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Innovation and Practical Exploration of Music Classroom Teaching Models Assisted by Digital Technology

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Abstract Currently, music education in higher education institutions relies solely on traditional music composition textbooks to fulfill teaching objectives, which no longer meets the demands for music talent. Digital music technology, as a revolutionary innovation in music technology, has transformed people's understanding of music production. This study first leverages AIGC and multimodal large-scale model technology to assist music classroom instruction, and proposes a personalized music learning path recommendation strategy based on ant colony algorithms. By aligning with students' learning needs, it precisely recommends scientifically sound learning paths to enhance learning efficiency. Experimental results show that the recommendation algorithm achieves high prediction accuracy, aligning with students' needs. Additionally, the recommendation system's surprise factor and real-time performance meet the requirements of resource recommendation systems, making it suitable for implementing teaching resource recommendations. Finally, based on practical analysis of the application of learning path recommendations in music education, results indicate that after practical teaching, the experimental group's aesthetic perception, artistic expression, cultural understanding, and creative practice levels were significantly higher than those of the control group.

Index Terms digital technology, AIGC, ant colony algorithm, music education, learning path, personalized recommendation

I. Introduction

In today's society, against the backdrop of the global digital revolution, the application of modern information technologies represented by digital technology is becoming increasingly widespread, gradually penetrating into all aspects of people's daily lives, including education [1]-[3]. Education informatization supported by digital technology is an important means of promoting educational equity, innovating talent cultivation models, and advancing lifelong learning [4], [5]. As is well known, music education is an integral part of basic education and an important means of implementing aesthetic education. It plays an irreplaceable role in cultivating moral character, fostering innovative spirit and practical abilities, enhancing cultural literacy and aesthetic capabilities, promoting students' physical and mental health, and facilitating their all-round development in morality, intelligence, physical fitness, and aesthetics [6]-[9]. Therefore, the application of digital technology in music education has become a significant trend in the teaching development of higher music institutions in the new century.

Currently, music education primarily focuses on hardware-based instruction, with teachers guiding students in playing various musical instruments. However, musical instruments are generally expensive, significantly limiting the availability of diverse music education tools in institutions, resulting in a relative shortage of music education resources [10]-[13]. Additionally, music classroom instruction generally remains focused on the transmission of textbook knowledge, with teachers preparing lesson content based on textbooks and students passively receiving the content prepared by teachers, lacking innovative teaching content [14]-[16]. With the rapid development of digital technology, it has provided the foundation and possibility for the innovation and development of music classroom teaching models [17]. In the digital age, relevant teaching tools can simultaneously present sound, video, and animation, making music classes vivid and intuitive [18], [19]. By utilizing digital music tools to capture fleeting sound materials, freeze musical moments, and conduct comprehensive and detailed analyses, many shortcomings in current basic music classroom teaching models can be addressed [20]-[22]. However, due to regional and economic development factors, the development of digital music classroom teaching varies significantly. In regions with better economic and educational conditions, the digitalization of music classroom teaching progresses rapidly, while in relatively underdeveloped regions, the digitalization process is relatively slow [23]-[26]. Therefore, it is necessary to explore innovative and practical strategies for information-based teaching in music classrooms to enhance the quality of music education.

With the rapid development of computer and internet technology, various digital technologies tailored for music education have emerged in abundance, injecting new vitality into music education. Reference [27] developed a free music notation software (MNS), whose virtual classroom functionality and melody editing sharing features provide effective support for students' listening practice outside the classroom. Reference [28] explored the application of information and communication technology (ICT) in music education, finding that personalized teaching projects based on ICT technology and students' musical abilities significantly promoted students' development in auditory and instrumental skills, effectively improving the quality of music education. Literature [29] indicates that digital tools alter the presentation methods and usage patterns in music practice and performance, a process that influences users' cognitive forms of music learning, holding significant implications for the music field. Literature [30] designed a music teaching method based on computer-assisted piano tuning, where this teaching model leverages computer recognition technology to not only cultivate students' music listening skills and enhance their musical perception abilities but also assist teachers in improving their own teaching skills. Literature [31] analyzed the characteristics of computer multimedia music education and, based on this, explored innovative teaching models that can further enhance teachers' service capabilities and teaching management capabilities, positively impacting the development of music education. Literature [32] emphasizes that music education models supported by multimedia technology significantly enhance students' interest in music learning. Therefore, it proposes a student vocal quality evaluation tool based on sound signal parameter analysis and extraction technology to further enhance the effectiveness of vocal music classroom teaching. Literature [33] integrates computer spectral analysis technology into vocal music teaching classrooms. By mapping students' singing breathing patterns and vocal organ dynamics, it visually describes the singing process to students. This innovative visual music teaching technology significantly improves students' learning efficiency. Literature [34] explores the integration of computer science with university music classrooms. The developed JythonMusic project supports algorithmic music composition, dynamic programming, and musical expressiveness, demonstrating strong auxiliary functions in music classroom composition instruction. The aforementioned music teaching auxiliary tools each have their own unique features. Some cultivate students' auditory skills, others expand their musical cognition, some enhance the quality of music classroom instruction, and others focus on auxiliary functions such as music notation. These music teaching software tools each have their own strengths and weaknesses, and their applicable scopes also vary. Therefore, in music education, selecting appropriate digital music teaching tools based on actual circumstances to assist instruction and designing reasonable teaching models holds significant importance.

This paper proposes a multimodal teaching framework for university music classrooms enabled by AIGC, based on teaching objectives, resources, methods, and environments. Based on this framework, a personalized music learning path recommendation strategy is developed using ant colony optimization (ACO). In this strategy, evaluation information from historical learners with similar learning styles and knowledge levels to the target user is used as pheromones, while the expressive features and difficulty levels of the learning objects serve as heuristic information to guide path search behavior. Ultimately, learning paths with higher recommendation probabilities are recommended to learners. The recommendation results are evaluated using prediction accuracy, real-time performance, and surprise factor. Subsequently, a survey was conducted with students from a music and art college in Shanghai as the research subjects. After the practice, the teaching effectiveness was comprehensively evaluated through quantitative analysis of pre- and post-test questionnaire data, and the practical effects of this model were analyzed.

II. Innovative teaching models for music classrooms based on digital technology

II. A. Digital Technology Empowering a Multimodal Framework for Music Classrooms

II. A. 1) Objective Level

In the era of artificial intelligence, reforms in higher education music education must also prioritize students' continuous learning and development as their core value, placing greater emphasis on cultivating students' ability for independent learning and innovation, thereby guiding them to better navigate the challenges and impacts of artificial intelligence on music creation, production, dissemination, and consumption in the future. Currently, the deep integration of music art and AI is accelerating further, especially with the emergence of music generation large models such as MuseNet, MusicLM, and SkyMusic, which are driving profound changes in the mediums and presentation methods of music expression. This presents numerous new requirements and challenges for talent cultivation in higher education music education. In this context, building creative collaborative music classrooms in higher education institutions based on AIGC large-scale model technology is not only about improving classroom teaching efficiency and quality but also about cultivating students' comprehensive literacy and their ability to adapt to the future development of the music industry.

II. A. 2) Methodological level

For a long time, music education in higher education institutions has been conducted under a standardized teaching model, primarily relying on traditional classroom lectures and limited “face-to-face” guidance, with insufficient attention and response to students' individualized learning needs. Unlike traditional music classrooms, the AIGC-enabled creative collaborative music classroom in higher education will adopt a generative intelligent teaching approach, leveraging technologies such as data mining, machine learning, smart education, and natural language processing. By precisely analyzing students' interests, ability levels, and developmental needs, it will tailor personalized learning and development pathways for each student. Under this teaching model, teachers can use AIGC large models to monitor students' learning progress and interests in real time, tailor learning plans to individual students, and help them accurately identify key issues and details in vocal performance, instrumental playing, and stage performances, significantly enhancing students' proactive and targeted learning.

II. A. 3) Resource Level

In traditional music classrooms, teachers primarily focus on language-based instruction, relying heavily on verbal explanations. There is insufficient utilization of non-verbal instructional resources such as images and videos, making it difficult to effectively engage students' multiple senses and stimulate their learning motivation. Currently, with the rapid iteration of multi-modal large-scale model technology, AIGC has gained the ability to efficiently integrate multi-modal subject knowledge and various teaching resources. Based on subject resource characteristics and learner learning styles, it can provide each student with personalized multi-modal teaching resource recommendations, such as online tutorials, singing libraries, and music databases, significantly enriching the content and format of music classroom instruction.

II. A. 4) Environmental aspects

Unlike the traditional "disembodied learning" model in music classrooms, in university music creative collaboration classrooms, teachers can also leverage AI-generated content (AIGC) large models to "create new multi-sensory, embodied learning environments." By employing intelligent generation methods, teachers can provide students with richer and more authentic intelligent interactive scenarios, enabling students to experience immersive music learning experiences. For example, teachers can integrate virtual reality (VR) and augmented reality (AR) technologies to create diverse, immersive simulated environments such as concert halls, theaters, and studios. By leveraging the integration of visual, auditory, kinesthetic, tactile, and proprioceptive senses, this approach effectively enhances students' enthusiasm and initiative in participating in learning and practical activities. Additionally, in a "multi-network integrated" online teaching environment, students can share creative resources, edit in real-time, and discuss on the AIGC large-model platform. This facilitates diverse teaching interactions, promotes collaboration and communication among students, and helps them identify issues and propose creative suggestions and solutions.

II. B. Digital Technology Empowering Innovative Practices in Music Classrooms

The integration of AIGC teaching solutions into creative collaborative music classrooms in higher education institutions involves numerous scenarios, including personalized learning content generation, innovative precision teaching management, and intelligent teaching evaluation reforms. This requires not only the comprehensive utilization of advanced AI models such as RNNs, LSTMs, and GPT to build teaching platforms, but also the development and design of corresponding AIGC multimodal concept tools based on different scenario requirements to achieve the perception, analysis, and intelligent application of multimodal teaching data. As shown in Figure 1.

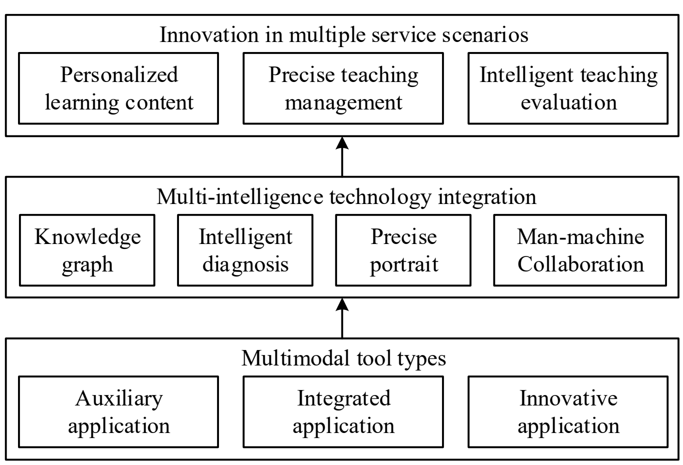

Figure 1: Development and application of AIGC multimodal conceptual tools

Currently, most universities are still in the early stages of utilizing AIGC technology, with integration not yet fully realized. Addressing this issue, this paper takes the university music general education course "Music Appreciation" as an example, combining specific teaching objectives and scenario requirements, to explore the development and application of AIGC multimodal conceptual tools. The aim is to promote the deep integration and comprehensive innovation of AIGC with university music education, providing new perspectives and methods for university music education reform. The application of AIGC multimodal conceptual tools in music classroom teaching is illustrated in Figure 2.

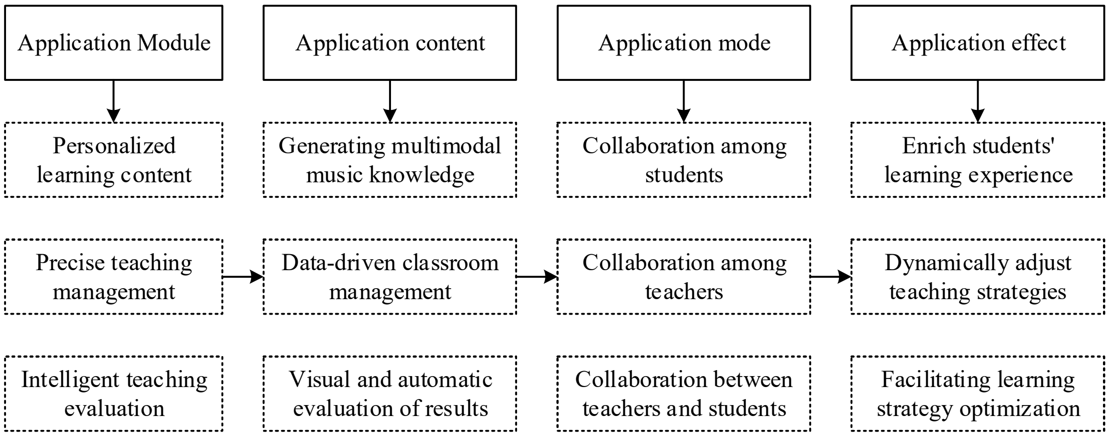

Figure 2: Application of AIGC multimodal concept tools in the course of Music Appreciation

III. Personalized music learning path recommendation based on ant colony algorithm

III. A. Knowledge Graph and Music Knowledge Point Recommendations

III. A. 1) Construction of a music course knowledge map

As a commonly used knowledge base, knowledge graphs primarily employ graphical structures to visually and intuitively represent the relationships between entities, events, and other information in the real world [35]. By applying knowledge graphs, machines can understand and process this knowledge in a manner similar to human thinking, thereby guiding students to better learn and master relevant knowledge about the real world. Knowledge graphs are represented as follows:

$$G = \{(h,r,t) \mid h \in E, r \in R, t \in E\} \tag{1}$$

In equation (1), E, R represents the vertex set and edge set of the knowledge graph, respectively.

During the construction of a knowledge graph, it is necessary to collect and organize the required data sources. Once the data sources have been organized, the following two methods should be used to process the organized data sources:

(1) Top-down processing method

Under this method, experts in related fields from both domestic and international sources provide precise definitions for concepts such as the top layer and edges, thereby promoting the standardization and normalization of the knowledge graph structure. Additionally, sub-concepts are categorized and defined, leading to the continuous expansion of the knowledge graph structure system.

(2) Bottom-up processing method

Under this method, experts in related fields need to redefine and label lower-level concepts, enabling the entire knowledge graph to achieve high coverage and further improve its accuracy. During the construction of the knowledge graph, the article prioritizes the use of the bottom-up processing method. By employing this method, precise updates and construction of the knowledge graph can be achieved, thereby reducing labor costs, material costs, and financial costs.

III. A. 2) Knowledge Point Recommendation Algorithm

The knowledge point recommendation algorithm execution process is as follows: First, extract knowledge point entities and their interrelationships from the knowledge graph. Second, use a mapping function to map knowledge point entities and relationships one-to-one, extract key features, and maximize the use of important information in the vector. Next, fuse the collected student vector information to obtain the student's learning attribute features. Finally, use knowledge point embedding technology to construct a systematic and comprehensive knowledge system for students. The formula for the knowledge point recommendation prediction function is as follows:

$$y = F(s,k,M,G,\theta) \tag{2}$$

In equation (2), y is the interaction probability between student s and knowledge point k; M represents the interaction matrix between students and knowledge points; G represents the knowledge graph; and θ represents the parameters of function F.

III. B. Problem Description

III. B. 1) Description of learner characteristics

Learners play a central role throughout the learning process, and the learning paths recommended by the learning system can only demonstrate their personalized characteristics if they meet the learning needs of different learners. Due to differences among learners in terms of learning styles, cognitive levels, and learning methods, different learners will choose different learning paths. Therefore, it is necessary to conduct in-depth research on the characteristics of learners in various aspects to provide them with suitable learning paths and ultimately achieve personalized recommendations for learning paths.

Learning styles are diverse in nature, and different learners exhibit varying degrees of preference for different learning styles. The same learner may exhibit preferences for multiple learning styles, so it is not appropriate to categorize them using an either/or approach. Therefore, we use vector K^s to describe the learning style of learner K:

$$K^s = \{k_i^s \mid k_i^s = (s_i^1, s_i^2, s_i^3, s_i^4,), i = 1, 2, \ldots, n\} \text{ And } s^1 + s^2 + s^3 + s^4 = 1 \tag{3}$$

In the formula, s^1, s^2, s^3, s^4 represents the degree of tendency toward four styles: polymeric, assimilative, divergent, and accommodative. This vector can be used to express the learner's composite style and the degree of tendency toward that style. The learner's learning style can be determined using the results of a short-term survey and the ID3 decision tree algorithm.

III. B. 2) Description of learning object characteristics

(1) Knowledge Structure Description

There can be no circular reasoning in the formation of a knowledge system, and the supporting relationships between knowledge points cannot form a closed loop. Therefore, the knowledge structure diagram is a directed acyclic graph. The nodes in the knowledge structure diagram correspond to each knowledge point and are connected by hyperarcs, pointing from the supporting knowledge point to the supported point. A knowledge structure diagram with a finite number of nodes must satisfy the following three conditions:

a) There is exactly one node a, and there are no arcs emanating from node a in the graph.

b) There is a non-empty set of nodes B, and none of the nodes in B have incoming arcs.

c) There are no cycles.

Based on the above description, establish a directed graph $G(Q, A)$ that describes the relationships between knowledge points, where $Q = \{q_1, q_2, q_3, q_4, \cdots\cdots q_n\}$ is the set of knowledge points and $A = \{(q_i, q_j); i \neq j\}$ is the set of vertex arcs:

$$A = \begin{cases} 1 & \text{If a learner studies } j \text{ after learning } i \\ 0 & \text{Otherwise} \end{cases} \tag{4}$$

(2) Characteristics of knowledge representation

The online teaching system contains numerous knowledge points. Descriptions of these knowledge points, along with multimedia digital resources designed for learners to study, form the basic teaching resources of the system. These multimedia resources include text resources, image resources, video resources, audio resources, example resources, and exercise resources. For a given knowledge point, multiple expression methods can be employed, each with distinct attributes or personalized tags. Vector Q^e is used to describe the expression methods for knowledge point q:

$$\begin{gathered} Q^e = \{q_i^e \mid q_i^e = (e_i^1, e_i^2, e_i^3, e_i^4, e_i^5, e_i^6,), i = 1, 2, \ldots, m\} \\ \text{And } e^1 + e^2 + e^3 + e^4 + e^5 + e^6 = 1 \end{gathered} \tag{5}$$

In the formula, $e^1, e^2, e^3, e^4, e^5, e^6$ represents six types of expression features: text, images, videos, audio, examples, and exercises. These can be adjusted according to actual conditions in different teaching systems. At the same time, relevant classification attributes or personalized tags can be added to enrich the description of knowledge points. This vector can be used to express the attributes of different knowledge points and the expression methods used.

(3) Knowledge difficulty coefficient

When providing teaching resources, teaching system administrators assign difficulty coefficients 1n1 and 1n2 based on the depth and breadth of the knowledge points. The closer $Q^l (0 \leq Q^l \leq 1)$ and Q^l are to 1, the more suitable the knowledge point is for expert learning; the closer they are to 0, the more suitable the knowledge point is for beginner learning.

III. B. 3) Learning Path Description

According to the relevant definitions of knowledge space theory, a learning path based on knowledge space theory is a path in a knowledge space graph that leads from an initial knowledge state to a target knowledge state. In a hypertext knowledge space, we define a learning path as follows: select a set of learning objects $Q_l = (q_1, q_2, ..., q_n)$ with a sequential order in a directed graph G. To complete the learning task, learners need to complete the learning of all learning objects on the learning path in sequence.

The knowledge network structure diagram is shown in Figure 3. Solid lines indicate parent-child relationships, while dashed lines indicate prerequisite relationships. Node q_1, q_2 is a node that requires the completion of learning for both of its child nodes before proceeding to learn parent node q_3. Node q_2 is a prerequisite knowledge point for node q_1; node q_3, q_4 is an OR node, meaning that completing the learning of either of its knowledge points allows progression to knowledge point q_5, ultimately completing the learning task. From this diagram, it can be seen that there are two learning paths: $Q_1 = (q_2, q_1, q_3, q_5)$ and $Q_2 = (q_2, q_4, q_5)$. Path Q_2 can complete the learning task with fewer nodes than path Q_1.

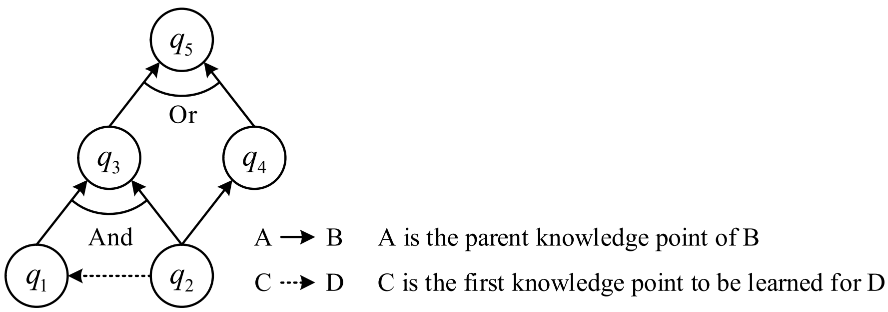

Figure 3: Learn the knowledge network

III. C. Implementation Process of Path Recommendation Model

III. C. 1) Data preprocessing stage

The data preprocessing in this study involves parsing learner log files line by line to extract data such as learners, learning behaviors, and behavior times. The parsed data is then cleaned, integrated, and transformed to filter out useless or incomplete records, providing effective data support for the establishment of learning path maps.

III. C. 2) Similar Learner Selection Stage

Similar learners refer to learners with similar personality traits. Selecting similar learners is key to constructing adaptive learning paths. This study defines learner personality trait vectors $S = \{s_1, s_2, s_3, s_4, k_1, k_2, \cdots, k_n\}$ based on two dimensions: cognitive style and knowledge level. Among these, s_1, s_2, s_3, s_4 represents the values of the four dimensions of the Felder-Silverman cognitive style model. Each dimension is transformed into numerical values and discretized into six levels from low to high, represented by the numbers 1 to 6. For example, the information processing dimension uses 1 to 6 to represent the transition from active to reflective, with smaller numbers indicating a greater tendency toward active processing and larger numbers indicating a greater tendency toward reflective processing. $k_1, k_2, \cdots, k_n$ is the knowledge level vector, indicating the learner's mastery of all previous knowledge units. According to Bloom's Taxonomy of Educational Objectives, learners' knowledge levels are categorized into six levels: recall, understanding, application, analysis, synthesis, and evaluation (represented by numbers 1 to 6, respectively).

Then, the Pearson correlation coefficient is used to calculate the similarity between learners, as shown in formula (6).

$$sim(u,v) = \frac{\sum_{i \in S}(S_{ui} - \overline{S_u})(S_{vi} - \overline{S_v})}{\sum_{i \in S}(S_{ui} - \overline{S_u})^2 \sum_{i \in S}(S_{vi} - \overline{S_v})} \tag{6}$$

Among these, $sim(u,v)$ represents the similarity between Learner u and Learner v, s_{ui} represents the component of Learner u on the personality trait vector i, and s_u represents the average value of Learner u across all personality trait vectors. Based on the range of Pearson correlation coefficients, the similarity between learners $sim(u,v)$ ranges from -1 to +1. A value of $sim(u,v) > 0$ indicates positive similarity between two learners, while $sim(u,v) < 0$ indicates negative similarity. The larger the absolute value of $sim(u,v)$, the stronger the similarity.

III. C. 3) Learning Pathway Map Construction Phase

A learning path map is a collection of all possible learning paths from the start of learning to the completion of testing. This study extracts the historical learning paths and test scores of similar learner groups to construct a learning path map. For example, if a learner's historical learning path is $\langle r_1, c_1, p_4, e \rangle$ and their normalized test score is 0.66, then the learner's path is shown in the upper part of Figure 4. In this diagram, nodes represent the learner's learning behaviors, directed arrows indicate the transfer of learning behaviors, and the numbers on the arrows represent the transfer weights, indicating the effectiveness of the transfer. For each path, this study specifies that the transfer weights are equal and equal to the corresponding test scores.

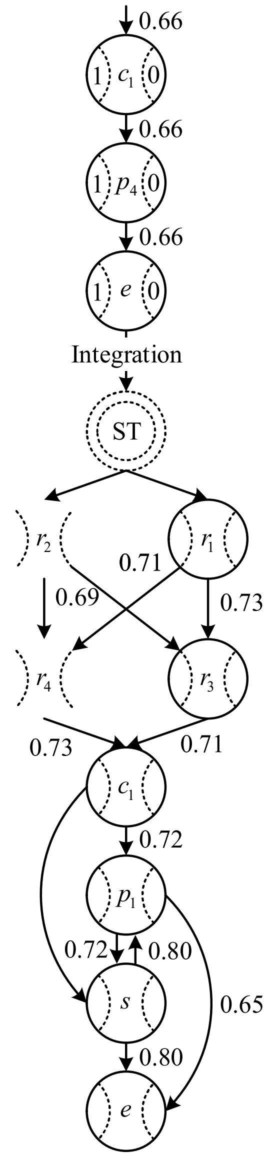

Figure 4: Learning path diagram harmonic construction example

Integrate the learning paths of all similar learner groups to construct a learning path map, as shown in the lower part of Figure 4. In this map, ST represents a virtual node, indicating the initial node of learning, while e (test) denotes the endpoint of knowledge unit learning. The learning behavior transfer weight is the weighted average of the transfer weights from multiple similar learners, calculated as shown in Formula (7). In the formula, xy represents the transfer of learning behavior x to y, w_{ny}^{u} represents the transfer weight of learner u to xy, $sim(u,v)$ represents the similarity between learners u and v, and N represents the set of all similar learners.

$$w_{xy}^{n}=\frac{\sum_{v\in N} sim(u,v)\times w_{xy}^{v}}{\sum_{v\in N} sim(u,v)} \tag{7}$$

III. C. 4) Adaptive learning path mining stage

In this algorithm, nodes correspond to learning behavior nodes in the learning path graph, where Formula (8) represents the probability that ant k selects to move from node i to node j at time t, $\eta_{ij}(t)$ denotes the heuristic information quantity between nodes i and j at time t, typically taken as the reciprocal of the path weight between nodes i and j.

$\tau_{ij}(t)$ denotes the pheromone concentration from node i to node j at time t; α and β respectively represent the influence of pheromone concentration and heuristic information quantity on the path selection probability, with γ_j being the penalty coefficient; T_k denotes the set of feasible nodes that ant k has not yet visited at time t:

$$p_{ij}^k(t)=\begin{cases}(\tau_{ij}(t))^{\alpha}\times(\eta_{ij}(t))^{\beta}, if\,(j\in T_k)\\ 0, if\,(j\notin T_k)\end{cases} \tag{8}$$

In fact, there are dependencies between knowledge points. For example, to learn "multiplication," one must first master "addition," so the knowledge point 'multiplication' depends on the knowledge point "addition." To represent this dependency relationship, this study introduces dependency conditions I and output results O for each learning resource (or learning activity), where I denotes the prerequisites required to learn the resource (or participate in the activity), and O denotes the learning outcomes generated by learning the resource (or participating in the activity). Since some path combinations in the learning path graph may not necessarily satisfy this dependency relationship, this study introduces a penalty coefficient γ_j, which represents the penalty coefficient for using node j as the next node. Its calculation method is shown in Formula (9):

$$\gamma_j=\begin{cases}1, if\,(I_j\subseteq\sum_{i\in\bullet I}(I_i\cup O_i))\\ 0, if\,(I_j\not\subset\sum_{i\in\bullet I}(I_i\cup O_i))\end{cases} \tag{9}$$

Among them, I_i and O_i represent the dependency conditions of node j, and I represents all nodes already present in the path (i.e., all nodes before node j). It is important to note that when determining set inclusion, higher-level knowledge points encompass lower-level knowledge points. The penalty coefficient serves to filter out paths that do not satisfy the dependency conditions.

After all ants complete a circuit, the pheromone concentration along the current optimal path must be updated. Suppose that from time t to time $t+1$, m ants travel from node i to node j. The pheromone concentration along this path at time $t+1$ can be calculated using formula (10). Here, $\Delta\tau_{ij}^k(t)$ refers to the pheromone concentration left by ant k when it passed from node i to node j. ρ refers to the evaporation rate of the pheromone. Formula (10) indicates that the pheromone concentration on the path from node i to node j is influenced by the number of ants that have passed through it; the more ants that have passed through, the higher the pheromone concentration on that path. Combining formulas (8) and (9), it can be seen that the higher the pheromone concentration on a path, the greater the probability that the next ant will choose that path, thereby forming a gradually reinforcing positive feedback loop. That is:

$$\tau(t+1)=(1-\rho)\times\tau_{ij}(t)+\sum_{k=1}^{m}\Delta\tau_{ij}^k(t) \tag{10}$$

IV. The impact of digital technology on innovation in music classroom teaching

IV. A. Recommendation Effectiveness Testing

IV. A. 1) Prediction Accuracy

The experiment was conducted in groups, with each group building on the previous group's experiment. The three groups were: recommended resources after searching for the knowledge points "sound waves," "average speed," "noise," and 'chords'; recommended resources after searching for the knowledge points "music style," "average speed," and "uniform linear motion"; and recommended resources after searching for the knowledge points "sound waves," "musical tones," "ultrasound," "infrasound," and "sound waves." Each group of experiments statistically analyzed the number of recommended resources based on historical records, the number of recommended resources based on similar users, and the final accuracy rate for every 10th multiple of resources. The purpose was to determine whether the sources of resources in the recommendation list were based on the strategy-based recommendation results and to assess the accuracy rate of the recommendation results. The statistical results of the three groups of experiments are shown in Table 1.

The experimental results indicate that the accuracy rate in the three experiments gradually decreases as the number of items in the list increases. This result aligns with the experimental expectations. The recommendation list is displayed in descending order based on recommendation values, meaning that the resources at the top of the list are those the system deems most aligned with user needs. Therefore, as the number of resources in the list continues to expand, the accuracy rate decreases. Calculations reveal that the accuracy rate of the first 10 resources in the list is above 0.9, nearly reaching 100%. This means that over 90% of the first 10 resources align with user needs, indicating a high accuracy rate. According to the system's design, the list displays 8 resources. Therefore, the accuracy rate of the resources in the displayed list is very high, sufficient to meet the user's current needs. The overall accuracy rate of the resources is above 0.67, which is relatively high compared to the 70 recommended resources. Therefore, the overall recommendation effect is good.

Table 1: Statistical prediction accuracy

Search for recommended resources on "sound wave", "average velocity", "noise", and "chord"							
List the resource count k	10	20	30	40	50	60	70
History	5	8	16	21	24	30	32
Similar users	8	12	14	15	18	19	20
Precision	1	0.893	0.9	0.865	0.83	0.80	0.763
Search for recommended resources for "musical style", "average speed", and "uniform motion"							
List the resource count k	10	20	30	40	50	60	70
History	6	12	16	25	29	34	39
Similar users	3	5	8	9	9	10	11
Precision	0.921	0.802	0.711	0.784	0.711	0.694	0.673
Search for recommended resources on "sound wave", "musical sound", "ultrasonic", "infrasonic", and "sound wave"							
List the resource count k	10	20	30	40	50	60	70
History	8	11	16	25	33	39	41
Similar users	1	7	8	9	9	9	9
Precision	1	0.9	0.9	0.853	0.8	0.749	0.733

IV. A. 2) Surprise factor

The surprise metric for recommendation systems refers to recommended resources that are unrelated to the user's historical browsing history but still provide the user with a certain degree of surprise and may be helpful to them. In this study, the resources in the recommendation list are sourced from two parts: the user's nearest neighbors and a similar resource graph.

The sublists of recommended resources from these two sources form the final recommendation list. Source 1 converts historical resource records into historical knowledge point records during the process from historical resource records to the final recommendation list, and then uses a user-based collaborative filtering algorithm to recommend resources that other users in the nearest neighbors have browsed but the target user has not. Some of the recommended resources are distinct from the user's historical resource records. Therefore, resources in the list that are unrelated to the user's own browsing history but meet the current user's needs are identified and statistically calculated, with only the top eight resources displayed in the list. The results are shown in Table 2.

It can be observed that the surprise levels of the last three groups are significantly lower than those of the first two groups. This is because, initially, the user's browsing history was limited, so most recommendations were based on user similarity, resulting in higher surprise levels. As the user's history increased, the surprise levels gradually decreased. During subsequent system usage, surprise levels were roughly estimated and found to be around 30%.

Table 2: Surprise statistics

Resources for searching	Resource surprise
"Sound wave", "average velocity", "noise", "chord"	77%
"Style of music", "average speed", "uniform motion in a straight line"	64.2%
"Sound wave", "musical sound", "ultrasonic", "infrasonic", "sound wave"	39.1%
"Sound method", "finger method", "music history"	28%
"Music beat", "note", "audiovisual", "instrumental performance"	39.1%

IV. A. 3) Real-time performance

The real-time nature of a recommendation system primarily encompasses two aspects: ① The system can update recommendation lists in real time to accommodate changes in user behavior. ② The recommendation system can recommend newly added resources to users. The calculation of similar users and the updating of user browsing records in this system are real-time. Every time a user refreshes the page, data is calculated and updated. Therefore, when a user returns to the system homepage to view recommended resources, the resources in the list are updated in real-time based on the user's new behavior, ensuring the system's ability to respond quickly to user behavior. Additionally, for newly added resources, most traditional recommendation systems prioritize the most popular resources—those with the highest click-through rates and readership—which can be unfavorable for new resources. This recommendation system avoids this issue by first performing semantic analysis on newly added resources, integrating them into the existing knowledge graph, then calculating similar resources, and storing them in a graph database for recommendation purposes. Therefore, new resources will not become increasingly niche due to having a click-through rate of 0. Additionally, this recommendation system displays the latest and most popular resources on the homepage, further preventing such situations from occurring. In summary, this recommendation system has good real-time performance.

IV. B. Experimental Design and Results Analysis

IV. B. 1) Determining Learning Units and Learners

To meet the requirements for the duration of learning units in music classes, learning resources that meet the criteria were downloaded from the internet and screened to ensure that each learning unit can be completed within 15 minutes. At the same time, an initial learning path with an appropriate number of learning units was selected, with each course containing 8 to 12 learning units.

After screening and organizing, a total of 100 music-related learning courses were obtained, comprising 579 learning units, which were divided into four learning domains: basic music theory, sight-singing and ear training, music appreciation, and vocal basics. Based on the difficulty of the knowledge content in the learning courses, their knowledge levels were marked. After organization, 167 initial learning paths with completed knowledge domain and knowledge level markings were obtained, with their basic information distribution shown in Table 3.

Table 3: Basic information about learning modules

Knowledge Domin	Number of initialization paths	Knowledge level 1	Knowledge level 2	Level of knowledge 3
Basic music theory	47	11	23	19
Field nebula	47	14	23	17
Music appreciation	50	11	29	15
Fundamentals of vocal music	39	15	15	17

In terms of learner selection, a total of 70 learners were selected for the experiment. To verify that the improved ant colony algorithm can effectively improve learners' learning efficiency, the 70 learners were divided into two groups: an experimental group and a control group, with 35 learners in each group. Both groups of 35 learners participated simultaneously, with each learner studying several learning units. To enhance the reliability and accuracy of the experimental results, a preliminary survey and statistical analysis of the basic information of the 70 learners was conducted to ensure that the two groups of learners had minimal differences in their initial knowledge domains and corresponding knowledge levels. The distribution of the learners' initial basic information is shown in Table 4.

Table 4: Basic information about the learner

Knowledge Domin	Group	Number of learners	Knowledge level 1	Knowledge level 2	Level of knowledge 3
Basic music theory Field nebula	Experimental group	10	1	4	3
	Comparative groups	10	1	4	5
Music appreciation	Experimental group	10	3	3	2
	Comparative groups	10	4	5	4
Basic music theory Field nebula	Experimental group	10	4	2	3
	Comparative groups	10	1	2	3
Music appreciation	Experimental group	5	2	3	2
	Comparative groups	5	2	2	2
Amount to	Experimental group	35	13	12	10
	Comparative groups	35	8	13	14

IV. B. 2) Determination of algorithm parameters

The selection of ant colony algorithm parameters has a significant impact on experimental results. When using the ant colony algorithm to recommend learning paths in music classroom learning, the first task is to determine how to set each parameter value, identify reasonable learning units, and determine the number of learners in order to better achieve learning path recommendations.

In the MATLAB environment, a program was used to simulate the learning process of learners, and the effects of parameters such as the heuristic information factor, pheromone concentration factor, pheromone concentration volatility factor, iteration count, number of learning units, and number of learners on the results were studied. Through multiple experiments, the changes in pheromone concentration distribution were analyzed, and the algorithm's time complexity was comprehensively considered. Ultimately, the basic parameters of the algorithm were determined. Specifically, the heuristic information factor α was set to 1.4, the pheromone concentration factor β was set to 1.1, the pheromone volatility concentration ρ was set to 0.7, and the number of iterations was set to 150.

IV. B. 3) Analysis of experimental results

Through the experiment, test scores were obtained for two groups of learners. Figure 5 shows how the average test scores for the experimental group and the control group changed as the number of learning units increased across four learning domains: basic music theory, sight-singing and ear training, music appreciation, and vocal basics. Among these, A01 and B01 represent the experimental group and control group, respectively, in the basic music theory domain; A02 and B02 represent the experimental group and control group, respectively, in the sight-singing and ear training domain; A03 and B03 represent the experimental group and control group, respectively, in the music appreciation domain; and A04 and B04 represent the experimental group and control group, respectively, in the vocal music fundamentals domain. Based on the experimental results, it can be concluded that learners in the experimental group achieved significantly higher average test scores after completing the same number of learning units, suggesting that the teaching method proposed in this study can enhance learners' learning efficiency.

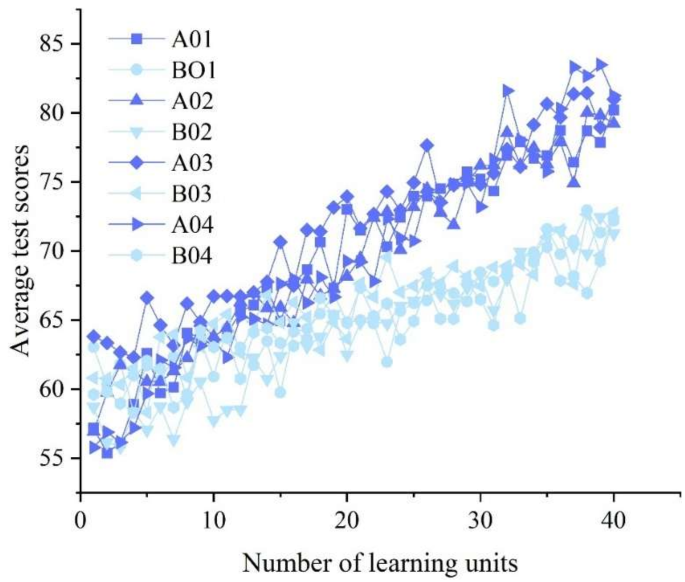

Figure 5: The relationship between the number of learning units and the average test score

IV. C. Analysis of Music Teaching Effectiveness

IV. C. 1) Practical Design

(1) Purpose of the survey

The main purpose of this survey is to understand whether the students in the experimental group achieved the expected learning outcomes and improved their abilities in each dimension of core literacy after participating in music teaching practices based on learning path recommendations, through the distribution and analysis of learning outcome questionnaires. This will provide a realistic basis for subsequent research on music teaching design.

(2) Scope and Subjects of the Survey

The subjects of the survey were students in four first-year classes at a music and art school in Shanghai. Class 1 and Class 3 were the experimental group, while Class 2 and Class 4 were the control group. There were a total of 218 students in the four classes. The experimental group consisted of 109 students, including 54 from Class 1 and 55 from Class 3. The control group consisted of 109 students, including 56 from Class 2 and 52 from Class 4.

(3) Design and Distribution of the Survey Questionnaire

The questionnaire structure is divided into four dimensions: Aesthetic Perception Ability Dimension, Artistic Expression Ability Dimension, Cultural Understanding Ability Dimension, and Creative Practice Ability Dimension, comprising a total of 27 questions. Questions 1–9 belong to the Aesthetic Perception Ability Dimension, questions 10–16 to the Artistic Expression Ability Dimension, questions 17–22 to the Cultural Understanding Ability Dimension, and questions 23–27 to the Creative Practice Ability Dimension. Each question has five options, with each option scored as 1 point per "☆." The ratings range from five stars to one star, representing "very appropriate," "somewhat appropriate," "basically appropriate," "not very appropriate," and "completely inappropriate," respectively.

A total of 106 valid questionnaires were collected. SPSS 27.0 software was used as the analysis tool to analyze the data collected from the pre-test and post-test, and to verify the effectiveness of music teaching design based on learning path recommendations.

IV. C. 2) Analysis of Practical Results

(1) Reliability and Validity Testing of the Questionnaire

The results of the reliability and validity testing are shown in Tables 5 and 6. The overall Cronbach's Alpha coefficient for the scale is 0.932, which is greater than 0.8. The Cronbach's Alpha coefficients for each dimension are 0.913, 0.745, 0.728, and 0.759, respectively, all of which are greater than 0.7. This indicates that the questionnaire has good reliability. Based on the validation results, the KMO value is 0.792, which is greater than 0.7, and the p-value is less than 0.05. This indicates that the questionnaire has good validity.

Table 5: Tests of faithfulness

	Kronbach α	Number of terms
Aesthetic perception	0.913	11
Artistic expression	0.745	8
Cultural understanding	0.728	6
Creative practice	0.759	4
Questionnaire overall	0.932	31

Table 6: Effect test

KMO and Bartlett test		
KMO sampling appropriateness measure		0.792
Bartlett's sphericity test	Approximate chi-square	5723.051
	Free degree	354
	Conspicuousness	0.001

Table 7: Descriptive statistics

		N	Least value	Crest value	Average value	Standard deviation
Aesthetic perception	Pre-test of the experimental group	109	2.86	5.89	4.19	0.93
	Post-test of the experimental group	109	3.64	5.89	4.59	0.7
	Pretest of the control group	109	2.86	5.78	4.04	0.72
	Post-test of the control group	109	3.08	5.78	4.08	0.58
Artistic expression	Pre-test of the experimental group	109	3.08	5.82	4.3	0.83
	Post-test of the experimental group	109	3.37	5.82	4.58	0.77
	Pretest of the control group	109	3.08	5.97	4.23	0.81
	Post-test of the control group	109	3.08	5.82	4.12	0.72
Cultural understanding	Pre-test of the experimental group	109	2.75	6.11	4.07	0.89
	Post-test of the experimental group	109	3.58	6.11	4.54	0.73
	Pretest of the control group	109	3.08	5.94	4.11	0.78
	Post-test of the control group	109	3.25	5.78	4.1	0.74
Creative practice	Pre-test of the experimental group	109	2.88	5.91	4.03	0.85
	Post-test of the experimental group	109	3.08	5.91	4.55	0.79
	Pretest of the control group	109	2.48	6.11	4.05	0.84
	Post-test of the control group	109	3.08	6.11	4.17	0.79

(2) Descriptive statistical analysis

This paper conducts descriptive statistical analysis on the pre-test and post-test results of the experimental group and the control group in four aspects: aesthetic perception, artistic expression, cultural understanding, and creative practice, as shown in Table 7. In terms of aesthetic perception, the minimum value of the pre-test for the experimental group was 2.86, the maximum value was 5.89, the average value was 4.19, and the standard deviation was 0.93. After the teaching practice, the minimum value of the post-test for the experimental group increased slightly to 3.64, the maximum value remained unchanged, the average value increased to 4.59, and the standard deviation decreased to 0.7, indicating that the experimental group's performance in aesthetic perception improved, and the differences between individuals decreased. The pre-test and post-test data for the control group also showed a similar trend, but the change in the average value was not as significant as that of the experimental group, and the change in the standard deviation was small. In terms of artistic expression, the pre-test and post-test data for both the experimental and control groups showed a certain degree of stability. The average score for the experimental group in the pre-test was 4.3, which increased to 4.58 in the post-test, with the standard deviation decreasing to 0.77, indicating that the teaching practice had a significant positive effect on artistic expression levels. The data for the control group also showed similar stability, but the changes in average scores were smaller. In terms of cultural understanding, the pre-test average score for the experimental group was 4.07, which increased to 4.54 in the post-test, indicating that teaching practices have a positive promotional effect on cultural understanding. Additionally, the standard deviation also decreased in the post-test, suggesting that individual differences are diminishing. The pre-test and post-test data for the control group were relatively stable, with small changes in both average scores and standard deviations. However, it is worth noting that the post-test mean of the control group was slightly lower than the pre-test, which may indicate that cultural understanding levels may fluctuate to some extent in the absence of teaching practices. In terms of creative practice, the pre-test mean of the experimental group was 4.03, which increased to 4.55 in the post-test, indicating that teaching practices have a certain positive impact on creative practice.

(3) Pre-test difference analysis between the experimental class and the control class

The results of the pre-test analysis for each dimension between the experimental class and the control class are shown in Table 8. In the experimental class and the control class, the pre-test mean scores for aesthetic perception were 2.57 (experimental class) and 2.13 (control class), respectively. This indicates that before the experiment began, the aesthetic perception level of the experimental class was slightly higher than that of the control class, but the difference was not significant. The pre-test mean scores for artistic expression were 2.74 (experimental class) and 2.65 (control class), respectively, indicating that prior to the experiment, the experimental class had a slightly higher level of artistic expression than the control class, but the difference between the two was very small. Overall, there were no significant differences between the experimental and control groups in terms of aesthetic perception, artistic expression, cultural understanding, and creative practice levels, with P-values all >0.001.

Table 8: Pre-test comparison between experimental class and control class (x±s)

Project	Experimental class N=109	Control classes N=109	T value	P value
Aesthetic perception	2.57±0.63	2.13±0.32	1.586	0.009
Artistic expression	2.74±0.53	2.65±0.51	0.744	0.119
Cultural understanding	2.18±0.75	2.47±0.59	-0.518	0.247
Creative practice	2.24±0.71	3.18±0.64	-0.238	0.815

(4) Comparison of post-test differences between the experimental class and the control class

The results of the pre-test for each dimension in the experimental class and the control class are shown in Table 9. In the experimental class, the post-test mean value for aesthetic perception was 2.86, while in the control class, the post-test mean value for aesthetic perception was 2.08. This indicates that after the teaching practice, the aesthetic perception level of the experimental class was significantly higher than that of the control class. Through a t-test, the t-value was 7.138, and the p-value was <0.001, indicating that the difference between the experimental and control groups in post-test aesthetic perception was statistically significant. Additionally, in other learning dimensions, the experimental group's levels of artistic expression, cultural understanding, and creative practice were significantly higher than those of the control group. This suggests that the music teaching model based on learning path recommendations can help improve students' learning levels.

Table 9: Post-test comparison between experimental class and control class (x±s)

Project	Experimental class N=109	Control classes N=109	T value	P value
Aesthetic perception	2.86±0.58	2.08±0.39	7.138	<0.001
Artistic expression	2.83±0.69	2.16±0.48	5.285	<0.001
Cultural understanding	2.79±0.56	2.11±0.58	5.275	<0.001
Creative practice	2.80±0.61	3.13±0.59	4.188	<0.001

V. Conclusion

This paper constructs a multi-modal teaching framework for music classrooms empowered by AIGC from four dimensions: teaching objectives, resources, methods, and environment, with the aim of improving students' learning efficiency. Subsequently, a personalized music learning path recommendation algorithm based on the ant colony algorithm is proposed, and the recommendation algorithm is tested and analyzed in practice. The conclusions are as follows:

(1) As user records increase, the number of recommended resources based on user history also increases, aligning with expected recommendation outcomes. Resources at the top of the list achieve an accuracy rate of 1, indicating that recommended

resources accurately capture user interests and provide precise recommendations, while also maintaining good surprise and timeliness.

(2) A comparison of the learning achievements of the experimental group and the control group in four learning areas—basic music theory, sight-singing and ear training, music appreciation, and vocal music fundamentals—shows that the algorithm described in this paper can optimize music learning paths and effectively improve learning efficiency.

(3) Practical analysis proved that before practical teaching, there was no significant difference between the experimental group and the control group in terms of aesthetic perception, artistic expression, cultural understanding, and creative practice. However, after practical teaching, the experimental group's aesthetic perception, artistic expression, cultural understanding, and creative practice were significantly higher than those of the control group.

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