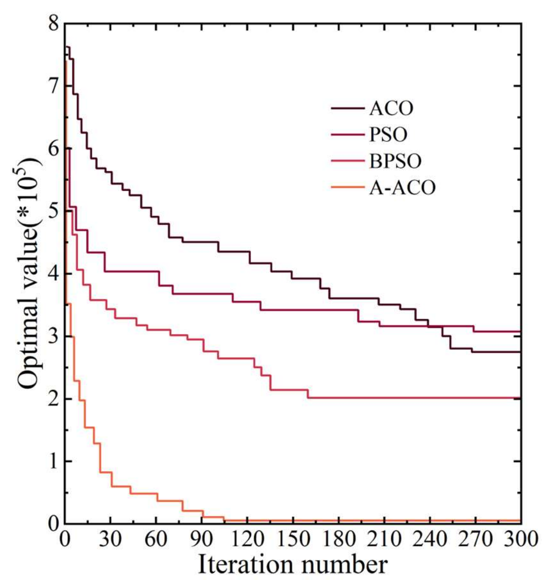
In this paper, four benchmark functions are selected to test and evaluate the performance of the algorithms: F1 and F2 are single-peak functions with only one optimal solution, which can be used to judge the convergence accuracy of the algorithms, and F3 and F4 are multiple-peak functions with multiple local optimal solutions, which can be used to judge the ability of the algorithms to jump out of the local optimal solutions. The comparison algorithms are ACO, PSO and BPSO algorithms. The mean and variance are used to evaluate the performance of the optimization algorithms, and Fig. 4 shows the results of the convergence curve comparison of different algorithms, in which Fig. 4(a)~(d) are the comparison of the convergence curves of the benchmark functions F1~F4, respectively, and Table 2 shows the experimental results of the algorithms on the benchmark functions.

From the figure, it can be seen that the A-ACO algorithm is better than other algorithms in terms of convergence accuracy and jumping out of local optimal solutions. Due to the optimized adjustment of the pheromone reward and punishment mechanism during iteration, the adaptation value of the single-peak function changes rapidly during the optimization process, and the success rate of the optimization search and the convergence accuracy are also significantly increased. For the multi-peak function problem with more local optimal solutions, the A-ACO algorithm improves the particles with poor fitness values through the improvement of the heuristic function to increase the diversity of its population, and at the same time interferes with the global optimal particles to promote them to jump out of the local optimum so that the algorithm can make a better local exploration.

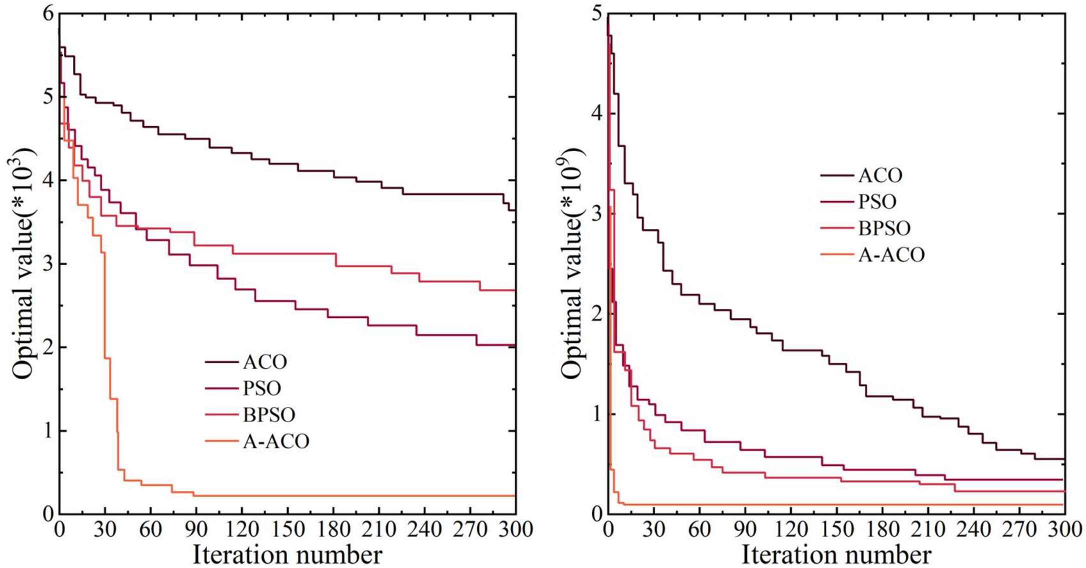
In addition, the single-peak function has only one locally optimal solution to detect its convergence accuracy. From the table, it can be seen that in the single-peaked functions F1 and F2, the mean value of the A-ACO algorithm is better than the other algorithms, which indicates that this algorithm has a higher convergence accuracy than the ACO, PSO, and BPSO algorithms. The multi-peak function has multiple local optimal solutions to evaluate whether the algorithm can jump out of the local optimum. In the multi-peak functions F3 and F4, the mean value of the A-ACO algorithm is significantly better than the other algorithms, indicating that it has a stronger ability to jump out of the local optimum solution. Overall, the variance of the A-ACO algorithm is better than the rest of the algorithms in both single-peak and multi-peak functions, indicating that the performance of the algorithm has also been further improved.



(a) F1 standard function



(b) F2 standard function



(c) F3 standard function (d) F4 standard function

Figure 4: The convergence curve compares the results

Table 2: The results of the algorithm on four benchmark functions

Functions	Index	ACO	PSO	BPSO	A-ACO
F1	Means	6.951E+01	5.816E+01	1.916E+01	1.214E+01
	Variance	3.127E+00	2.748E+00	2.361E+00	9.627E-01
F2	Means	2.127E+02	1.869E+02	1.384E+02	9.283E+01
	Variance	5.476E+00	5.173E+00	3.746E+00	2.617E+00
F3	Means	8.972E+02	8.892E+02	8.854E+02	8.716E+02
	Variance	3.312E+00	3.492E+00	1.451E+00	1.411E+00
F4	Means	1.842E+00	1.679E+00	9.923E-01	3.427E-01
	Variance	1.729E-02	1.647E-02	4.015E-03	2.128E-03

(2) Algorithm stability analysis

Stability analysis is also an important indicator for evaluating the performance of an optimization algorithm. Whether the algorithm can consistently find similar or the same optimal solution in the case of multiple runs is the key to measure its stability.

First, the effect of the change in the number of ants on the stability of the A-ACO algorithm is tested with the Rastrigin function optimization problem. In the experiment, for the A-ACO algorithm, the maximum and minimum values of the dynamic pheromone evaporation coefficients are set to be 0.65 and 0.15, respectively.Fig. 5 shows the results of the algorithm's running time on solving the Rastrigin function optimization problem as a function of the number of ants. It can be seen that for the number of iterations, as the number of ants increases, the number of iterations to find the global optimal solution is less for the A-ACO algorithm compared to the ACO algorithm.

For stability, when the number of ants is too small, it makes the pheromone concentration on the searched and unsearched paths differ greatly, which will weaken the algorithm's global search ability and randomness, and the number of iterations decreases, which improves the convergence speed of the algorithm but leads to the algorithm's stability deterioration. When the number of ants is large, the global search ability of the algorithm and its stability can be enhanced. However, when the number is too high, there will be an insignificant change in the pheromone concentration on the paths that have been searched, reducing the positive feedback effect of the algorithm and making the convergence speed slower. According to Figure 5, it can be seen that in the whole process of the change of the number of ants, the advantages of the A-ACO algorithm over the ACO algorithm in terms of global search ability and convergence reflect that the improved algorithm has stronger stability.

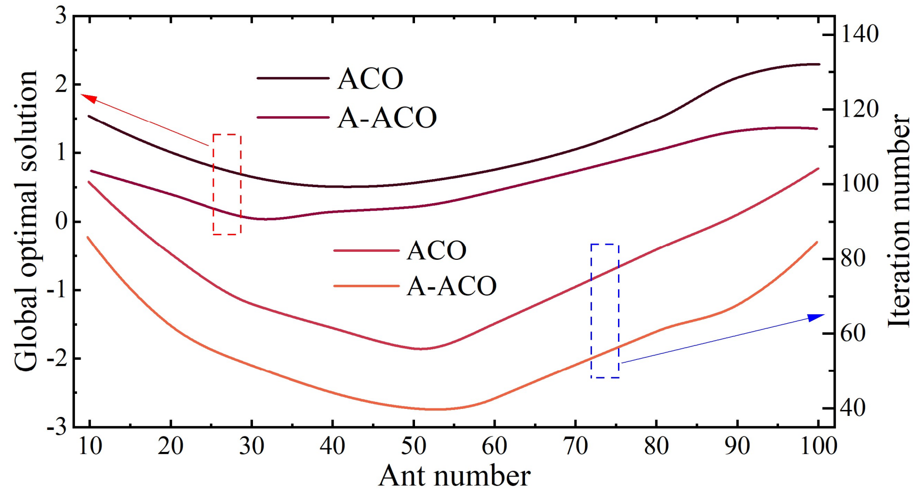


Figure 5: The influence of the number of ants on the running results

Second, the effect of heuristic pheromone weights on the stability of the algorithm is tested. In the experiment, for the A-ACO algorithm, the same number of ants is set and the maximum and minimum values of the dynamic pheromone evaporation coefficients are set to be 0.65 and 0.15, respectively.Fig. 6 shows the results of the algorithms' running time on solving the Rastrigin function optimization problem with the change of heuristic information weights. It can be seen that the number of iterations and the global optimal solution of the A-ACO and ACO algorithms increase approximately linearly with increasing heuristic information weights. When the weight of the heuristic information is too small, both algorithms converge prematurely and are easy to fall into the local optimum, resulting in a less stable algorithm. However, from the point of view of finding the global optimal solution and convergence speed, the stability of A-ACO algorithm is better than that of ACO algorithm. When the weight of the heuristic information increases, the number of iterations of the two algorithms increases, resulting in slower convergence speed, which causes the global optimal solution to become larger and larger due to the positive feedback effect. In the whole process of the change of the weight of the heuristic information, the advantage of the A-ACO algorithm over the ACO in finding the global optimal solution and convergence reflects the stability of its algorithm is better than the ACO algorithm.

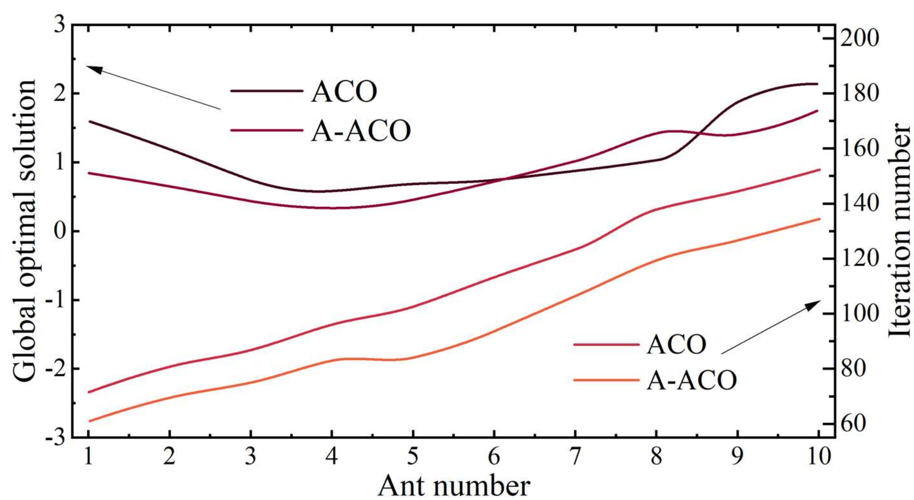


Figure 6: The influence of heuristic information weights on the running results

(3) Model performance comparison

In this paper, the A-ACO algorithm is used to solve the English vocabulary learning path optimization model for undergraduate college students, and its main purpose is to effectively obtain the optimal learning path of English vocabulary that meets the needs of college students. In order to verify the effectiveness of the algorithm, the English vocabulary learning data from the MOOC platform is used as the data source, and the proposed model in this paper is compared with BKT, CKT, DKT and DKVMN. In order to fully evaluate the model performance, this paper uses F1S, Diversity of Knowledge Points (DP), Learning Coverage (LC) and Average Length of Personalized Learning Path (APL), and additionally introduces RMSE and MAE as a supplement to the evaluation metrics, and the combined use of these evaluation metrics helps to gain a deeper understanding of the model's performance on the dataset.

In this paper, each model is classified into three categories, Struct, Semi, and Unstru, which represent the English vocabulary learning paths after structuring, semi-structuring, and unstructuring, respectively, and the performance of each model is evaluated. Table 3 shows the performance comparison results of different models on the dataset. As can be seen from the table, the personalized English vocabulary learning path optimization model for undergraduate college students proposed in this paper shows the best performance on all evaluation metrics, with the highest mean values of F1S, DP, LC, and APL, while the performance of the other models has decreased. In this dataset, the structured data has the best MAE performance, which is due to the fact that the English vocabulary learning data about undergraduate college students in the MOOC platform is more complete, and the learning paths embodied are more complete and structured, so the structured model has the best performance.

Table 3: Performance comparison results of different models

Model	-	RMSE	MAE	F1S	DP	LC	APL
BKT	Struct	0.501	0.427	0.361	0.286	0.293	0.061
	Semi	0.428	0.041	0.132	0.108	0.286	0.384
	Unstru	0.317	0.405	0.815	0.903	0.501	0.127
CKT	Struct	0.345	0.683	0.764	0.225	0.005	0.751
	Semi	0.904	0.267	0.045	0.884	0.851	0.028
	Unstru	0.798	0.963	0.552	0.916	0.354	0.736
DKT	Struct	0.062	0.349	0.148	0.419	0.463	0.627
	Semi	0.391	0.652	0.551	0.752	0.782	0.248
	Unstru	0.912	0.181	0.387	0.183	0.571	0.421
DKVMN	Struct	0.865	0.247	0.582	0.934	0.879	0.164
	Semi	0.748	0.485	0.883	0.527	0.593	0.318
	Unstru	0.382	0.704	0.247	0.543	0.176	0.191
A-ACO	Struct	0.921	0.981	0.223	0.228	0.351	0.496
	Semi	0.653	0.382	0.816	0.969	0.268	0.957
	Unstru	0.547	0.835	0.872	0.145	0.952	0.542

III. C. Analysis of the effect of English vocabulary optimization

III. C. 1) Learning Effectiveness of English Vocabulary

In order to verify the learning path optimization effect of this study in the actual teaching environment of English vocabulary, I carried out relevant experiments based on the MOOC online learning platform. In order to confirm whether the results of English vocabulary learning path optimization are scientific and reasonable and can meet the needs of undergraduate college students, this experimental process is applied individually and in groups. Forty students from the College of Foreign Languages of University Z were selected as the experimental subjects and randomly divided into two groups, K1 and K2, each with 20 students, K1 group following the traditional English vocabulary teaching method, and K2 group teaching with the results of learning path optimization. After the students in the two groups finished learning the chapter content, the intelligent grouping module of the system automatically generates the post-test questions to test the learning effect of the students.

The experimental results were added to the SPSS data analysis tool, and the information collected by the system was analyzed in terms of the length of students' study time and their grades, respectively. Table 4 shows the results of independent samples t-test for students' grades and length of study. As can be seen from the table, before the English vocabulary teaching was carried out in groups, the difference between the pre-school grades of the students in groups K1 and K2 was only 0.14 points, and the result of the t-test was 0.429 ($P=0.841>0.05$), which indicated that there was no significant difference between the two groups in their English vocabulary learning performance before the teaching began. At the end of the teaching experiment, the English vocabulary learning achievement of the students in group K2 reached 81.59 points, which was 14.87 points higher than that of group K1, and the t-test result was 6.987 ($P=0.002<0.01$), indicating that there was and is a significant difference between the two groups in terms of their English vocabulary learning achievement. In addition, the average learning duration of the K1 group is about 102.48 minutes, which is longer than the average learning duration of the K2 group, and the whole degree of discrete is larger. It can be seen that controlling the variable of personalized learning path, the learning duration of K2 group with learning path recommendation is shorter than that of K1 group without learning path recommendation, and the average achievement of students in K2 group after learning is significantly higher than that of K1 group. This also indicates that the optimization results of the personalized learning path of English vocabulary provided by the model in this paper are relatively effective in the actual teaching of English vocabulary, and the optimized learning path of English vocabulary can improve the learning efficiency and quality of students to a certain extent.

Table 4: Independent sample t detection method

-	Group	N	M	STD	T	P
Pre-school achievement	K1	20	64.94	8.627	0.429	0.841
	K2	20	65.08	9.491		
Postschool achievement	K1	20	66.72	8.165	6.987	0.002
	K2	20	81.59	3.336		
Learning length	K1	20	102.48	6.518	4.271	0.014
	K2	20	90.37	4.084		

III. C. 2) Exploring Student Vocabulary Enrichment

In order to further explore the variation differences in students' vocabulary richness, this paper additionally extracted three groups of students to carry out teaching experiments, noted as Groups A, B, and C. Among them, Group C adopts the optimization results of learning paths designed in this paper to carry out English vocabulary teaching, while Group B adopts learning paths recommended by collaborative filtering, and Group A doesn't use the recommendation of learning paths. After 8 weeks of study, the students in the three groups are required to complete 50 timed as in the classroom, the length of which is required to be around 350 words. The acquired data were collected and entered into SPSS software used for statistical analysis.

To explore the vocabulary variability of the compositions of different groups of students, length is an important parameter that affects the vocabulary variability of the compositions, and in general, the longer the compositions are the more vocabulary is likely to be reused. Therefore, when comparing the lexical variability of different compositions, it is necessary to consider how to minimize the interference of length if the length of the compositions varies greatly from one to another. Table 5 shows the results of comparing the differences in vocabulary variability between groups, where * indicates $p<0.05$.

As can be seen from the table, Group A's vocabulary variability in their compositions is significantly lower than that of Groups B and C. To a certain extent, this indicates that with the development of vocabulary learning level, the learners are able to learn to vary their vocabulary and avoid more repetition of words in their compositions. However, the fact that the two groups, Group B and Group C, were not significantly different from each other makes the development of vocabulary variability show another complication, but the p-value shows that there is a tendency for vocabulary variability to be greater in Group C than in Group B. When controlling for length, vocabulary variability may not necessarily differ between groups, and the degree of variability in vocabulary change may also depend on the magnitude of the actual level differences between the different groups of learners. There was a reduction in vocabulary variability differentiation between Groups B and C perhaps due to smaller differences in writing levels. After controlling for text length, there was no significant difference in vocabulary variability between the different level groups. Overall, the introduction of learning path optimization can significantly improve students' vocabulary variability and make them more likely to adopt different types of English vocabulary when completing English compositions, which to a large extent improves their English vocabulary application ability.

Table 5: Intergroup variation of vocabulary change

-	-	Mean difference	Std.Er	P	95% CI	
					Lower	Upper
A	B	-4.621*	0.815	0.001	-6.512	-2.956
	C	-6.478*	0.815	0.002	-8.427	-4.334
B	A	4.513*	0.815	0.000	2.587	6.573
	C	-1.826	0.815	0.056	-3.816	0.128
C	A	6.771*	0.815	0.000	4.473	8.612
	B	1.852	0.815	0.082	-0.115	3.827

III. C. 3) Synergistic relations in lexical semantics

After clarifying the effect of English vocabulary learning path optimization on vocabulary richness, this paper explores the synergistic relationship between lexical semantics and the development of vocabulary complexity, diversity and density on the basis of different levels of learner corpus. In this paper, the learner corpus is divided into a total of 14 levels, and the semantic similarity, complexity, diversity and density of English vocabulary under different levels are solved, and the linkage between lexical semantics and the development of lexical complexity, diversity and density under different registrations is obtained as shown in Figure 7.

There is a high correlation between learners' English lexical semantic development and lexical complexity (R=0.901, P=0.000) as well as diversity (R=0.937, P=0.002), showing linkage development, and the statistical correlation with lexical density is negative (R=-0.704, P=0.005), which indicates that there is a certain degree of mutual divergence between the two. Obviously, English lexical diversity is closest to the trend of lexical semantics. Although the trends of English lexical complexity and lexical semantics are also relatively similar, local perturbations are more frequent. Vocabulary density does not seem to reflect the differences in learners' English vocabulary learning levels, which is basically similar to existing related studies.

There are both periods of linkage development and stages of mutual deviation between different English vocabulary dimensions. Most notably, vocabulary density shows a significant downward trend before Level 9, while semantic similarity, lexical complexity and lexical diversity show a general upward trend, and the four English vocabulary dimensions show a more or less synchronized development trend after Level 9. Vocabulary density reflects the proportion of real words (verbs, adjectives, nouns and adverbs) in learners' written output, with the more real words, the higher the density. It can be inferred that before Level 9, learners focus on enhancing the use of function words, which leads to significant development in lexical semantics, lexical complexity, and lexical variety, but the proportion of real words used is temporarily suppressed to a certain extent, resulting in a negative growth in vocabulary density. At this stage, there is a certain competitive relationship between the development of vocabulary density and the development of lexical semantics, complexity and diversity. After Level 9, vocabulary density no longer continues to fall, indicating that the growth rate of learners' functional word development slows down, and gradually shifts to be dominated by the growth of real words, and enters a higher stage of synergistic development with the other three dimensions. With Level 9 as the inflection point, vocabulary density and the other dimensions change from competing to synergistic growth, reflecting the non-linear change process of learners' vocabulary use development from one stage to another. The interactive relationship between vocabulary density and the development of vocabulary semantics, complexity and diversity fully illustrates the importance of English vocabulary learning and the significance of this paper to carry out the research on the optimization of English vocabulary learning path.

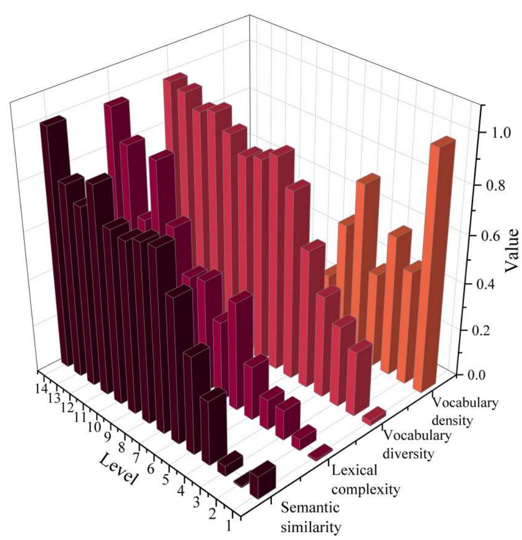


Figure 7: Cooperative relationship of lexical semantics

IV. Conclusion

In this paper, a learning path optimization method for undergraduate college students' English vocabulary learning based on the improved Ant Colony algorithm is proposed, and its effectiveness is verified through simulation experiments and practical applications. With the optimized learning path for English vocabulary teaching, the post-learning English vocabulary score of students in K2 group reaches 81.59, which is 14.87 points higher than that of

K1 group, and the optimized English vocabulary learning of the learning path can significantly improve the vocabulary richness of the students, and also effectively promote vocabulary diversity and density, which can better help the students to write in English. Students are allowed to observe, analyze, evaluate, and construct an effective vocabulary knowledge framework in the process of vocabulary learning, effectively internalize vocabulary knowledge, build vocabulary networks, and realize the flexible application of vocabulary.

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