International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-18

https://doi.org/10.70917/ijcisim-2025-0287
Article

Design of a personalized music theory knowledge pushing system using artificial bee colony algorithm in music education

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Abstract: The application mode of “intelligent algorithm + education industry” has a broad application prospect nowadays. The article explores the design of intelligent algorithms in personalized music theory knowledge delivery system from the perspective of intelligent music education. Aiming at the problems of low recommendation efficiency and large computation in traditional collaborative filtering algorithms, a K-means clustering collaborative recommendation algorithm based on improved artificial bee colony algorithm is proposed. The artificial bee colony algorithm is improved through initialization and fitness function, combined with K-means iteration to get more accurate clustering effect, and then merged into collaborative filtering algorithm to complete the music theory knowledge recommendation. The experimental analysis proves that the algorithm reduces the average absolute error value, shortens the running time, and improves the recommendation quality and recommendation efficiency. The system is used in S-school for practical teaching. Students' scores increased from 61.52 to 69.96. T-test results show that there is a significant difference in music scores with a significant probability of $P=0.019$ ($0.01<P<0.05$). It shows that the music theory knowledge pushing system based on IABC's K-means clustering collaborative filtering algorithm can make music education more visualized and intelligent, and have a far-reaching impact on the music teaching career.

Keywords: Artificial bee colony algorithm; K-means; Collaborative filtering algorithm; Music theory knowledge pushing

1. Introduction

As an important part of quality education, music education plays an indispensable role in the overall development of students. It can not only cultivate students' musical literacy and enhance their aesthetic ability, but also stimulate their imagination and creativity, and promote their emotional expression and healthy physical and mental development [1-2]. Through learning music, students can learn to appreciate beauty, feel beauty, and then create beauty, which has far-reaching significance in shaping students' sound personality and enriching the spiritual world [3-4].

However, the traditional music teaching mode has many problems. In traditional teaching, a “one-size-fits-all” approach is usually adopted, with the teacher as the center, and lessons are conducted in accordance with a unified syllabus and schedule [5-6]. Based on the traditional “one-size-fits-all” teaching method, Thien and Chan [7] examined the applicability of the Western theory of distributed leadership and the teacher academic optimism scale, and verified the effectiveness of the new method, which played an important role in improving teaching effectiveness and parental trust, etc. Yin [8] examines the challenges facing music education in this century and the need for reform, describes the limitations of traditional teaching methods, and proposes innovative solutions such as digital music workstations and online platforms to improve teaching efficiency and student engagement. Economidou [9] analyzes the importance of implementing differentiated instruction in music teaching and learning, emphasizing its role in promoting inclusiveness as well as in meeting students' diversity needs, ensuring that each student's potential is recognized and nurtured. There are significant differences between students in terms of their musical talent, interests, and learning abilities, and this approach ignores individual differences and fails to meet the learning needs of each student [10-12].

In addition, traditional teaching resources are relatively scarce and teaching methods are single, mainly relying on textbooks and teachers' explanations, which lacks vividness and interest [13-14]. Fu [15] emphasized that the traditional education model can not meet the current social demand for high-quality talents, discussed the positive significance of the reform and innovation of music teaching in colleges and universities at present and put forward specific reform and innovation strategies for reference. Zhai [16] studied the reform of piano music education teaching mode based on literature review and questionnaire survey, and found that the students who adopt the new teaching mode have more significant improvement in accuracy and obvious progress. Classroom teaching is often limited to the classroom space, students lack the opportunity to practice and experience, and it is difficult to truly feel the charm of music. Moreover, the traditional teaching evaluation method is also relatively single, mainly based on test scores as the standard for evaluating students' learning outcomes, which cannot comprehensively and objectively reflect the students' music learning process and the improvement of comprehensive quality [17-19].

With the rapid development of artificial intelligence (AI) technology, the application of AI-based teaching personalized recommendation system in the field of education provides a new way of thinking to solve the problems of traditional music teaching [20-21]. As an important part of AI, the artificial bee colony algorithm is an optimization method proposed by imitating the behavior of bees, which is a specific application of the idea of cluster intelligence [22-24], and is characterized by the fact that it does not need to understand the special information of the problem, but only needs to compare the advantages and disadvantages of the problem, and through the local optimal-seeking behaviors of the individual worker bees, the global optimum is finally made to emerge in the group, and it has a relatively fast convergence speed [25-28]. Xue et al. [29] introduced the artificial bee colony (ABC) algorithm and proposed the adaptive ABC algorithm based on global optimal candidate solutions (SABC-GB) for global optimization, and experimentally verified the feasibility of SABC-GB in practical applications, and it outperforms other algorithms in solving complex optimization problems. Sarumaha et al. [30] introduced an ABC algorithm for the vehicle path planning in the capacity problem, ABC algorithm was introduced and in order to determine the effectiveness of the algorithm in optimizing vehicle paths with capacity constraints, eight different benchmark problems will be completed and compared with other algorithms and the excellence of the algorithm was verified. Jacob and Darney [31] illustrated the impact of ABC algorithm and its evaluation characteristics on the communication in wireless networks, emphasizing that the algorithm effectively improves the throughput of the wireless network, which not only reduces the interference but also improves the performance of the network. Ghambari and Rahati [32] described the effective application of ABC algorithm in optimization problems and its lack of convergence speed, in order to overcome this shortcoming an improved ABC algorithm IABC is proposed, the improved algorithm has a superior performance in terms of convergence speed and robustness.

In music education, designing a personalized music theory knowledge pushing system based on the artificial bee colony algorithm can provide students with personalized music theory knowledge and teaching guidance according to their learning situations and characteristics, and satisfy their diverse learning needs [33-34]. In this regard, Venkatesh et al. [35] proposed a system for personalized recommendation of e-learning based on ABC optimization, which is based on K-mean clustering to build a recommendation structure and uses ABC to determine their optimal learning path.

The study designed IABC-based K-means clustering collaborative filtering algorithm for use in music theory knowledge push system to realize accurate recommendation of music theory knowledge content. The artificial bee colony algorithm is improved and processed by both initialization and fitness function, which can not only accelerate the convergence speed, but also find the global optimum. The IABC algorithm is combined with K-means clustering algorithm to cluster the data and solve the shortcomings of K-means clustering algorithm which is greatly influenced by the initial point and easily falls into the local optimum. The IABC-based K-means clustering collaborative recommendation algorithm recommends users and ensures the superiority in recommendation performance and recommendation accuracy.

2. Research on music theory knowledge pushing system based on artificial bee colony algorithm

2.1. Personalized music theory knowledge push system process

The essence of personalized music theory knowledge push is a system with the help of machine learning algorithms, which is able to according to the user's prior input of information request to the system, which includes the user's personalized information profile, the user's personalized information topics, etc., the system will be able to take the initiative to search for these music theory information in the music theory knowledge base with the user's needs. And after screening, categorizing and sorting, it will be delivered to the user at the right time and in the right way according to the specific requirements of each user. The push process of this system is shown in Fig. 1.

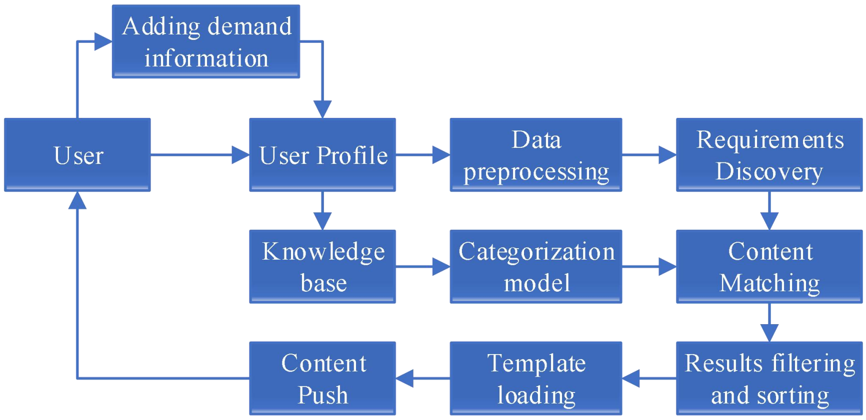


Figure 1. Personalized knowledge push system process.

2.2. K-means clustering algorithm based on improved bee colony algorithm

For the content pushing part of the personalized music theory knowledge pushing system process, a K-means clustering algorithm based on the improved bee colony algorithm is designed in this chapter.

2.2.1. K-means clustering algorithm

K-Means algorithm is a clustering algorithm based on division. The algorithm has been widely used in various fields for its advantages of simplicity, speed and higher clustering efficiency. The basic idea of the K-Means algorithm is to find the K cluster centers of the sample set to be clustered and divide the sample set into K class clusters according to these K centers, such that the sum of squares of intraclass errors (i.e., the sum of the squares of the distances of each point therein from the cluster centers of the class clusters in which it is embedded) of the sample set is minimized [36]. Its formalization is expressed as:

$$U = \bigcup_{j=1}^{k} C_j \tag{1}$$

$$C_j (j = 1, 2, \cdots, k) \neq \varnothing \text{ and } C_i \cap C_j (i, j = 1, 2, \cdots, k; i \neq j) = \varnothing \tag{2}$$

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} d\left(x_i, C_j\right) \tag{3}$$

where $U = \left\{C_1, C_2, \cdots, C_k\right\}$ represents the set of samples to be clustered, C_j represents a certain class of clusters, $j = \{1, 2, \cdots, k\}$, and $d\left(x_i, C_j\right)$ represents the sample The distance between the point x_i and the center of the cluster C_j to which it belongs. J is a measure criterion function of the clustering result, denoting the sum of the squared distances of each point from the center point of the cluster of the class it belongs to. From equation (3), the smaller J is, the better the clustering result is.

2.2.2. Artificial Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm is a new type of swarm intelligent optimization algorithm proposed to solve multivariate and multi-objective numerical optimization problems. Based on the self-organization and division of labor of the swarm, the algorithm achieves information sharing and collaboration among individuals in the swarm, and then simulates the foraging behavior of the swarm. It is characterized by a simple comparison of the advantages and disadvantages of the feasible solutions of the problem, and does not need to understand the special information about the problem, so as to find the global optimal solution of the problem through the local optimization behavior of individual bees, and the convergence speed is faster [37].

The flow of the artificial bee colony algorithm is shown below:

(1) Initialization of honey source phase

The ABC algorithm randomly generates SN initial solutions ($x_1, x_2, \cdots, x_{SN}$) to represent the nectar source, and accordingly, the number of both employed bees and observed bees are initialized to SN. The stochastic initialization formula is shown in equation (4):

$$x_{ij} = x_{\min j} + rand(0,1)\left(x_{\max j} - x_{\min j}\right) \tag{4}$$

where each solution $x_i = \left\{x_{i1}, x_{i2}, \cdots, x_{iD}\right\}$ is a D-dimensional vector of the problem to be optimized, and $i = \{1, 2, \cdots, SN\}, D$ represents the number of parameters of the function to be optimized. x_{ij} represents the jth dimensional component of the solution vector x_i , and $j = \{1, 2, \cdots, D\}, x_{\max j}, x_{\min j}$ represent upper and lower bounds on the values of the jth dimensional components of the solution vector x_i, respectively.

(2) Hired bee stage

Hired bees will perform local search and compare the fitness of the old and new honey sources based on the information of the corresponding honey sources, and use the greedy algorithm to select the better honey sources and abandon the bad ones. The formula for local search is shown below:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{5}$$

where $v_i = \left\{v_{i1}, v_{i2}, \cdots, v_{iD}\right\}$ represents the new nectar sources searched, $x_i = \left\{x_{i1}, x_{i2}, \cdots, x_{iD}\right\}$ represents the old nectar sources, v_{ij}, x_{ij} represent the jth dimensional components of v_i and x_i , respectively, $i = \{1, 2, \cdots, SN\}, j = \{1, 2, \cdots, D\}$. φ_{ij} is a random real number and $\varphi_{ij} \in (-1,1), k$ is a random integer not equal to i and $k = \{1, 2, \cdots, SN\}$.

(3) Observation bee stage

Observer bees will select in some way (e.g., roulette, etc.) based on the nectar source adaptation information fed back by hired bees, and their selection expression is as follows:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{6}$$

where fit_i is the fitness value of the solution vector x_i, $i = \{1, 2, \cdots, SN\}$.

When an observation bee selects a nectar source it will continue to search and select the locally superior nectar source according to equation (5). At the same time, if the hired bees and the observer bees cannot improve the quality of the corresponding nectar source after $limit$ times, the nectar source will be abandoned and its corresponding bees will be changed to scout bees.

(4) Scout bee stage

Scout bees will randomly search for new nectar sources globally. Its search formula is shown in equation (4).

From the above analysis, it can be seen that the ABC algorithm requires three user-defined parameters: the number of honey sources SN , the abandonment threshold $limit$, and the maximum number of iterations $maxCycle$ (i.e., the termination condition of the algorithm), respectively. At the same time this algorithm contains a total of four selection processes: the hired bees and the observation bees perform a neighborhood search based on their own information to select the local optimum (local selection). The process in which observation bees combine the fitness value of the nectar source to select the nectar source (global selection). The process by which all bees compare the advantages and disadvantages of the old and new nectar sources and select the better nectar source (greedy selection). The process by which scout bees randomly select a new nectar source (random selection). These four selection processes ensure that the algorithm has a better control of its global and local search capabilities and can achieve a better balance, which greatly improves the performance of the algorithm.

2.2.3. K-means clustering algorithm based on IABC algorithm

K-means clustering algorithm is sensitive to noise and outliers. The selection of initial points has a great influence on the clustering results, and it is easy to produce local optimal results. In this paper, for the shortcomings of K-means clustering algorithm, artificial bee colony algorithm is introduced, which can make up for its shortcomings based on its own strong characteristics of exploring the global optimal solution, and the two algorithms are fused and improved in this section [38].

(1) Initialization based on reverse learning

Artificial bee colony algorithm in the user behavior samples in the optimization process, the initial solution is the starting point of the iteration, and the initial solution in the distribution of the candidate solution space will directly affect the efficiency of the algorithm solution. However, the initial solution generated by the artificial bee colony algorithm does not guarantee that the initial solution has a more uniform distribution in the alternative solution space, and the initialization method of reverse learning can make the initial solution uniformly distributed in the candidate solution space, increase the diversity of the population, and improve the algorithm's efficiency of the solution and the collection of the solution, so this paper is to carry out the initialization in the way of reverse learning. The realization process is as follows:

1) Randomly generate SN initial solutions within the search range. Using the user's clustering centers as nectar sources, each of which is represented by a sequence of real numbers of length $L_i = k*d$, k is the number of user clusters, and d is the number of dimensions of the user's behavioral data samples, the encoding of the user's clustering centers can be expressed as:

$$Z_i = \left[z_{11}, z_{12}, L, z_{1d}, L, z_{k1}, z_{k2}, L, z_{kd}\right] \tag{7}$$

Each dimension of the randomly generated initial solution for user clustering satisfies $z_{ij} \in \left[a_j, b_j\right](j = 1, 2, Ld)$, a_j and b_j are the upper and lower limits of the corresponding user behavior sample data dimension.

2) Based on the initial solution generated from the user behavior sample data, the inverse solution is generated, and each dimension of the inverse solution is obtained from Eq. (8):

$$v_{ij} = a_j + b_j - z_{ij} \tag{8}$$

3) Finally, SN data with high adaptability are selected as initial user clustering centers from the concatenation of the two solution sets, the initial solution and the inverse solution.

(2) Nonlinear selection strategy

Numerous ABC algorithm applications have chosen the proportional selection operator approach, but such an operator approach leads to potentially two problems, one is that the diversity of user clustering centers will decline during the iteration process, and the other is that it will make the algorithm converge earlier, which is not conducive to the search efficiency of the algorithm.

To address this problem, a nonlinear search strategy is used in this paper for clustering users. Each user clustering center in accordance with the fitness of the order from large to small, then each user clustering center for a serial number number r_i, according to the serial number in accordance with some rules to make the front of the row has more opportunities to be selected, the specified selection rules as in equation (9):

$$p_i = c(1-c)^{\tau_i - 1} \tag{9}$$

Eq. $c \in [0,1]$, for the choice of c is important, c is too large easily make a few user clustering centers with large adaptations to cover the whole user samples, leading to the problem of convergence too early. And a smaller c will behave for random search behavior.

(3) Dynamic adjustment strategy for domain search

In the optimization process of user clustering, the ABC algorithm has different requirements for the global search capability and the local search capability. In the initial stage of optimization, in order to determine the location of the optimal solution as soon as possible, it is often required to search a large range of user sample data. After the location of the optimal solution is determined, a more careful local search is required to improve the speed of convergence. However, in the typical ABC algorithm, the optimization strategy is not adjusted according to the different stages of optimization of user data, resulting in slow convergence of the algorithm. Therefore, in this paper, a linear adjustment strategy is added to the ABC algorithm in the process of user optimization, and the specific formula is shown in (10):

$$v_{ij} = x_{ij} + \alpha r_{ij} \left(x_{ij} - x_{kj} \right) \tag{10}$$

where is the dynamic adjustment parameter of the neighborhood search range, calculated as in equation (11):

$$\alpha = r_{\max} - \frac{cyc\left(r_{\max} - r_{\min}\right)}{MCN} \tag{11}$$

where MCN is the maximum number of user clustering iterations, cyc is the current number of user clustering iterations, and $r_{\max}$, $r_{\min}$ are used to control the size of the ranges in the user data samples.

(4) Global optimal bootstrap detection bee

When a user clustering center remains unchanged after $limit$ iterations, it indicates that it is currently caught in a local optimum. At this time, the leading bee will transform into a detecting bee to make Eq. (4) generate a new solution, but there is a problem with the new solution generated in this way: the newly generated solution, because of its low fitness, will be quickly discarded in the next selection process. The quality of the newly generated solution in the user behavior sample data can be improved by using the global user clustering optimal solution b_{best} generated in each round of iteration, and the new solution is generated as in Eq. (12):

$$x_i^j = x_{\min}^j + \varphi\left(x_{\max}^j - x_{\min}^j\right) + (1-\varphi)\left(x_i^j - x_{best}^j\right) \tag{12}$$

where φ is a uniformly distributed random number between $[0,1]$, and x_{best}^j is the j th dimensional component of the global user clustering optimal solution b_{best} .

(5) Steps of K-means clustering algorithm based on IABC algorithm

The flow of K-means clustering algorithm based on IABC algorithm is shown in Fig. 2.

1) Input data and set parameters. Set the number of leading bees and following bees in the algorithm in user clustering both as SN , and set the number of users to be clustered as k , the maximum number of user clustering iterations as MCN , and the control parameter as $limit$.

2) Calculate the length L of each user clustering center based on the dimension d of the user behavior sample data and the set number of user clusters k , generate the initial SN user clustering centers by the method of reverse learning, and calculate the fitness of each user clustering center according to equation (3).

3) Based on Eq. (10), the leading bee will search the neighborhood of the user clustering center and adopt the "greedy principle" to select the old and new solutions based on the fitness of the old and new solutions.

4) Based on the calculated fitness, the probability of each user clustering center being selected is calculated using Eq. (9), and the following bees are recruited by a non-linear strategy, and the domain search is performed again using Eq. (10).

5) After $limit$ iterations unchanged, and the fitness is not the global optimal user clustering center, the corresponding leading bee becomes a scouting bee, and a new user clustering center is generated using Eq. (12).

(6) For each user clustering center, the user clustering center of each user clustering center is iterated by K-means, and the user type is further updated by the "greedy principle".

7) Record the current optimal user clustering center, the number of iterations is less than MCN , then go to step 3 for the next iteration. Otherwise, the optimal solution is output as the clustering result.

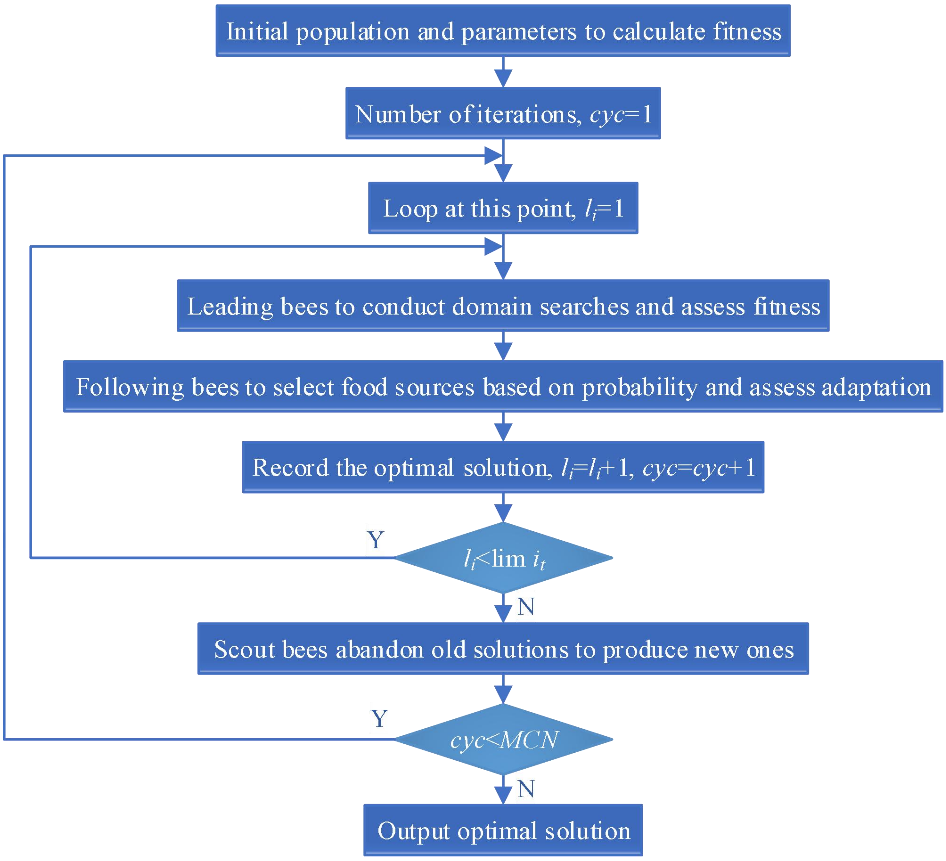


Figure 2. Based on IABC algorithm, the K-means clustering algorithm process.

2.3. IABC-based K-means clustering collaborative filtering algorithm

2.3.1. Algorithm design

Through the combination of ABC algorithm and K-means clustering algorithm, it can make up for the shortcomings of K-means clustering algorithm and improve the clustering effect, initialize the ABC algorithm as well as improve the fitness function to further improve the clustering algorithm, and apply the improved clustering algorithm to collaborative filtering recommendation.

First, the initial data of user-music knowledge is analyzed, and users of the same type are aggregated into a user group, and there is a high degree of similarity between users in such user groups, and the similarity between the target user and other users in the class is calculated separately. It is then possible to recommend music theory knowledge based on the preferences of these similar users, which can greatly reduce the amount of computation compared to searching for similar users among all users.

Secondly, the calculated similarities of the target user's users within the class are sorted from largest to smallest, and the top k users are selected as nearest neighbors. Finally, according to the idea of collaborative filtering, the nearest neighbor users of the target user predict the score of the music theory knowledge that the target user has not paid attention to, and in accordance with the prediction score formula, the first n music theory knowledge with high scores are recommended to the target user, which greatly improves the accuracy of the recommendation.

2.3.2. Algorithmic steps

The steps of K-means clustering collaborative filtering algorithm based on IABC algorithm are as follows:

(1) Input the initial matrix of user-music theory knowledge and process the data initially. The general user-music theory knowledge matrix will have a vacant item, indicating that the user has no history of behavior for this music theory knowledge, this music theory knowledge is not interested, in order to ensure the completeness of the user-music theory knowledge matrix, so it is necessary to supplement this matrix. The main purpose of user browsing behavior is to identify the validity of the user's web browsing behavior, for example, when the server records that the user is browsing a certain music theory

knowledge page, it does not ensure that the user has a clear interest in this music theory knowledge. For example, when the server records that a user is browsing a page of music theory knowledge, it does not ensure that the user has a clear interest in that knowledge. First, if the user stays on the page for too short a period of time, he or she may mistakenly click on the page during browsing, or may immediately find that a certain topic is not suitable for his or her own conditions. Second, the user stays on the page for too long, the user may open the page and leave halfway or forget to close the browser, in fact, the user does not have an interest in the page content of the behavior, both of these data can not be recorded as valid data. Based on the above two situations, the user's browsing behavior, i.e., the user's time spent on the web page of the lexile knowledge will be divided as follows: when no clicking behavior occurs, the user's time spent on the web page is zero, i.e., the user did not browse the web page, which is labeled as 0 under this lexile knowledge. Marked as 0. When the behavior of normal web browsing occurs, the time the user spends browsing the web page is within the set threshold, indicating that the user has some interest in this music theory knowledge, marked as 1. When the behavior of timeout web browsing occurs, the time the user spends browsing the web page is greater than the set threshold, then it is recorded as an invalid behavior, indicating a lack of interest in this content, marked as 0.

(2) Clustering of users in the user-music theory knowledge matrix according to the K-means clustering algorithm of the IABC algorithm. The matrix data in (1) is input and the users are clustered into K classes using the improved clustering algorithm.

(3) Nearest neighbor users are sought in the class where the target user is located. Use the similarity formula to derive the degree of similarity between each user in the class and the target user, and in descending order, take the first n users as the nearest neighbor users of the target user.

(4) Infer the target user's rating of unfollowed music theory knowledge from the nearest neighbor users. Assuming that the set of n nearest neighbors of the target user i is $U=\left\{N_1,N_2,\cdots,N_n\right\}$, the prediction rating formula is expressed as:

$$P_{i,a}=\overline{R}_t+\frac{\Sigma_{j\in U}sim(i,j)\times\left(R_{j,a}-\overline{R}\right)}{\Sigma_{j\in U}\,|\,sim(i,j)\,|} \tag{13}$$

In the formula $sim(i,j)$ is the similarity value between the target user i and the user j in the nearest neighborhood, $\overline{R}_t$ is the mean value of user i's attention to the music theory knowledge that has a history of behaviors, $\overline{R}_j$ is the user j's attention to the music theory knowledge a with history of behavior. knowledge, $R_{j,a}$ is the mean value of user j's attention to music theory knowledge a.

(5) Provide the final recommendation result to the target user via TOP-N recommendation. The results of target users' ratings on unfollowed music theory knowledge derived in (4) are arranged in descending order, and the first few music theory knowledge with high ratings are recommended to the target users.

The flow of K-means clustering collaborative filtering algorithm based on improved artificial bee colony algorithm is shown in Fig. 3.

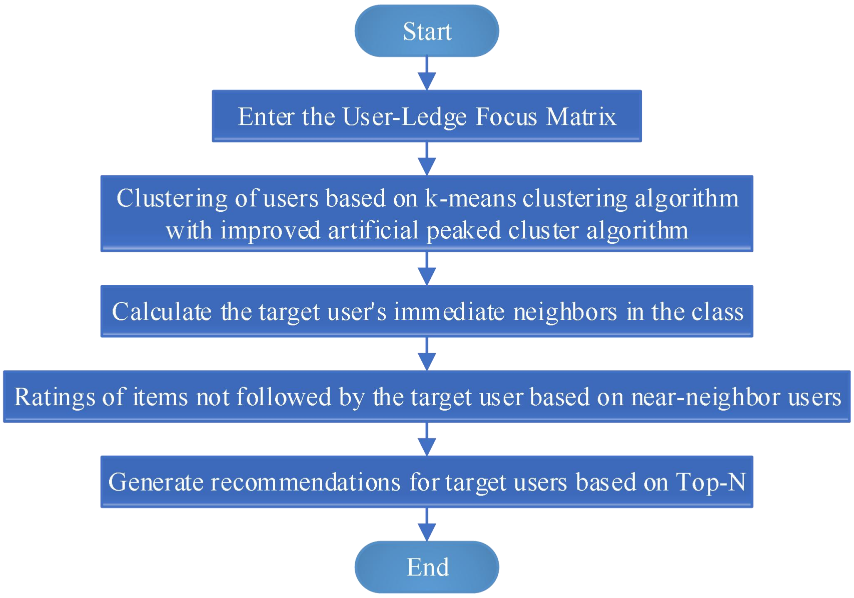


Figure 3. Based on IABC's k-means clustering collaborative filtering algorithm.

3. System testing

This chapter conducts experimental tests on the recommendation model in the personalized music theory knowledge push system, and empirically analyzes the effect of the system's practical application.

3.1. Push Performance Analysis

3.1.1. Data set and parameterization

The dataset is derived from the MusicPlie dataset. It contains 100,532 rating records for general music knowledge, knowledge quizzes from over 900 users. The rating values are distributed within [1,5] and the rating values are integers, with higher scores indicating that the user is less knowledgeable about that music theory knowledge rating. Comparison of the recommendation accuracy rate under different number of clusters, the accuracy rate is highest when k = 8, so this paper also sets the user clustering k to 8, and for some basic parameters of the swarm algorithm, such as MCN and $limit$ are set to 23 and 105, respectively.

3.1.2. Evaluation indicators

In this paper, the mean absolute error MAE is used as an index to evaluate the quality of recommendation. It measures the prediction correctness by calculating the difference between the predicted and real ratings, and the smaller the value of MAE, the higher the recommendation quality of the algorithm. Assuming that the user u predicts the rating table as $P_u=\{P_{u1},P_{u2},\cdots,P_{uN}\}$, the actual rating table is $Q_n=\{Q_{n1},Q_{n2},\cdots,Q_{nV}\}$, where N denotes the number of test sets, the mean absolute error is defined as:

$$MAE=\frac{\sum_{i=1}^{N}\left|P_{ui}-Q_{ui}\right|}{N} \tag{14}$$

3.1.3. Analysis of experimental results

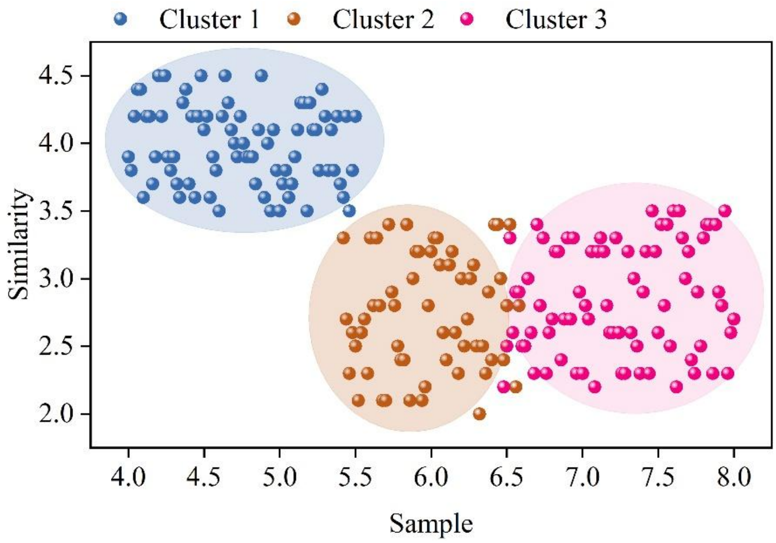
(1) Initial clustering center method effectiveness

In the swarm K-means clustering algorithm, this paper proposes to initialize the clustering center by using a reverse learning-based approach. In this section, the validity of the clustering results and the effectiveness of the recommendation algorithm are verified from 2 aspects respectively.

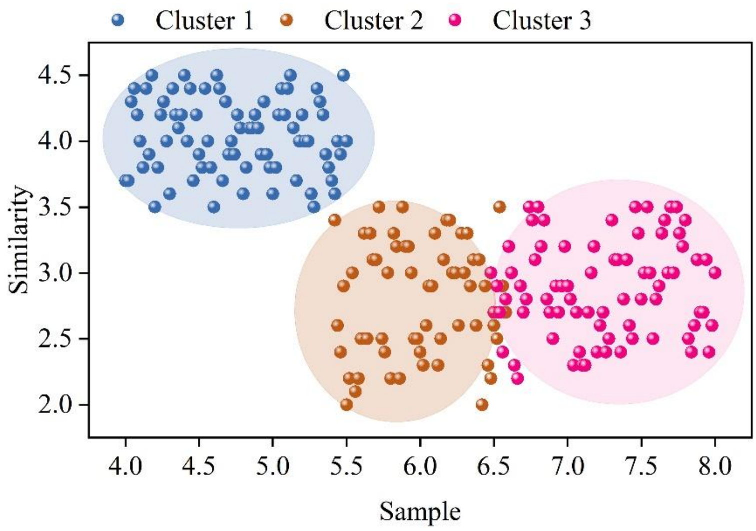
1) Analysis of the effectiveness of clustering results.

The dataset selected for the experiments in this section is the CoCoPops dataset, and three different methods of initializing the clustering center are used to cluster the CoCoPops dataset. These 3 initialized clustering center methods are: maximum distance product method (Method 1), maximum minimum distance method (Method 2) and the reverse learning method (Method 3) proposed in this paper.

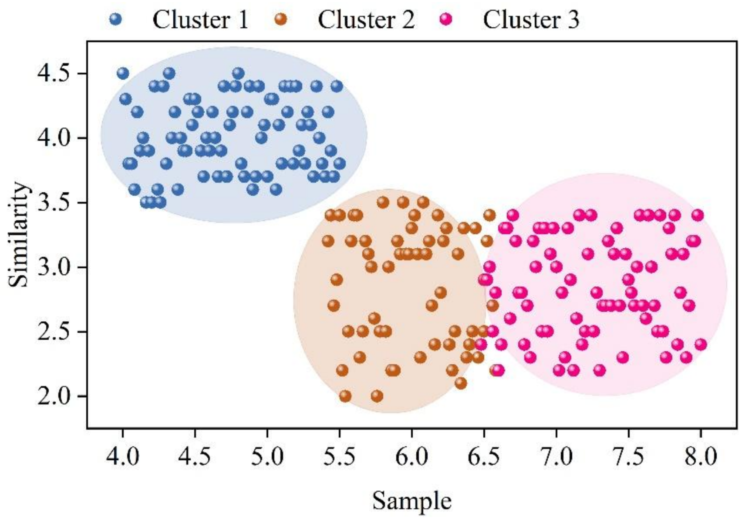
The results of three different initialized clustering center methods for clustering the CoCoPops dataset are shown in Fig. 4, and (a)~(c) represent the results obtained by the maximum distance product method, the maximum minimum distance method, and the reverse learning method, respectively. It can be seen that all three methods have achieved better clustering performance.



(a) Maximum distance product method



(b) Maximum minimum distance method



(c) Reverse learning method

Figure 4. CoCoPops clustering results of three initial clustering center methods.

To further illustrate the effectiveness of the initial clustering center method proposed in this paper, the F_a value is used to evaluate the final clustering performance. F_a is a commonly used external evaluation metric for clustering, and the defined formula is shown in equation (15):

$$F_a = \frac{2P_a R_a}{P_a + R_a} \tag{15}$$

where P_a is the check accuracy rate and R_a is the check completeness rate. $P_a = N_{ab} / N_b$, $R_a = N_{ab} / N_a$, N_{ab} is the number of categorizations a in the clustering b. N_b is the number of all objects in the cluster b. N_a is the number of all objects in the classification a.

F is obtained by weighted average of F-measure for each classification a as shown in equation (16):

$$F = \frac{\sum_a [|a| \times F_a]}{\sum_a |a|} \tag{16}$$

where $|a|$ is the number of all objects in the classification a.

In this paper, F_a and F are used to evaluate three different initialized clustering center methods, and the experimental results are shown in Table 1. It can be seen that the F_2 and F_3 values of the reverse learning method proposed in this paper are better than those of the maximum distance product method and the maximum minimum distance method, respectively, and its F value is 0.4519, which is larger than that of the other 2 methods' F value, which indicates that the reverse learning method proposed in this paper has a better clustering performance.

Table 1. Evaluation comparison.

Method	F_1	F_2	F_3	F
Method 1	0.46	0.4736	0.3714	0.4463
Method 2	0.46	0.4723	0.3854	0.4436
Method 3	0.46	0.4956	0.3966	0.4519

2) Recommendation result effectiveness

The collaborative filtering recommendation algorithm proposed in this paper is based on the swarm K-means clustering model, and the strength of this clustering model directly affects the performance of the recommendation algorithm. In this clustering model, this paper proposes the reverse learning method to initialize the clustering center, in order to illustrate that the method of initializing the clustering center proposed in this paper can improve the performance of the collaborative filtering recommendation algorithm, this section compares the three different methods of initial clustering center for different parameters of the number of nearest neighbors KN for collaborative filtering recommendation, and the obtained recommendation results are shown in Figure 5. It can be seen that no matter whether the average value or the number of wins is used to evaluate the recommendation quality, the average absolute error of the reverse learning method proposed in this paper is 0.779, and the recommendation quality is better than that of the other 2 methods, which also shows that the initial clustering center method proposed in this paper can improve the recommendation quality.

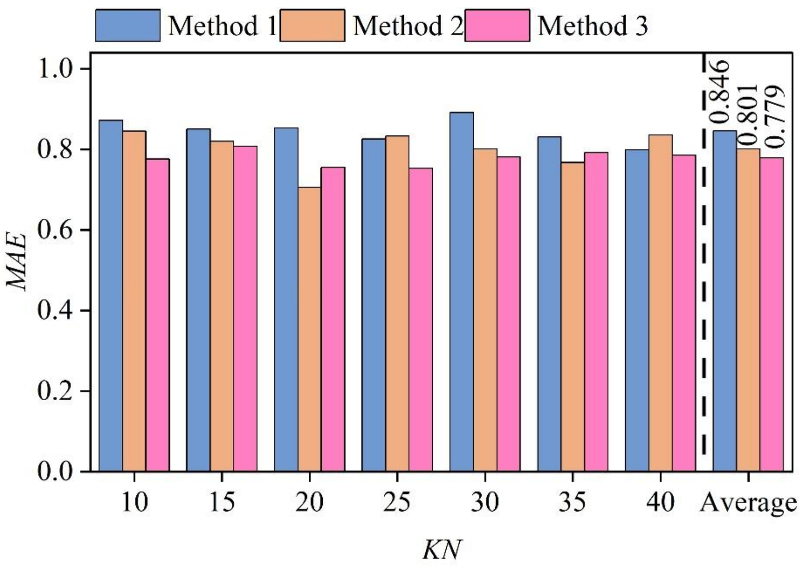


Figure 5. MAE value of the recommendation results of three initial clustering methods.

(2) Effectiveness of the fitness function

The collaborative filtering recommendation algorithm proposed in this paper is based on the swarm K-means clustering model, and the merit of the swarm algorithm's fitness function directly affects the performance of the recommendation algorithm. In the swarm algorithm, this paper proposes a new fitness function, in order to show that the fitness function proposed in the text can improve the performance of the collaborative filtering recommendation algorithm, the new fitness function and the traditional fitness function are compared to discuss the impact of the 2 fitness functions on the recommendation results. The MAE values under different fitness functions are shown in Figure 6. It can be seen that the mean absolute error of the fitness function proposed in this paper is 0.072 smaller than that of the traditional fitness function.Whether the average value or the number of wins is used to evaluate the quality of recommendations, the quality of the recommendations of the fitness function proposed in this paper is better than that of the traditional fitness function, which also shows that the new fitness function proposed in this paper can improve the quality of recommendations.

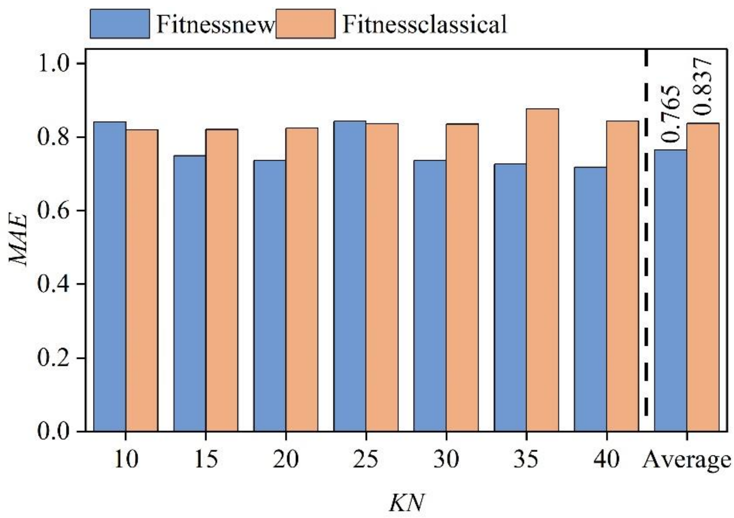


Figure 6. MAE value under different fitness functions.

(3) Analysis of Recommendation Results

To verify that the collaborative filtering recommendation algorithm proposed in this paper has good recommendation quality, This paper integrates the algorithm with the CF algorithm (Model 1), the recommendation algorithm based on the CA-UI Model (Model 2), the user clustering collaborative algorithm based on the CA-UI Model (Model 3), the collaborative filtering recommendation algorithm based on clustering (Model 4), and the collaborative filtering recommendation algorithm based on the bee colony algorithm (Model 5) Make a comparison. First, for the users in the dataset, 500 are selected to constitute the training set, denoted as T500, and 300 are selected to constitute the test set, denoted as T300.Setting different values of KN , the MAE error values of the six recommendation algorithms are shown in Fig. 7. From the figure, it can be seen that the average absolute error of this paper's algorithm is overall lower than that of the other five algorithms, and when $KN = 40$, the MAE is 0.72, which indicates that the algorithm proposed in this paper specifies a better recommendation quality. This is because the collaborative filtering recommendation algorithm based on swarm K-means clustering model firstly clusters the class clusters to which the users to be predicted belong, and then carries out the similar neighbor query, and the combination of clustering and swarming algorithm can make up for the shortcoming that the K-means mean clustering often converges to the local optimal solution. Therefore, this approach not only has the advantage of reducing the lookup space of the collaborative filtering algorithm based on clustering, but also the combination of the swarm algorithm and the clustering algorithm makes the clustering effect more stable and the quality of clustering better.

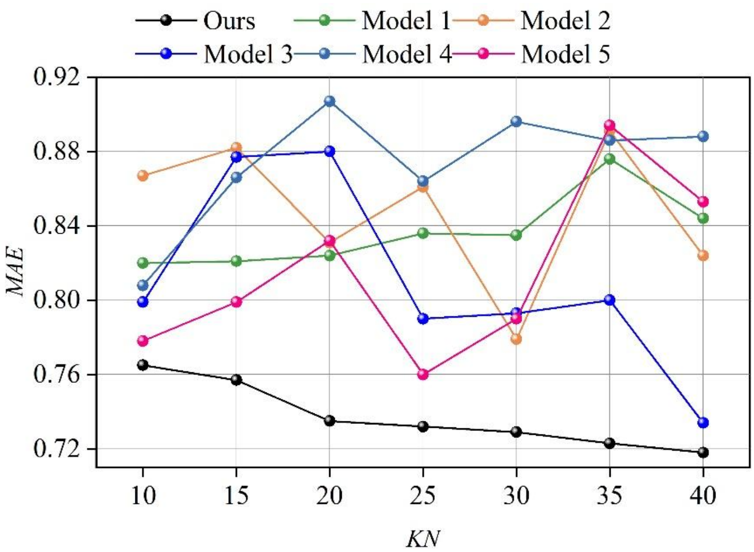


Figure 7. Average absolute error comparison.

3.2. System application effect analysis

In order to find out whether the IABC-based K-means clustering collaborative filtering algorithm for music theory knowledge push system can improve students' music theory knowledge, the study was conducted with the first year (1) class of School S as an experimental class (45 students) and the first year (2) class as a control class (45 students) for the end of semester test. The experimental class underwent a 12-week music instruction guided by the IABC-based K-means clustering collaborative filtering algorithm for music theory knowledge push system, and the control class had been using the traditional teaching method during these 12 weeks. The following students' music achievement test data were processed for statistical analysis using SPSS 23.0 software.

3.2.1. Comparison of music performance pre-test between students in experimental and control classes

A music touch test was administered to all students in both classes before the experiment using the same test paper, and the difference between the pre-tests of music performance of students in the experimental and control classes is shown in Figure 8. Before the start of the teaching experiment, the average music achievement scores of the experimental and control classes were 61.52 and 60.93, respectively, with a difference of only 0.59 points. Secondly, the T-test results of the two groups of data before the experiment yielded a two-tailed Sig. (2-tailed) probability of significance P=0.832 (P>0.05) for the music scores of these two classes. There is no significant difference (P>0.05) between the music achievement of the students in the experimental class and the control class before the beginning of the experiment, which is basically comparable and meets the requirements of the reference and comparison, so that the teaching experiment can be carried out in these two classes.

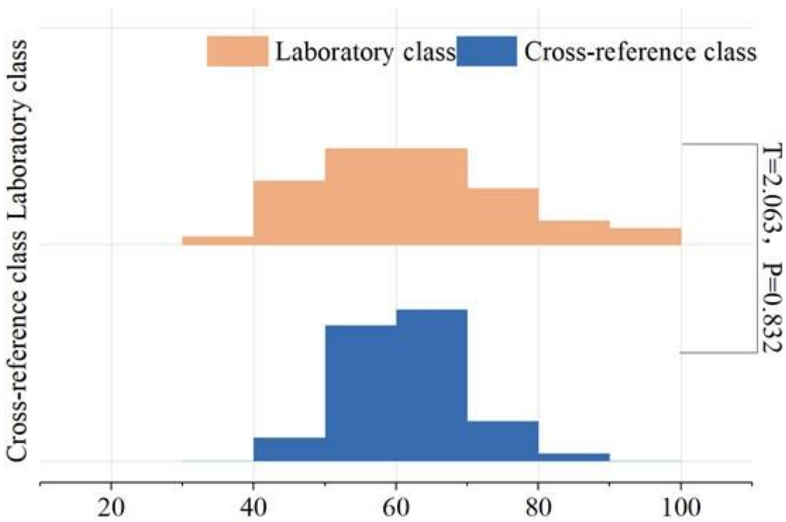


Figure 8. Comparison of the experimental class and the comparison of the music.

3.2.2. Comparison of posttests of music scores of students in experimental and control classes

At the end of the 12-week experimental teaching, all the students in the experimental class and the control class were tested by exam for the experimental post-test of music achievement, and the test results are shown in Fig. 9. After the teaching experiment based on the artificial bee colony algorithm of the music theory knowledge pushing system, the average score of the total music achievement of 45 students in the experimental class is 69.96, which is 7.93 points higher than the control class, and the music level of the experimental class is obviously better than the control class, with a relatively obvious difference. The result of the T-test of the two groups of data after the experiment concluded that the two-tailed Sig. (2-tailed) probability of significance of the music scores of these two classes P=0.041 (0.01<P<0.05). There was a significant difference between the music scores of the students in the experimental and control classes after the teaching experiment (0.01<P<0.05)). It shows that IABC based K-means clustering collaborative filtering algorithm for music theory knowledge pushing system is effective and the system helps to improve students' music performance.

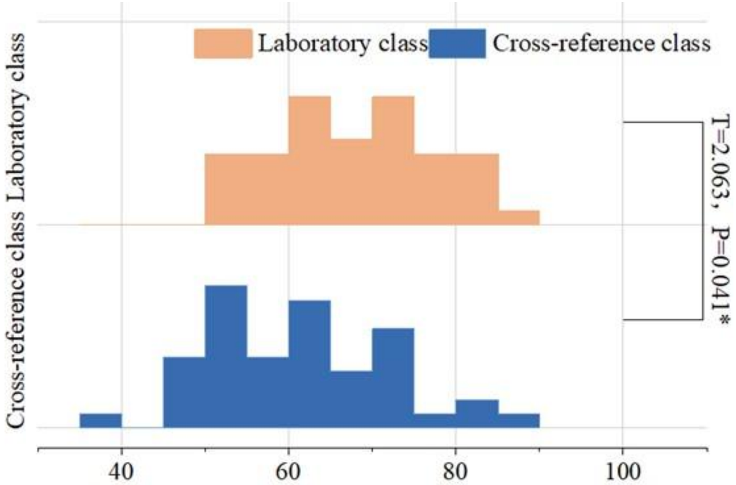


Figure 9. The experimental class was compared with the student music grade.

3.2.3. Comparison of Pre- and Post-tests of Music Achievement of Students in Control Classes

In order to find out whether there is a difference between the pretest and posttest of the music achievement of the students in the control class, the data on the music achievement of the 45 students in the control class before and after the experiment were processed for statistical analysis, and the music achievement of the class was analyzed in a longitudinal comparative manner, and the results are shown in Figure 10. After the teaching experiment, the comparison between the pre-test and post-test data of the music achievement of the students in the control class, the mean score and standard deviation of the pre-test of the control class were 60.93 and 62.03 respectively, and the average score of the music achievement of the students in the control class were improved. The t-test results of the two sets of data from the pre-test and post-test of the control class yielded the following results: the probability of significance of the two-tailed Sig. (2-tailed) for the music achievement of the 45 students in the control class before and after the experiment P=0.762 (P>0.05). The data indicate that there is no significant difference (P>0.05) in the music performance of the students in the control class before and after the experiment and it has not been effectively improved.

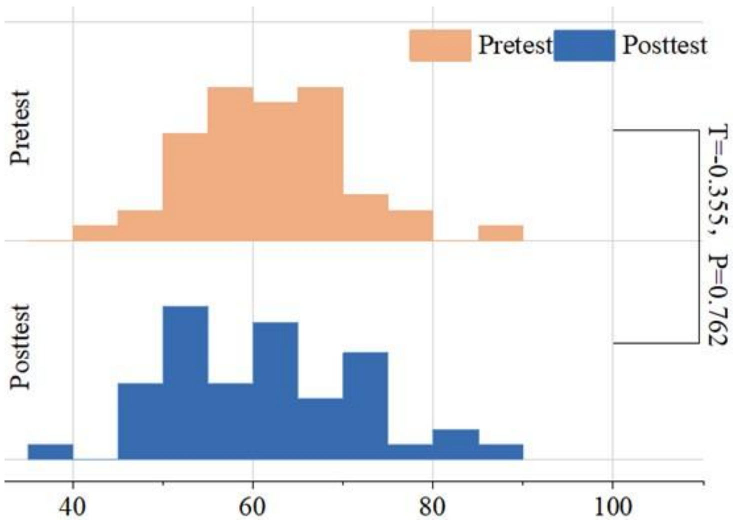


Figure 10. Comparison of students' music scores.

3.2.4. Comparison of Pre- and Post-tests of Music Achievement of Students in Experimental Classes

In order to find out whether there is any difference between the pretest and posttest of music achievement of the students in the experimental class before and after the administration of the teaching, the same longitudinal comparative analysis of the total music test scores of the 45 students in the experimental class before and after the experiment was carried out, and the results are shown in Fig. 11. Comparison between the pre-test and post-test of music achievement of the students in the experimental class, the mean score of the pre-test and post-test of the experimental class were 61.52 and 69.96 respectively, and the mean score of music achievement of the students in the experimental class was greatly improved. The result of the T-test showed that the probability of significance of the two-tailed Sig. (2-tailed) for the music achievement of the 45 students was $P=0.019$ ($0.01<P<0.05$). The data indicate that there is a significant difference in the music achievement of the students in the experimental class before and after the experiment ($0.01<P<0.05$). It indicates that the use of IABC-based K-means clustering collaborative filtering algorithm of music theory knowledge pushing system in the teaching of experimental class is effective in improving students' music performance.

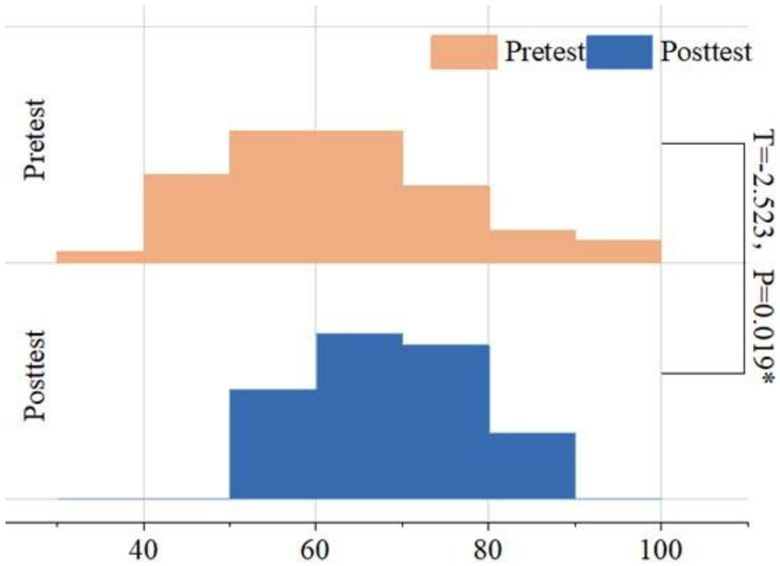


Figure 11. Comparison of students' music scores in experimental classes.

In summary, by comparing and analyzing the results of pre- and post-test data of music performance of students in experimental and control classes, it can be concluded that the K-means clustering collaborative filtering algorithm based on IABC's Music Theory Knowledge Pushing System for practical teaching can improve students' music performance.

4. Conclusion

In order to improve the recommendation accuracy of music theory knowledge, the study designed IABC-based K-means clustering collaborative filtering algorithm for use in music theory knowledge pushing system. It is experimentally verified that initializing the clustering center by using the reverse learning method can produce better clustering performance and recommendation quality. The new fitness function can overcome the shortcomings of the traditional fitness function and thus improve the recommendation quality. The recommendation algorithm proposed in this paper has a MAE of 0.72 when the number of nearest neighbors is 40, and the recommendation quality and recommendation efficiency are better than compared to other recommendation algorithms. Based on the artificial bee colony algorithm of music theory knowledge push system under the guidance of music teaching, the students' performance is significantly improved, $P=0.019$ ($0.01<P<0.05$), the design of this paper is very far-reaching significance for the future teachers' actual classroom teaching, the improvement of the quality of teaching, and the change of the quality of the operation of the music education platform.

About the Author

Yingru Wang, female (1984.12-), Han ethnicity, native of Yuncheng, Shanxi Province, holds a Master of Arts degree and is an associate professor. Her research focuses on music and dance.

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