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Article

Construction of a personalized learning path for vocal music teaching through cloud platform in college music courses

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Abstract: How to effectively use artificial intelligence technology to achieve the purpose of optimizing teaching resources and realizing personalized teaching has become an important research field. In this paper, with the help of development software, the functional modules, database and interface of the music teaching cloud platform are designed respectively, and the music teaching cloud platform is finally constructed. In view of the application prospect of ant colony algorithm in personalized learning path, in this regard, ant colony algorithm is introduced into the music teaching cloud platform to realize the personalized learning path planning and recommendation for vocal music teaching. Finally, the form of algorithm comparison is used to verify and analyze the method of this paper. The output results of the three algorithms are 0.7436, 0.6972, 0.6751 respectively, indicating that the priority of the ant colony algorithm is greater than the genetic algorithm and simulated annealing algorithm in the personalized learning path of vocal music teaching.

Keywords: ant colony algorithm; personalized learning path; vocal music teaching; cloud platform

1. Introduction

Under the background of digitalization, colleges and universities should face the opportunities and challenges of music courses in colleges and universities given by digital technology, and explore the potential of digital technology at multiple levels such as changing teaching concepts, reforming teaching methods, innovating teaching modes, optimizing teaching environments, perfecting teaching mechanisms, and reforming teaching evaluation methods, so as to broaden the channels of cultivating students' musical and artistic talents, and to promote the innovative development of music teaching [1-5]. As an important part of the music curriculum in colleges and universities, vocal music teaching, as a cradle for cultivating students' musical literacy and nurturing musical and artistic talents, is urgently needed to change the traditional mode of classroom lectures and face-to-face practical guidance.

Under the development of globalization and diversification, the era of education is constantly changing, and the form and content of education need to be constantly updated and improved to keep up with the pace of the times, in order to meet the diversified needs of students and the requirements of individualized development [6-8]. Traditional vocal music teaching often uses standardized teaching methods and teaching materials, and all students use the same teaching materials, which is difficult to take into account the individual needs of students. Due to the personalized differences in the voice qualities, vocal fundamentals, and musical pursuits of different students, the “one-size-fits-all” teaching mode is difficult to meet the unique needs of each student in vocal learning, resulting in a lack of innovative thinking, restricting the overall development of the students' vocal art quality, and making it difficult for them to stand out from the crowd in the fierce competition in the music market [9-13].

Cloud platform is a form of digital classroom and future classroom. It promotes education to a new form and revolutionizes modern teaching methods, and the new modern cloud platform based on Internet technology integrating intelligent teaching and environmental intelligent regulation is an effective part of promoting the construction of future schools and classroom teaching [14-17]. To some extent, the education cloud platform subverts the traditional education model, which not only accelerates the speed

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and breadth of resource updating, but also integrates the functions of teaching and management, learning and entertainment, communication and display through advanced cloud technology, providing a shared space for the education sector, teachers, students, and allowing education to break the limitations of time, space, and situation, and realizing the real all-around education with a high degree of flexibility and convenience Networking [18-22]. Therefore, in the teaching of vocal music, students can achieve interactive classroom teaching between teachers and students through the cloud platform to better achieve personalized learning, enhance students' independent learning ability, and promote the formation of students' core literacy.

In the field of students' personalized learning, cloud platforms provide a powerful support role. Zaporozhko [23] (2018) in order to provide personalized services in cloud platform courses, based on students' individual information and learning characteristics, heuristic algorithms are used to dynamically plan personalized learning paths for students in the courses. Zhang [24] (2022) introduces a multimodal multimedia education cloud platform in which a deep learning algorithms to analyze semantic information and sentence features of textual contexts in courses and extract key information in sentences to achieve personalized educational resource recommendation. Shanmugavadivelu [25] (2025) introduced a cloud-based educational platform to realize digital classrooms, access virtual resources with the help of artificial intelligence and other technologies, and build an adaptable and inclusive educational ecology that promote personalized teaching. Yang [26] (2025) revealed that the computer cloud platform can link industry and education, promote the cultivation of innovative and entrepreneurial talents that meet the needs of the industry, and make the students more attuned to the development of the industry and more competitive themselves in personalized needs.

In college vocal music teaching, the application of cloud platform has made certain achievements. Li [27] (2017) used Azure-PaaS platform cloud computing technology and intelligent PPT technology to design a platform-based online vocal music course, which covers three functions of learning, interaction, and assessment, and improves students' independent learning effect. Tianle [28] (2020) developed a mobile classroom cloud platform for university music teaching, on which students can access fragmented music resources, providing a path for students' personalized learning. Xue [29] (2022) created an interactive teaching platform for vocal music based on cloud platform technology and streaming media technology, which utilizes modules such as online live broadcasting, independent learning, extracurricular expansion and personal display to promote students' theoretical knowledge learning, to enhance teacher-student interaction and cultivate students' subjective initiative. Shi [30] (2023) evaluated the effect of various mobile Internet platforms (VoCo Vocal Coach, Sound Cloud, etc.) on vocal training, which can be combined with the current digital trends for vocal training, while students can obtain accurate feedback, which contributes to personalized learning. Zhang [31] (2024) tested the effectiveness of choral vocal training through online platforms and cloud storage services, and technology-enabled choral vocal training could achieve higher performance. Xie [32] (2024) designed a cloud platform for integrating vocal teaching and traditional music culture teaching methods, which facilitates students' learning about changes in vocal teaching and at the same time improves the boost for students' understanding of vocal culture. Xue [33] (2025) used a two-way long and short-term memory network model to build a music cloud teaching platform, within which musical elements can be simulated, musical features can be acquired, students' musical performance can be assessed, and personalized learning paths can be constructed for students based on students' platform interaction data and learning data.

With reference to the existing research data and literature, this paper designs a music teaching cloud platform for mobile terminal, and explores and analyzes the platform from the aspects of function, performance and satisfaction, aiming at proving the practical value of the platform in the teaching of vocal music in colleges and universities. Next, in order to realize the personalized learning path planning and recommendation of the music teaching cloud platform, the ant colony algorithm is introduced on the basis of the original one, and the effectiveness and feasibility of the ant colony algorithm in the personalized learning path problem of vocal teaching are verified by means of algorithmic comparison and analysis.

2. Mobile-oriented music teaching cloud platform

Commonly speaking, the music teaching cloud platform for mobile terminals is the cell phone version of the music teaching platform, and its development environment includes two parts: software and hardware. Among them, the most important hardware environment is the video server, the platform system developed in this paper purchased MyComm server. The software environment includes the operating system, database, platform code and debugging tools used in the development, the server operating system selection of Windows 2003 Server, database selection of SQL Server2000, platform code selection of JAVA language, and in the MyEclipse development platform under the platform

interface development and debugging.

2.1. Design of platform functional modules

2.1.1. Video acquisition module

Users can access the Music Teaching Cloud Platform through their smartphones, and by selecting the menu to get the required video passages, they can watch the course videos, course PPTs and related works for each course. It is divided into six parts according to the content: voice course, string course, dance course, piano course, folk music course and video and audiovisual. The module can be used as a preview and practice for courses and musical works, as well as a personalized appreciation and adaptation production tool. Store multimedia materials related to music teaching, including documents, pictures, PPT, audio and video information.

2.1.2. Seat management

The platform sets up voice seat and video seat respectively, which can manually answer users' demands, and the seat personnel can interact with users by voice and video through the computer, provide users with the required video or service, or transfer experts to answer questions, etc. The seat management module carries out unified management of the seat functions.

2.1.3. System administration

It is mainly responsible for the management of platform operation parameters, intermediate data and user rights, and provides system administrators with interfaces to enter each module to ensure the smooth operation of the whole platform.

2.2. Platform database design and platform interface

2.2.1. Platform database design

General college music teaching resources database named MusicData, including eight data tables, used to record information related to music education resources, these four data tables are teacher-course information table courseware information table, document information table, PPT information table, picture information table, audio information table, video information table and user management information table.

2.2.2. Platform interface

(1) Mobile phone login interface

Users can log in to the mobile terminal of the platform by dialing the number of the Music Teaching Cloud Platform. When “Video” is on, it is a video call, and when “Video” is off, it is a voice call.

(2) Platform User Interface

Users can select the corresponding operation according to the prompts of the platform user interface, and enter the number to watch the course content according to the selected course name.

(3) Platform Agent Interface

The platform agent can provide different services according to the user's needs. The agent can record the user's information, transfer inbound signals, and play the video required by the user. This function is an important reference for teachers to understand the learning interests and difficulties of different students in the process of music education, and a large amount of real-time information about students' needs can provide valuable hints and participation in enriching and perfecting the contents and methods of music education.

3. Platform testing and satisfaction analysis

3.1. Platform testing

3.1.1. Platform functionality testing

Functional testing before the need for music teaching cloud platform for preliminary testing, in the preliminary test is completed on the basis of the completion of the music teaching cloud platform according to the test cases to complete the in-depth testing of the various functions of the platform, the test needs to be completed at the beginning of the test items are as follows:

(1) Test the interface of the entire music teaching cloud platform. The main interface menu is tested for click events to check whether the specified operation interface is reached.

(2) Page link test: the functions of the music teaching cloud platform are not all completed in one page, and some processes need to be completed through multiple processes and interfaces, so it is necessary to pay attention to whether the links and jumps of each page are normal.

(3) Check button function: the launch and end of each business in the Music Teaching Cloud Platform requires the use of buttons, so it is necessary to check whether the buttons can be clicked and whether the functions accomplished after clicking are consistent with the design purpose.

(4) Required fields check: focus on the filling of required fields when saving data, and whether it is prompted when they are not filled.

(5) Interface check: focus on whether the interface of the music teaching cloud platform is consistent in terms of color and framework.

(6) Format checking: When saving or updating data, the format of each field must be checked, and users should be prompted when there are problems.

On the basis of the completion of the above tests, it is necessary to design test cases for each function, and then test according to the test cases, this section will introduce the test cases for the password reset function, and the test cases for the password reset function are shown in Table 1.

Table 1. Test case for password reset function.

Module Name	Student registration		
Test purpose	Test the correctness of the password reset function		
Preset conditions	Music teaching cloud platform		
Use case number	Use case description	Input data	Expected Results
1	1.Log in to the system successfully and enter the password reset page 2. Enter the correct old password. The two new passwords should be consistent and meet the format requirements. 3. Click the "Reset" button	Old password: x202408# New password: x202408$ Confirmation password: x202408$	Prompt: Password reset successful
2	1.Log in to the system successfully and enter the password reset page 2. Enter the error old password. The two new passwords should be consistent and meet the format requirements. 3. Click the "Reset" button	Old password: x202408$ New password: x202408$ Confirmation password: x202408$	The prompt indicates that the old password is incorrect and the password reset failed.
3	1.Log in to the system successfully and enter the password reset page 2. Enter the correct old password. The two new passwords However, the two new passwords were inconsistent 3. Click the "Reset" button	Old password: x202408# New password: x202408$ Confirmation password: x202408%	The prompt indicates that the two passwords are inconsistent and the password reset failed
4	1.Log in to the system successfully and enter the password reset page 2. Enter the correct old password. The two passwords are the same, but do not meet the format requirements. 3. Click the "Reset" button	Old password: x202408# New password: Open Confirmation password: Open	The password format is incorrect and the password reset failed

3.1.2. Platform performance testing

This section focuses on testing the performance of the music teaching cloud platform, the concurrency of the music teaching cloud platform, fault tolerance and real-time testing, the performance system of the music teaching cloud platform and the instantaneous peak of the server, in addition to the functionality test should also be the load of the music teaching cloud platform as well as fault-tolerant concurrency and real-time testing. When conducting performance testing, it is necessary to select the appropriate test occasion in order to analyze the performance of the music teaching cloud platform, the

details of the pressurized situation in this scenario are shown in Table 2.

Table 2. Pressurization conditions for performance testing.

Serial Number	Item	Value	Remarks
1	Total duration (including pressurization/decompression)	3 hour, 30 minutes, 50 seconds.	
2	The maximum number of running Vusers	5,1200	
3	Total throughput (bytes)	148,836,227	
4	Average throughput (bytes per second)	44,523	
5	Total number of clicks	22,621	
6	Average number of clicks per second	3.942	

With the pressurization during the testing process and on the basis of recording various information, the performance of the music teaching cloud platform can be obtained. The number of people online on the platform is shown in Figure 1, the overall response time of the application is shown in Figure 2, the memory used by java is shown in Figure 3, and the CPU used by java is shown in Figure 4. Comprehensive Figure 1~Figure 4 shows that the maximum number of users of the music teaching cloud platform reaches 4,000~5,000 people, which can well meet the needs of vocal music teaching in colleges and universities. The overall response time is less than 400ms, JAVA load memory is less than 600M, and most of the CPU load is less than 10M, which indicates that the platform can meet the performance test standard requirements, and can give students a high-quality experience, which in turn improves the quality of teaching in colleges and universities.

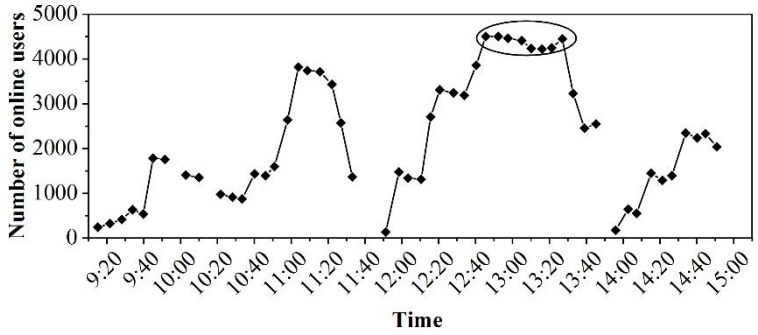


Figure 1. The number of online users on the platform.

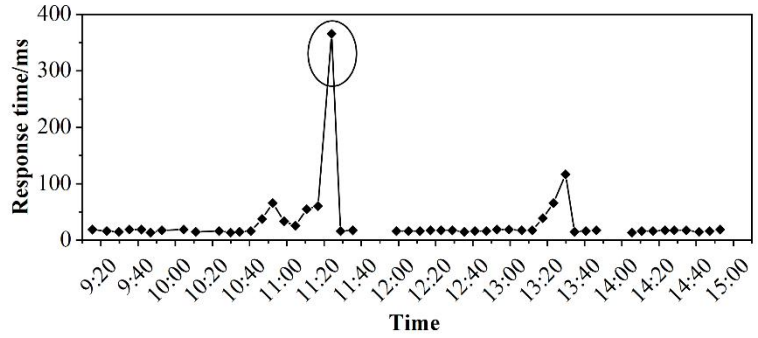


Figure 2. Overall application response time.

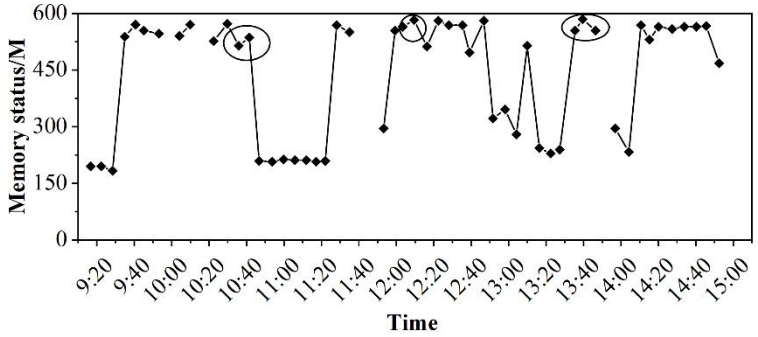


Figure 3. Memory usage in java.

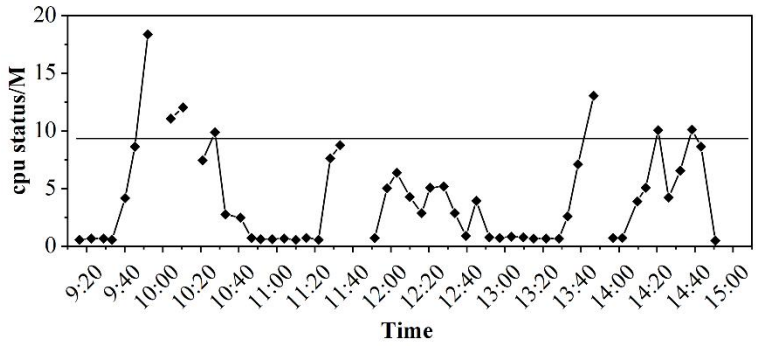


Figure 4. The CPU usage of java

3.2. Analysis of platform satisfaction

3.2.1. Questionnaire

The questionnaire was based on a five-level Likert scale (i.e., very dissatisfied, not very satisfied, fair, satisfied, and very satisfied). Each of these five levels corresponds to a corresponding score, very dissatisfied = 1 ..... very satisfied = 5, with a total of 8 question items. The details are as follows:

Item 1: Using the platform can improve your learning efficiency.

Item 2: Using the platform can improve your learning effect.

Item 3: Your overall feeling of using the platform.

Item 4: You think the platform is convenient to operate all functions.

Item 5: The extended resources provided by the platform support your efficient learning.

Item 6: The extended resources provided by the platform are indispensable for your learning.

Item 7: The number of extended resources provided by the platform can meet your learning needs.

Item 8: The extended resources provided by the platform are easy to find.

The reliability and validity of the questionnaire was examined by means of a pre-survey, and the reliability and validity of the questionnaire met the requirements of the study. The questionnaire is centrally distributed and centrally recovered, 500 questionnaires are distributed, 500 are recovered, and 500 questionnaires are valid.

3.2.2. Analysis of results

With the help of the questionnaire, the satisfaction of the music teaching cloud platform was analyzed, and the results of the satisfaction analysis are shown in Table 3. The results show that the mean value of each question item is maintained between 4 and 5, and the corresponding standard deviation is 0.9 to 1.2, indicating that students hold a satisfactory attitude towards the music teaching cloud platform. Although textbooks are the main content of traditional teaching, the music teaching cloud platform can make the teaching content spread more quickly through the Internet. Music teaching cloud platform can use the Internet to quickly download the rich content of the network material edited into courseware to make the content richer, while the material contains video, pictures, text so that students are more receptive to the combination of learning through fun. The traditional teaching method is to require a specified time to class, music teaching cloud platform can not be restricted by time, students are free to arrange time for

online teaching. Traditional teaching methods are relatively fixed location, network teaching is spread through the Internet is not limited by space, students at any time through the Internet any place to log in to learn. In the traditional teaching, the teaching object is very fixed, music teaching cloud platform is the object of education by the school of the specific population to expand to vocational training, social personnel, so that the object of education is more extensive. Anyone can do personalized learning mode and content, educational resources have been very reasonable distribution, for the development of a new model of education provides a fertile ground.

Table 3. Satisfaction analysis results.

Item	Sample size	Mean	Standard deviation
1	500	4.668	1.142
2	500	4.828	0.915
3	500	4.686	0.906
4	500	4.906	1.198
5	500	4.842	1.017
6	500	4.817	0.926
7	500	4.681	0.947
8	500	4.739	0.905

4. Personalized Learning Path for Vocal Music Teaching on Cloud Platform

4.1. Principles of Ant Colony Algorithm and its Applications

4.1.1. Principles of Ant Colony Algorithm

Ant Colony Optimization (ACO) algorithm is a new evolutionary computational method inspired by the foraging mechanism of a real ant colony, and is now widely used in the field of optimization [34]. Ants are social insects, and ants can collaborate with each other to accomplish complex tasks: individual ants secrete pheromones on pathways, and the colony is able to find a shortest path between the colony and the food according to the strength of the pheromone on each pathway when foraging. The ant colony algorithm simulates the foraging mechanism of a real ant colony and introduces the concept of pheromone and the related pheromone updating mechanism. However, unlike the ants in a real colony, the ants in the ant colony algorithm are endowed with partial memory and can perceive certain inspiring information, which is not stored in individual ants but distributed on the path. The ant colony communicates by sensing pheromones on the path. Individual ants do not directly interact with each other, but rather interact by changing the environment in which they co-exist, and individuals in turn influence the behavior of other individuals by changing the environment, thus forming a positive feedback mechanism that allows shorter paths to have a greater chance of being selected, and because of the probabilistic algorithm, it is able to go beyond the local optimal solution.

The basic principles of ant colony algorithm include four parts: "constructing the solution set", "constructing heuristic information", "pheromone update" and "local search". The following takes the "traveling salesman problem" as an example to illustrate the basic principles of ant colony algorithm:

(1) Constructing the solution set: assuming there are n cities, the traveler's problem can be described as finding the shortest path that a traveler needs to travel to visit each city once. d_{ij} is the length of the path between city i and city j. Represent the problem by a finite set $C=\{c_1,c_2,\cdots,c_n\}$, and the expression of the problem x consists of a finite number of elements in the set C, i.e., $x=\langle c_i,c_j,\cdots,c_n,\cdots\rangle$, X denotes all possible problem expressions, and the solution set S is a subset of X. On this basis, the ant constructs the solution set by randomly selecting paths on the constructed directed graph $G_C=(C,L)$, where the nodes in the directed graph denote the components C,L denote the relationships between the components C. In each step of constructing the solution set, ant k selects the node to pass next based on the transfer probability. In the ant colony algorithm, the transfer probability of ant k moving from node i to the next node j is:

$$P_{ij}^{k}=\tau_{ij}{}^{\alpha}\eta_{ij}{}^{\beta}/\sum_{j\in A}\tau_{ij}^{\alpha}\eta_{ij}^{\beta} \tag{1}$$

where $\tau_{ij}{}^{\alpha}$ is the strength of the pheromone on the path from i to j, $\eta_{ij}{}^{\beta}$ is the heuristic information, Λ denotes the set of all the nodes that can be chosen next by the ant k when it is at the

node i, and α and β are the weights of the pheromone and heuristic information, respectively.

(2) Heuristic information: Heuristic information is an awareness constant that represents the heuristic preference of moving from node to node. In general, $\eta_{ij} = 1/d_{ij}, d_{ij}$ denotes the distance between node i to j.

(3) Pheromone update: After all ants finish foraging, the pheromone needs to be updated. Firstly, the pheromone on all arcs is decreased by a constant, and then the pheromone on the arcs that the ants have traveled is increased. The formula for pheromone volatilization is as follows:

$$\tau_{ij} = (1-\rho) \times \tau_{ij} \tag{2}$$

where ρ is the evaporation coefficient of the amount of pheromone on the path. After the pheromone evaporates, the ants leave the pheromone on the path arcs they traveled:

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3}$$

where $\Delta\tau_{ij}^{k}$ is the number of pheromones left by ant k on that arc. It is defined by the following equation:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1/C^{k}, if\ \ arc(i,j) belongs\ to\ T^{k} \\ 0, otherwise \end{cases} \tag{4}$$

where C^{k} denotes the length of the shortest path T^{k} that the ant k has traveled, and the computation is obtained by summing the arc lengths in T^{k}.

(4) Local search: q denotes a random number obeying a uniform distribution $[0,1]$, and $q_0 \in [0,1]$ denotes the relative importance parameter for determining the existing paths and developing the new paths when $q \le q_0$.

$$P_{ij}^{k} = \begin{cases} 1, \text{if } s = \arg\max_{j \in \Lambda} \left\{ \tau_{ij}^{\alpha} \eta_{ij}^{\beta} \right\} \\ 0, otherwise \end{cases} \tag{5}$$

Otherwise, the

$$P_{ij}^{k} = \begin{cases} {\tau_{ij}}^{\alpha} {\eta_{ij}}^{\beta} / \sum_{j \in \Lambda} \tau_{ij}^{\alpha} \eta_{ij}^{\beta}, j \in \Lambda \\ 0, otherwise \end{cases} \tag{6}$$

4.1.2. Ant Colony Algorithm Applications

Ant colony algorithm is well used in the field of learning path recommendation due to its features such as self-organization, parallelism and positive feedback [35]. In system theory, a system can be classified as self-organized and it-organized based on whether the organizational instructions come from inside or outside the system. At the beginning of the ant colony algorithm, individual artificial ants search for solutions in an unorganized manner, the algorithm evolves over a period of time, and the artificial ants spontaneously tend to find some solutions close to the optimal solution more and more through the pheromone effect, and there is no external role in this process [36]. Learning path recommendation problem due to the cloud platform contains a large number of knowledge points of vocal teaching, in its data processing process there is a huge number of possible solutions, ant colony algorithm's self-organization makes it able to find the optimal solution without external intervention. The second is parallelism. Ant colony algorithm can be regarded as a distributed multi-subject system, where each ant searches independently of each other and communicates only through pheromones. Each subject starts an independent solution search at multiple points in the problem space at the same time, which not only increases the reliability of the algorithm, but also makes the algorithm have a strong global search capability. When performing learning path recommendation, the collaborative mechanism of distributed multiple subjects of the ant colony algorithm makes it possible to find an acceptable path quickly. Then there is positive feedback. From the foraging process of real ants, we can easily see that ants can finally find the shortest path, which directly depends on the accumulation of pheromone on the shortest path, and the accumulation of pheromone is a positive feedback process. Its features of mutual collaboration

among subjects and thus obtaining positive feedback make it possible to take similar students' evaluation of the path into consideration when making path recommendations, improve the adaptability and personalization of the recommended results, and make timely adjustments to the personalized learning path of vocal music teaching.

4.2. Personalized Learning Path Based on Ant Colony Algorithm

4.2.1. Overall framework

Learning path refers to the learning routes and resource sequences selected by users based on certain strategies when they are in vocal music teaching activities, recommending learning paths for them that meet their own characteristics, influencing the final results according to the goals, styles, cognitive abilities, knowledge difficulty, etc., and presenting the learning activities that the learners need to complete to the learners after organizing and sequencing them with different teaching strategies. For the study of learning path personalization, it is inevitable to deeply explore the learning process of learning objects, i.e., the structure of resources, the connection of knowledge points, the state of knowledge, etc., which is the result of synthesizing cognitive levels, learning styles, historical records, and learning analysis. An ant colony algorithm is introduced on the music teaching cloud platform to select the optimal learning path and present the results to the learners.

4.2.2. Operational processes

The formula and operation process applied by the ant colony algorithm are fixed, and in the process of application, the pheromone, heuristic information, the probability of selection of learning paths and other related parameters need to be modified appropriately according to the actual problem. In the process of use, the pheromone needs to be updated randomly, while the heuristic information is relatively on the stable side. The solution process of the algorithm is mainly based on the probability transfer formula step by step, and the pheromone and heuristic information determine its probability. In the personalized learning system, pheromone depends on the suitability of the learner's learning tendency and the characteristics of the learning object, while heuristic information depends on the strength of the connection between knowledge points. The ACO algorithm calculates the transfer probability at any time according to the overall situation, and the learning path recommendation process based on the ACO algorithm is shown in Fig. 5.

According to the processing of the above ACO algorithm, the first step needs to calculate the pheromone, in the personalized learning path of the music teaching cloud platform, the pheromone Q_{ij} is the learner's rating of the section of the path, and this section of the pheromone will be updated when the user u completes the section of the roadway $\left(S_i, S_j\right)$, the The update formula is:

$$Q_{ij}(t+1) = (1-G) \times Q_{ij}(t) + \Delta Q_{ij}^{u} \tag{7}$$

where G represents the volatilization factor of the pheromone and the prescribed range takes the value range $[0,1.0]$; at moment t, the pheromone on learning path $\left(S_i, S_j\right)$ is $Q_{ij}(t)$; and learner u's rating of learning path $\left(S_i, S_j\right)$ is $\Delta \mathrm{Q}_{ij}^{u}$.

The second step calculates the heuristic information, which is the degree of matching between the learner and the learning object, and mainly contains 2 matching degree variables d_{k-l} and d_{s-c}: the cognitive level of the student k and the difficulty of the learning object l; and the range of values of the learning styles s and the types of the learning resources $c; k, l, s, c$ are all $[0,1.0]$.

$$d_{k-l} = 1 - |k - l| \tag{8}$$

$$d_{s-c} = 1 - |s - c| \tag{9}$$

The third step calculates the probability of learning path selection, when the user completes the learning of S_i knowledge point, the probability of the next knowledge point S_j is:

$$P_{ij} = \frac{\left(d_{k-l}\right)^{\mathrm{m}} \times \left(d_{s-c}\right)^{n} \times \left(p_{ij}(t)\right)^{w}}{\sum \left(d_{k-l}\right)^{m} \times \left(d_{s-c}\right)^{n} \times \left(p_{ij}(t)\right)^{w}}, \left(S_i, S_j \in S(i)\right) \tag{10}$$

m, n is the parameter of the influence of d_{k-1} and d_{s-c} on the probability of path selection, w is a constant, and $S(i)$ is the set of knowledge points on the path containing S_i. When the user has mastered the knowledge point S_i, the probability of proceeding to the next knowledge point as $S(i)$ is:

$$P_{i+1} = \sum_{S(i)} P_{ij} \tag{11}$$

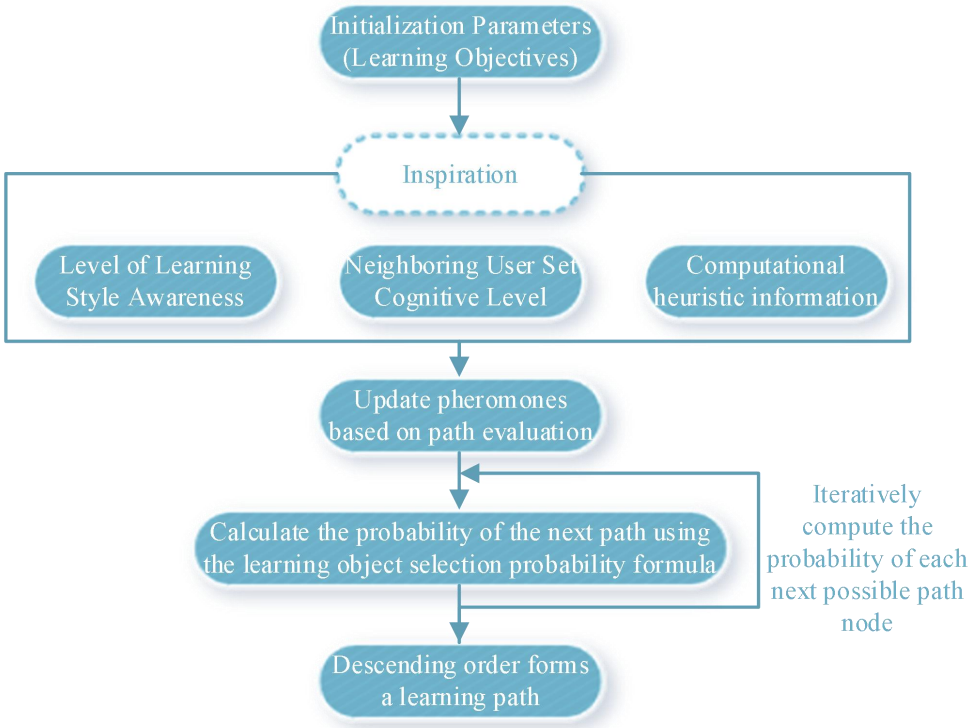


Figure 5. The principle of personalized learning paths based on ant colony algorithm.

Learning path recommendation process:

(1) After the learner goes into the learning system, obtain the learning content objectives, construct the knowledge point relationship graph T (a, z), and find out the possible learning paths for the learner.

(2) Initialize the path influence parameters m, n, volatility factor G, and pheromone Q_{ij}; obtain the current students' learning style s and cognitive level k.

(3) Determine the set of similar students U_{sim} and obtain the learning paths of the set of students U_{sim} under the content.

(4) Adjust the pheromone on the current learning path according to the evaluation of the resource S_i that the students are currently learning according to the formula.

(5) Calculate the probability of the next knowledge point S_j that a student may be studying, based on the history of resources that the student is studying, using the formula analysis.

(6) Calculate the probability that each resource on the path is selected according to the order of learning resources on the learning path, and finally calculate the selection probability of the path according to the formula.

(7) Calculate the probability of all possible path choices, and select the five knowledge points with the highest probability as the next knowledge points on the learning path to be recommended to learners.

4.3. Results and analysis

The online learning path planning method proposed in this paper aims to plan efficient learning paths for users that are suitable for their learning styles and in line with the actual learning process, helping

them to effectively and quickly master the knowledge of vocal music teaching. This subsection verifies the feasibility and effectiveness of the personalized learning path based on ACO algorithm proposed in this paper from two perspectives by comparing it with two algorithms, namely Genetic Algorithm (GA) and Simulated Annealing Algorithm (SA), in which the data are obtained from the music teaching cloud platform. The details are as follows:

4.3.1 Feasibility

In order to verify the feasibility of this paper's method, this paper compares the results derived from this paper's algorithm with those derived from the GA and SA methods in terms of both user experience and the degree of matching between the paths and the users' learning styles, and the experimental results of the different methods for the four types of users are shown in Fig. 6, in which (a) ~ (d) Users 1~4. This experiment has been conducted on all the four experimental users, and it can be clearly seen that that all the three methods continuously arrive at learning paths with higher user experience as the number of iterations increases, and gradually stabilize after reaching a certain height. It can be seen that for users with different learning styles, all three methods are able to plan online learning paths for users. However, from the experimental results of all four users, it can be seen that through 200 iterations, the results iterated by this paper's method are better than the other two, that is, this paper's method is able to obtain a higher degree of user experience. Secondly, the learning paths derived from the three methods were compared to assess the degree of matching between the learning paths and the user's learning style, taking User 2 as an example. The similarity between the learning path and the user's learning style of user 2 is shown in Table 4, and the similarity between the learning path and the user's learning style is the average of the similarity of 10 nodes, which shows that the learning path planned by this paper's method is more in line with the user's learning style of user 2, and the result of which is 0.7436.

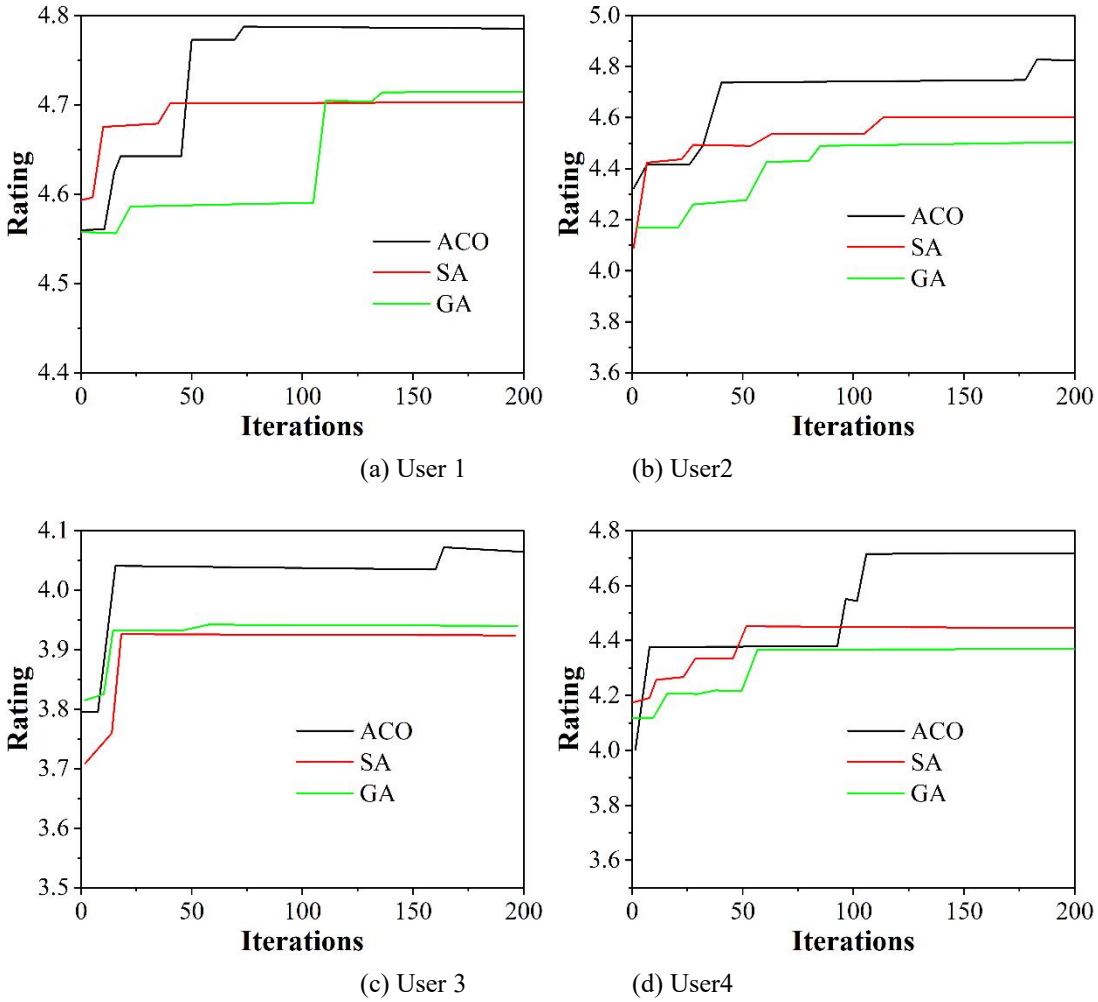


Figure 6. Experimental results of different methods for four types of users.

Table 4. The similarity between the learning path and the learning style of User 2.

Method	Learning Path										Matching degree
	1	2	3	4	5	6	7	8	9	10	
ACO	0.742	0.742	0.793	0.815	0.811	0.845	0.673	0.707	0.722	0.586	0.7436
GA	0.773	0.617	0.662	0.535	0.711	0.711	0.746	0.815	0.793	0.609	0.6972
SA	0.693	0.605	0.724	0.802	0.744	0.715	0.657	0.654	0.535	0.622	0.6751

4.3.2. Effectiveness

In order to further verify the effectiveness of the Ant Colony Algorithm (ACO) in solving the personalized learning path of the music teaching cloud platform, this paper changes the values of the three variables of the initial population size, the number of nodes, and the number of candidate learning resources, respectively, and compares the results of the experiment with those derived from the GA and SA algorithms. For the objectivity of the experiment, this experiment still uses four users as test subjects while testing the effectiveness of the method. All the experimental results were obtained after 200 iterations.

(1) Changing the initial population size

This experiment is based on 1513 candidate learning materials, while the initial population size, i.e., the number of ants, gradually increases from 0 to 200 in units of 20. The experimental results of the three methods for the four users are shown in Figure 7. With the increasing number of initial populations, the user experience obtained from the optimal learning paths iterated by the three methods fluctuated. However, in the test results for the four experimental users, this paper's method yields better learning paths, i.e., higher user experience (ratings), than the Genetic Algorithm (GA) and Simulated Annealing Algorithm (SA) in most cases.

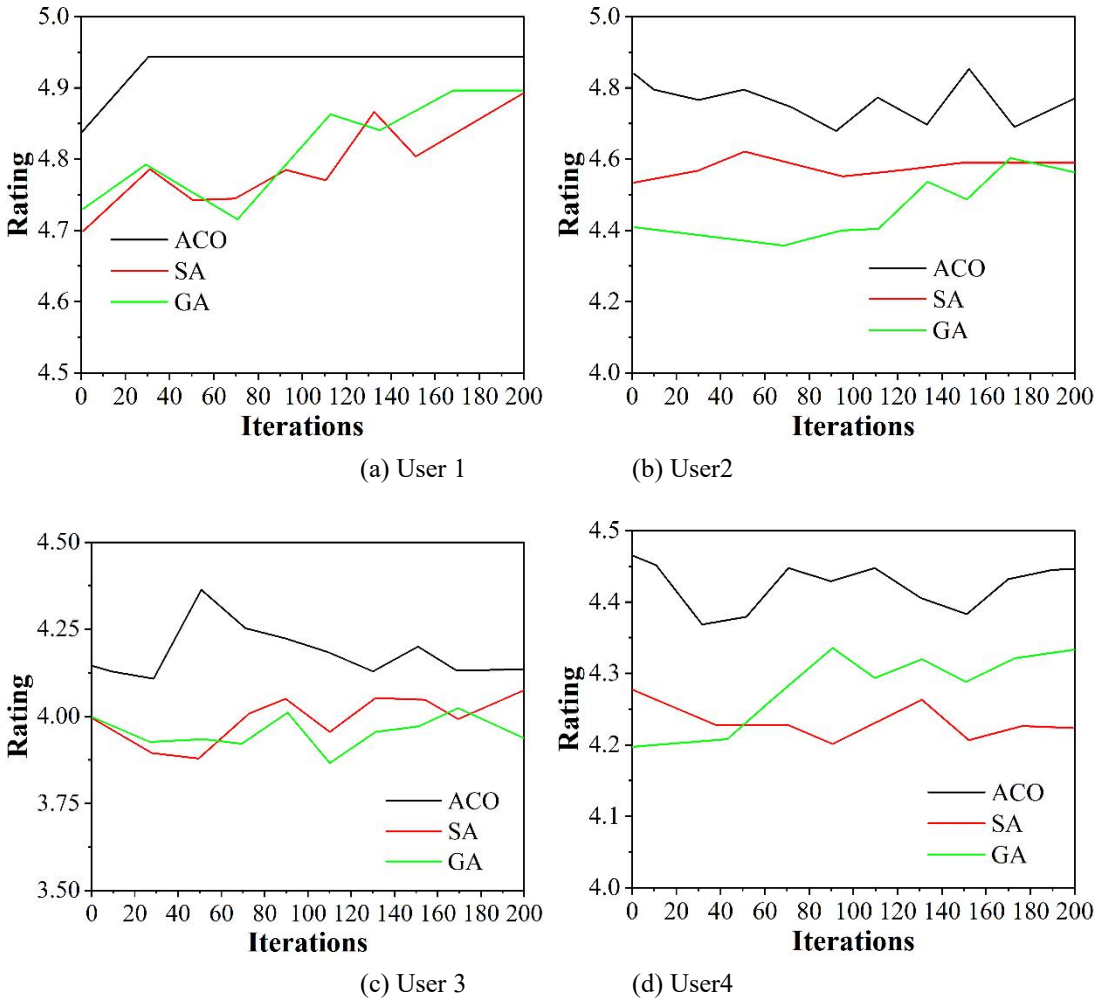


Figure 7. Experimental results of three methods for four types of users.

(2) Changing the number of nodes

This experiment is also based on 1513 candidate learning materials, set the initial population number as 10, the number of nodes increases gradually from 0 to 200 in units of 20, and the experimental results of the four users are shown in Fig. 8. With the increase of the number of nodes, the user experience obtained from the optimal learning paths iterated by the three methods decreases, however, the results of the method proposed in this paper are better than the GA and SA methods in most cases. That is to say, the learning paths planned for users by this paper's method in different numbers of nodes can lead to greater user experience.

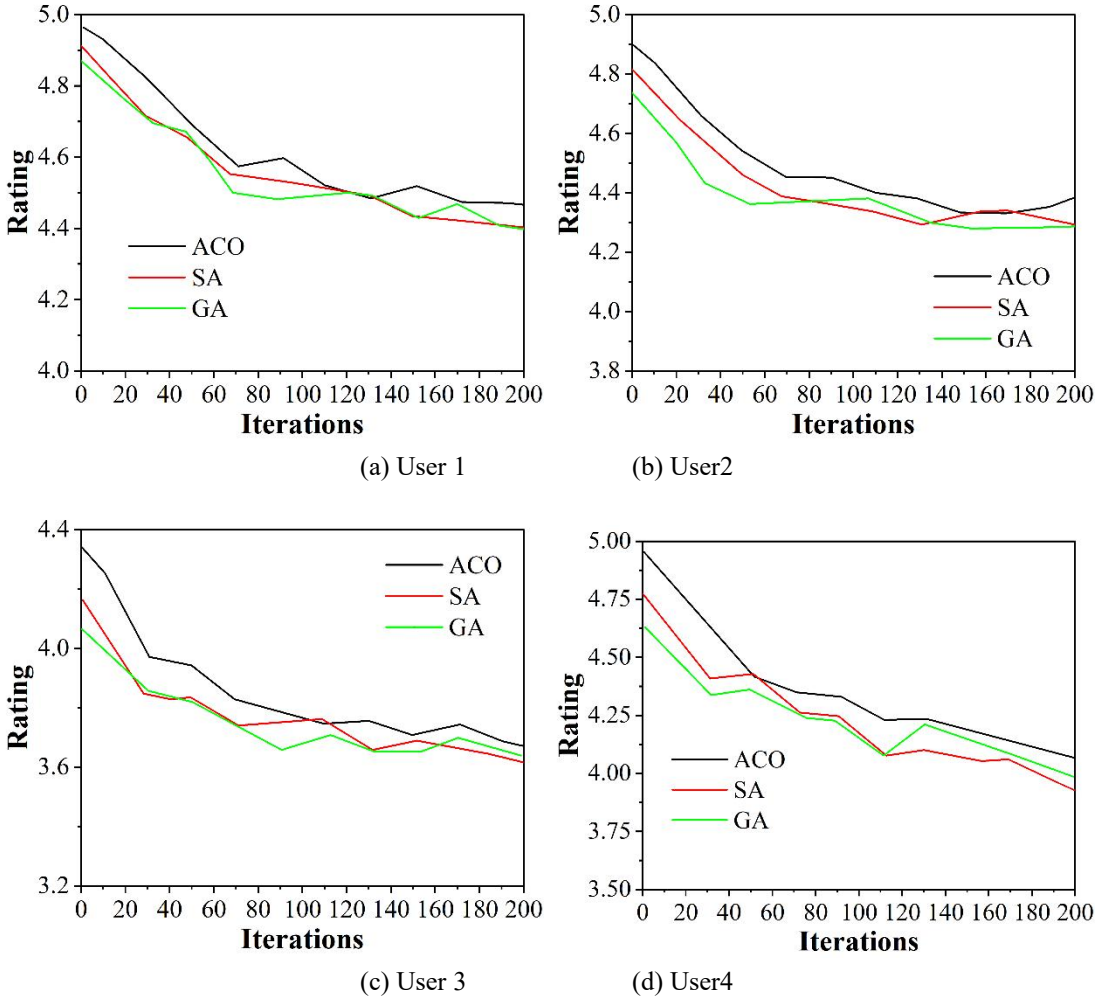
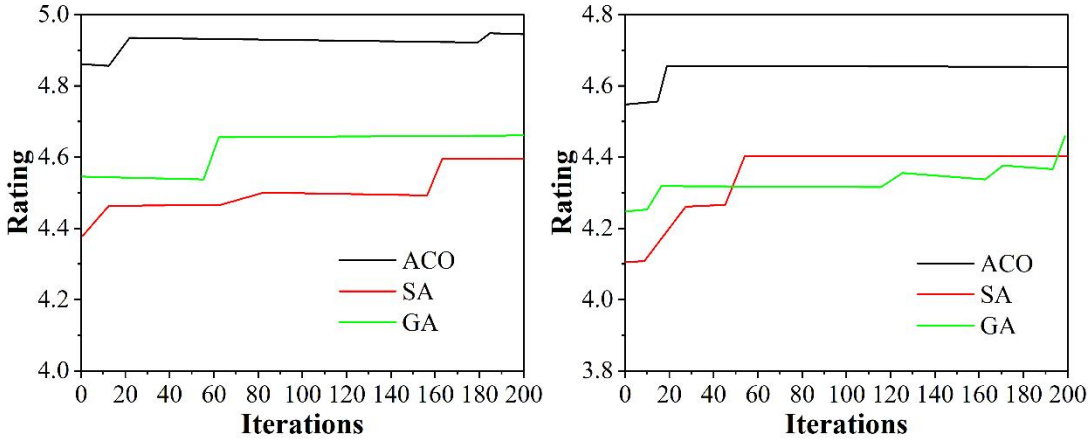


Figure 8. The experimental results of four types of users.

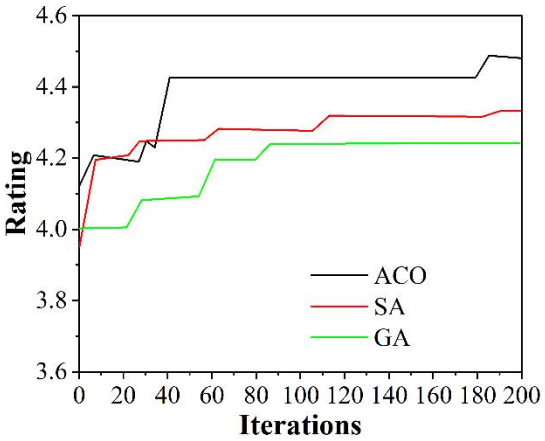
(3) Changing the number of candidate learning resources

This experiment is conducted based on 892 candidate learning materials in the music domain, 621 candidate learning materials in the vocal domain and all 1513 candidate learning materials respectively. The initial population number is set to 10, the number of nodes is 10, and the optimal learning path is planned for user 2 through 1-200 iterations, and the optimal learning path analysis is shown in Fig. 9, where (a) ~ (c) are 892 candidate learning resources, 621 candidate learning resources, and 1513 candidate learning resources, respectively. Even in the case of different numbers of candidate learning resources, the ACO system algorithm based on learning styles proposed in this paper is able to effectively construct learning paths for users that match their learning styles and actual learning sequences after 200 iterations, and is able to obtain a higher user experience compared to the GA and ACO algorithms. In order to further verify that the learning paths derived from this paper are more suitable for the user's learning style than the GA and ACO algorithms, this paper adopts a similarity calculation method based on Euclid to calculate the similarity between the optimal learning paths derived from the three methods and the user's learning style in the case of different candidate resources. Taking user 2 as an example, the matching degree results are shown in Table 5. The online learning path obtained by this paper's method has a higher degree of matching with the user's learning style. It can be seen that this paper's algorithm in

solving the online learning path planning problem, compared with the genetic algorithm (GA) and simulated annealing algorithm (SA), can give users with different learning styles a greater degree of user experience, and the optimal personalized learning path is not only more suitable for the user's learning style, but also in line with the actual learning sequence, so it can help users efficiently master the music theory, which This can help users to master music theory knowledge efficiently, which is helpful and instructive for improving the overall quality and teaching level of vocal music learning in colleges and universities.



(a) 892 candidate learning resources (b) 621candidate learning resources



(c) 1513candidate learning resources

Figure 9. Analysis of the Optimal Learning Path.

Table 5. Matching degree result.

Quantity	Method	Learning Path										Matching degree
		1	2	3	4	5	6	7	8	9	10	
621	ACO	0.852	0.862	0.796	0.895	0.878	0.884	0.797	0.752	0.887	0.769	0.8372
	GA	0.808	0.848	0.783	0.866	0.855	0.825	0.688	0.745	0.773	0.757	0.7948
	SA	0.807	0.843	0.762	0.82	0.728	0.804	0.682	0.71	0.689	0.756	0.7601
892	ACO	0.832	0.849	0.721	0.82	0.827	0.82	0.738	0.678	0.87	0.698	0.7853
	GA	0.807	0.829	0.781	0.83	0.797	0.817	0.673	0.727	0.746	0.738	0.7745
	SA	0.754	0.802	0.712	0.79	0.715	0.775	0.614	0.639	0.656	0.756	0.7213

5. Conclusion

With the development of the Internet and cloud computing, there is an abundance of resources on the network, which facilitates learners' access to knowledge, and at the same time there are certain problems, such as easy to get lost in the process of music learning, duplicated construction of resources, and low

utilization rate. In view of the above problems, from the three dimensions of function module, database and interface, to the mobile-oriented music teaching cloud platform, and introduce ant colony algorithm on the basis of this platform to achieve the effect of personalized learning path planning. Finally, combined with the corresponding research data, the research scheme of this paper is explored and analyzed. The conclusions are as follows:

(1) The maximum number of users (4,000~5,000), overall response time (<400ms), JAVA load memory (<600M), and CPU usage load (<10M) of the music teaching cloud platform all meet the requirements of the performance test standards, and are able to meet the needs of vocal music teaching in colleges and universities, and the mean values of the other 8 platform satisfaction test questions items are all maintained in the range of 4~5, which indicates that the students music teaching cloud platform maintains a satisfactory attitude.

(2) In the personalized learning path planning problem of vocal music teaching, the iterative results of this paper's method (ACO) are better than the genetic algorithm and simulated annealing algorithm (SA), and the output result is 0.7436, which indicates that this paper's algorithm is superior in the personalized learning path of vocal music teaching.

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