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APPLYING COMPOSITION TECHNOLOGY THEORY IN COLLEGE MUSIC INSTRUCTION VIA EDGE COMPUTING ON A DIGITAL PLATFORM

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Incorporating smart technologies into composition-technology teaching can open new avenues for innovation in music education. This study integrates edge computing with college-level instruction in composition technology and proposes a smart digital teaching platform that includes knowledge tracking and personalized practice recommendation. The approach builds a knowledge-tracking model using a self-attention mechanism combined with a hypergraph module, and then formulates exercise recommendation as a POMDP-based decision process to deliver individualized practice resources. Experimental results show the proposed knowledge-tracking model exceeds the accuracy of the DKT baseline by more than 3%, while the recommendation model achieves mean metric values above 0.8, indicating recommendations that are more targeted, novel, and diverse. After deployment, students' course attitude, learning willingness, and interaction with the platform increased by 25.25%, 30.53%, and 37.68%, respectively. Additionally, over 60% of students reported improvements in teacher–student interaction, recommendation quality, course interest, and learning outcomes. Overall, the platform strengthens interactive teaching, supports personalized learning in music courses, and contributes to enhancing instructional quality in higher education.

Index Terms — edge computing, self-attention, knowledge tracking model, exercise recommendation model, music teaching

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INTRODUCTION

An excellent musical work centers around a certain theme, comprehensively utilizes the laws and techniques of music composition, and presents a complete musical story through the organization of musical language. In the whole process of music creation, both vocal music and instrumental music have to achieve the purpose of expressing philosophical thoughts and emotions through melody, rhythm, and comprehensive sound effects, and how to realize the perfect combination of melody, rhythm, sound effects and other elements is the problem to be solved by the theory of composition technology, which is indispensable to the theory of composition technology [1, 2, 3].

The importance of compositional technology theory in college music teaching can be summarized in two aspects. On the one hand, compositional technology theory can further improve the content of music teaching through its systematic and comprehensive knowledge of music technology theory, so that music teaching not only emphasizes on the teaching of music history and theory, but also emphasizes on the teaching of music sense, meter and compositional technology [4, 5, 6]. On the other hand, although the theory of composition technique is a music theory system, many of its contents are inclined to practical operation, such as the conception of polyphonic music weave [7]. These contents, on the basis of theoretical exposition, can guide students to master the use of the main key and polyphony, and learn to deal with the musical melody as well as the arrangement of the musical language, so as to comprehensively consolidate students' musical skills [8].

In addition, in all the music-related courses, the theory of composition technology is not only highly practical in content, but also includes the practice of music creation and composition technology of many genres from traditional to modern, so that students can come into contact with different music styles through appreciation, practice and other ways, so that students can learn from a variety of music styles in the process of micro-comparison learning, and can make up for the students' musical practice caused by the teaching content being too biased in favor of the theoretical. It can make up for the problem that students' practical ability is weak due to the fact that the teaching content emphasizes too much on theory [9, 10, 11].

However, in the process of teaching composition, the traditional indoctrination teaching method is still used, which leads to the low interest of students in learning, and is difficult to meet the current stage of society's requirements for music creation talents, resulting in poor comprehensive ability of students, which is not conducive to the development of the music industry [12, 13]. In addition, composition is the core link of music creation, and composition technology, as an important part of supporting the practice of composition, has a crucial impact on the quality and creative efficiency of composition [14]. However, there exists a unilateral tilt of composition technology and composition art in composition creation and teaching, resulting in a serious sense of fragmentation on the finished music, which is not conducive to artistic expression [15, 16].

With the advancement of digitization in various industries, music education and music creation have undergone a whole new transformation. From artificial experience-oriented to intelligent technology for music evaluation and guidance, from musical instrument digital interface technology to intelligent music generation form of music creation, all of them are marking the intelligent technology basis to become an indispensable tool in the field of music education and creation [17, 18, 19].

The digitization process has been accompanied by the rapid development of various technologies such as the Internet of Things, 5G communication, and cloud computing, which provides a platform for the development of edge computing. Edge computing is an emerging computing paradigm that integrates the core capabilities of network, computing, storage, and applications on an open platform, which moves computing resources from data centers to edge devices close to the data source in order to process data faster and provide a better user experience, presenting characteristics such as discrete, real-time, data-aware, and network edge [20, 21]. Edge computing and cloud computing synergize with each other to help digital transformation in various industries. It provides intelligent interconnected services in close proximity to satisfy the critical needs of the industry for real-time business, business intelligence, data aggregation and interoperability, security and privacy protection during the digital transformation process [22, 23, 24]. This provides the possibility of real-time, interactive, flexible, dynamic adjustment, and personalized services for music teaching and creation.

In this paper, we utilize edge computing technology to build a smart music teaching platform consisting of five parts, and explore its application teaching in the theory teaching of composition technology. Based on this, a hypergraph and self-attention mechanism are used to model students' historical interaction sequences, and the construction of a hypergraph self-attention knowledge tracking model oriented to knowledge states is realized by considering historically relevant interactions to predict students' interactions in the next exercise. Using this knowledge tracking model as a student simulator to complete the interaction with the environment, the exercise recommendation process is modeled as a POMDP process, and the exercise recommendation strategy is optimized by the REINFORCE algorithm based on the strategy gradient to obtain the knowledge tracking and exercise recommendation method based on music teaching. Three datasets are selected to carry out experiments to test the knowledge tracking performance of this paper's method as well as the accuracy, novelty and diversity of exercise recommendation through the comparative analysis of models. Finally, the teaching experiment of the smart music teaching platform is designed, and its application effect in the teaching of the theory course of composition technology is evaluated multidimensionally by means of a questionnaire survey.

SMART MUSIC TEACHING PLATFORM BASED ON EDGE COMPUTING

With the continuous development of the Internet and 5G technology, the era of smart education has arrived. The great achievements of edge computing technology in the fields of smart city, smart transportation, smart industry, etc. provide favorable reference for the design of smart teaching environment. Relying on the existing resources of the intelligent environment, the intelligent music teaching platform based on edge computing is constructed as a means of realizing the intelligent teaching of the theory course of composition technology, making education more personalized and management more intelligent, and providing a powerful technical support for innovative teaching practice activities.

Overall framework

Based on the analysis of the advantages of edge computing technology and its application prospects in the intelligent teaching environment, this paper constructs the intelligent music teaching platform architecture based on edge computing technology as shown in Figure 1. By introducing edge nodes to pre-process the data collected by the terminal devices in real time using machine learning/artificial intelligence algorithms and make decisions quickly, it meets the requirements of intelligent, personalized, and real-time learning environment of the theory course of composition technology.

The intelligent music teaching platform based on edge computing technology is mainly composed of five layers: sensor layer, communication interface layer, edge computing layer, core network layer and cloud processing layer, as described below.

Sensor layer

The IoT devices in this layer can obtain multi-source heterogeneous data from the smart music classroom platform, such as environmental data (classroom temperature, humidity, CO_2 concentration, etc.), identity

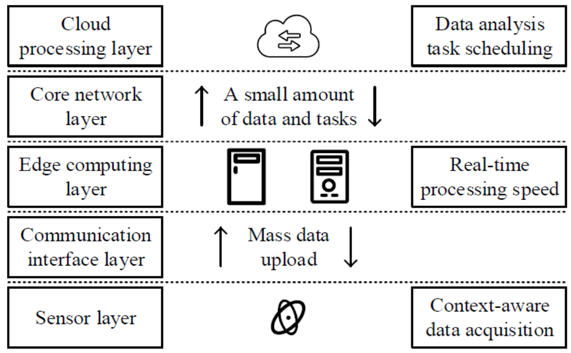

Figure 1: The intelligent music teaching platform architecture based on edge computing technology

data (student name, student number, face image, etc.), student gesture (head down, head up, emotion, etc.), device data (device location, operation status, malfunction message, etc.), and student physiological data from the wearable devices (electrical skin response emotional states, ECG signals, health detection data, etc.), etc.

Communication interface layer

This layer is the one that connects to the edge nodes through various communication interface protocols (e.g., Wi-Fi, ZigBee, Bluetooth, RS232/485, etc.) and collects various heterogeneous and educational data from the sensors through synchronous or asynchronous modes.

Edge computing layer

The edge computing layer is configured as a fixed edge node (SEN) or a mobile edge node (MEN) depending on the user requirements. Each edge node has its own storage and computing device for storing information about the data transmitted from the associated edge nodes, IoT sensing devices, and pre-processing and analyzing the collected data to speed up the decision-making process.

Core network layer

The role of the core network layer is to transmit information to exchange data and act as a bridge between the edge computing layer and the cloud computing service layer. In general, the core network layer can be based on public telecommunication networks, the Internet, and industrial private communication networks (e.g., 4G/5G cellular mobile networks).

Cloud processing layer

The cloud processing layer is the brain of the intelligent music teaching platform, which is mainly responsible for conducting in-depth analysis and mining of data processed by the edge modules to provide teachers and students with intelligent teaching support. The cloud processing center can use cloud computing technology and artificial intelligence algorithms to conduct in-depth analysis of the teaching data and discover the patterns and trends behind the data, so as to provide targeted teaching suggestions for teachers and personalized learning paths for students. In addition, the cloud processing layer contains different edge application service packages to provide support for updating and iterating edge nodes.

Pedagogical applications

With the continuous development of edge computing technology, the intelligent music teaching environment will be more intelligent, personalized and real-time. It is specifically manifested in the following aspects:

- Intelligent recommendation of teaching resources.
- Personalized learning path planning.
- Intelligent teaching assistance.
- Real-time student assessment and feedback.
- Online interactive teaching.

KNOWLEDGE TRACKING MODEL AND EXERCISE RECOMMENDATION STRATEGY

The research in this chapter is centered on a smart music teaching platform based on edge computing and proposes a knowledge tracking model and an exercise recommendation strategy. The model consists of two parts, the hypergraph self-attentive knowledge tracking model (HTNKT) for knowledge states and the exercise recommendation model.

Knowledge tracking model

Hypergraph Self-Attention Neural Network is a knowledge tracking model proposed in this paper, which combines hypergraph with self-attention. The hypergraph module not only groups exercises based on knowledge concepts, but also generates interaction embeddings for learners directly. After that, a gate recursion unit is used to obtain the students' knowledge states at different moments. For the self-attention module, this paper uses a converter to capture the long dependencies of the interaction sequences, assigning more attention weights to the previous exercises related to the current exercise. Finally, a gating mechanism is used to assess the student's mastery of a particular exercise in the current time period, thus predicting whether the learner will be able to correctly answer the provided exercise. In this paper, we improve the self-attentive knowledge tracking model by introducing a deeper attention mechanism module applied to knowledge tracking.

Hypermap module

Hypergraph Self-Attention Knowledge Tracking constructs an interaction hypergraph structure for a music student's history doing sequence. The student's correct answer v_i^+ and incorrect answer v_i^- to the *i*th exercise will be generated by hypergraph convolution to embed x_i^+ and x_i^-, respectively, and the interaction nodes belonging to the same knowledge concept construct the dependencies between interactions based on the hyperedges of the knowledge concepts:

$$h(v,e) = \begin{cases} 1, & v \in e, \\ 0, & v \notin e. \end{cases} \tag{1}$$

$h(v,e)$ denotes the matrix representation of the generated hypergraph.

The hypergraph module of hypergraph self-attentive knowledge tracking extracts the features of the hyperedge using hypergraph convolution based on the features embedded in the learner's historical interactions and the hypergraph adjacency matrix. Then, the features of the hyperedge are subjected to an aggregation operation thus completing the update of the interaction embedded features:

$$Y = D_v^{-\frac{1}{2}} H W D_e^{-1} H^T D_v^{-\frac{1}{2}} X, \tag{2}$$

$$D_v(v) = \sum_{e \in E} \omega(e)\, h(v,e), \tag{3}$$

$$D_e(e) = \sum_{v \in V} h(v,e), \tag{4}$$

where H is the feature matrix of the hyperedge, D_v is the degree of the node and D_e is the degree of the hyperedge. ω is the weight matrix of the hyperedge initialized with all values of 1, and θ denotes learnable parameters (absorbed in W here).

Self-attention module

The self-attention module of the hypergraph self-attention knowledge tracking model is a converter-based encoder-decoder structure. Residual linking and layer normalization are applied at each layer of the self-attention module. First the learner's historical interactions are embedded as the encoder's attentional keys, values and queries. The attentional weights between interactions are computed and output, and then this information is returned to the decoder:

$$\begin{aligned} M &= \text{LayerNorm}(\text{SkipConct}(\text{MHA}(Q,K,V))), \\ O &= \text{LayerNorm}(\text{SkipConct}(\text{FFN}(M))). \end{aligned} \tag{5}$$

The first layer of the decoder uses multi-head attention to determine the attentional weights between the exercise embeddings, while the second layer computes the connections between the interactive activities and the exercises:

$$\begin{aligned} M_1 &= \text{LayerNorm}(\text{SkipConct}(\text{MHA}(Q,K,V))), \\ M_2 &= \text{LayerNorm}(\text{SkipConct}(\text{MHA}(M_1,O,O))), \\ \text{Dec} &= \text{LayerNorm}(\text{SkipConct}(\text{FFN}(M_2))). \end{aligned} \tag{6}$$

In conclusion, the self-attention module can be described as:

$$\begin{aligned} O &= \text{Encoder}(I), \\ \text{Dec} &= \text{Decoder}(E,O). \end{aligned} \tag{7}$$

The multi-head attention form:

$$\text{MHA}(Q,K,V) = \text{Concat}(\text{head}_1,\ldots,\text{head}_T)W^O, \tag{8}$$

$$\text{head}_i = \text{Softmax}\left(\text{Mask}\left(\frac{Q_i K_i^T}{\sqrt{d}}\right)\right) V_i, \tag{9}$$

and the feed-forward network:

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2. \tag{10}$$

GRUs and gating mechanisms

After initializing the learner's interaction hypergraph, the learner's interaction sequence corresponds to a path in the hypergraph, and in this paper, we use a cyclic gating unit (GRU) to further update the learner's knowledge state.

At each time step t, the reset gate r_t decides which past information to forget, and the update gate u_t decides how much new information will be merged into the current knowledge state h_t. The new information to be added is represented by memory unit C_t:

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r), \tag{11}$$

$$u_t = \sigma(W_u[h_{t-1}, x_t] + b_u), \tag{12}$$

$$C_t = \tanh(W_c[r_t \odot h_{t-1}, x_t] + b_c), \tag{13}$$

$$h_t = (1 - u_t) \odot h_{t-1} + u_t \odot C_t, \tag{14}$$

where $\odot$ denotes elementwise multiplication, and $\sigma(\cdot)$ and $\tanh(\cdot)$ are nonlinear activation functions.

The hypergraph state for exercise e_i is denoted s_i^h, and the self-attention state is denoted s_i^t. A gating mechanism integrates the two:

$$s_i^e = \text{gate} \odot s_i^h + (1 - \text{gate}) \odot s_i^t, \tag{15}$$

with

$$\text{gate} = \sigma\left(W_{g1} s_i^h + b_{g1} + W_{g2} s_i^t + b_{g2}\right). \tag{16}$$

Finally, the predicted value $\hat{r}_i$ of the learner's answer to exercise e_i is:

$$\hat{r}_i = \text{Sigmoid}(s_i^e w_o + b_o). \tag{17}$$

Exercise recommendation model

In this paper, we use the POMDP process to model the exercise recommendation task and optimize the recommendation strategy using deep reinforcement learning algorithms. In it, the hypergraph self-attentive knowledge tracking model (HTNKT), proposed above, is used as a student simulator.

Overall structure

The optimization process is shown in Figure 2.

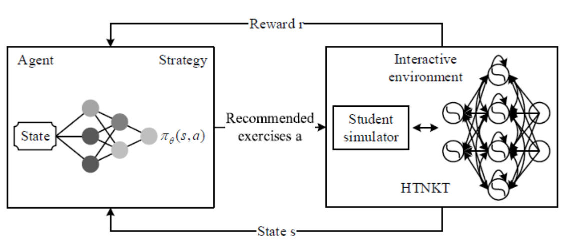

Figure 2: Process of exercise recommendation model optimization

Decision-making process

There are different probabilities of choosing different actions from the initial state, using $\pi_\theta(a|s)$ to denote the probability of choosing action a in state s. A neural network is used to fit the policy, and θ denotes the parameters. The trajectory can be written as $\tau = \{s_0, a_0, \ldots, s_T, a_T\}$, and with observations $\tau = \{s_0, a_0, o_1, s_1, \ldots, o_T, s_T, a_T, o_{T+1}\}$. The probability of the trajectory is:

$$p_\theta(\tau) = p(s_0) \prod_{t=0}^{T-1} p(s_{t+1}|s_t, a_t)\, p(o_{t+1}|s_t, a_t)\, \pi_\theta(a_t|s_t). \tag{18}$$

Reward settings

The single-step reward is:

$$r_t = \frac{1}{K} \sum_{i=1}^{K} w_i P(q_i)_{t+1}, \tag{19}$$

where K is the number of exercises under a certain knowledge point, $P(q_i)_{t+1}$ is the probability of correctly answering after the state transfers to s_{t+1}, and w_i is determined by exercise difficulty.

The total discounted reward:

$$R(\tau) = \sum_{t=0}^{T} \gamma^t r_t, \qquad \gamma \in (0,1]. \tag{20}$$

Monte Carlo approximation of expected return:

$$R_\theta \approx \frac{1}{N} \sum_n \sum_\tau R(\tau)\, p_\theta(\tau). \tag{21}$$

Strategy Optimization

Policy gradient:

$$\nabla R_\theta = \frac{1}{N} \sum_n \sum_t \nabla_\theta \log \pi_\theta(a_t|s_t)\, R(\tau). \tag{22}$$

Cumulative reward recursion:

$$R_t(\tau) = r_t + \gamma R_{t+1}(\tau). \tag{23}$$

Parameter update:

$$\theta \leftarrow \theta + \alpha \nabla R_\theta, \tag{24}$$

and loss used in implementation:

$$\text{Loss} = -R_t(\tau) \log \pi_\theta(a_t|s_t). \tag{25}$$

Experimental design

Experimental data

(1) **ASSISTment:** ASSISTment2009 and ASSISTment2015.
(2) **Math dataset:** from Wisdom Learning Network.
Data are cleaned for missing/duplicate anomalies and split into training/validation/test with ratio 7:2:1.

Knowledge tracking performance

Five-fold cross validation is used. Metrics: ACC, AUC, RMSE.

Baseline methods: DKT and DKVMN. Results are shown in Table 1.

Table 1: Knowledge tracking performance of different models

Index	Dataset	DKT	DKVMN	HTNKT
AUC	ASS09	79.21%	80.06%	82.43%
	ASS15	72.24%	73.67%	76.94%
	Math	73.90%	74.51%	77.35%
ACC	ASS09	70.01%	71.08%	74.83%
	ASS15	66.73%	68.84%	72.99%
	Math	72.05%	73.09%	76.62%
RMSE	ASS09	27.92%	26.29%	24.05%
	ASS15	28.34%	27.99%	24.86%
	Math	26.34%	24.25%	21.88%

Recommended model evaluation indicators

Comparison methods: User-CF, DKT, DKT-CF. Metrics: accuracy, novelty, diversity (cosine similarity used).

Analysis of the results of comparative experiments

Figures 3–5 show comparisons of accuracy, novelty and diversity.

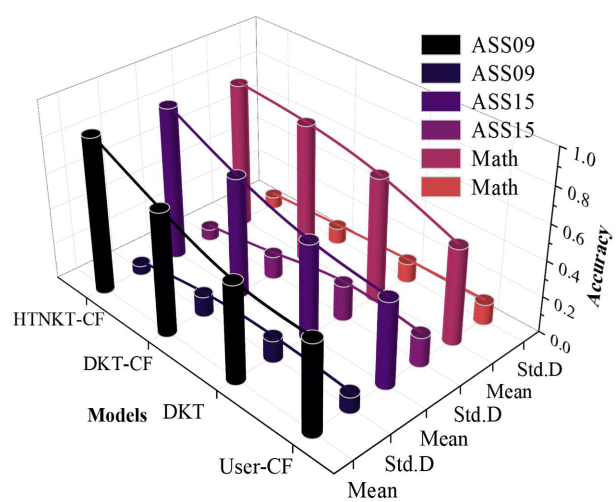

Figure 3: Comparison results of the recommended accuracy of exercise

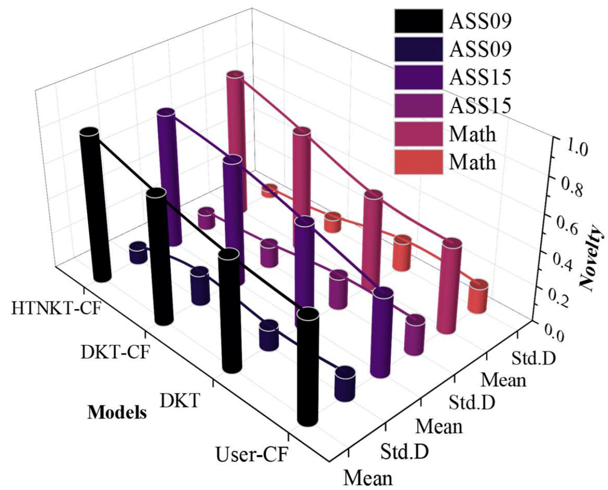

Figure 4: Comparison results of the recommended novelty of exercise

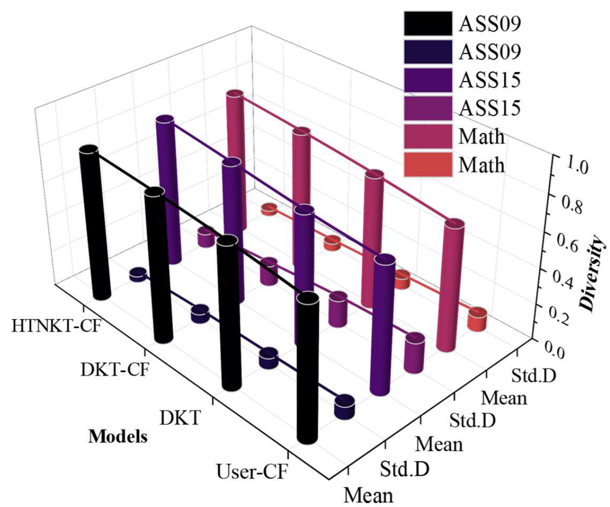

Figure 5: Different models differ in diversity indicators

THE APPLICATION EFFECT OF THE INTELLIGENT MUSIC TEACHING PLATFORM

This chapter conducts a semester-long classroom experiment in compositional technology theory to test the effectiveness of using an edge computing-based smart music teaching platform.

Experimental design

The project deployed the Smart Music Teaching System between September and January 2024 on four classes of Theory of Composition Techniques at a conservatory. The experiment thus started in September and ended in December, lasting 4 months. A total of two teachers participated in the study, each teaching two classes with a total of 215 students.

Prior to the field deployment, the participating teachers were introduced to the features and UI interactions of the Smart Music Teaching Platform, and then their students were introduced to the system in the classroom, as well as to the Knowledge Tracking Nurturing Exercise recommendation model. After the introduction to the students, this paper conducted a pre-deployment survey via questionnaire with students in four classes to obtain initial measures of student opinions, including attitudes toward course learning, willingness to interact with teachers and students, and attitudes toward the teaching platform.

At the end of the 4-month classroom deployment, post-deployment surveys were administered to students and faculty. In the student survey, in addition to the same indicators as in the pre-deployment survey, four additional indicators were added: perception of changes in faculty-student interactions, effectiveness of exercise recommendations, course interest, and course learning effectiveness.

Experimental results

Changes in attitudes and willingness

The results of students' attitude and willingness to change are shown in Figure 6. Students' attitudes towards course learning, willingness to teacher-student interaction and teaching platform attitude have significantly improved from 3.01, 2.85 and 2.76 points before the practice of the course "Theory of Composition Technology" to 3.77, 3.72 and 3.80 points, which is an increase of 25.25%, 30.53% and 37.68%, respectively.

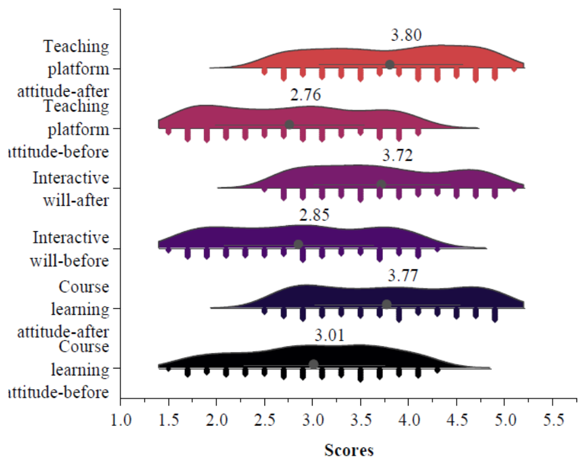

Figure 6: Changes in attitudes and willingness of students

Overall learning outcomes

The overall music course learning effect is shown in Figure 7. 64.92% of the students perceived that the classroom interaction increased a little bit, and 11.43% of the students perceived that the teacher-student interaction increased a lot. The number of students who thought that they had gained an increase in the evaluation of the effect of exercise recommendations, course interest and course learning effect were all above 60%, and the number of students who thought that they had gained a large amount of increase was 9.8% to 13.57%.

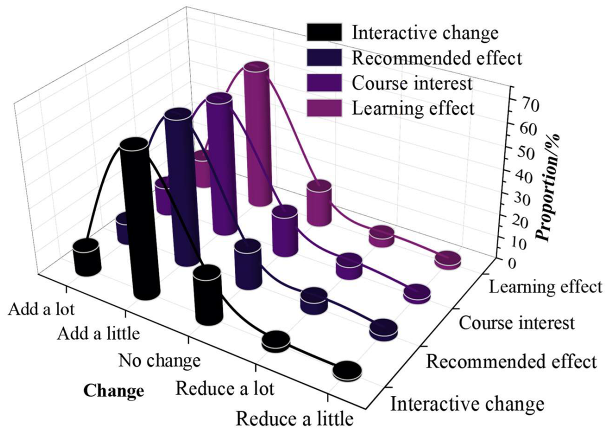

Figure 7: The learning effect of the whole music course

CONCLUSION

The study designs a smart music teaching platform based on edge computing, and constructs a knowledge state-oriented hypergraph self-attention knowledge tracking model and a music exercise recommendation model, and carries out experiments to explore the knowledge tracking and exercise recommendation performance of the method. Then the music teaching platform is used in the teaching of the theory course of composition technology, and its application effect is evaluated through questionnaire surveys.

(1) In different datasets, the knowledge state-oriented hypergraph self-attentive knowledge tracking model proposed in this paper outperforms the comparison method in all indicators, and the ACC value is more than 3% higher than that of the classical DKT method, which has better knowledge tracking performance. In terms of accuracy, novelty and diversity of exercise recommendations, the experimental average results of this paper's method are all greater than 0.8, which can provide students with more accurate, novel and diversified exercise practice.

(2) At the end of the teaching practice of the smart music teaching platform, students' attitudes toward course learning, willingness to interact with teachers and students, and attitudes toward the teaching platform increased by 25.25%, 30.53%, and 37.68%, respectively. And more than 60% of the students agree that the change of course teacher-student interaction, the effect of exercise recommendation, the interest in the course and the learning effect of the course get some improvement. The experiment proves that the music teaching platform based on edge computing can well assist the teaching of the theory course of composition technology, improve the online interaction between teachers and students and students' learning interest, and improve the quality of music teaching.

The application of edge computing and intelligent technology in intelligent music teaching is promising and will have a profound impact on the music education industry. The government, schools, enterprises and all sectors of the society should work together to promote the wide application of edge computing and intelligent technologies in the field of education, and make positive contributions to improving the quality of music education in colleges and universities.

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