Music Learning Path Optimization System Integrating Graph Neural Network

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ABSTRACT Traditional music learning path recommendation systems often fail to model multidimensional correlations within knowledge structures, resulting in incomplete path coverage and limited adaptability. This study proposes a learning path optimization system integrating GraphSAGE and Dueling DQN. A heterogeneous music knowledge graph is first constructed to represent knowledge points, skills, styles, and their prerequisite or coupling relationships. GraphSAGE with an LSTM aggregator is then used to dynamically fuse multimodal features into unified node embeddings. On this basis, the Dueling DQN algorithm uses cognitive state vectors, including mastery level and cognitive load, to optimize path strategies under coverage-gain and load-penalty constraints. Experiments show that the recommended paths achieve 89.6% knowledge coverage with an average length of 12.4 steps for beginners. Compared with standard DQN, Dueling DQN improves coverage by 3.3%. The system increases the path completion rate of beginners to 94.2%, outperforming traditional models such as DySAT, and achieves an average ABRSM score of 128.3. By combining heterogeneous graph modeling with reinforcement learning, the proposed framework improves path coverage, reduces route redundancy, and may provide methodological reference for graph-based optimization in electromagnetic-system training and wireless network planning.

INDEX TERMS learning path optimization, graph neural network, dueling DQN, knowledge graph, electromagnetic systems

I. INTRODUCTION

WITH the rapid development of online music education platforms, how to achieve personalized learning recommendations based on individualized teaching and scientific paths has become an important direction for the intelligent upgrade of music education. The ability to customize a knowledge journey based on individual needs holds significant value for industrial training and control. This principle is vital for the intelligent upgrade of systems in the industry, guiding the development of machinery to provide highly individualized process adjustments and optimized control paths for specific material batches [1,2]. However, the music knowledge system has obvious multi-dimensional and nonlinear characteristics. There are complex prerequisite dependencies, skill coupling and style associations between knowledge points. Traditional methods based on collaborative filtering [3,4] or sequential models are difficult to effectively model their structural and semantic relationships, resulting in a lack of depth and precision in learning path recommendations [5,6]. At the same time, ignoring the differences in individual cognitive states of learners also reduces the adaptability and effectiveness of recommendations. Therefore, there is an urgent need for an intelligent optimization method that can integrate knowledge graph modeling and personalized path planning to promote the intelligent and personalized development of music learning paths. Recognizing this necessity for advanced, integrated methods is not limited to education. It highlights a similar, urgent need for intelligent optimization in manufacturing, where integrating graph modeling and personalized control strategies is key to promoting the intelligent and personalized development of material quality control processes within the industry.

This paper proposes an optimization system that integrates GraphSAGE and Dueling DQN for the task of music learning path recommendation. In view of the complex dependency structure between music knowledge points, this paper constructs a heterogeneous music knowledge graph, with nodes covering knowledge points, skills, styles and other types, and edge relationships including prerequisite dependencies, style similarity and skill coupling, to truly restore the diversity and hierarchy of music knowledge structure.

The GraphSAGE model is introduced in the graph representation learning stage, and combined with the LSTM aggregation function to achieve dynamic integration of multimodal node features, which is more scalable and effective in expressing heterogeneous relationships and processing large-scale graph data. By introducing the Dueling DQN reinforcement learning method for path optimization, the state value and advantage function are separated to improve the stability of strategy learning. This paper conducts experiments on real data from the Yousician platform, compares multiple graph neural networks and reinforcement learning benchmark models, and systematically verifies the significant advantages of the proposed model in terms of knowledge coverage and path length control. The system in this paper has the ability to provide visualized path display and large-scale graph support, and possesses good application prospects in educational scenarios. It provides new ideas for the integration of graph neural networks and reinforcement learning in complex music education tasks. This powerful methodological integration is also directly relevant to industrial process management, offering new ideas for using graph neural networks and reinforcement learning to model and support the large-scale interdependencies of supply chains and production schedules within the industry.

II. RELATED WORKS

The development of educational recommendation systems has gone through multiple stages from collaborative filtering, content-based recommendations, to path planning based on knowledge graphs.

Traditional collaborative filtering [7,8] methods are based on historical user-item interactions and can capture group preferences well, but they perform poorly in cold-start scenarios with new users and new knowledge points, and it is difficult to understand the structural associations between learning content. Content-based recommendation [9,10] methods analyze the attributes of skills for personalized matching and have certain interpretability, but lack the ability to model the sequential and prerequisite dependencies between knowledge points in the learning path. In recent years, some studies have introduced prerequisite graphs or cognitive graphs to model the structural relationship between knowledge points [11,12], which has improved the path rationality and learning coherence to a certain extent. However, such methods are mostly based on static graph structures [13], which cannot fully utilize multimodal data for feature expression and fail to consider the changes in learners' cognitive states. In addition, most recommendation systems [14] focus on single-point knowledge recommendation and ignore the overall optimization of the entire path, making it difficult to meet the systematic needs of skill chains and style transfer in music learning. Therefore, building a music education recommendation framework with structural expression ability, multimodal perception ability and personalized path planning mechanism has become a key direction of current research.

Graph neural networks have received extensive attention in the field of intelligent education in recent years, especially in tasks such as knowledge representation, cognitive path modeling and learning behavior prediction. GCN (Graph Convolutional Network) [15, 16] is a basic model that has the advantages of high efficiency and strong generalization in constructing structures such as prerequisite knowledge graphs and question graphs, but its modeling ability for heterogeneous graphs is limited. GraphSAGE [17,18] supports efficient learning of large-scale graph structures by introducing scalable neighbor sampling and feature aggregation mechanisms, and has shown good performance in tasks such as music recommendation and course sequence optimization. In the music scene, different types of nodes are heterogeneous and the relationships between multimodal features are complex. Models with attention mechanisms such as GAT (Graph Attention Network) [19] have also been tried to capture the heterogeneous contributions of different neighbors to node representation. In addition, heterogeneous graph neural networks have begun to be applied to educational tasks to support the flow of information between different node/edge types, effectively improving the representation ability of the model. Heterogeneous graphs can simultaneously model multiple types of nodes and multiple semantic edges, which is suitable for expressing complex structural relationships and helps to improve the accuracy and semantic integrity of information representation [20,21]. Despite this, existing graph models still face the problems of insufficient modeling and weak generalization ability when facing the complexity of multimodal fusion, dynamic knowledge updating, and cognitive state interaction in real music education data. There is an urgent need for a framework and task coordination mechanism with more flexible structure and richer expression.

As a key method for path optimization, reinforcement learning has been widely used in educational recommendation systems [22,23] for learning strategy optimization, task sequence planning, and resource allocation. The classic Q-learning and DQN models have been used in personalized learning path recommendation [24,25] to predict the optimal learning path by learning the state-action value function. In recent years, with the increase in the dimension of the state space and the complexity of environmental feedback, improved models such as Dueling DQN [26], Double DQN, A3C (Asynchronous Advantage Actor- Critic), PPO (Proximal Policy Optimization) [27,28], etc., have been gradually applied to educational tasks.

Among them, Dueling DQN can separate the state value and advantage function, effectively alleviate the problem of sparse rewards or insufficient state information, and show better convergence speed and strategy stability. In the field of music education, the learning path needs to consider the order of mastering knowledge points, and also involves the progressive relationship between skills and the dynamic changes of cognitive load, which puts higher requirements on the reinforcement learning model. At present, some studies have attempted to combine reinforcement learning with knowledge graphs [29,30] for path optimization, but most of them did not incorporate cognitive state modeling or graph structure features into the state space, resulting in limitations in the educational practicality and personalization of recommendation results. Therefore, the deep integration of graph structure learning and reinforcement strategy optimization is an important development direction to improve the quality of music learning path recommendation.

III. METHODS

A. SYSTEM OVERALL ARCHITECTURE

The music learning path optimization system proposed in this paper consists of six core modules: data input, heterogeneous music knowledge graph construction, graph neural network node representation learning, cognitive state modeling, path optimization, and result recommendation and feedback. The overall architecture of this system is shown in Figure 1.

The core innovation of the system framework in this paper lies in the integration of heterogeneous graph neural networks and reinforcement learning mechanisms, which provides efficient solutions to the structural complexity and individual differences in music learning paths. The system builds a heterogeneous music knowledge graph that integrates multiple types of nodes such as knowledge points, skills and styles, supports multi-semantic edge modeling such as prerequisite relationships, skill dependencies and style similarities, and fully captures the structural characteristics of multi-dimensional knowledge in music learning.

The system receives two types of data sources: one is the learner's historical behavior data, such as completion status, error rate, time consumption, etc.; the other is music knowledge content data, including text descriptions of tracks, performance audio summaries, and style labels. After the knowledge graph is constructed, the system introduces a graph neural network based on GraphSAGE for node representation learning, and uses the LSTM aggregation function to fuse the multimodal features of adjacent nodes to obtain a node embedding representation that co-expresses structure and semantics. In terms of path optimization, the system designs a cognitive state space, integrates cognitive load indicators, and uses the Dueling DQN structure to separate state value and advantage functions, making strategy learning more stable and converging faster, and more effectively adapting to the path planning needs of learners at different levels. In the dynamic interaction process, the system updates the graph embedding and strategy model in real time according to learner feedback, realizing continuous optimization and personalized adjustment of the learning path.

B. MODELING OF HETEROGENEOUS MUSIC KNOWLEDGE GRAPH

In order to effectively represent the semantic relationship and performance dependency between different knowledge elements in the music education process, this paper constructs a heterogeneous music knowledge graph [31,32] as the basis for graph neural network node representation learning and path optimization strategy. The graph contains multiple types of nodes [33] and edges [34], and also integrates multimodal feature information to support the modeling of multidimensional elements such as music theory, skill movements, style and emotion.

To explicitly utilize the heterogeneity of graphs, the GraphSAGE model adopts a type aware neighbor sampling and feature aggregation strategy during the representation learning stage. Specifically, the LSTM aggregator performs ordered serialization input on neighboring nodes based on edge types, thereby distinguishing different semantic relationships during information propagation. At the same time, the learnable weight matrix in the node update formula is associated with the node type, allowing the model to adaptively adjust feature transformations for different types of nodes, achieving effective fusion of multimodal and multi semantic heterogeneous information. The structural comparison loss function further ensures that connected heterogeneous nodes maintain semantic similarity in the embedding space.

The heterogeneous music knowledge graph is represented as a four-tuple:

$$G = (\mathcal{V}, \mathcal{E}, \mathcal{T}_V, \mathcal{T}_E) \tag{1}$$

In Formula 1, $\mathcal{V}$ is a node set, each node represents a knowledge element; $\mathcal{E}$ is an edge set, representing the semantic or performance association between nodes; $\mathcal{T}_V$ is a node type set; $\mathcal{T}_E$ is an edge type set.

The node types defined in this system include three categories: knowledge points, skills, and styles. Each node is assigned a type label, and its semantics and structural position determine the function and transitive relationship of the node in the graph. Edges represent semantic or skill dependency relationships between nodes. Prerequisite relationship: directed edges represent the order of learning; skill dependency: directed edges represent the skill development path; style similarity: undirected edges connect nodes with similar styles.

Knowledge nodes mainly use text features to extract 768 Uyghur semantic vectors from textbook content and skill description texts through the BERT model. The skill node contains both text and audio features, with the audio features extracted from the performance samples as Log mel spectrograms and converted into 128 dimensional spectral vectors. The style node adopts multi label style vectors and represents different music style categories through one hot encoding. Before entering the LSTM aggregator, these heterogeneous features are first aligned and normalized through a type specific linear transformation layer, and then weighted fused to form a unified node initial embedding. This preprocessing process ensures the semantic and scale consistency of multimodal features, providing effective input representations for subsequent graph neural network aggregation.

Node and edge information is shown in Table 1.

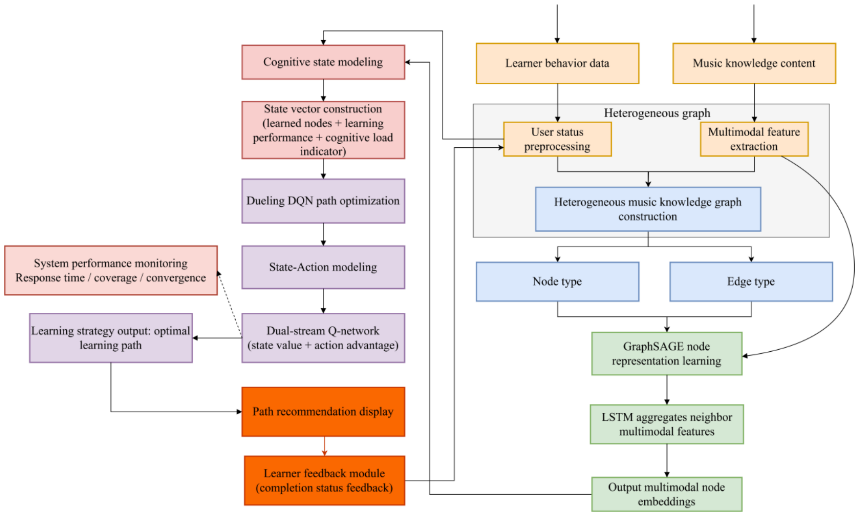

FIGURE 1. Overall system framework

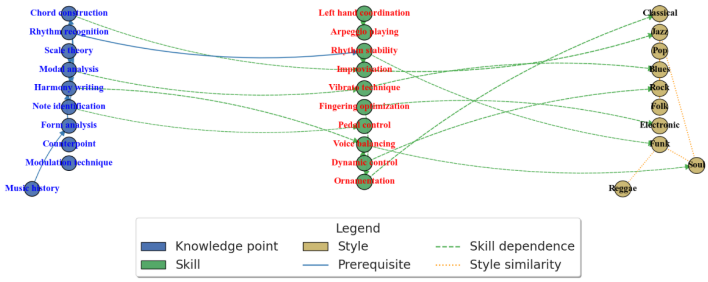

FIGURE 2. Heterogeneous music knowledge graph

TABLE 1. Node and edge information

Category	Type name	Examples	Description
Node type	Knowledge point	Chord construction, rhythm recognition	Represents the cognitive unit in music theory knowledge
Node type	Skills	Left-hand coordination, arpeggio performance	Specific operational skills in the process of music performance
Node type	Style	Classical, jazz, pop	Classification of the style of music, used to express the performance emotion and music attributes
Edge type	Prerequisites	C major $\rightarrow$ harmony writing	The order of dependence in knowledge learning
Edge type	Skill dependency	Rhythm recognition $\rightarrow$ rhythm stability	Describes the support or foundation of one skill to another in skill training
Edge type	Similar style	Jazz – Blues	Expresses the high similarity of two styles in rhythm, mode or emotional expression (no direction)

In order to improve the semantic expression ability of nodes, this paper introduces multimodal input features and constructs a unified node feature vector. For any node v_i, its feature representation is:

$$x_i = \text{Concat}\left(x_i^{\text{text}}, x_i^{\text{audio}}, x_i^{\text{style}}\right) \tag{2}$$

In Formula 2, x_i^{text} is the text features from the textbook content, skill description, or repertoire description, extracted using BERT; x_i^{audio} is the audio features of the performance sample; and x_i^{style} is the multi-label style vector representation.

C. GRAPHSAGE NODE REPRESENTATION LEARNING AND COGNITIVE STATE SPACE CONSTRUCTION

In heterogeneous music knowledge graphs, node types are diverse and structural dependencies are complex.

In order to effectively obtain the contextual information of nodes and maintain their semantic consistency, this paper adopts GraphSAGE [35,36] as the main framework for graph embedding learning, and introduces LSTM aggregators and multimodal fusion mechanisms to improve the model's modeling capabilities for prior dependencies, skill evolution, and style semantics.

Although the graph structure is topologically non sequential, there is an inherent cognitive order and logical progression in the learning process of music knowledge points, for example, specific chord progressions must be learned after mastering the basic scale. The standard mean aggregates neighboring nodes in an unordered and symmetrical manner, but cannot capture this implicit path dependence and learning sequence. The LSTM aggregator models the sampled sequence of neighboring nodes through its gating mechanism (input gate, forget gate, output gate), which can learn and preserve the dependency order and structural evolution information between nodes. This enables the generated node embeddings to not only contain local structural information, but also reflect the potential sequence patterns of knowledge acquisition, thereby providing support for subsequent reinforcement learning modules to generate learning paths that are more in line with cognitive laws. Therefore, in the specific scenario of music knowledge graph, LSTM aggregator outperforms standard non sequential aggregators in modeling ability.

GraphSAGE is an inductive graph neural network model whose core idea is to update node embedding representations through local neighbor aggregation. For each node v, the neighbor sampling is:

$$N(v) = \mathrm{SAMPLE}(v) \tag{3}$$

Using LSTM for neighbor aggregation:

$$h_{N(v)}^{(k)} = \mathrm{LSTM}\left(\{h_u^{(k-1)} \mid u \in N(v)\}\right) \tag{4}$$

The LSTM aggregator inputs the ordered neighbor sequence to capture the relationship between temporal order and structural evolution. Node update:

$$h_v^{(k)} = \sigma\left(W^{(k)} \cdot \mathrm{CONCAT}\left(h_v^{(k-1)}, h_{N(v)}^{(k)}\right)\right) \tag{5}$$

In formula 5, $W^{(k)}$ is a learnable weight matrix.

The nodes of the music knowledge graph contain information of different modalities. In order to unify the input dimension, this paper linearly transforms and fuses the features of different modalities to generate a unified initial embedding. The modality fusion formula is:

$$h_v^{(0)} = \alpha_1 W_{\text{text}} x_{\text{text}} + \alpha_2 W_{\text{audio}} x_{\text{audio}} + \alpha_3 W_{\text{style}} x_{\text{style}} \tag{6}$$

Compared with traditional Mean or Max aggregators, LSTM aggregators have the ability to model adjacency order and local dependency paths, which is particularly suitable for the prerequisite relationship between nodes and skill conversion sequence in the learning path. Input sequence: $\{h_{u1}^{(k-1)}, h_{u2}^{(k-1)}, \ldots, h_{un}^{(k-1)}\}$. Aggregation output:

$$h_{N(v)}^{(k)} = \frac{1}{n}\sum_{t=1}^{n} h_t \tag{7}$$

In order to keep the structural adjacency consistent with the similarity of the embedding space, this paper introduces a loss function based on structural contrast. The goal is to minimize the distance between adjacent nodes and maximize the separation between non-adjacent nodes:

$$\begin{aligned}\mathcal{L}_{\text{contrastive}} = &-\sum_{(v,u)\in\mathcal{E}} \log\sigma(h_v^T h_u) \\ &-\sum_{(v,u^-)\notin\mathcal{E}} \log\sigma(-h_v^T h_{u^-})\end{aligned} \tag{8}$$

In Formula 8, $\sigma(\cdot)$ is Sigmoid activation, (v, u^-) is negative sampling, and $\mathcal{E}$ is the real edge set in the knowledge graph.

In the process of music learning path optimization, the current knowledge state of the learner is determined by the learning units he has completed, and is also significantly affected by factors such as learning effectiveness and cognitive load. Therefore, accurately modeling the learner's cognitive state space is the key foundation for strategy decision-making and path planning in reinforcement learning. This paper comprehensively considers structural knowledge mastery, individual learning performance and dynamic learning load, and defines the state vector s_t in the reinforcement learning environment to represent the comprehensive learning state of the agent at time step t.

The evaluation of mastery level includes three dimensions: the knowledge state vector is represented by embedding the mean of the graph of the mastered knowledge points; The success rate of learning is calculated based on the user's historical practice accuracy for each knowledge point; The historical error frequency is used to calculate the frequency of errors in various knowledge points in recent learning. The quantification of cognitive load adopts a multi index fusion approach, taking into account two key factors:

task failure rate and task duration. The task failure rate reflects the user's recent experience of learning setbacks, while the task duration reflects the intensity of time investment in the learning process. The two are combined by weighting to form a unified cognitive load assessment index. These quantitative indicators together constitute the observable state space for optimizing the Dueling DQN strategy, providing a reliable cognitive state representation basis for personalized recommendation of learning paths.

This paper represents each state s_t as the concatenation of feature vectors:

$$s_t = [K_t \| P_t \| E_t \| C_t] \tag{9}$$

In formula 9, K_t is the embedding representation of the knowledge points that have been mastered, P_t is the learning success rate feature, and E_t is the historical error frequency. C_t is the cognitive load indicator. Record the node set $\kappa_t \subseteq V$ that the learner has completed, and use the mean of its graph embedding as the overall knowledge representation:

$$K_t = \frac{1}{|K_t|}\sum_{v\in K_t} h_v \tag{10}$$

In Formula 10, h_v is the node embedding representation obtained by GraphSAGE. P_t is the average accuracy of each knowledge point, calculated according to the hierarchical course structure and constructed in vector form:

$$P_t = [p_1, p_2, \ldots, p_m] \tag{11}$$

E_t represents the error frequency statistics of each node in the most recent w learning times, w is the number of learning times in time t, and E_t reflects short-term learning obstacles:

$$E_t = [e_1, e_2, \ldots, e_m] \tag{12}$$

D. DUELING DQN PATH OPTIMIZATION

In order to realize personalized learning path planning under cognitive constraints in heterogeneous music knowledge graphs, this paper introduces reinforcement learning methods into the path recommendation process and adopts the Dueling DQN architecture to realize strategy learning. This method can estimate the overall value of the state and effectively distinguish the advantage function of each action, which is conducive to improving the stability and generalization ability of the strategy in complex state space.

The reward function consists of three weighted parts: coverage gain reward, learning success reward, and cognitive load penalty. The coverage gain reward is quantified by calculating the extent to which newly added nodes extend the coverage of the knowledge graph structure. It is specifically defined as the ratio of the cardinality difference between the reachable node sets of the current step and the previous step to the total number of nodes in the graph. The reward for successful learning is based on the user's rating of the completion quality of the new learning node. Cognitive load penalty is calculated through linear weighting, taking into account two dimensions: recent task failure rate and task duration. The final immediate reward is the weighted sum of these three components, where the weight coefficients are used to balance the relative importance between different optimization objectives. The design of this reward function ensures that the path optimization process takes into account the comprehensiveness of knowledge coverage, the quality of learning outcomes, and the cognitive burden of learners.

The action is the next learning node recommended in the current state, that is, selecting the node that has not been learned in the graph:

$$a_t \in A(s_t) = \{v \mid v \notin K_t\} \tag{13}$$

After completing the learning of node a_t, the system updates the state information and transfers to s_{t+1}. In order to balance knowledge expansion, learning effectiveness and cognitive load, this paper designs the following three joint reward functions:

$$r_t = \lambda_1 \cdot R_{\text{coverage}} + \lambda_2 \cdot R_{\text{success}} - \lambda_3 \cdot R_{\text{cognitive}} \tag{14}$$

R_{coverage} represents the structural coverage gain of the newly added nodes to the entire knowledge graph. The formula is:

$$R_{\text{coverage}} = \frac{|\text{1-hop}(K_{t+1})| - |\text{1-hop}(K_t)|}{|V|} \tag{15}$$

R_{success} is a score based on the completion quality of the new node:

$$R_{\text{success}} = \text{score}(a_t) \in [0, 1] \tag{16}$$

$R_{\text{cognitive}}$ means introducing cognitive fatigue indicators for punishment, combining the time and error rate of recent tasks:

$$R_{\text{cognitive}} = \gamma_1 \cdot \text{failurerate}_t + \gamma_2 \cdot \text{duration}_t \tag{17}$$

Traditional DQN directly fits the Q(s, a) value function, and Dueling DQN splits it into two branches: state value function V(s) and action advantage function A(s, a), the formula is:

$$Q(s,a) = V(s) + \left(A(s,a) - \frac{1}{|A|}\sum_{a'} A(s,a')\right) \tag{18}$$

The state branch is used to evaluate whether the current learning state is generally beneficial, and the action branch is used to evaluate the specific benefits of selecting a node in the current state. Store historical interactions through experience replay to prevent sample correlation from affecting training.

Update the main network parameters every fixed number of steps to alleviate training instability, and adopt the ϵ-greedy learning strategy:

$$a_t = \begin{cases} random(a), & \text{with probability } \epsilon, \\ \arg\max_a Q(s_t, a), & \text{with probability } 1-\epsilon. \end{cases} \tag{19}$$

E. SYSTEM FUNCTION AND INTERFACE

In order to effectively support the dynamic planning and cognitive adaptive recommendation of personalized music learning paths, this paper designs and develops a system platform that integrates data modeling, intelligent recommendation, learning feedback and visual analysis. The system interface of this paper is shown in Figure 3.

The system supports the automatic construction, graph structure editing and relationship display of music education knowledge graphs. Users can view the relationship graphs of various types of nodes (such as knowledge points, skills, styles) and their edges (such as prerequisite relationships, style similarities, skill dependencies). Through the GraphSAGE+Dueling DQN joint modeling framework, the learning path is generated in real time based on the learner's history, ability performance and current status. The system collects and evaluates the user's interactive data in real time during the learning process, and provides cognitive state modeling and feedback mechanism.

IV. EXPERIMENT

A. DATASET AND PROCESSING

The experimental data comes from the open learning log and performance interaction record data provided by Yousician [37], an online music education platform. The platform provides intelligent music learning services covering a variety of instruments (piano, guitar, ukulele, etc.) to users around the world. The system records the user's detailed behavior, performance data, and learning results during the learning process.

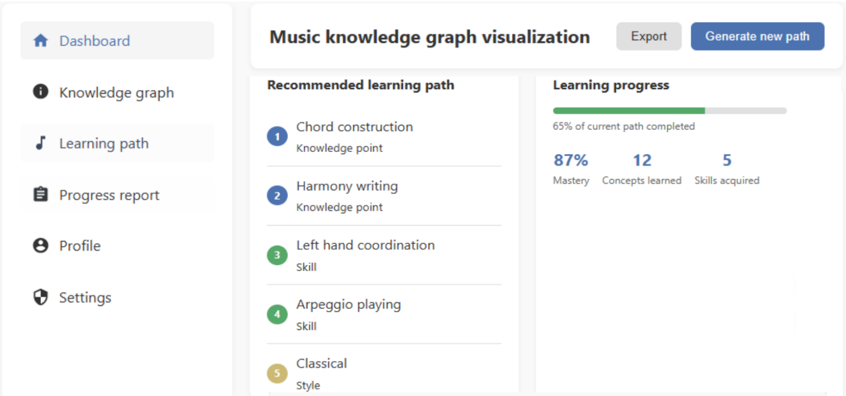

FIGURE 3. System interface

Data collection time range: October 2022-September 2023; User sample size: 12,456 users in total, including beginner, intermediate and advanced levels; Platform course structure: covers three modules: music theory, performance skills, and style recognition; Log sources: including practice scores, error logs, completion time, audio tracks, and user feedback tags; Task units: The platform contains a total of 320 knowledge points and 570 track task units, which are constructed into a heterogeneous music knowledge graph.

Each track task contains a user's performance audio clip, which is converted using the Log-Mel spectrum diagram. The formula is:

$$\mathrm{Mel}(t, f) = \log(1 + \mathrm{power}(t, f)) \tag{20}$$

Each audio segment is frame-segmented (50ms per frame, 25ms step length) to extract a 128-dimensional Mel spectrum vector.

Each knowledge point node is accompanied by a structured text description, which is embedded using BERT, and each node obtains a 768-dimensional semantic vector. Style nodes such as "classical" and "jazz" are discrete classifications, which are one-hot encoded and then connected to the embedding layer to form a style vector.

$$s_i = \mathrm{Embedding}(\mathrm{onehot}(label_i)) \tag{21}$$

The data structure statistics are shown in Table 2.

TABLE 2. Data statistics

Category	Content Description	Quantity
Number of users	Effectively train users	12,456
Number of knowledge points	Scales, rhythms, harmony, modes, etc.	320
Number of track tasks	Standard task units in the platform	570
Style category	Classical, pop, jazz, blues, etc.	14

B. EVALUATION INDICATORS AND COMPARISON MODELS

In order to systematically evaluate the effectiveness of the "GraphSAGE + Dueling DQN" model proposed in this study in the music learning path recommendation task, this paper designs evaluation indicators from two dimensions: path coverage and path length, and selects 5 representative graph neural network and reinforcement learning combined models as comparison baselines to ensure the fairness and professionalism of the experiment.

To ensure the fairness and scientificity of the experimental comparison, all participating models, including GCN+DQN, GAT+PPO, R-GCN+A3C, DySAT, and TGN, use the unified node embedding features generated by the GraphSAGE component of this system as input. This setting eliminates the impact of feature representation differences on model performance, allowing each model to learn and optimize in the same feature space, thereby ensuring that subsequent performance differences in indicators such as knowledge coverage and path length can truly reflect the essential capabilities of each algorithm model in path recommendation tasks. In addition, the reinforcement learning state space, action space, and reward function of all models remain consistent, further ensuring the rigor of the comparative experiment.

Knowledge coverage measures the proportion of knowledge points that the recommended path can cover in a given graph structure and is a key indicator of the global effectiveness of the path. The formula is:

$$\mathrm{Coverage@}T = \frac{\left|\bigcup_{t=1}^{T} K_t\right|}{|V|} \tag{22}$$

In formula 22, K_t is the set of learned nodes in the tth step; $|V|$ is the total number of knowledge points in the graph; T is the maximum path length.

Knowledge coverage is used to measure the completeness of the recommended path's coverage of the knowledge system. Its calculation formula is the ratio of the number of different knowledge nodes learned in the path to the total number of predefined core knowledge nodes in the knowledge graph. Among them, the denominator is explicitly limited to the number of nodes marked as core knowledge points in the constructed heterogeneous music knowledge graph, which cover essential learning content such as music theory, performance skills, and style cognition. Molecules are the set of core knowledge nodes in the learning path sequence that have been deduplicated. This definition ensures that coverage assessment is based on a stable, pre-defined knowledge system benchmark that objectively reflects the exploration ability of path recommendation systems in structured knowledge spaces.

In order to fully verify the advantages of this system, this paper designs and compares with 5 mainstream models. The model comparison information is shown in Table 3.

TABLE 3. Model comparison information

Model	Graph neural networks	Optimization algorithm	Features
This paper model	GraphSAGE	Dueling DQN	Multimodal embedding aggregation + cognitive load perception strategy optimization
GCN + DQN	GCN	DQN	Structure is stable, but does not support heterogeneous graphs and dominant branches
GAT + PPO	GAT	PPO	With attention mechanism, can handle some heterogeneous structures
R-GCN (Relational Graph Convolutional Network) + A3C	R-GCN	A3C	Strong multi-relation heterogeneous graph processing capability, but high state control dimension
DySAT (Dynamic Self-Attention Network)	DySAT	–	Time-aware graph attention model, suitable for sequence learning modeling
TGN (Temporal Graph Network)	TGN	–	Support graph time evolution modeling, complex structure

V. RESULTS AND ANALYSIS

A. LEARNING PATH DISPLAY

This paper selects a "beginner level" user to compare the music learning paths generated by GraphSAGE + Dueling DQN (this paper's model) and three other models (GCN + DQN, GAT + PPO, R-GCN + A3C). The selected user information is shown in Table 4.

TABLE 4. Selected user information

Attributes	Information description
User	U_03795
Current level	Beginner
Instrument direction	Piano
Current knowledge points	Basic scales (C major), basic rhythms
Error rate	Average error rate 21% (more errors in rhythmic patterns)
Style preference	Classical, light jazz
Cognitive load status	Low sustained error rate, but sensitive to complex structures

The learning path is shown in Figure 4.

There are significant differences in the performance of different models in music learning path planning. From the perspective of path rationality and cognitive adaptability, the GraphSAGE + Dueling DQN model proposed in this paper shows the best performance. The generated path strictly follows the knowledge dependency order, first introducing basic rhythm recognition and left-hand coordination, and then gradually expanding to style recognition and arpeggio skills, achieving dual optimization of knowledge point coverage and skill gradient, and effectively controlling cognitive load to avoid sudden learning jumps. Although GCN + DQN has the ability to model basic graph structures, it cannot recognize multi-type edges and multi-modal features, and there are inappropriate skills and styles introduced in the path. The structure is simple and lacks personalization. GAT + PPO has certain advantages in modeling attention weights, but the path order is prone to fluctuations, there is a problem of skill chain breaks, and the style is introduced late, affecting learning continuity. R-GCN + A3C can capture complex dependency structures, but the path design tends to explore breadth, resulting in a lengthy learning process and increased cognitive load. The proposed model can better balance structural rationality, cognitive efficiency, and style guidance, and is a better music learning path recommendation method.

B. EFFECT OF IMPROVING KNOWLEDGE POINT COVERAGE

The effect of graph node type on path knowledge point coverage is shown in Figure 5.

The GraphSAGE + Dueling DQN model proposed in this paper achieves the highest knowledge point coverage in all node type combinations, showing a strong ability to optimize the global learning path. In particular, under the three-type composite structure of "knowledge point-skill-style", the model in this paper can still maintain a coverage level of 89.6%, which is significantly better than GCN + DQN (70.4%) and GAT + PPO (76.1%). Its advantage mainly comes from GraphSAGE's ability to aggregate multi-type node features in heterogeneous graphs. Combined with Dueling DQN's policy evaluation mechanism, it can more finely guide learning paths through dense areas of semantics and skill dependencies. However, GCN and GAT are difficult to model complex associations across types of nodes under the constraints of homogeneous graphs, resulting in local convergence of paths and insufficient coverage. Although R-GCN can handle multi-relational graph structures, the A3C strategy used in the reinforcement learning part is unstable, resulting in large fluctuations in path quality. DySAT and TGN have certain advantages in processing dynamic graphs, but the path guidance accuracy is insufficient for static learning tasks. In summary, the strong generalization ability and stable strategy optimization mechanism of this model make it the most superior in complex node type interaction scenarios.

C. LEARNING PATH LENGTH CONTROL CAPABILITY

Users are divided into beginner, intermediate, and advanced levels according to their musical proficiency. The average learning path length and average redundant nodes for different musical proficiency levels are shown in Figure 6.

GraphSAGE + Dueling DQN shows the best path compression capability at all musical levels. The average path for beginners is 12.4 steps, for intermediate users it is 16.2 steps, and for advanced users it is 19.5 steps, which is shorter than other models (e.g. GCN + DQN reaches 26.1 steps). This model integrates knowledge points, skills, and style nodes through heterogeneous graph modeling to avoid

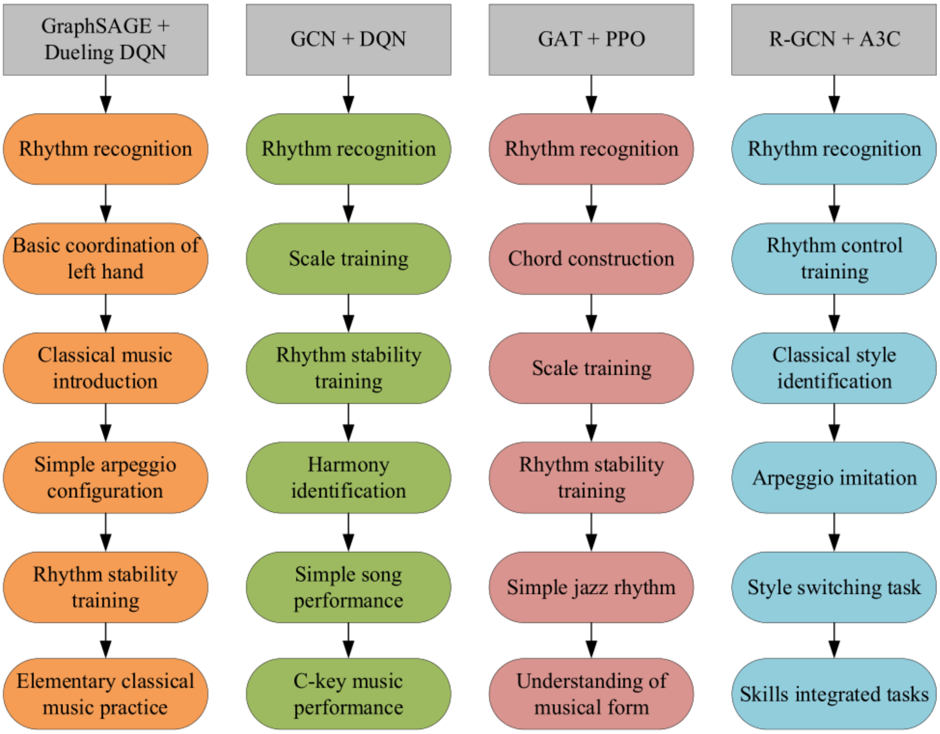

FIGURE 4. Learning path display

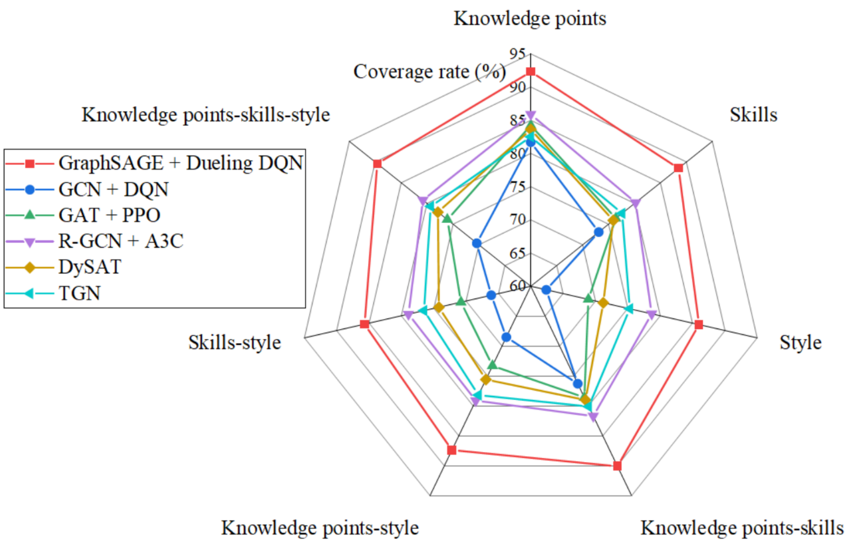

FIGURE 5. Knowledge point coverage

redundant jumps, and combines Dueling DQN's refined state value evaluation mechanism to effectively guide the path to high-value nodes and reduce the possibility of invalid stops and repeated training. Isomorphic models such as GCN and GAT are difficult to express complex prerequisite dependencies and skill transfer paths, resulting in path expansion, especially when facing high-level tasks. Although DySAT and TGN can handle time dynamics, they lack task structure constraints and the path advancement direction is not clear enough. Overall, the model in this paper is suitable for multi-stage users and can also achieve the maximum knowledge gain under the shortest path. It is an effective path planning method to improve the efficiency of personalized learning. The number of redundant nodes directly reflects the proportion of invalid, repeated or mismatched knowledge points in the path. In this experiment, GraphSAGE + Dueling DQN always maintains the lowest average redundancy (0.8 for primary, 1.1 for intermediate, and 1.4

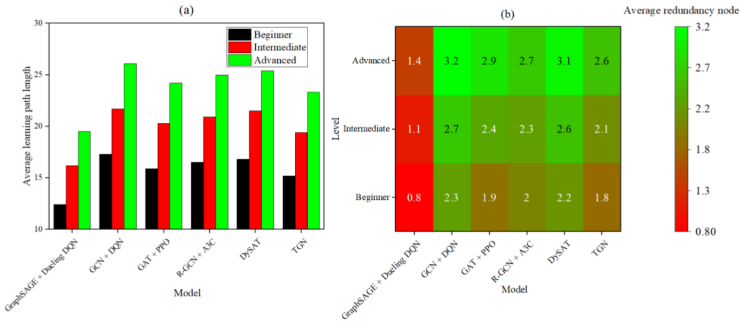

FIGURE 6. Average learning path length and average redundant nodes: (a) Average learning path length; (b) Average redundant nodes

for advanced), which is significantly reduced compared to GCN + DQN, showing a strong learning path convergence ability. Redundancy is caused by two situations: one is that the graph structure fails to clearly express the dependency logic, and the other is that the reinforcement learning strategy update is unstable, resulting in strategy divergence. GraphSAGE, adopted in this paper, uses neighbor sampling and LSTM aggregation mechanism to enhance node representation, which can accurately determine whether skills or styles are necessary to introduce in the current state. The dual-stream network structure in Dueling DQN separates the value function and the advantage function, making the action selection more stable and reducing the behavior of "detour" or repeated training. Especially for advanced users, traditional models are more prone to redundancy due to their complex structure, while the model in this paper still maintains a compact path, highlighting its planning stability in multi-stage tasks. Overall, the control of redundant nodes is an important manifestation of the system in this paper to improve learning efficiency and reduce cognitive load.

D. CHANGES IN TRAINING LOSS

Taking GraphSAGE as the graph neural network model, in order to explore the impact of different depths of reinforcement learning, the training loss decrease curve is shown in Figure 7.

By comparing the training loss curves of different deep reinforcement learning methods under the architecture of GraphSAGE as the graph neural network encoder, it can be found that the overall loss value of Dueling DQN is significantly lower than that of PPO, DQN and A3C. The main reason is that Dueling DQN effectively alleviates the Q value estimation bias and improves the stability of strategy evaluation by introducing a separate modeling mechanism of state value function and action advantage function. At the same time, the combination of the target network and the experience replay mechanism enables it to have higher sample utilization efficiency and gradient update stability. In contrast, the traditional DQN is prone to overestimation due to its single Q value update path; although PPO has good policy optimization characteristics, it is based on probability updates and has high losses in the later stages of training and A3C has a large gradient variance in asynchronous parallel updates. In summary, Dueling DQN can more effectively capture the distribution of policy values in heterogeneous graphs with the support of graph neural network embedding, showing lower training loss.

E. ABLATION EXPERIMENT

An ablation experiment is set for the model in this paper, and the results are shown in Table 5.

TABLE 5. Ablation experiment results

Components	Choice					
GraphSAGE	√	√	√	√	√	√
Mean Aggregator	√					
Max Aggregator		√				
LSTM			√	√	√	√
Heterogeneous graph modeling				√	√	√
DQN					√	
Dueling DQN						√
Coverage (%)	73.2	75.4	79.8	83.5	86.3	89.6
Average path length	21.8	20.7	19.2	18.3	17.2	16.0

It can be seen from Table 5 that different module combinations have a significant impact on model performance, especially in the two core indicators of knowledge point coverage and average path length. First, in terms of aggregators, replacing Mean Aggregator with Max Aggregator brings a slight performance improvement, indicating that Max has certain advantages in local saliency modeling for the identification of important features in the music knowledge graph. However, when LSTM is further introduced as an aggregator, the model can significantly improve the coverage (coverage increased to 79.8%), which shows that LSTM is more expressive in capturing complex structural relationships and sequential dependencies between heterogeneous nodes. The subsequent introduction of heterogeneous graph modeling further strengthened the type-aware structural information between nodes, indicating that the integrity of structural modeling is crucial for path optimization.

After replacing the reinforcement learning strategy from traditional DQN to Dueling DQN (the model in this paper), the model achieved the best results in both indicators: the coverage rate increased to 89.6% and the path length was

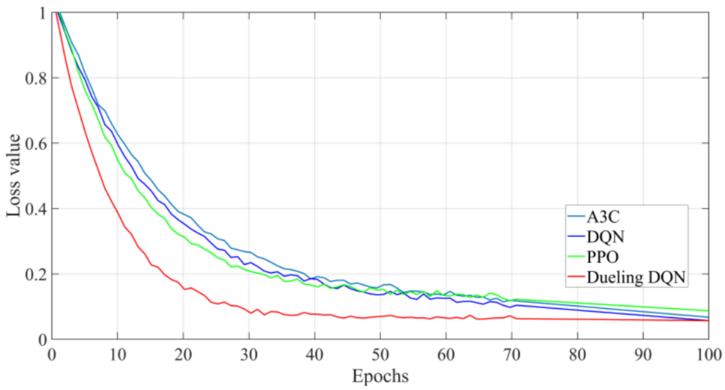

FIGURE 7. Training loss decreases

shortened to 16.0. The Dueling structure separates state value and action advantage to more effectively estimate the long-term benefits of strategy selection, thereby achieving a better balance between cognitive load and learning efficiency. Overall, LSTM aggregation, multimodal heterogeneous graph modeling, and Dueling DQN are key factors in improving the performance of this model. The three work together to effectively improve the intelligent and personalized recommendation capabilities of music learning paths.

F. SYSTEM PERFORMANCE

In order to explore the responsiveness of the system, the impact of the number of concurrent user requests on the system response time is analyzed. The number of concurrent user requests refers to the number of users who request path planning at the same time; the response time is the time required to generate a learning path. The systems built by various models are compared, and the results are shown in Figure 8.

As the number of concurrent user requests increases, the response time of each model system shows an overall increasing trend. Among them, the GraphSAGE + Dueling DQN system proposed in this paper shows better response efficiency at all concurrency levels. At low concurrency (10-100 users), the response time difference of all models is relatively small, but the system in this paper maintains the advantage of (65ms, 83ms), mainly due to its lightweight graph aggregation structure and efficient reasoning mechanism of the dual-stream Q network. As the number of concurrent users increases to 1000 and above, GCN + DQN and GAT + PPO encounter bottlenecks in parameter synchronization and state caching, resulting in a significant increase in response time. Since the system in this paper completes the strategy optimization in advance during the training phase, the prediction process relies on pre-trained embedding and reinforcement strategy lookup, which reduces the load of real-time graph convolution and action evaluation, thereby maintaining a low response time in a high-concurrency environment. Under 10,000 concurrency, the response time of this system is controlled at 761ms, showing good response performance. Therefore, this method is suitable for online music education platforms that meet the needs of real-time personalized recommendation in complex task environments.

G. LEARNING EFFECT

The user's music level includes elementary, intermediate and advanced. The learning period is set to 6 months, and the learning effect is tested by ABRSM (full score 150 points). The user's learning effect is shown in Figure 9.

In terms of path completion rate, the GraphSAGE + Dueling DQN system proposed in this paper performs best among all user levels, especially for beginner-level users, with a completion rate of up to 94.2%. This is due to the system's introduction of a cognitive load modeling mechanism in path planning, which avoids recommending nodes that exceed learners' current capabilities, thereby increasing the possibility of completion. In contrast, although graph neural networks combined with reinforcement learning such as GCN+DQN and GAT+PPO have structural recognition capabilities, they are deficient in dynamic individual modeling, and are prone to path interruptions or repeated nodes, resulting in a decrease in the overall completion rate. DySAT and TGN are slightly more adaptable to advanced users, but they still have not achieved the optimal path structure. Overall, the system in this paper is better in terms of stability and adaptability of path completion.

In terms of knowledge point mastery rate, the system in this paper shows a leading advantage in all three user levels, especially at the intermediate and advanced levels, with a mastery rate of more than 93%. This is mainly due to the efficient representation capability of GraphSAGE in multimodal feature fusion, which makes the embedding of music theory, style labels and skill nodes more accurate; at the same time, the advantage function separation design of Dueling DQN can strengthen the strategic focus on high-yield nodes and increase the frequency of practice of important knowledge points. Others such as GAT + PPO also have a certain selective attention mechanism, but lack dynamic regulation of the user's historical cognitive state,

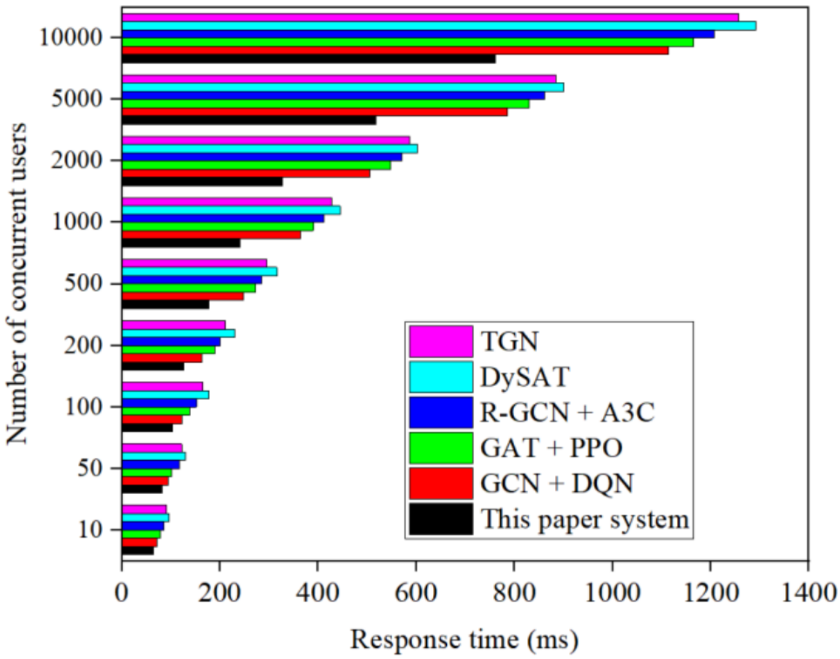

FIGURE 8. Responsiveness

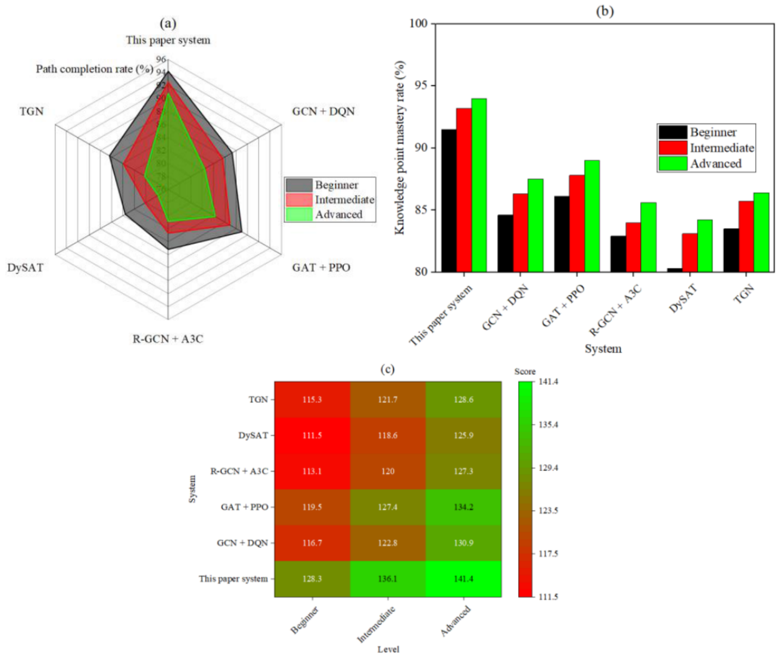

FIGURE 9. Learning effect: (a) Path completion rate; (b) Knowledge point mastery rate; (c) ABRSM score

which can easily lead to frequent repetition of low-value nodes during training, affecting learning efficiency.

In particular, although DySAT and TGN consider time factors, they do not adequately handle the non-balanced semantic weights between nodes, resulting in a relatively low mastery rate.

Taking the ABRSM test scores as the final learning effect evaluation indicator, the system in this paper is significantly better than other systems among users of all levels, and the average score of primary users has reached 128.3 points. The scores of intermediate and advanced users reached 136.1 and 141.4 respectively, showing the system's ability to significantly improve long-term learning outcomes. The superior performance of the proposed system is mainly attributed to two factors: first, the fine structure modeling of nodes and edges in heterogeneous knowledge graphs makes the path content more reasonable; second, the cognitive load adjustment strategy avoids the interference of overly difficult tasks on the learning rhythm. In contrast, GCN+DQN and R-GCN+A3C showed relatively low scores in the evaluation, reflecting their limitations in complex path design and multimodal semantic processing. Therefore, this paper systematically improves learning efficiency, optimizes actual performance and theoretical examination results, and has high educational practice value.

VI. CONCLUSION

This study proposes a music learning path optimization system that integrates GraphSAGE and Dueling DQN, which effectively solves the problem of incomplete path coverage caused by the difficulty of traditional methods in modeling the multi-dimensional correlation structure of music knowledge. This success in mapping complex relationships is highly transferable; the integrated system provides a methodological solution for optimizing complex industrial processes, offering a means to effectively model the multi-dimensional correlation structure between machine parameters, material inputs, and defect causes in the industry. The learning path knowledge coverage rate of this system based on the Yousician platform is as high as 89.6%, and the path length is shortened compared to the baseline. This paper constructs a heterogeneous music knowledge graph (nodes cover knowledge points, skills, styles; edges include prerequisite dependencies, skill coupling and style similarity), combines GraphSAGE's LSTM aggregator to dynamically fuse multimodal node features, and introduces Dueling DQN to optimize the path strategy under cognitive load constraints. Users can effectively improve their music learning effects by using this system. This study provides an intelligent and feasible path planning solution for online music education. The limitation is that social learning factors and multi-instrument collaboration scenarios are not integrated. Recognizing the need to evolve with complex, real-world systems, future work will integrate the time-series graph network to achieve dynamic knowledge update and explore the cross-instrument skill transfer mechanism. This approach to continuous, dynamic modeling is also crucial for the industry, where integrating a time-series graph network can help achieve dynamic knowledge updates regarding complex machine interactions and explore the transferability of operational skills across different types of machinery.

AUTHOR CONTRIBUTIONS

Danning Zhao designed, collected and analyzed the data, and drafted the manuscript. Danning Zhao conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Danning Zhao participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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