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Innovation and Practical Exploration of Music Classroom Teaching Models with the Assistance of Digital Technologies

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SUMMARY: *In music classroom teaching, traditional digital applications mostly stay at the level of courseware display and resource playback, which is difficult to form a continuous recognition of students 'learning status, and it is difficult to support immediate regulation in the classroom. To solve this problem, this paper constructs a music classroom teaching model assisted by digital technology, which integrates audio collection, behavior log analysis, learning feedback processing and resource intelligent matching into the same teaching link, forming a classroom operation mechanism of "data perception - state recognition - interaction support - result reflux". The study adopted a 16-week quasi-experimental design, and took 96 students as objects to compare and analyze the implementation effect of digital teaching mode and conventional teaching mode. The results showed that the comprehensive score of music skills in the experimental group increased from 68.42 to 84.76 points, the correct rate of pitch recognition increased from 71.08% to 89.63%, the rate of rhythm stability increased from 72.35% to 90.27%, and the classroom participation index reached 87.56 points, which were significantly better than those in the control group. The research shows that embedding computer data processing methods into music classroom is helpful to improve the timeliness of teaching feedback, the pertinence of resource support and the controllability of learning process, which has practical significance for the optimization of music classroom teaching mode.*

KEYWORDS: *Digital technology; Music class; Teaching model innovation; Intelligent interaction support*

1 Introduction

After digital technology continues to enter the education scene, the organization mode of classroom teaching, resource form and evaluation logic are undergoing detailed and profound changes. Music curriculum originally has the characteristics of strong perception, prominent process and high interactive density, which not only relies on the synchronous construction of sound, image, movement and situation, but also highly depends on teachers 'immediate judgment of students 'singing, rhythm grasp, listening reaction and participation state. Although traditional music classroom can retain the advantages of face-to-face demonstration, collective chorus and emotional transmission, there are still some problems in the process of teaching promotion, such as relatively single resource presentation path, insufficient identification of students 'differences, practice feedback mainly relying on teachers 'experience, and it is difficult to continuously track learning data after class. Especially when

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the class size expands and students' music foundation is differentiated obviously, teachers often find it difficult to give consideration to both generic teaching and individual guidance in limited class hours, which also makes the fine regulation of music classroom face realistic pressure [1-3].

In recent years, artificial intelligence, learning analysis, digital audio processing, mobile terminal acquisition and interactive platform technologies have gradually matured. Music teaching is no longer just a simple move of courseware, video or accompaniment materials into the classroom, but has begun to form a compound teaching environment that is driven by data to support teaching decisions, aided by algorithms to optimize learning paths, and connected by platforms to train scenes inside and outside the class. The value of digital technology is not only reflected in the "richer presentation", but more importantly, it can transform the originally scattered, instantaneous and difficult to remember music learning process into behavioral data that can be recorded, analyzed and feedback. For example, students' rhythm click accuracy, melody singing deviation, class speech frequency, resource call records, practice duration and stage learning feedback can be collected, summarized and analyzed through the digital system, and further transformed into the basis for teachers to adjust teaching rhythm and task difficulty [4-6]. This means that the operation logic of music classroom is gradually shifting from the experience-led single-line promotion to the circular optimization of "teaching implementation - data reflux - state recognition - strategy correction".

However, the introduction of digital technology into the music classroom does not naturally equal the improvement of teaching quality. Practice has shown that although some classrooms are equipped with smart blackboards, mobile terminals, online resource libraries and even virtual reality equipment, teaching activities still remain at the level of tool superposition, and there is a lack of stable structural connection between technology use and curriculum objectives. Although the resources are rich, the content that really matches students 'cognitive level, singing ability and classroom tasks is not necessarily sufficient. Although the platform can record data, it is difficult to convert these data into operational teaching suggestions if there is no effective student status recognition mechanism. In other words, to truly serve the music classroom, digital technology not only needs the access of hardware and software, but also needs to reconstruct a set of computable, interactive and evaluable teaching mode around the teaching scene, so that technology is not only a display medium, but also an internal component supporting classroom organization, learning support and effect evaluation [7-9].

Based on this understanding, this paper focuses on the innovation and practical exploration of music classroom teaching mode assisted by digital technology, and tries to re-examine the operation mechanism of music classroom from the perspective of teaching system design. This paper did not regard the digital platform as an automatic device to replace teachers, but positioned it as an intermediary system connecting teachers 'decision-making, students 'behavior, teaching resources and learning evaluation. In terms of research ideas, on the one hand, combining classroom behavior data and learning feedback, a student state recognition method is constructed to analyze students 'dynamic performance in rhythm training, melody modeling, music understanding and classroom participation. On the other hand, it established a digital resource matching and intelligent interaction support mechanism for music classroom, so that the system could push more suitable resource content and interactive feedback according to teaching theme, student level and task process. At the same time, the application effect of the model was tested through teaching experiments, and its influence on classroom participation, learning performance and teaching regulation efficiency was investigated. It was hoped that the digital transformation of music classroom should not stay at the level of equipment updating, but should be implemented as the synchronous transformation of teaching structure, data mechanism and interaction mode, so as to provide more explanatory and practical research basis for the continuous optimization of music teaching mode [10-12].

2 Related Research

After the introduction of digital technology into music classroom, the research field has shifted from the pure media update to the reconstruction of teaching process. The existing achievements mainly focus on three aspects: digital resource supply, intelligent interaction support and immersive learning environment. Some studies focus on the application of digital audio technology, mobile learning platform and online course resources in music teaching, emphasizing their role in promoting resource expansion, in-class and out-of-class cohesion and learning continuity [1-3]. Some studies have also introduced artificial intelligence into music classroom to explore the feasibility of algorithm support in scenarios such as smart piano teaching, flipped classroom, teaching skill assessment and classroom auxiliary generation, trying to improve feedback efficiency and teaching suitability through data analysis [4-6]. Another group of studies apply VR, audio-video interaction and multimodal perception technology to music theory, harmony learning and teaching of special groups, hoping to enhance auditory understanding, action participation and spatial experience with the help of virtual situations [7-9]. From the overall trend, the digitization of music classroom is no longer "putting resources on the screen", but is evolving to the direction of "organizing teaching with data, supporting learning with interaction, and optimizing decision-making with calculation".

As shown in Figure 1, the technical chain involved in the existing research has been initially formed: the sound, image, motion, click behavior and learning feedback in the classroom can be collected by the terminal equipment in real time, and converted into computable learning representation through the feature extraction and behavior analysis module, and then the student state recognition, resource matching and process evaluation are completed. This change enabled the music classroom to obtain a finer scale of observation than the traditional empirical judgment. Teachers can no longer rely on on-site impression to grasp students' learning status, but can combine rhythm deviation, pitch sing-along, task completion rate, interactive response time and resource call records to determine whether students are in different states of "smooth understanding", "partial lag" or "need reinforcement support". Because of this, the combination of digital technology and computer methods is changing the basic way of "what to teach, how to teach, and how to evaluate" in the music classroom.

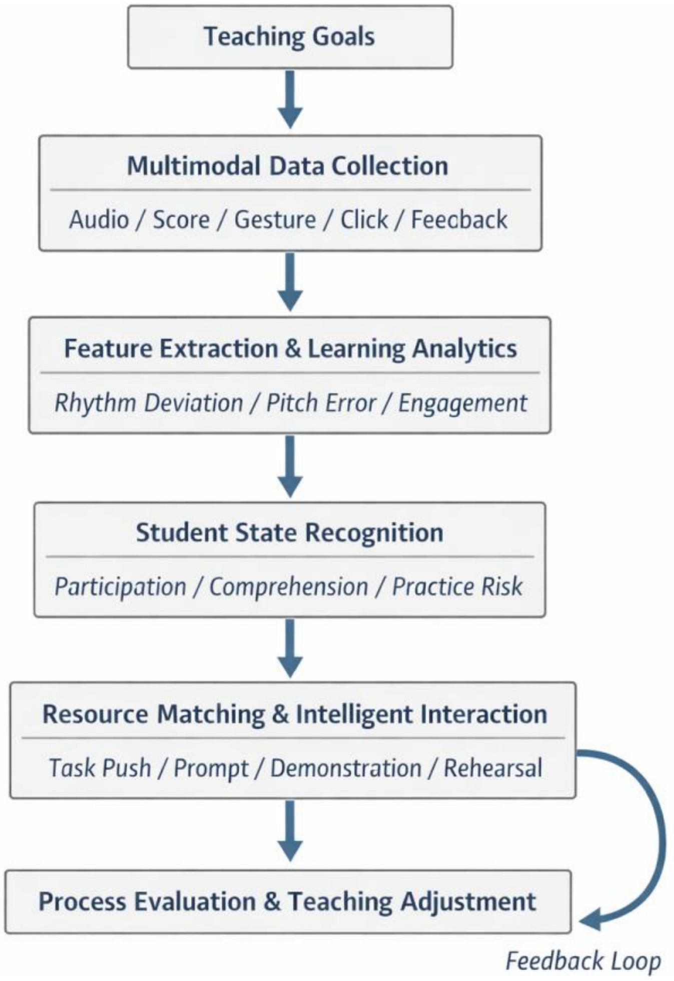

Figure 1: Technical logic of digital technology supporting research on music classroom teaching

However, there are still obvious breakpoints in the existing studies. Some achievements focus on resource construction and platform functions, which can solve the problem of "whether the materials are abundant", but rarely go into the immediate regulation mechanism inside the classroom, resulting in that although the system can display content, it is difficult to accurately respond to the subtle differences in the learning process of students [10-13]. Although some studies have introduced artificial intelligence and learning analysis methods, they often focus on a single training scenario, such as piano performance, composition assistance or skill evaluation, and the research objects are relatively concentrated, which has not fully covered the complex tasks such as chorus, listening, rhythm training, work understanding and classroom collaboration that are ubiquitous in normal music classes in primary and secondary schools or colleges [14-16]. Research related to immersive technology has outstanding performance in experience enhancement, but device cost, deployment complexity and classroom popularity still limit its large-scale application [9-12, 18]. This shows that although the research on the digitization of music classroom has made rich progress, there is still room for further integration and deepening in the construction of the complete closed-loop of "classroom behavior data - student state recognition - resource intelligent matching - teaching effect evaluation".

For comparison, Table 1 summarizes the focus, main implications and shortcomings of related research. It can be seen that the existing achievements provide an important foundation for the digitization of music teaching, but there are generally problems such as scattered technical modules, insufficient classroom process modeling, and low closure of feedback mechanism. Based on this reality, this paper does not regard digital technology as an external tool attached to the classroom surface, but puts it inside the teaching organization structure, and designs the system around classroom state recognition, resource matching and interactive support, trying to transform the multi-source behavior data in the music classroom into a computational basis that can serve the teaching decision. So as to promote the teaching mode from resource-driven to data-driven, from static teaching to dynamic regulation.

Table 1: Summary of research related to music classroom digitization

Research Direction	Representative References	Main Content	Existing Limitations
Digital Audio and Online Learning Systems	[4][13][19]	Digital audio, mobile terminals, and online platforms are used to expand the space for music learning and improve resource accessibility and learning continuity.	More attention is given to platform access and resource dissemination, while in-class learning state recognition is less explored.
AI-Assisted Music Teaching	[1][3][16]	Artificial intelligence is applied to teaching support, content generation, flipped classrooms, and personalized learning recommendations.	Research on full-process regulation in routine music classrooms remains insufficient, and the real-time classroom feedback chain is not yet complete.
Intelligent Skill Training and Assessment	[8][15][17]	Data analysis and intelligent judgment are introduced into vocal training, piano instruction, and teacher skill evaluation.	The research scenarios are relatively narrow and cannot directly cover comprehensive music classroom tasks.
VR and Immersive Music Learning	[9][10][11][12][18]	VR and audio-video interaction are used to enhance harmony learning, theoretical learning, and perceptual experience.	This approach is highly dependent on equipment, has high promotion costs, and still has limited classroom universality.
Teachers' Digital Literacy and Classroom Adaptation	[6]	Focuses on teachers' digital competence and technology integration in the "new normal."	Most studies remain at the level of competence investigation and provide limited support for reconstructing teaching models.
Comprehensive Effects in Music Education	[2][7]	Explores the positive effects of technology intervention on creativity, sociality, and classroom participation.	Descriptions of computer-supported teaching mechanisms are relatively general and lack an operational technical chain.

3 Materials and Methods

3.1 The overall architecture design of music classroom teaching mode assisted by digital technology

The music classroom teaching mode assisted by digital technology is not a simple juxtaposition of electronic whiteboard, tablet terminal, audio software and resource platform, but a teaching link that can be perceived, calculated and feedback is constructed around the classroom operation process. Combined with the characteristics of "listening, singing, practicing and evaluating" interweaving in music discipline, this paper divides the classroom system into five parts: teaching goal generation layer, classroom data collection layer, learning state analysis layer, resource matching and interactive support layer, result evaluation and strategy reflux layer, and connects them through a unified data interface to form a closed-loop teaching structure. As shown in Figure 2, the framework not only retains the leading role of teachers in demonstration, guidance and aesthetic judgment, but also uses computers to process multi-source classroom information, so that teaching regulation no longer completely depends on experience and impression, but can be built on continuous data and dynamic analysis.

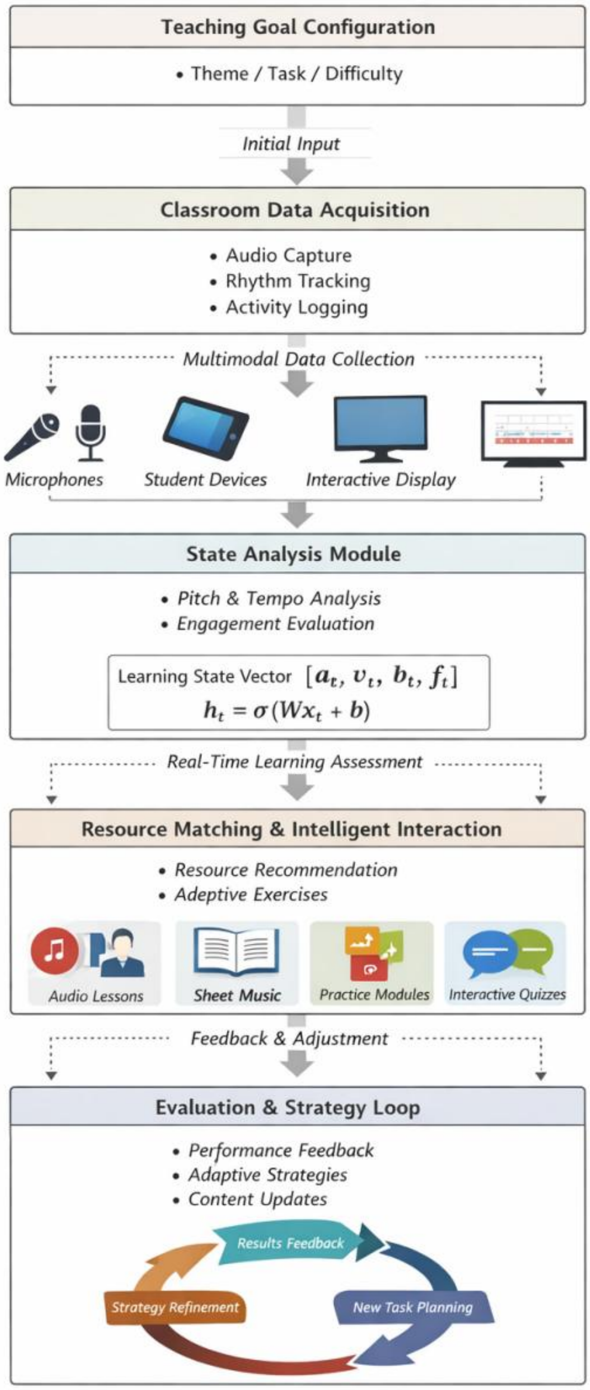

Figure 2: Overall architecture of music classroom teaching mode assisted by digital technology

In the early stage of system operation, teachers input teaching topics, teaching objectives, repertoire types, training difficulties and class basic information into the platform, and the system generates teaching task templates and calls the corresponding digital resource library. The resource library includes demonstration audio, track accompaniment, music score images, rhythm training units, micro-lesson videos, action demonstration clips and interactive evaluation questions. After the class started, the system synchronously collected students 'singing pitch, rhythm click, answer response, page stay, interaction frequency and instant feedback text through microphone array, mobile terminal, interactive screen and learning platform log, and transformed the learning traces originally scattered in different links into structured data. In order to avoid misjudgment caused by single indicator, this paper uses multi-feature fusion to construct classroom state vector:

$$x_t = [a_t, v_t, b_t, f_t] \tag{1}$$

where, a_t represents the intonation feature at time t, v_t represents the rhythm and speed control feature, b_t represents the classroom behavior participation feature, f_t represents the learning feedback and task completion feature. Based on this vector, the system further generates the student classroom state representation:

$$h_t = \sigma(Wx_t + b) \tag{2}$$

Here, W is the feature mapping matrix, b is the bias term, and σ is the nonlinear activation function. The significance of vector h_t is not to replace teacher judgment, but to provide teachers with a relatively stable set of state references, so that they can identify students' differences in rhythm grasp, melody sing-along, task understanding and classroom engagement in a more timely manner.

On this basis, the system enters the stage of resource matching and interaction support. Considering that task difficulty, resource form and student state in music classroom do not always correspond strictly, this paper uses weighted matching method to calculate the adaptation score between student state and candidate resources:

$$S_{ij} = \lambda_1 \, \mathrm{sim}(h_i, r_j) + \lambda_2 c_j + \lambda_3 q_j \tag{3}$$

where S_{ij} represents the matching score between student i and resource j, $\mathrm{sim}(h_i, r_j)$ represents the similarity between the state vector and the resource feature vector, c_j represents the consistency between the resource content and the current teaching goal, q_j represents the resource quality coefficient,λ_1 , λ_2, λ_3 are weight parameters, and it satisfies $\lambda_1 + \lambda_2 + \lambda_3 = 1$. The system pushes differentiated exercise content according to the score ranking results, such as adding a split-beat training module for students with large rhythm deviation, pushing sentence demonstration and slow singing resources for students with unstable pitch, and providing expanded listening and discrimination tasks for students with fast completion, so as to realize dynamic support for the classroom process.

3.2 Student state recognition method based on classroom behavior data and learning feedback

Considering the multi-source heterogeneous characteristics of music classroom data, this paper divides the original data into four categories: singing performance, interactive behavior, task completion and feedback evaluation, and enters the state recognition module through unified coding. Singing performance mainly comes from pitch deviation, rhythm deviation and sing-along integrity. The interactive behaviors mainly included the number of classroom responses, the frequency of terminal clicks, the number of resource calls and the page stay time. The task completion index reflects the submission of exercises, the completion rate of evaluation and the improvement range after error correction. The feedback evaluation comes from the real-time classroom questionnaire, self-assessment text and teacher annotation results. In order to reduce the influence of dimension differences on model judgment, this paper first conducts range standardization on each index:

$$\tilde{x}_{ik} = \frac{x_{ik} - x_k^{min}}{x_k^{max} - x_k^{min}} \tag{4}$$

where x_{ik} represents the original value of the ith student on the KTH index, $\tilde{x}_{ik}$ is the normalized result, x_k^{min} and x_k^{max} represent the minimum and maximum value of the index in the sample, respectively. After normalization, data from different sources are mapped to a unified space for subsequent fusion calculations.

In order to enhance the pertinency of state recognition, this paper constructs a feature index system combined with the actual music classroom, as shown in Table 2. The system does not pursue the simple expansion of the number of indicators, but emphasizes that it can form a relatively complete description of the classroom learning process. The intonation and rhythm indicators were used to reflect students' music skill performance, the interaction participation indicators were used to describe their classroom engagement, the task completion indicators were used to reveal students' execution quality, and the feedback indicators were used to make up for the problem that behavioral data did not capture enough learning experience and difficulty perception. Through this structure, state recognition is no longer limited to the one-sided judgment of "can sing" or "participate", but turns to the comprehensive recognition of learning quality and learning response.

Table 2: Characteristic index system of student status identification

Indicator Dimension	Specific Indicator	Data Source	Indicator Meaning
Singing Performance	Pitch deviation rate, rhythm error rate, singing completion rate	Microphone acquisition, audio analysis module	Reflects students’ mastery of melody and rhythm
Classroom Participation	Number of responses, click frequency, page dwell time	Interactive terminals, platform logs	Reflects students’ classroom engagement and interaction activity
Task Completion	Practice submission rate, assessment completion rate, error-correction improvement range	Assignment module, assessment records	Reflects the quality of task execution and correction ability
Learning Feedback	Self-evaluation score, difficulty markers, teacher observation labels	Questionnaire system, teacher-side records	Reflects subjective experience and external evaluation results

In the fusion stage, this paper uses the weighted method to generate the classroom status scores of students at time t:

$$s_i^{(t)} = \alpha_1 p_i^{(t)} + \alpha_2 b_i^{(t)} + \alpha_3 m_i^{(t)} + \alpha_4 f_i^{(t)} \tag{5}$$

Among them, $p_i^{(t)}$ represents the singing performance score, $b_i^{(t)}$ represents the classroom participation score, $m_i^{(t)}$ represents the task completion score, $f_i^{(t)}$ represents the learning feedback score, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the corresponding weights, and satisfies $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. Combined with the characteristics of music classroom that attaches great importance to process training and instant correction, this paper assigns relatively high weights to singing performance and task completion to avoid the system's excessive reliance on surface activity indicators such as click frequency.

Considering that the classroom state has time continuity, a single abnormal fluctuation should not be directly regarded as learning instability. Therefore, this paper introduces a time smoothing mechanism to modify the current state score:

$$\hat{s}_i^{(t)} = \beta s_i^{(t)} + (1 - \beta)\hat{s}_i^{(t-1)} \tag{6}$$

where $\hat{s}_i^{(t)}$ is the smoothed state estimate and β is the weight at the current time. The processing can reduce the interference of short-term noise on the recognition results, and make the system more suitable for the phased mind wandering, transient errors and temporary fluctuations common in the classroom scene. According to the smoothed scores, this paper divided the student states into three categories: good state, fluctuation state and support demand state, which were used for subsequent resource push and classroom intervention design. The result of state recognition is not a summative evaluation, but serves for teachers to adjust the classroom rhythm, exercise difficulty and support mode immediately. In other words, the core purpose of this method is not to attach static labels to students, but to provide a more timely and detailed basis for the regulation of music classes through the continuous perception of the learning process by the computer.

3.3 Digital Resource matching and intelligent interaction support mechanism for music classroom

After the completion of student status recognition, the key problem faced by the classroom system is no longer "whether we have enough digital resources", but how to push the appropriate content to the appropriate students in the appropriate way within the limited teaching time. The types of resources in the music classroom are obviously different, including demonstration audio, track accompaniment, music score images, rhythm training units, as well as micro-lecture videos, action tips, listening problem groups and instant error correction information. If the method of uniform distribution or fixed order of presentation is still adopted, the larger the number of resources, the greater the classroom interference may be. Based on this, this paper constructs a digital resource matching and intelligent interaction support mechanism for music classroom, which brings student status, teaching task and resource characteristics into the same computing framework, so that digital resource call turns from static configuration to dynamic matching.

Before the resource enters the system, it needs to complete the structured coding. In this paper, each class of resources is represented as a vector:

$$r_j = [d_j, c_j, m_j, l_j] \tag{7}$$

Among them, d_j represents the difficulty level of resources, c_j represents the content category, such as rhythm, intonation, listening, appreciation or singing, m_j represents the media form, such as audio, video, images or interactive exercises, and l_j represents the duration of resources and the intensity of classroom occupancy. Correspondingly, the learning state of students at time t can be written as $h_i^{(t)}$, and the teaching task vector is denoted as g_t. The goal of resource matching is not simply to find the "most similar" material, but to calculate the support value of resources for classroom tasks under the constraints of classroom goals, considering students' current weaknesses, resource suitability and interaction costs. To this end, this paper defines the matching score of student i to resource j as:

$$M_{ij}^{(t)} = \omega_1 \operatorname{sim}(h_i^{(t)}, r_j) + \omega_2 \operatorname{sim}(g_t, r_j) + \omega_3 q_j - \omega_4 l_j \tag{8}$$

where sim(·) represents the similarity function, q_j is the resource quality coefficient, l_j is the resource call cost, $\omega_1, \omega_2, \omega_3, \omega_4$ are the weight parameters, and $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$ is satisfied. This formula reflects two basic judgments: first, resources must be adapted to the state of students, and the difficulty is not too high or the content is misplaced; Second, resources must serve the current teaching process, and cannot destroy the overall progress of the classroom because of individual recommendation. The system sorts the candidate resources according to the matching score, and then outputs the resource scheme according to the level of "whole class sharing - group difference - individual supplement".

In the level of interactive support, the system is not designed as a closed automatic recommender, but a collaborative mechanism of "system prompt-student response-teacher correction" is constructed. After pushing resources, the system continuously records students' click reactions, exercise completion rate, pitch correction range, hard of hearing times and instant feedback text, and updates and estimates the interaction effect. If a resource fails to bring significant improvement in a short period of time, the system will automatically reduce its priority and move to an alternative resource in the adjacent difficulty level. Its update rule can be expressed as:

$$q_j^{(t+1)} = \eta q_j^{(t)} + (1 - \eta) e_j^{(t)} \tag{9}$$

Here, $q_j^{(t+1)}$ represents the effectiveness estimate of the resource in the next round of matching, $e_j^{(t)}$ represents the actual interaction effect of the resource in the current class, and η is the historical weight coefficient. Through this feedback update, the resource library is no longer a static storage space, but a dynamic system that can gradually form an adaptation experience in the classroom operation.

Table 3 shows the core resource types and trigger conditions in the proposed resource matching and interaction support mechanism. It can be seen that different resources are not equally distributed, but assume different functions according to the classroom scene: the demonstration audio is used to establish auditory reference, the rhythm training module is used to correct the beat deviation, the clause singing video is suitable for dealing with melody instability, and the interactive test questions are more suitable for stage detection and attention recovery. In this way, resource push is no longer just "supplementary material", but becomes an actual part of classroom regulation.

Table 3: Types of digital resources and intelligent interaction triggering methods

Resource Type	Main Content	Trigger Condition	Interactive Support Objective
Demonstration Audio	Standard singing, separated accompaniment tracks	Large pitch deviation, unstable vocal imitation	Establish auditory reference and correct melodic perception
Rhythm Training Module	Beat-based exercises, rhythm tapping	High rhythm error rate	Strengthen beat control and tempo stability
Phrase-by-Phrase Singing Video	Segmented demonstration, movement prompts	Insufficient singing completion	Reduce task difficulty and support phrase-level mastery
Musical Score Images and Annotations	Melodic contour, key symbol prompts	Difficulty in score reading or distracted attention	Enhance visually assisted understanding
Interactive Assessment Items	Listening discrimination, selection tasks, instant feedback	Stage assessment or in-class review	Examine comprehension and promote relearning

It can be seen that the core of the digital resource matching and intelligent interaction support mechanism for music classroom does not lie in the accumulation of resources, but in the establishment of dynamic association between resources, tasks and students 'states through computer methods. It makes the technology intervention in the classroom have a clear direction: on the one hand, it alleviates the burden of teachers in resource screening and instant judgment, on the other hand, it provides students with a support path closer to their learning state. With the continuous feedback in the classroom, the system can gradually improve the matching accuracy, which also provides a method basis for the effect test in the subsequent teaching experiments.

3.4 Teaching experiment design and evaluation method

In order to test the actual effect of music classroom teaching mode assisted by digital technology, this paper uses quasi-experimental design to carry out continuous teaching experiments among students of similar majors in the same college. The experimental subjects were 96 students in two natural classes, including 48 students in the experimental group, who adopted the digital technology-assisted teaching model constructed in this paper. The control group of 48 students followed the conventional music classroom organization, that is, teachers completed unified teaching, demonstration singing, segmented practice and homework assignment. Both groups of students were taught by the same teacher, and the number of teaching weeks, teaching content, repertoire difficulty and assessment requirements were consistent to reduce the interference caused by differences in teacher style and teaching content. The experimental period was set for 16 weeks, with 2 class hours per week, covering the main teaching tasks such as rhythm training, melody modeling, work appreciation, choral collaboration and stage display. Before the experiment, the music basic pre-test and digital learning background investigation were carried out for the two groups of students, including the accuracy of pitch modeling, rhythm recognition ability, music recognition foundation, classroom participation habits and mobile terminal use proficiency. The results showed that there was no significant difference in pre-test scores and technology use experience between the two groups, which provided the basic conditions for subsequent comparison.

The classroom operation of the experimental group relies on the digital teaching platform.

Teachers import teaching objectives, important and difficult points and task structures before class, and the system generates resource call sequences according to preset rules and classroom historical data. During the class, the system synchronously recorded students 'rhythm click, singing deviation, page stay, resource call, interactive response and instant feedback information through interactive terminal, audio acquisition module and platform log, and dynamically pushed exercise content according to the state recognition and resource matching mechanism described above. The control group did not enable the state recognition and intelligent matching module, and only used conventional multimedia courseware, piano accompaniment and teacher oral feedback to complete the teaching. As shown in Figure 3, the whole teaching experiment was carried out according to the path of "sample selection and pre-test -- group intervention -- classroom data collection -- result evaluation and statistical analysis". The experimental group and the control group were consistent in teaching content and class time arrangement, while the difference was mainly reflected in whether the classroom support mechanism based on data analysis was introduced. The purpose of this setting is to try to focus the differences on the core variable of "whether the digital teaching mode forms a data-driven closed loop", rather than simply comparing the number of devices or the differences in the form of courseware。

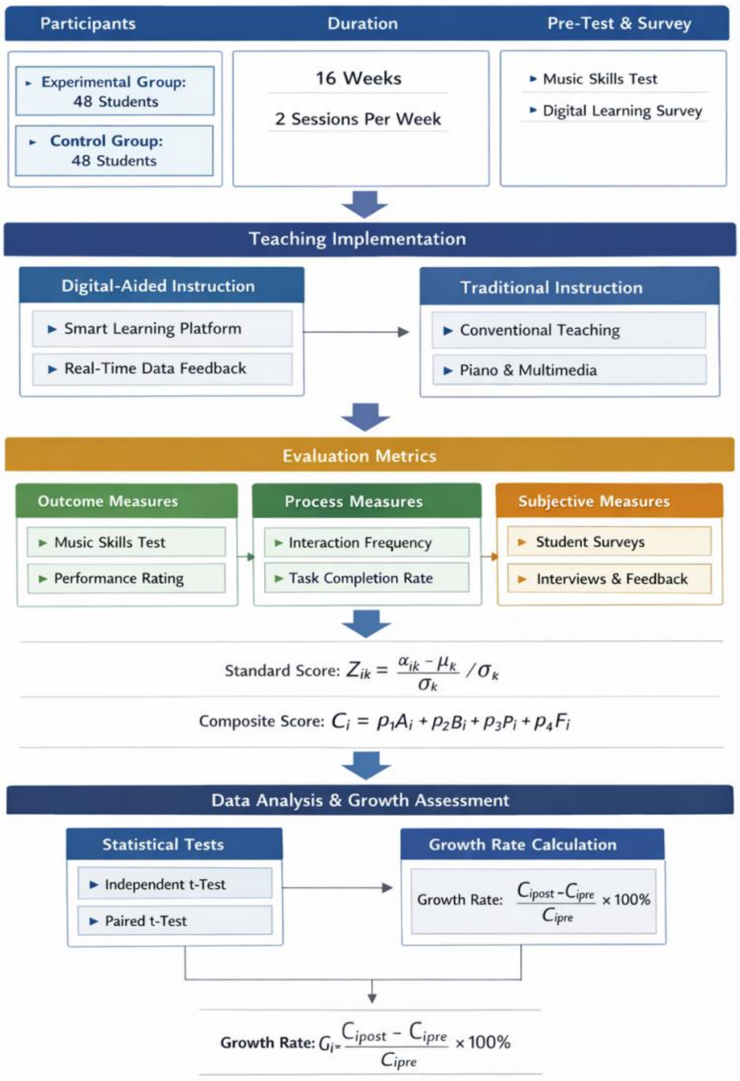

Figure 3: Teaching experiment design and evaluation process

The evaluation method adopts the idea of "outcome measurement, process measurement and subjective feeling measurement" to avoid the single outcome score covering up the real changes in the classroom process. The former examined intonation, rhythm, music recognition and listening ability. The latter was blindly evaluated by three music teachers with experience in music teaching according to a unified scale. The process measurement mainly extracted the behavioral data formed in the classroom platform, including the average interaction frequency, task completion rate, resource use efficiency and classroom focus time. Subjective feelings were measured by questionnaires and interviews after class to collect students' evaluation on the difficulty of classroom understanding, participation experience, feedback timeliness and learning confidence. In order to enhance the comparability between different indicators, this paper first standardizes each indicator, and then constructs the comprehensive evaluation score:

$$Z_{ik} = \frac{x_{ik} - \mu_k}{\sigma_k} \tag{10}$$

where x_{ik} represents the original value of the ith student on the KTH evaluation index, μ_k and σ_k represent the sample mean and standard deviation of the index respectively, Z_{ik} is the standardized result. On this basis, the student comprehensive performance score is defined as:

$$C_i = \rho_1 A_i + \rho_2 B_i + \rho_3 P_i + \rho_4 F_i \tag{11}$$

Among them, A_i represents music skill test score, B_i represents work performance score, P_i represents classroom process behavior score, F_i represents subjective feedback score, $\rho_1, \rho_2, \rho_3, \rho_4$ are evaluation weights, and $\rho_1 + \rho_2 + \rho_3 + \rho_4 = 1$ is satisfied. Considering that music classroom emphasizes both result performance and process participation, this paper appropriately increases the proportion of skills and process indicators in weight allocation, so as to reflect the actual value of digital technology in the regulation of learning process.

In order to investigate the change range before and after the teaching intervention, this paper further calculates the individual growth rate of students:

$$G_i = \frac{C_i^{post} - C_i^{pre}}{C_i^{pre}} \times 100\% \tag{12}$$

where, C_i^{pre} and C_i^{pre} respectively represent the comprehensive performance scores of students before and after the experiment, and G_i is the growth rate. This index can intuitively reflect the influence of different teaching modes on students 'learning improvement, and is not limited to the absolute achievement at a certain stage. In the statistical analysis part, the independent sample test and paired sample test were used to compare the differences between groups and the changes within groups. At the same time, the class log and interview content were cross-interpreted to improve the credibility of the conclusion.

4 Results

In order to verify the practical application effect of the music classroom teaching mode assisted by digital technology, this paper statistically analyzed the classroom behavior data, music skill assessment results, work performance scores and learning feedback information of the experimental group and the control group during the 16 weeks of teaching intervention according to the above experimental scheme. A total of 96 students participated in the experiment, including 48 students in the experimental group and 48 students in the control group. The two groups of students completed the music foundation pre-test and the digital learning background investigation before the experiment, and the pre-test results were not significantly different, indicating that the samples were comparable. In the teaching process, the experimental group accessed the digital teaching platform, and the classroom status recognition, resource matching and interactive support were completed by the system. The control group adopted conventional multimedia assisted teaching methods, without dynamic recognition and intelligent push functions. During the whole experiment, the platform recorded a total of 27,648 classroom interaction logs, 5376 rhythm click data, 3072 sections of singing audio, and 1536 instant feedback questionnaires after class, with a data integrity rate of 97.8%.

Table 4 lists the platform operating environment and data acquisition configuration of this teaching experiment. It can be seen that this study does not rely on high-cost and redeployed complex hardware, but completes the teaching model verification in the conventional smart classroom and general computing environment. In the audio acquisition part, 44.1 kHz sampling rate and 16 bit quantization accuracy are used to ensure the availability of students singing along, rhythm clicking and demonstration audio analysis. The back-end of the platform uses Python 3.10 and MySQL 8.0 for data management and status calculation, and the front-end realizes classroom interaction through smart screens and student mobile terminals. During the experiment, the average response time of the system is 0.83 s, and the success rate of resource push is 98.4%, which shows that the mode has a stable operation foundation in daily teaching scenarios.

Table 4: Teaching experiment platform configuration and data acquisition environment

Item	Configuration
Operating System	Windows 11
Server CPU	Intel Xeon Silver 4310 2.10 GHz
GPU	NVIDIA RTX 3060 12 GB
Memory	32 GB
Database	MySQL 8.0
Backend Environment	Python 3.10, Flask
Frontend Environment	Vue 3, Chrome 122
Audio Acquisition Parameters	44.1 kHz, 16 bit
Classroom Terminals	Smart Display, Teacher Control Terminal, Student Mobile Terminals

In the level of learning results, the experimental group showed a more obvious improvement. As shown in Table 5, there were no significant differences between the two groups before the experiment in the comprehensive score of music skills, the correct rate of pitch recognition, the rate of rhythm stability, the score of work performance and the classroom participation index. After 16 weeks of intervention, all indicators in the experimental group were higher than those in the control group, and the differences in classroom participation index and rhythm stability rate were more prominent. The comprehensive score of music skills in the experimental group increased from 68.42±6.15 to 84.76±5.48, with an increase of 23.9%; In the control group, the score increased from 68.17±6.03 to 75.31±5.92, with an increase of 10.5%. In terms of the accuracy of pitch recognition, the experimental group increased by 18.55 percentage points, and the control group increased by 10.18 percentage points. In terms of work performance score, the experimental group increased 17.18 points, while the control group increased 7.85 points. It shows that the intervention of digital technology does not stay at the level of resource display, but effectively improves the process quality and final performance of music learning through continuous perception of students 'state and dynamic adaptation of resource call.

Table 5: Comparison of main teaching effect indicators between the two groups of students

Indicator	Experimental Group (Pre-Intervention)	Experimental Group (Post-Intervention)	Control Group (Pre-Intervention)	Control Group (Post-Intervention)	Between-Group Difference (p)
Comprehensive Music Skills Score / points	68.42 ± 6.15	84.76 ± 5.48	68.17 ± 6.03	75.31 ± 5.92	0.003
Pitch Recognition Accuracy / %	71.08 ± 7.42	89.63 ± 5.37	70.74 ± 7.11	80.92 ± 6.28	0.001
Rhythm Stability Rate / %	72.35 ± 6.94	90.27 ± 4.96	72.04 ± 7.08	82.11 ± 5.84	0.002
Performance Rating / points	67.96 ± 6.51	85.14 ± 5.26	68.23 ± 6.44	76.08 ± 5.73	0.004
Classroom Participation Index / points	64.87 ± 7.23	87.56 ± 4.88	65.11 ± 7.05	73.84 ± 6.12	< 0.001

Figure 4 provides a more intuitive view of the differences in core indicators between the two groups of students after the end of the intervention. The experimental group showed a higher level in the three dimensions of pitch recognition, rhythm control and classroom participation, especially in the classroom participation index with a large distance from the control group. The results were consistent with the behavior records in the platform logs. The average frequency of interaction in the experimental group was 13.8 times per class hour, which was higher than that in the control group of 8.6 times. The average effective rate of resource invocation is 88.4%, which indicates that there is a high matching degree between the content pushed by the system and the learning needs. The teacher's records also showed that the time of repetitive error correction in the experimental group was significantly shortened, and the number of pauses caused by "unable to keep up with the rhythm" or "unable to find the entry point" in a single class was reduced by 31.7% compared with the control group. It can be seen that the digital support mechanism has a practical effect on the efficiency of classroom organization.

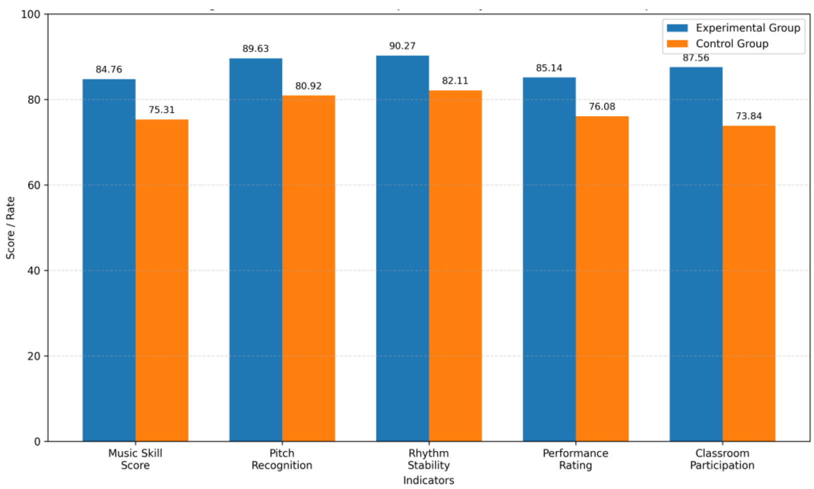

Figure 4: Comparison of main teaching effect indicators between the two groups of students after intervention

In addition to the improvement of the result score, what is more noteworthy is the continuous change of the classroom process. Figure 5 shows the trend of the average weekly task completion rate of the two groups of students during the 16 weeks of instruction. At the beginning of the experiment, the completion rate of the two groups was close, 71.3% in the experimental group and 70.8% in the control group. After the 8th week, the completion rate of the experimental group increased to 84.7%, and reached 92.4% in the 16th week, showing a relatively stable increasing trend. Although the control group also had a certain increase, the increase was slower, and only reached 81.2% by week 16. This difference indicates that the teaching model supported by digital technology not only improves the performance of a single class session, but also enhances the ability of students to continuously complete learning tasks. Combined with the questionnaire and interview, it can be seen that the students in the experimental group are easier to find supplementary materials that are consistent with the class progress after class, and the practice path is also clearer, so the frustration of repeated practice is lower.

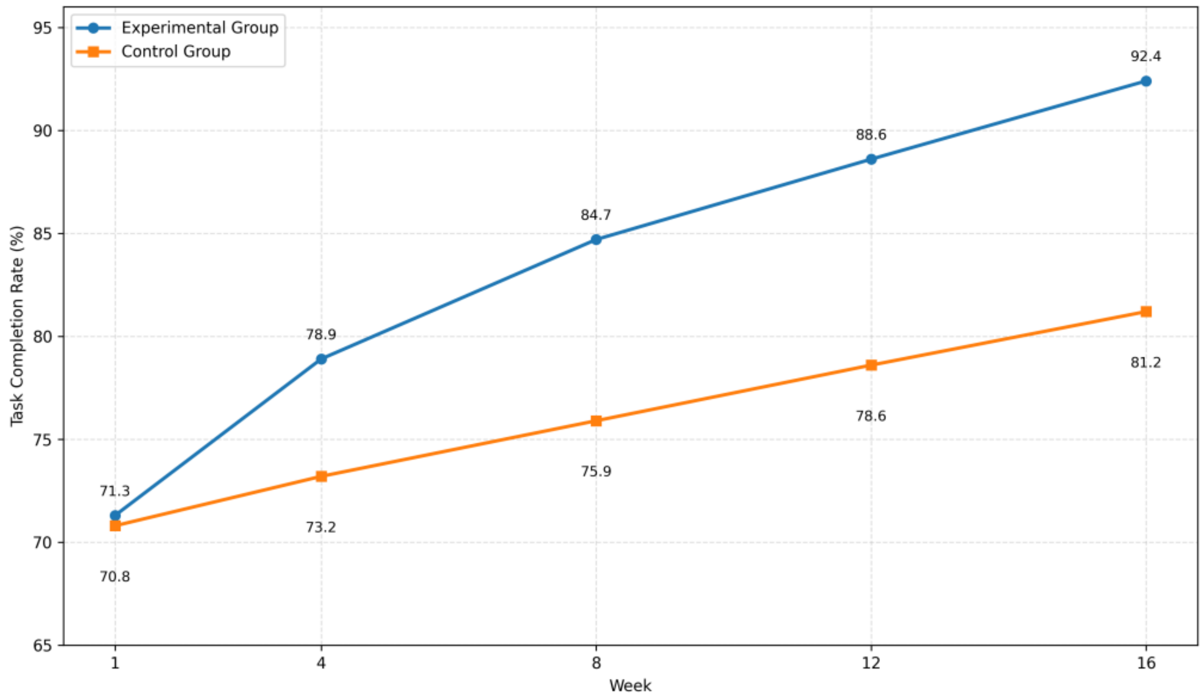

Figure 5: Change trend of weekly average task completion rate between experimental group and control group

Further analysis of the platform operation data can find that the student status recognition and resource matching mechanism play a mediating role in classroom support. Taking the teacher's manual labeling results as reference, the system's recognition agreement rate of students 'classroom states reaches 91.7%, and the recognition effect of "rhythm lag" and "attention fluctuation" is relatively stable. The average effective rate of resource recommendation after being adopted by students was 86.5%, that is, a high proportion of corresponding indicators improved in the next round of exercises after pushing resources. More importantly, the average time for teachers to sort out classroom records and reissue exercise materials after class was reduced from 23.6 minutes before the experiment to 11.4 minutes, which indicated that the platform not only improved students 'learning performance, but also reduced teachers 'repetitive affairs burden to a certain extent.

Synthesizing the above results, it can be seen that the music classroom teaching mode assisted by digital technology shows good application value at multiple levels. It does not change the basic attributes of music classroom with teacher guidance, student experience and aesthetic construction as the core, but enhances the responsiveness of classroom to different learning states through the continuous integration of computer behavior data, audio information and learning feedback. The advantages of the experimental group in skill scores, participation degree, task completion rate and classroom operation efficiency showed that the model had good teaching adaptability and practical feasibility, and also provided sufficient results for the subsequent discussion of its action mechanism and promotion boundaries.

5 Discussion

The digital technology-assisted music classroom teaching model proposed in this paper is not an external decoration to the traditional classroom, but introduces a set of computing mechanisms that can continuously perceive, instantly analyze and participate in regulation inside the teaching organization. Compared with conventional multimedia teaching, the technology in this mode is no longer mainly used for courseware display, accompaniment playback or resource supplement, but the pitch deviation, rhythm stability, task completion, interactive behavior and learning feedback in the classroom are transformed into tractable data objects, and then the state recognition and resource matching module is used to complete the teaching support. This change makes the music classroom change from the relatively linear structure of "teachers promote uniformly and students follow passively" to the dynamic structure of "data reflux and differentiated response under the leadership of teachers". From the results, the improvement of music skill score, rhythm stability rate, work performance score and classroom participation index in the experimental group were better than those in the control group, which indicated that the effectiveness of digital technology intervention was not only reflected in the active classroom atmosphere, but also reflected in the substantial improvement of learning quality. The reason is that the system can identify the learning status according to the specific performance of students in the classroom, and push more suitable exercise materials and interactive tips in time, which reduces the mismatch between resource supply and learning demand. In other words, technology does not play the role of replacing teachers, but strengthens teachers 'perception ability and control accuracy of classroom differences, so that learning fluctuations that are difficult to be continuously captured can be identified more clearly.

Compared with the classroom adjustment method relying solely on manual experience, this model has certain advantages in the speed of teaching feedback and the stability of process support. Especially in the teaching scene of music classroom, which emphasizes real-time demonstration, repeated practice and continuous correction, the synchronous processing of multi-source data by computers helps to shorten the time interval between teachers 'detection of problems and implementation of interventions, and also improves the pertinence of resource invocation. Still, there are boundaries to this model. Students' emotional state, aesthetic experience and classroom generative response cannot be completely exhausted by structured indicators, and the system recognition results still need to be judged by teachers combined with specific context. Therefore, digital technology is better understood as an auxiliary node in the teaching community rather than the sole basis for classroom decision making. In the future, if more detailed multi-modal recognition methods can be further introduced, and the sample scope and course types can be expanded, the interpretation power and generalization of music classroom digital research still have room for further improvement.

6 Conclusions

This paper focuses on the innovation and practice of music classroom teaching mode assisted by digital technology. Based on the combination of music classroom teaching needs and computer support mechanisms, a teaching implementation framework consisting of classroom data collection, student status recognition, digital resource matching and intelligent interactive support is constructed, and its application effect is tested through a 16-week quasi-experiment. The results show that the model can be better embedded in the normalization of music teaching process, which not only improves the method of classroom resource invocation, but also enhances the timeliness and differentiated support ability of teaching feedback. After the experiment, the comprehensive score of music skills in the experimental group increased from 68.42 to 84.76, with an increase of 23.9%. The correct rate of pitch recognition increased from 71.08% to 89.63%, the rate of rhythm stability increased from 72.35% to 90.27%, and the classroom participation index increased from 64.87 to 87.56, which were significantly better than those of the control group. This shows that classroom support based on data analysis has a relatively stable role in promoting music learning effects. At the same time, the research shows that the value of digital technology in music classroom is not to replace teachers 'teaching judgment, but to help teachers identify students 'differences faster, adjust task rhythms more accurately, and allocate resources more pertinently by using computers to continuously process multi-source behavior data and learning feedback. That is to say, the intervention of technology really changes the operation mechanism of the classroom, rather than the humanistic attribute of music teaching itself. The improvement of students in pitch control, rhythm grasp, task completion and classroom engagement is the specific embodiment of this mechanism optimization. Of course, there are still some limitations in this study. The sample size is small, the experimental subjects are concentrated in the same college, and the course type is also dominated by conventional classroom training, which is not enough to cover more complex music teaching scenarios. At the same time, students 'aesthetic experience, emotional fluctuations and creative expression are still difficult to be completely quantified, and the system recognition results cannot be used separately from teachers 'professional judgment. In the future, more detailed multi-modal analysis methods can be introduced while expanding the sample scope, and virtual reality, intelligent audio analysis and learning portrait technology can be combined to continue to improve the accuracy and adaptability of music classroom digital support, so as to provide more sufficient practical basis for the continuous optimization of music teaching mode.

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