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# Research on the Design of Intelligent Instructional Paths for English Grammar Teaching Based on Ant Colony Algorithm under Higher-Order Cognitive Computing Framework

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ABSTRACT

Higher-order cognitive computational modeling focuses on the large amount of data generated by learners during their educational activities in order to make predictions and inferences and obtain their cognitive characteristics. In this paper, the original ant colony system algorithm is improved. Considering learners as ants, through state transfer probability calculation, pheromone updating, and continuous iteration of multiple ants with the same cognitive characteristics, the optimal teaching path suitable for the learner can be derived. After analyzing, it can be seen that comparing with the data of other GA and ACO algorithms, the improved ACO algorithm in this paper achieves the optimal training effect. By setting up the experimental group and the control group, it can be found that the teaching paths of the five students who did not use the method of this paper were all longer. Therefore, a concise and precise teaching path can be designed from the complicated learning resources and activities. Compared to the control group, the students in the experimental group presented more significant grammar scores and grammar learning attitudes ($p<0.001$).

*Keywords:* ant colony algorithm, cognitive computing, teaching path, state transfer, pheromone update

## 1. Introduction

English grammar is a basic core course for English and translation majors at the undergraduate level, and according to the setting of the talent cultivation program, the cultivation goal of this course aims to educate and cultivate students in the basic theory and basic skills of English grammar [1-3]. Due to the course's complex content, multiple and fragmented knowledge points, coupled with the limited classroom time, many students are full of fear of grammar learning because of insufficiently solid grammar foundation and insufficiently systematic grammar knowledge system, thus affecting their confidence in English learning and limiting their self-study ability [4-7]. This requires teachers to

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improve the educational model during teaching, scientifically adopt the auxiliary tools based on intelligent algorithms, improve the level of teaching guidance, and cultivate students' competence literacy.

The traditional college English grammar teaching follows the theory of prescribed grammar, which both teaches the rule grammar to students according to the content of the grammar book, and seldom provides the explanation behind the grammatical phenomenon [8-9]. However, when the grammatical points within each category continue to be extended in detail down the line, these knowledge points are fractured, both vertically and horizontally, and a variety of knowledge points are intertwined, which is a bit difficult to understand for college students, especially English majors, who are taught traditional English grammar [10-13]. Therefore, the development of intelligent teaching guidance tools under the framework of higher-order cognitive computing can provide corresponding innovative paths for grammar teaching, thus providing more high school English teachers with a direction for thinking, improving the English subject literacy of the high school student population, and promoting the sustainable development of China's education field [14-16].

Combining a higher-order cognitive computing framework with an improved ant colony algorithm to construct an intelligent instructional path planning model for teaching English grammar. The cognitive computing model applied in the field of education dynamically captures learners' emotions, physical states, and cognitive features in multiple forms to provide real-time data for the teaching process and make decision-making judgments. Based on the learner's cognitive characteristics, they are substituted into the state transfer probability calculation, and the above steps are continuously iterated through pheromone updating, so as to arrive at the optimal teaching path suitable for this user. The ASSISTment dataset is selected to verify the sexual validity of the improved ACO algorithm. Taking the English majors of a teacher training college as the research object, we analyze the performance and achievement of the intelligent instruction path planning for English grammar teaching through the experimental comparison method, and discuss the effect of its role in practice.

## 2. Applications of higher-order cognitive computing models in education

Entering the era of artificial intelligence, cognitive computing based on cognitive science and the joint support of machine learning and big data has brought personalization into every corner of our social life, and has been used in a variety of fields such as medical diagnosis, business applications and decision-making evaluation.

The introduction of cognitive computing models in education is also based on the above advantages. By collecting the cognitive feature data generated by learners during the learning process that can reflect individual differences and incorporating them into the feature space of learner profiling, a more complete user model can be constructed for learners. In turn, the learners who generate this data are similar to each other because they have a certain degree of similarity (e.g., similar cognitive backgrounds and learning environments, etc.), making the feature data reflective of the group cognitive commonalities of the learners. Similar to the framework for using cognitive computational modeling in other domains, the constructive framework for cognitive computational modeling in education consists of three main components: the feature space, the constructor, and the goal task as shown in Figure 1. Various physiological data are composited, for example, EEG EEG data are used to determine whether a student is effectively engaged in a learning task; and physical behaviors such as facial micro-expressions, gestures, body gestures, and eye movements are composited. For example, facial expressions, deep gesture detection and posture tracking algorithms are used to predict student learning engagement.

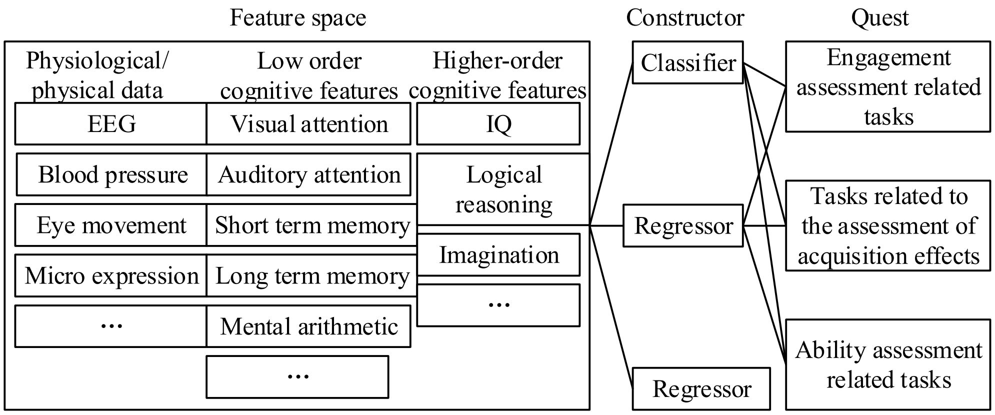



**Fig. 1.** Framework of cognitive computing model construction

There are usually three types of cognitive data sources: gauge test collection, cognitive data generated by interaction with the task environment, and physiological data collected from cognitive devices. Conventional cognitive data usually comes from gauge test collection, but the range of data collected is very limited, so it is difficult to ensure the accuracy of the computational model. Therefore, the feature data in the cognitive computational models in the educational domain are usually also derived from cognitive data generated by interaction with the task environment and physiological data collected from cognitive devices. In complex interactive tasks, cognitive assessment data collected from learners during game interactions are better predictors of their academic achievement than data from traditional scale tests. Physical devices are used to collect physiological and physical data from learners and to correlate these data with specific cognitive traits through a neurologically established factual basis. Learner cognitive data are acquired through biosensors, infrared imaging, and other devices, including eye movements (EM), electroencephalography (EEG), event-related potentials (ERP), galvanic skin response (GSR), electromyographic signals (EMG), electrocardiograms (ECG), expression recognition (FER), and hormone secretion, etc. The use of these underlying physiological/physical data allows for a more accurate fit to the learning process with regard to cognitive Transformation. It can be seen that the three data acquisition methods complement each other and are mutually exclusive, each with its own advantages and disadvantages, which makes the integration of multiple data acquisition methods a mainstream trend in building cognitive computing models.

The feature space refers to a set of cognitive features, usually with specific labels or attributes assigned to these parameters, such as “computational ability” and “short-term memory ability”, etc. These features are called by the constructor and the mathematical parameters of the constructor itself are likelihood inferred from the data collected about the subject. These features are called by the constructor, and the mathematical parameters of the constructor itself are likelihood inferred by collecting relevant data from the experimental subjects. The mathematical model that best fits these data and the associated parameters are then found. The constructors used to fit the classification problem are usually chosen as classifiers, such as Support Vector Machine SVM, Convolutional Neural Network CNN, etc. In discovering models of associations between cognitive elements PSTM, VA, the models need to reflect whether and how one core cognitive element is affected by another core cognitive element. Based on the above needs, the model constructors that are often used in this type of model building are correlators, such as frequent sequence mining techniques etc. to discover and generate various possible patterns consisting of eigenvalues to obtain better interpretability than purely statistical patterns.

In this study, the data were collected from learners at the primary stage of second language learning, and the main task was English grammar acquisition, cognitive computational modeling of the cognitive elements and the effect of the acquisition of target language features, this modeling may use a classifier or regressor In order to find out the relationship between the effect of the acquisition of target language features, Y, and the level of the learner's basic skills, PKA, difficulty of input information IN, cognitive element performance CE = (phonological short-term memory PSTM, visual attention VA), the strategic form of intervention X, and the number of times the intervention is carried out R, a computational model is needed. The model can be defined by equation (1):

$$Y = (PKA)(IN)(CE)(X)(R) \tag{1}$$

The model constructors that are often used in this type of model construction are classifiers and regressors. The constructors used to fit the classification problem are usually chosen as classifiers, such as decision trees, convolutional neural networks CNNs, etc. The output of a classifier is discrete category values that are able to map samples of unknown categories to one of the given categories. These types of algorithms are able to derive whether a learner with a certain cognitive feature space is better or worse, whether the behavior is engaged or not, and whether the ability is mastered or not for this category result.

## 3. Improved Ant Colony Algorithm Teaching Path Planning Model

Therefore, this chapter makes the following improvements to the original ACO system algorithm:

1) Take the correlation between learning resources as the value of heuristic information.

2) Calculate the similarity of user's cognitive features and substitute them into the formulas for local search strategy and state transfer probability.

3) Substitute user satisfaction (i.e., user's rating) as pheromone into the pheromone update formula.

### *3.1. Cognitive feature similarity calculation*

In this paper, we adopt the similarity calculation method based on Euclidean distance to calculate the similarity of users based on cognitive features, instead of roughly classifying or clustering users.

First, the cognitive feature scores calculated based on ILSQ are normalized to the learning preference scores of the four dimensions according to the departure normalization method as follows:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

where, $X$ represents the original data, $X_{\max}$ and $X_{\min}$ represent the maximum and minimum scores respectively, in this case $X_{\max} = 11, X_{\min} = -11$. After normalizing the scores, the similarity between user $U_m$ and user $U_n$ can be derived as follows:

$$LS\_Sim(U_m, U_n) = \frac{1}{1 + d(LS_m, LS_n)} \tag{3}$$

The cognitive features of a user are considered as a four-dimensional vector space, from which the coordinates of the cognitive features of user $U_m$ and user $U_n$ are derived, i.e., $LS_m$ and $LS_n$. $d(LS_m, LS_n)$ represents the Euclidean distance between $LS_m$ and $LS_n$.

### *3.2. Calculation of state transfer probabilities*

In this paper, this is used as the value of the heuristic information and substituted into the formula for calculating the state transfer probability. Assuming that the learning material that the user has already learned is $s = < c_1 c_2 \ldots c_i >$, the value of the heuristic information from the current node $c_i$ to the next node $c_j$ is shown below:

$$\eta_{ij} = v \times Sup(c_j \mid s_1) + (1-v) \times Sup(c_j \mid s_2) \tag{4}$$

where $s_1$ and $s_2$ are sub-sequences of $s$. $s_1 =< c_i >, s_2 =< c_{i-1}c_i > (i \geq 2)$. If $i = 1$, then $s_2$ is the empty set, and if $i < 1$, then both $s_1$ and $s_2$ are empty sets. $v$ is a weight factor between (0, 1). And the values of $Sup(c_j \mid s_1)$ and $Sup(c_j \mid s_2)$ can be found according to equation (4).

In the ant colony algorithm, the state transfer probability is the probability that the ants transfer from the current node to the next node, i.e., the possibility of choosing the next node. Therefore the calculation of state transfer probability should not only consider the pheromone value left by the ants on the edges of the connected nodes, but also the inspired information value. In addition to the continuity between learning materials as the heuristic information value, this paper also substitutes the cognitive characteristics of users as a third consideration into the formula for calculating the state transfer probability. The higher the similarity of cognitive characteristics between users, the higher the reference value of their pheromones. Assuming that $s =< c_1c_2 \ldots c_i >$ is a sequence of learning materials that the target user $U_m$ has already learned, which means that user $U_m$ is at node $c_i$ at this moment, the probability $p_{ij}^m$ of this user transferring from node $c_i$ to the next node $c_j$ is shown below. In this case, the ACS algorithm incorporates a local search strategy. If $q \leq q_0$, then:

$$p_{ij}^m = \begin{cases} 1 & \text{if } j = \arg\max\left\{[\tau_{il}(0.5+\lambda_{il})] \cdot [\eta_{il}]^\beta\right\} \\ 0 & \text{other} \end{cases} \tag{5}$$

Otherwise:

$$p_{ij}^m = \begin{cases} \dfrac{[\tau_{ij}(0.5+\lambda_{ij}{}^m)]^\alpha \cdot [\eta_{ij}]^\beta}{\sum\limits_{c_l \in N_m(c_i)} [\tau_{il}(0.5+\lambda_{il}{}^m)]^\alpha \cdot [\eta_{il}]^\beta} & \text{if } c_j \in N_m(c_i) \\ 0 & \text{other} \end{cases} \tag{6}$$

where $q$ is a random number between [0, 1] and $q0$ is a coefficient that determines the probability of whether the ant explores other paths or chooses the next path according to the rule. $\alpha$ and $\beta$ denote the relative importance of pheromone trajectories and heuristic information, respectively. $\tau_{ij}$ is the pheromone on edge $(c_i, c_j)$ and heuristic information $\eta_{ij}$. $N_m(c_i)$ represents the set of material that the user has not yet learned at node $c_i$. $\lambda_{ij}^m$ is the similarity between the user $U_m$ at node $c_i$ and the user who has already learned the material $c_j$ based on cognitive features. If $c_j$ is suitable for user $U_m$, the value of $\lambda_{ij}^m$ is usually greater than 0.5. Conversely, if the value of $\lambda_{ij}^m$ is less than 0.5, it represents that the learned material at node $c_j$ is not suitable for the cognitive features of user $U_m$. The formula for $\lambda_{ij}^m$ is shown below:

$$\lambda_{ij}^m = \frac{\sum\limits_{k}^{n} LS - Sim(U_m, U_k)}{n} \tag{7}$$

where $LS\_Sim(U_m, U_k)$ represents the cognitive feature similarity between user $U_m$ and the $k$th user $U_k$ who has learned $c_j$, and $n$ represents the number of users who have learned $c_j$.

1) Local pheromone update. When user $U_m$ has completed the learning material $c_j$ and passed the assessment, local pheromone updating is required for the pheromone on edge $(c_i, c_j)$. The

pheromone update consists of pheromone volatilization and new pheromone addition, as shown below:

$$\tau_{ij}(t) = (1-\rho_1)\cdot\tau_{ij}(t) + \Delta\tau_{ij} \tag{8}$$

where $\rho_1$ represents the local pheromone volatilization rate and $\Delta\tau_{ij}$ represents the pheromone added by the user, as follows:

$$\Delta\tau_{ij} = \begin{cases} \dfrac{r_j^m}{r_{\max}} & \text{if } r_j^m \geq r_{good} \\ 0 & \text{other} \end{cases} \tag{9}$$

where $r_j^m$ represents the rating of the learning material $c_j$ by the user $U_m$, and $r_{\max}$ represents the maximum value of the rating. In addition, this paper qualifies the user's added pheromone, if the user's rating of learning material $c_j$ is less than $r_{good}$, it means that the user is dissatisfied with the evaluation of $c_j$, and no local pheromone update is performed for the pheromone on edge $(c_i, c_j)$. Instead, the user rating is used in planning the teaching path for the user:

$$r_j^m = RS(U_m, c_j) = \varphi \times MaxR \times PS_R S(U_m, c_j) + (1-\varphi)\times CG_R S(U_m, c_j) \tag{10}$$

where $PS\_RS(U_{m,cj})$ represents the recommendation score of learning material $c_j$ for user $U_m$ obtained using the PrefixSpan algorithm, and $PS\_RS(U_m, c_j)$ represents the personalized recommendation score based on the user's career goals. $\varphi$ is a weight factor between (0, 1), and MaxR represents the upper limit of the scoring value.

2) Global pheromone update. Over a period of time, when all the ants have completed the path, a global update of the pheromone on the path is required. However, not all edges passed by the ants will have their pheromone increased, and only those edges belonging to the current globally optimal path will be updated as follows:

$$\tau_{ij}(t+1) = (1-\rho_2)\cdot\tau_{ij}(t) + \Delta\tau_{ij} \tag{11}$$

Among them:

$$\Delta\tau_{ij} = \begin{cases} \dfrac{\sum_{n=1}^{N} r_n}{r_{\max}\cdot N} & \text{If } (c_i, c_j) \in \text{current optimal path} \\ 0 & \text{other} \end{cases} \tag{12}$$

where $\sum_{n=1}^{N} r_n$ is the sum of the user's ratings for each node in the path, representing the overall user satisfaction with the teaching path. $\rho_2$ represents the global pheromone volatilization rate, $N$ is the number of nodes in the path, and $r_{\max}$ represents the maximum value of the ratings.

## 4. Research on the analysis of intelligent guidance paths for teaching English grammar

### *4.1. Performance experiment section*

4.1.1. Data pre-processing. Two datasets on the public teaching platform ASSISTment were selected for the experiment to collect learners' question answering information. The datasets are shown in Table 1, the datasets ASSISTment2018 and ASSISTment2024 both contain more than 500,000 records of elementary school math exercises submission, the two datasets are processed, and the information is counted after deleting the duplicated data in the original data. The data of learners, cognitive characteristics (cognitive characteristics data of individual differences) and behavioral time are separated, and the parsed data are cleaned, integrated and transformed to filter out useless records or defective records, which provide effective data support for establishing teaching paths.

**Table 1.** Information of dataset

| Data set | Number of learners | Quantity of knowledge | Submission number |
|---|---|---|---|
| ASSISTment2018 | 4420 | 125 | 330312 |
| ASSISTment2024 | 19215 | 110 | 712725 |

In this study, the cognitive data of learners (e.g., attention to browsing resources, memory ability, EEG, blood pressure, eye movement, micro-expression, logical reasoning ability, imagination, etc.) are grouped into eight categories by the calculation of cognitive model, and the corresponding mapping methods are specified, as shown in the column of “Cognitive Characteristics Mapping”. Then, with learner ID as the main keyword, knowledge unit and behavior time as the second keyword, the learner behavior is sorted (repeated behaviors of the same learner are only counted for the first time, and subsequent repeated behaviors are not counted), and then the original cognitive characteristic data is converted into teaching path data, “Teaching Path Mapping” is shown in Table 2. The “teaching path mapping” is shown in Table 2, where the score is the normalized test score of the knowledge unit. For example, the actual sequence of cognitive features of a student is {attention r5, eye movement p3}, {attention r6, eye movement p1, EEG d}, {memory t1, EGG d, blood pressure e}, and the mapped teaching path is <r5, p3, r6, p1, d, t1, e>.

**Table 2.** Data preprocessing phase

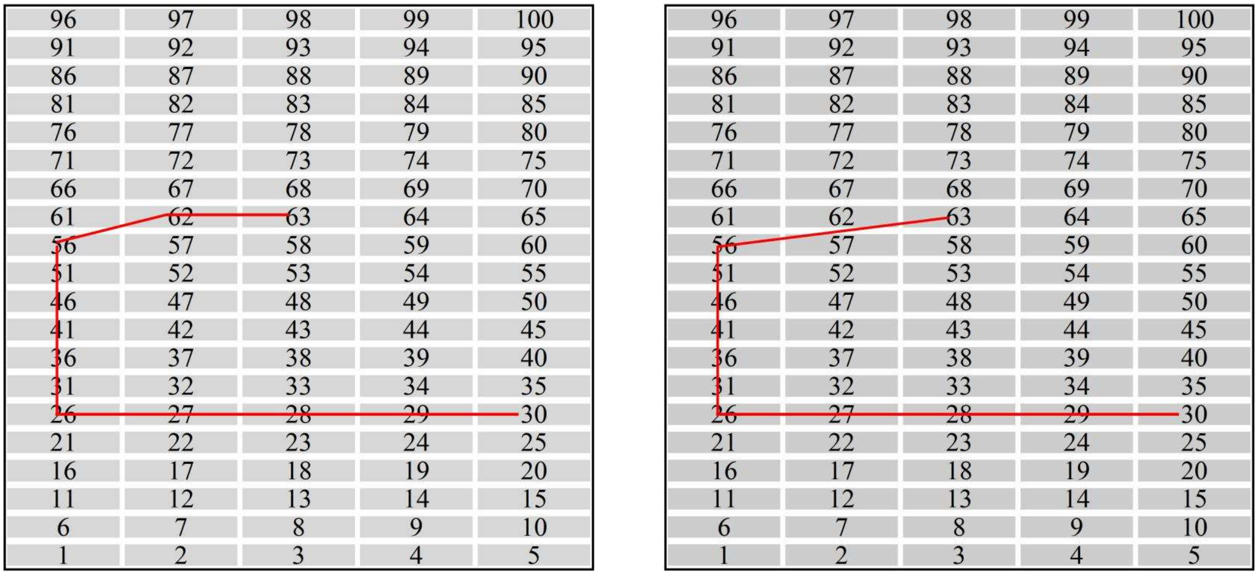
| Learning behavior mapping | | Learning path mapping | | |
|---|---|---|---|---|
| Specific behavior | Mapping | Learners | Teaching path | Grade |
| Attention | r | Stu01 | <r3, r6, d, p1, e> | 0.78 |
| | | Stu02 | <r1, c1, d, p4, e> | 0.67 |
| EEG | d | Stu03 | <r5, p3, r6, p1, d, t1, e> | 0.91 |
| | | Stu04 | <r1, r4, c2, p2, s, e> | 0.82 |
| | | Stu05 | <r1, c1, d, p2, e> | 0.62 |
| Blood pressure | e | Stu06 | <r1, c1, r3, c4, p2, s, e> | 0.93 |
| Eye action | p | Stu07 | <r3, d, p1> | 0.66 |
| Microexpression | s | Stu08 | <r7, p2, r4, d, s, e> | 0.74 |
| Memory | t | ...... | ...... | ...... |
| Logical reasoning ability | c | ...... | ...... | ...... |
| Imagination | o | StuN | <r1, r3, d, p2, e> | 0.72 |

4.1.2. Performance Experiments of Ant Colony Algorithm. The effectiveness of the algorithm was measured by dividing the dataset into 80% training set and 20% test set. Mapping each knowledge point according to the relationship between knowledge points as the raster map location points of ant colony algorithm path planning. Combined with the syllabus and the opinions of experts in the field, the difficulty of the knowledge points was categorized into 3 levels of easy, normal and difficult after the formula calculation. Different difficulty of knowledge points in the map corresponding to the path distance is different, simple knowledge points of the path length is set to 1, general knowledge points of the path length of 2, difficult knowledge points of 3. In the raster map there are knowledge points of the location of the passable points, no knowledge points of the location is set as an obstacle point, if B is the advanced knowledge of A, it is set to go from A to B can be passable, the distance of the knowledge of the difficulty of the B corresponding to the length of the path, and vice versa. The distance is infinite and impassable, thus the raster map is populated as a rectangular map as an input for ACO path planning, and the specifics of the knowledge points are shown in Table 3.

**Table 3.** Partial knowledge node information

| Knowledge point number | Knowledge point name | Difficulty in knowledge | Corresponding path distance | Node |
|---|---|---|---|---|
| 1 | Adverb | Simplicity | 1 | 1 |
| 2 | Comparative of adverbs | Simplicity | 1 | 6 |
| 3 | Superhighest adverb | General | 2 | 16 |
| 4 | Adjective | Simplicity | 1 | 21 |
| 5 | Adjective comparison | General | 2 | 31 |
| 6 | Superhighest adjective | Simplicity | 1 | 36 |
| 7 | Interrogative pronoun | Simplicity | 1 | 41 |
| 8 | Possessive pronoun | General | 2 | 51 |
| 9 | Personal pronoun | Simplicity | 1 | 56 |
| 10 | Proper nouns | Difficulty | 3 | 71 |
| 11 | Plural | Simplicity | 1 | 76 |
| 12 | Noun singular | Difficulty | 1 | 81 |
| 13 | Was+ verb now | General | 2 | 91 |
| 14 | Is+ verbs are now participle | General | 2 | 1 |
| 15 | Never+ in the original form of the verb | Simplicity | 1 | 63 |
| 16 | Do+ verb | Simplicity | 1 | 30 |
| ...... | ...... | ...... | ...... | ...... |

The result of similarity between learners was calculated, and all learners were categorized into "excellent" learners and "ordinary" learners according to the similarity threshold, in which those with a higher level of knowledge were excellent learners. Those with higher knowledge level are the excellent learners, while those with lower knowledge level are the ordinary learners. Correspondingly, the ant colony is divided into superior ants and ordinary ants. Due to the higher level of knowledge mastery of the excellent class learners, the superior ants tend to favor the coherence of the knowledge nodes in the path selection, and will directly start from the next associated knowledge node to the end point. Ordinary ants correspond to ordinary learners with lower knowledge level, so the ordinary ants tend to backtrack to the previous knowledge nodes before advancing to the end point in path selection, which can be regarded as the review process of the ordinary class learning test. This categorization idea enables learners of different classes to get the teaching path recommendation that contains the characteristics of their own knowledge level. Excellent learners can finish learning more quickly and master new knowledge points, while ordinary learners can review the last learning knowledge to build up a solid knowledge foundation before proceeding to the subsequent learning. Setting arbitrary starting and ending points of the teaching paths leads to different paths. The path results obtained by ACO are shown in Figure 2. The learner wants to start learning from "do + the original form of the verb" to "never + in the original form of the verb", and input the map order points 30 and 63.




(a)Ordinary ant (b) Excellent ant path

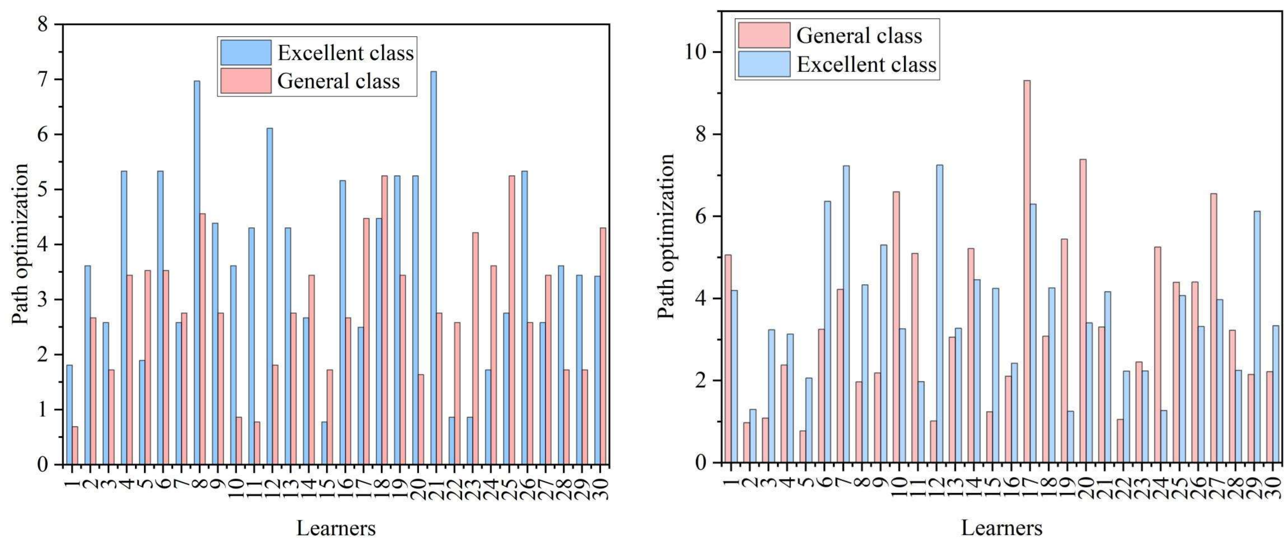
**Fig. 2.** Ant colony path selection

Calculate the data of each index of this algorithm and the other two algorithms of GA and ACO respectively, in addition, calculate the complexity of the algorithm, and the comparison results are shown in Table 4. It can be seen that the present algorithm achieves optimal training results.

**Table 4.** Experimental data contrast

| | ASSISment2018 | | | ASSISment2024 | | |
|---|---|---|---|---|---|---|
| | GA | ACO | This algorithm | GA | ACO | This algorithm |
| Coverage | 0.702 | 0.778 | 0.881 | 0.668 | 0.748 | 0.814 |
| Precision | 0.869 | 0.815 | 0.915 | 0.844 | 0.819 | 0.856 |
| Recall | 0.363 | 0.486 | 0.623 | 0.367 | 0.422 | 0.547 |
| F1 | 0.514 | 0.612 | 0.718 | 0.516 | 0.558 | 0.669 |
| Time complexity | $o(n^3+\log_n)$ | $o(m+n^2)$ | $o(m+n^2)$ | $o(m+n^2)$ | $o(m+n^2)$ | $o(m+n^2)$ |

4.1.3. Path distance optimization volume. For a randomly selected sample of 30 learners, the amount of distance optimization (the difference between the effective distance of the paths) between the recommended paths and the original teaching paths was calculated as shown in Fig. 3, and the optimization of the teaching paths was achieved for the learners in the sub-general and excellent categories, with an average optimization amount of 3.69 and 2.89 in ASSISment2018, and 3.74, respectively, and 3.55 in ASSISment2024, respectively. 3.55.




(a)ASSISment2018 (b)ASSISment2024

**Fig. 3.** Path distance optimization

## 4.2. *Experimental Analysis of Instructional Pathway Performance*

In this study, 59 second-year students majoring in English studies in a teacher training college were taken as the research subjects, and the 59 students were divided into the experimental group and the control group, and all the students were introduced to the knowledge of English grammar before the beginning of the experiment, so as to eliminate the influence of the difference in the starting point of learning on the results of the experiment. During the experiment, students were asked to complete each knowledge unit and test. The data collected in the experiment included: learning achievement, learning time, learning satisfaction and path scores.

Five students were randomly selected from each of the experimental and control groups, and their cognitive characteristics, knowledge levels and teaching paths are shown in Table 5. As can be seen from the table, all five students in the control group had longer teaching paths. For example, Student 2 and Student 5 in the control group have the same cognitive characteristics and different knowledge levels, but their teaching paths are <r3, r5, p4, r12, r13, p11, d, t1, e>. This is because the instructional path construction model takes into account factors such as students' personality traits as well as learning performance, so the instructional paths for each student are different. The instructional paths for students in the control group are mainly generated based on the platform resource sorting and search results, which leads to the fact that students with different knowledge levels but similar cognitive characteristics will have the same instructional paths. In conclusion, the teaching path construction method proposed in this study can design concise and precise teaching paths from complicated learning resources and activities.

**Table 5.** Teaching path comparison

| Serial number | Experimental group | | | Control group | | |
|---|---|---|---|---|---|---|
| | Cognitive style | Knowledge level | Teaching path | Cognitive style | Knowledge level | Teaching path |
| 1 | <1,4,3,2> | <3,4,3,3> | <r3, p2, r12, p7 d, t2, e> | <2,4,3, 3> | <4,5,3,2> | <r3, r5, p4, r12, r13, p11, d, t1, e> |
| 2 | <3,5,3,4> | <4,5,3,3> | <r3, p5, r15, p8, d, t3, e> | <2,5,1,3> | <3,5,3,3> | <r4, r5, p2, r12, r13, p9, d, t3, e> |
| 3 | <4,3,2,5> | <3,3,3,2> | <r5, c2, r13, c8, p2, s, e> | <4,2,1,5> | <3,4,3,2> | <r6, r7, c2, r12, r15, c10, p2, s, e> |
| 4 | <5,2,3,1> | <4,3,2,3> | <r8, c4, r13, c6 P4, s, e> | <5,1,3,4> | <4,2,1,3> | <r6, r8, c5, r13, r16, c8, p4, s, e> |
| 5 | <3,4,1,2> | <3,3,1,3> | <r5, p7, r14, p9, d, t6, e> | <2,4,3,1> | <3,2,1,2> | <r3, r5, p4, r12, r13, p11, d, t1, e> |

After the completion of each knowledge point, students' ratings of the quality of the teaching path are collected through the online learning platform. The ratings are based on a 5-point scale, with higher scores indicating that the quality of the teaching paths is higher and better able to meet students' learning needs. At the end of the whole course, the quality ratings of all the teaching paths were averaged out on a student-by-student basis, and the results are shown in Figure 4. The independent samples t-test on the scores of the two groups of students shows that there is a significant difference between the experimental group and the control group of students in the quality scores of teaching paths ($P < 0.01$). As can be seen from the figure, the ratings of students in the experimental group on the adaptive teaching path are generally higher than the ratings of students in the control group on the autonomous teaching path, indicating that the adaptive teaching path constructed in this study is of better quality compared to the autonomous teaching path, which is due to the fact that the latter recommends suitable teaching paths for the students and reduces the learning load.

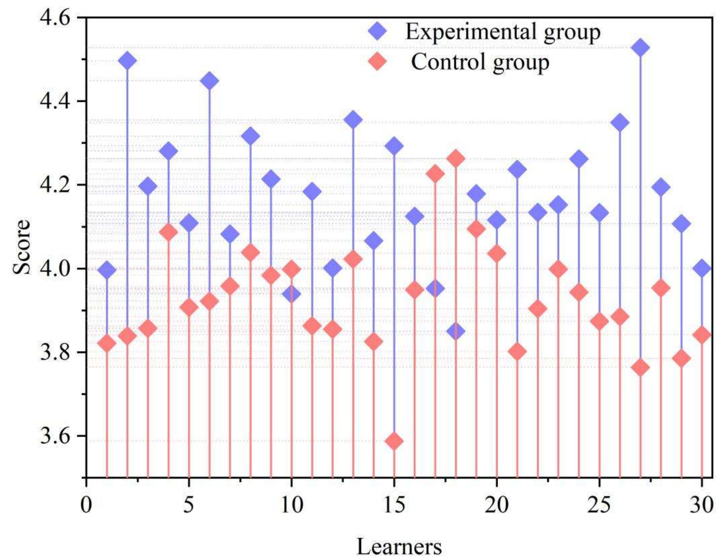



**Fig. 4.** Study path quality rating comparison

### *4.3. Analysis of Grammar Learning Achievement*

In order to understand the extent to which the implementation of the English grammar teaching design model has an impact on students' English grammar scores, an independent sample T-test was carried out to verify whether the English grammar teaching path design model based on the higher-order cognitive computing model and ant colony algorithm was significantly higher than that of the control group after the grammar posttest scores of the experimental group and the control group were applied to the teaching practice. Sample data are subject to normal distribution is a prerequisite for independent samples t-test, the grammar posttest scores of the experimental group and the control group were tested for normal distribution, and the specific results are shown in Table 6. The students' grammar posttest scores in the experimental group and the control group are 73.49, 67.12 respectively, and there is a big difference between the two groups' grammar posttest scores.

**Table 6.** Analysis of legal study scores

| | Class | Number | Mean value | Standard deviation | Standard error mean |
|---|---|---|---|---|---|
| Pretest | Experimental group | 50 | 66.25 | 14.281 | 2.479 |
| | Control group | 48 | 65.78 | 12.243 | 3.217 |
| Posttest | Experimental group | 50 | 73.49 | 14.723 | 2.084 |
| | Control group | 48 | 67.12 | 17.537 | 2.536 |

The grammar-specific test papers used in the grammar achievement post-test for both the experimental and control groups were scored out of 100, with 60 being the passing score. In order to see in more detail the ratio of the number of people in each score band above the passing mark, this study classified test scores of 86-100 as band A (excellent), 71-85 as band B (good), 60-70 as band C (pass), and less than 59 as band D. The test scores of the experimental group and the control group in the post-test of grammar achievement were divided into two bands. The number and proportion of each score band of the grammar posttest scores of the experimental and control groups are shown specifically in Figure 5. Most of the experimental group's scores are concentrated in 70-100, while the control group is concentrated in 60-70.

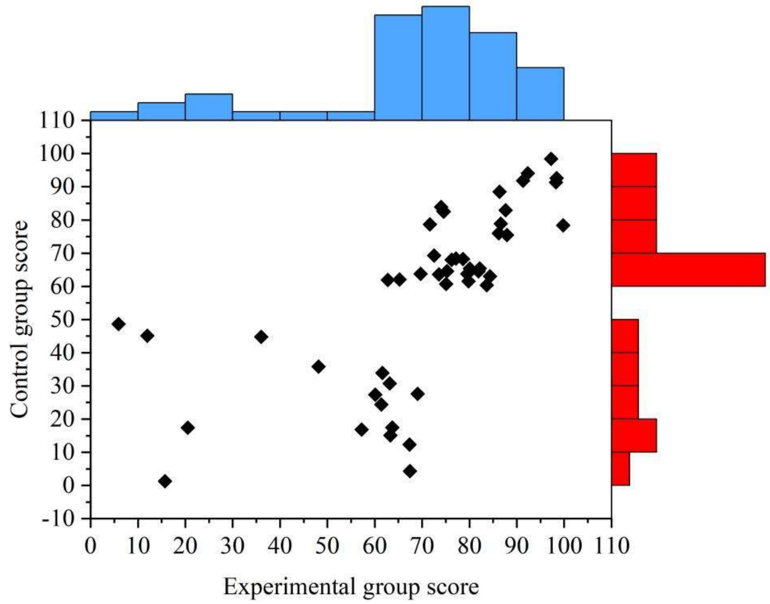



**Fig. 5.** The number and proportion of each divider

At the end of the teaching experiment, a post-test on attitude towards grammar learning was administered uniformly to all student subjects in both groups. An independent samples t-test was conducted on the questionnaire data of the two classes in order to test whether there was a significant difference between the students in the experimental group and the students in the control group in terms of their attitudes towards grammar learning at the end of the teaching experiment. The results of the test are shown in Figure 6. The independent samples t-test results of the experimental group and the control group on the total grammar learning attitude scale and the three dimensions of affective, cognitive and cognitive trait intention in grammar learning t were 4.969, 4.922, 4.527, 3.618 and $P<0.001$ respectively, i.e., all of them satisfy $P<0.05$, which indicates that there is a statistically significant difference between the experimental group and the control group in the overall level of the attitude to grammar learning and the three dimensions of the attitude to grammar learning after the teaching experiment. There are statistically significant differences between the experimental group and the control group in the overall level of attitude toward grammar learning and the three dimensions, and the mean scores of the experimental group students in the overall level of attitude toward grammar learning and the dimensions are higher than those of the control group students. Thus, the implementation of the English grammar teaching path design model based on the cognitive computing model and the ant colony algorithm in the experimental group has led to the students in the experimental group showing significantly better attitudes toward grammar learning than the students in the control group.

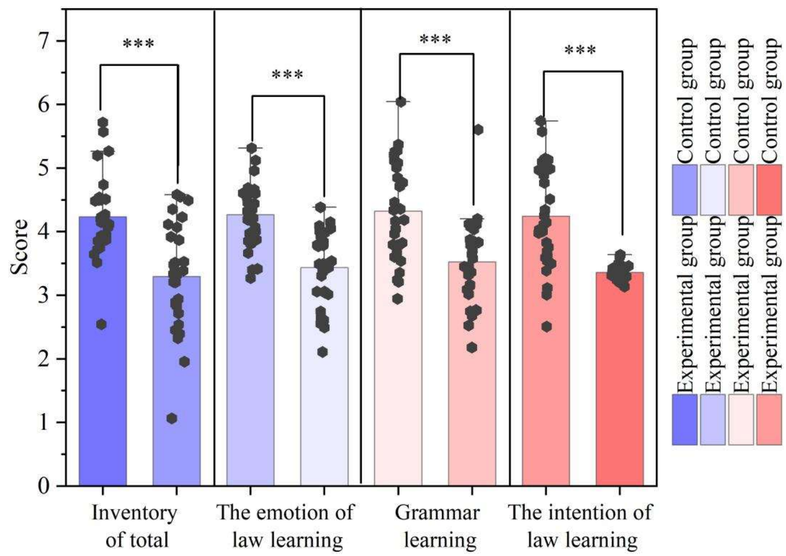



**Fig. 6.** Test results of the independent sample t of English grammar

## 5. Conclusion

This paper proposes an integrated framework for higher-order cognitive computing applied in the field of education. Based on this, an improved ant colony algorithm is used to realize the intelligent guidance path design for teaching English grammar. Through performance testing and comparative analysis, the following conclusions can be drawn:

1) Comparing the coverage rate, recall rate, F1 value, algorithm complexity and other index data of this paper's algorithm and the two algorithms of GA and ACO, this paper's algorithm has achieved the optimal training effect.

2) After the implementation of the English grammar teaching path design model based on cognitive computing model and ACO algorithm in the experimental group, the teaching paths in the control group are all longer. Therefore, the construction method of this paper can make the teaching path more concise and precise. And the students in the experimental group presented significantly better grammar performance and grammar learning attitude than the students in the control group.

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