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Cross-disciplinary Teaching for Chinese College Students Based on Enhanced Graph Neural Network - Taking Piano Class as an Example

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Abstract:

The aim of this study is to comprehensively understand and optimize the curriculum of interdisciplinary course settings in piano courses for Chinese university music students, with the goal of enhancing educational quality and student learning outcomes. The study proposes an intelligent piano teaching recommendation feedback system based on the Knowledge Graph Enhanced Graph Neural Network (KGEGNN). This system leverages deep learning techniques combined with knowledge graphs to extract features from user learning behaviors, thereby providing personalized teaching recommendations and real-time feedback. Additionally, it utilizes enhanced graph neural networks to extract reinforcement items from indirect interactions among users, aggregates embeddings of users and items, and makes recommendations through prediction functions to offer personalized music teaching suggestions and feedback. In terms of experimental results, the KGEGNN algorithm achieves 94.58% for Top1-Accuracy and 91.29% for Top1-F1 score, while achieving 95.36% for Top5-Accuracy and 92.81% for Top5-F1 score, representing at least a 6% improvement in prediction accuracy. Thus, the Intelligent Piano Teaching Recommendation System constructed in this study demonstrates significant advantages in multi-candidate prediction and recommendation accuracy, with important potential and practical value in enhancing learning outcomes and promoting curriculum optimization.

Keywords: Music Discipline; Deep Learning, Interdisciplinary Course Settings; University Students; Piano Teaching Recommendation Feedback System.

INTRODUCTION

Research Background and Motivations

With the continuous development and widespread adoption of educational technology, interdisciplinary teaching models have gradually become an important trend in higher education [1-3]. In the field of music education, particularly in piano courses, traditional teaching methods have revealed certain issues over time, such as limited teaching resources, methodological uniformity, and insufficient personalized guidance. To address these challenges, an increasing number of educational researchers and practitioners have begun exploring interdisciplinary course settings, leveraging theories and methods from other disciplines to enhance the effectiveness and quality of music education. By integrating knowledge and approaches from disciplines such as psychology, education, and information technology, interdisciplinary courses not only enrich curriculum content but also enhance students' overall abilities and innovation skills [4-7].

In the design of interdisciplinary course intersections, the advancement of intelligent technologies, particularly machine learning, presents new opportunities for the education sector. By developing intelligent teaching aids, such as intelligent piano practice systems, machine learning algorithms can analyze students' performances and provide real-time feedback, thus facilitating personalized teaching and improving students' learning efficiency and outcomes [8,9]. Furthermore, machine learning technologies can be employed to assess the effectiveness of various interdisciplinary course settings, offering scientific decision support for optimizing curriculum systems [10-12].

Research Objectives

This study aims to explore and construct a curriculum system for interdisciplinary course settings in piano courses within Chinese university music programs. Through the development and application of teaching aids and research into curriculum optimization strategies, the goal is to enhance the teaching effectiveness and student learning experience in piano courses. Specific research objectives include utilizing machine learning algorithms to develop intelligent teaching aids for analyzing student performances and providing real-time feedback to help improve their playing skills. Additionally, through machine learning models, the study experimentally analyzes and evaluates the impact of different interdisciplinary course settings on student learning outcomes, thereby providing data-driven support and a decision-making basis for optimizing the curriculum system. These outcomes offer effective guidance for practical teaching, promoting reform and innovation in Chinese university music piano courses.

LITERATURE REVIEW

Interdisciplinary course settings have become a significant research focus in the field of education in recent years. The core idea is to break down disciplinary barriers and foster students' comprehensive qualities and innovation capabilities through the integration of knowledge from different disciplines. Numerous scholars have conducted related research. Zhang et al. introduced the design and implementation of interdisciplinary courses in university settings aimed at cultivating innovative talents for the future [13]. Chittle et al. through qualitative research, found that teachers generally believed interdisciplinary courses contributed to enhancing students' comprehensive qualities and developing diverse abilities [14]. Kao et al. explored interdisciplinary courses in product and media design education, revealing that such courses effectively promoted students' innovative thinking and interdisciplinary qualities [15]. Lam elucidated the importance of interdisciplinary general education course design, highlighting its role in cultivating students' comprehensive qualities and critical thinking across multiple disciplines [16]. Shen emphasized the positive role of interdisciplinary courses in enhancing students' comprehensive qualities and sense of social responsibility [17]. Rafiq et al. pointed out that interdisciplinary education helped develop students' comprehensive abilities and their capacity to solve complex problems, yet faced challenges such as integrating teaching resources [18].

The application of intelligent teaching aids in music education has emerged as a current research hotspot. For instance, Al Ka'bi enhanced teaching quality and promoted personalized learning and educational equity through intelligent teaching aids [19]. Yun et al. analyzed the teaching quality of an innovative political education platform based on deep learning, finding that the platform effectively improved student learning outcomes and engagement [20]. Wang et al. proposed a unified interpretable intelligent learning diagnosis framework to enhance student learning outcomes and teacher teaching strategies [21]. Lin et al. systematically reviewed the impact of artificial intelligence in intelligent tutoring systems on sustainable education, demonstrating that deep learning technology significantly enhanced personalized teaching and learning diagnostics [22]. Song discovered that deep learning technology provided personalized teaching recommendations, enhancing students' musical expressiveness and learning efficiency [23]. Chiu et al. developed a deep learning system supporting college students' appreciation of art and painting creation, significantly improving the quality of students' artistic works and appreciation levels [24]. Zhang & Ma uggested that applying deep learning technology could enhance teaching effectiveness and students' sports skills, promoting the development of intelligent physical education [25].

Machine learning models can be used to assess the teaching effectiveness of different course settings. Zhang et al. proposed a deep learning model for innovative assessment of political learning and provided strong support for personalized teaching [26]. Sanusi et al. proposed that machine learning technology significantly enhanced students' interest and learning outcomes, promoting innovative teaching methods [27]. Arashpour et al., combining machine learning with optimization methods based on teaching-learning, predicted individual learning performances, demonstrating that this hybrid approach effectively enhanced the accuracy of course teaching effectiveness assessments [28]. Zhai et al. utilized deep learning-based artificial intelligence electronic image technology to effectively enhance teachers' teaching capabilities and students' learning outcomes [29]. Wu through meta-analysis, explored the impact of digital technology on deep learning, revealing that digital technology significantly enhanced students' learning depth and understanding, thereby improving teaching effectiveness [30].

Meanwhile, deep learning algorithms can also optimize existing curriculum systems. Shukla et al. empirically evaluated teaching-learning optimizations, genetic algorithms, and particle swarm optimization, demonstrating their significant role in improving educational recommendation systems and enhancing teaching effectiveness [31]. Chen et al. applied machine learning algorithms to optimize personalized educational recommendation systems, showing effective improvements in student engagement and personalized learning outcomes [32]. Ahmadian Yazdi et al. proposed a dynamic educational recommendation system based on improved LSTM neural networks, which excelled in real-time analysis and personalized recommendations, contributing to optimizing teaching effectiveness [33]. Siva Shankar et al. introduced a novel optimization approach based on deep learning and artificial intelligence, demonstrating its effectiveness in enhancing cybersecurity education [34]. Li et al. explored the forgetting mechanism in recommendation systems, revealing its potential to optimize privacy protection and teaching effectiveness in education recommendation systems [35].

In summary, significant progress has been made in interdisciplinary course settings and intelligent teaching aids in existing literature. However, specific evaluation models and optimization strategies are still lacking in interdisciplinary course research. Long-term application effects of intelligent teaching platforms require further research, and the interpretability and universality of intelligent learning diagnostic frameworks need enhancement. Moreover, machine learning technology plays a crucial role in evaluating and optimizing curriculum systems but lacks specific applications in higher education music courses. This study's innovation lies in integrating intelligent teaching aids with interdisciplinary course settings. By developing intelligent teaching aids and utilizing machine learning algorithms to optimize curriculum systems, it provides scientific decision support for university-level music piano courses, enhancing teaching effectiveness and student learning experiences.

RESEARCH MODEL

Demand Analysis for Interdisciplinary Course Settings in Music Disciplines

In today's complex and rapidly changing social context, nurturing music talents with comprehensive qualities and innovative capabilities has become a crucial goal of higher education. Traditional single-discipline course settings are no longer adequate to meet this demand, thus interdisciplinary course settings have emerged [36]. Specifically, the necessity of interdisciplinary course settings in music disciplines is illustrated in Figure 1.

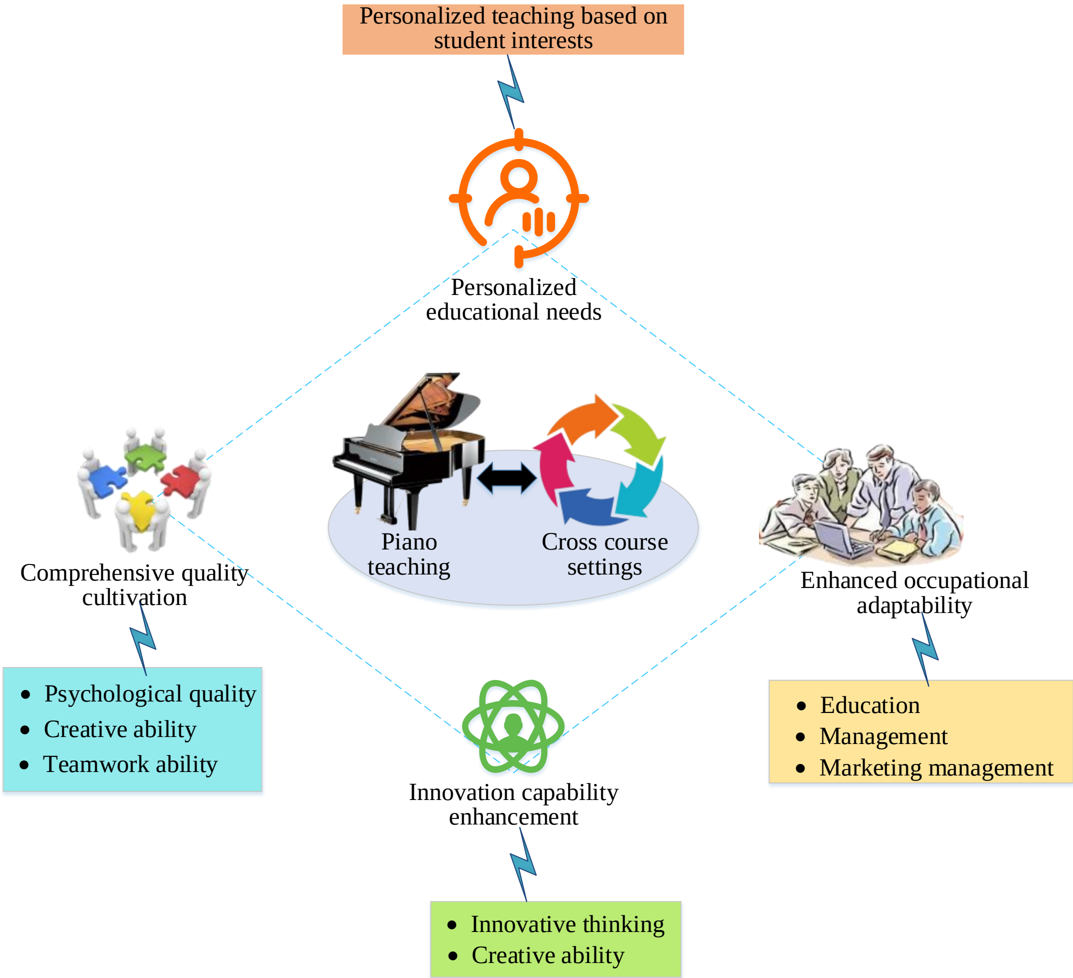

Figure 1. Illustration of the Necessity of Interdisciplinary Course Settings in Music Disciplines

In Figure 1, setting interdisciplinary courses in music education can cultivate comprehensive qualities, enhance innovation capabilities, improve career adaptability, and meet personalized educational needs. Thus, the integration of interdisciplinary course settings with intelligent teaching tools further enhances the effectiveness of music education. Intelligent teaching tools, such as the Deep Learning-based Intelligent Piano Teaching Recommendation Feedback System (IPTRFS), can analyze students' performance data in real-time, providing personalized teaching suggestions and feedback. The introduction of such technology not only enhances students' learning efficiency but also provides data support for optimizing interdisciplinary course settings.

Construction Analysis of the Deep Learning-based IPTRFS

To enhance the personalization and intelligence of piano teaching, this study proposes an IPTRFS based on Knowledge Graph Enhancement Graph Neural Network (KGEGNN) [37-40]. This system utilizes knowledge graph and graph neural network technologies to integrate user learning behaviors and offer personalized teaching suggestions and real-time feedback. The system's construction mainly includes collaborative knowledge graph layer, user indirect feedback layer, and feature fusion prediction layer, as depicted in the framework flow in Figure 2.

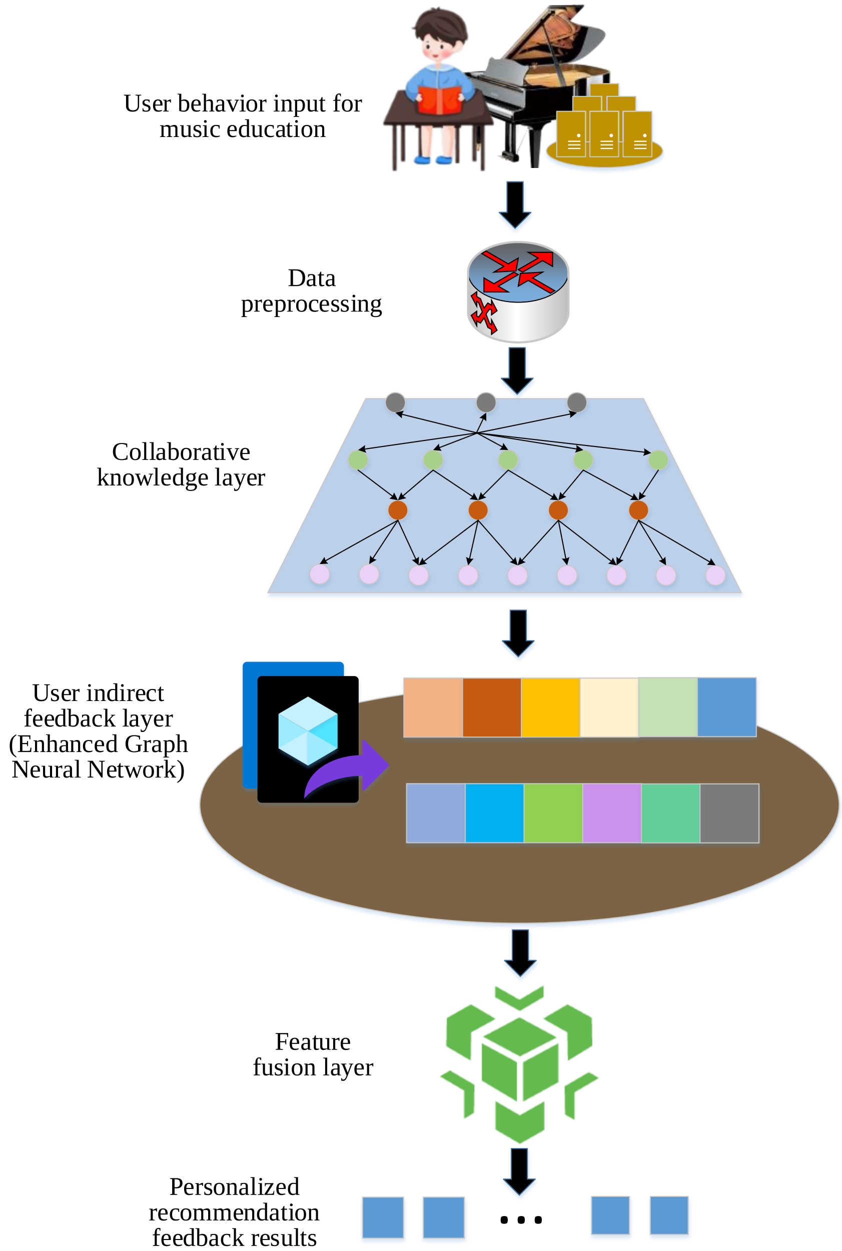

Figure 2. Framework Diagram of the IPTRFS based on KGEGNN

In Figure 2, the model first collects and preprocesses user performance data and learning behavior data, including noise filtering, feature extraction, and standardization.

In the collaborative knowledge graph layer, project nodes serve as intermediate nodes to concatenate user interaction bipartite graphs and project knowledge graphs into a collaborative knowledge graph. Here, ul-u3 represent user nodes, il-i5 represent project nodes, and el-e6 represent entity nodes of project attributes. The collaborative knowledge graph fusion extracts relationships between users, projects, and project attribute entities. Introducing intent nodes further transforms the user-project bipartite graph into a user-intent-project tripartite graph, denoted as set K, where the triples in the graph are represented as $\{(u,k,i)\,|\,k \subset K\}$. Intent embeddings are obtained by aggregating relationship embeddings from the collaborative graph. By assigning different weights to relationships and ensuring intents are as independent as possible, intent representations are derived, as shown in Equations (1) and (2):

$$e_k = \sum_{r \in R} \alpha(r,k) e_r \tag{1}$$

$$\alpha(r,k)=\frac{\exp(w_{rk})}{\sum_{r'\in R}\exp(w_{r'k})} \tag{2}$$

In Equations (1) and (2), e_k denotes the embedding vector of intents, e_r denotes the embedding vector of relationships in the collaborative graph, e_r denotes the weight coefficients of intents on relationships, R denotes the set of all relationships, and w_{rk} denotes the trainable parameters of the model. The model assigns learnable weight parameters to intents and relationships, which are normalized to obtain coefficients α representing different intents on relationships. The final intent embedding representation is obtained by summing over all relationships.

The original knowledge graph model provides two loss functions to model the independence between intents. This study utilizes the minimum correlation loss function for training, as shown in Equations (3) and (4).

$$L_{IND}=\sum_{k,k'\in K,k\neq k'} dCor(e_k,e_{k'}) \tag{3}$$

$$dCor(e_k,e_{k'})=\frac{dCov(e_k,e_{k'})}{\sqrt{dVar(e_k)\cdot dVar(e_{k'})}} \tag{4}$$

In Equations (3) and (4), L_{IND} denotes the loss function, $Cov(e_k,e_{k'})$ denotes the covariance between intents, and $dVar(e_k)$ denotes the variance of intent vectors.

In educational settings, overfitting of training data can lead to difficulty in recommending items that users have not interacted with but may be interested in. Therefore, in the user indirect feedback layer, an enhanced graph neural network is utilized to extract indirect feedback information from users. The aggregation of specific user indirect enhancement terms is detailed in Equations (5)-(7).

$$e^*_{u_{a,b}}=f_{IE}\left(N_{u_a},N_{u_b},e_u^{(0)},e_k,e_i^{(0)}\right) \tag{5}$$

$$e^*_{u_{a,b}}=\delta\sum_{(k,i)\in N_{u_b}\&(k,i)\notin N_{u_a}}\beta(u_a,k)e_k \odot e_i^{(0)} \tag{6}$$

$$\delta=\frac{\left|N_{u_a}\cap N_{u_b}\right|^2}{\left|N_{u_a}\right|\left|N_{u_b}\right|} \tag{7}$$

In Equations (5)-(7), $e^*_{u_{a,b}}$ denotes the enhancement item for user a through user b, N_{u_a} and N_{u_b} respectively denote the interaction record sets of users a and b. δ represents the coefficient of indirect enhancement items between users, and β denotes the weight of intents for users. When users perform indirect enhancement, they need to obtain enhancement items from all similar users.

After filtering out enhancement items beyond the threshold, user ul obtains all indirect enhancement items in the collaborative graph. Then, summing up all enhancement items yields the final enhancement item, as shown in Equation (8).

$$e^*_{u_1}=e^*_{u_{1,2}}+e^*_{u_{1,3}}+\cdots+e^*_{u_{1,n}} \tag{8}$$

After performing indirect enhancement for all users, the enhancement items are integrated into the user embeddings to obtain the first-order user embedding representation, as shown in Equation (9):

$$e_u^{(1)} = e_u^{(1)\sim} + \gamma_u e_u^* \tag{9}$$

In Equation (9), $e_u^{(1)}$ denotes the enhanced first-order user embedding vector, $e_u^{(1)\sim}$ denotes the original first-order user embedding vector, γ_u represents the coefficient of the enhancement items, and e_u^* denotes the enhancement item.

In the feature fusion layer, after obtaining the first-order embeddings of users and items, the information aggregation can be applied to aggregate information about users and items. Based on the l−1 order embedding vectors, the aggregation function used can yield l-order embedding vectors, as shown in Equations (10) and (11).

$$e_u^{(l)} = f_{IG}\left(\left\{\left(e_u^{(l-1)}, e_k, e_i^{(l-1)}\right) | (k,i) \in N_u\right\}\right) \tag{10}$$

$$e_i^{(l)} = f_{KG}\left(\left\{\left(e_i^{(l-1)}, e_r, e_v^{(l-1)}\right) | (r,v) \in N_i\right\}\right) \tag{11}$$

In Equations (10) and (11), f_{IG} denotes the user information aggregation function, and f_{KG} denotes the item aggregation function. N_i represents the set of item neighbors, e_r denotes the embedding vector of the relationship between items and entities, and e_v denotes the embedding vector of the entity. r and v represent the relationship and entity, respectively. Higher-order user embeddings can be calculated based on higher-order item embeddings, and higher-order item embeddings are obtained by aggregating higher-order entity neighbors. When the distance between items and entities in the knowledge graph is greater, less information should be aggregated. Therefore, at each order, the number of entity neighbors is divided, and then the relationship and entity information is aggregated, as shown in Equation (12).

$$e_i^{(l)} = \sum_{s \in N_i^l} \frac{e_{r_1}}{\left|N_{s_1}\right|} \square \frac{e_{r_2}}{\left|N_{s_2}\right|} \square \cdots \square \frac{e_{r_l}}{\left|N_{s_l}\right|} \square e_{s_l}^{(0)} \tag{12}$$

In Equation (12), N_i^l denotes the l-th order neighbor set of item i, e_{r_l} denotes the l-th order relationships of item i, and $e_{s_l}^{(0)}$ denotes the l-th order neighboring entities of item i. Users and items aggregate embedding vectors within all l orders to obtain the final embeddings of users and items. The aggregation function selected in this study is the sum aggregation function (agg_{sum}), which sums up the l vectors obtained to obtain the final embedding representation, as shown in Equations (13) and (14).

$$e_u^{\sim} = agg_{sum}\left(e_u^{(0)}, \cdots, e_u^{(l)}\right) \tag{13}$$

$$e_i^{\sim} = agg_{sum}\left(e_i^{(0)}, \cdots, e_i^{(l)}\right) \tag{14}$$

After obtaining the final embedding representations of users and items, predictions are made using a prediction function for recommendation. The recommendation prediction $\hat{y}_{ui}$ is obtained by taking the dot product of user and item embedding vectors, as shown in Equation (15).

$$\hat{y}_{ui} = e_u^{\sim T} e_i^{\sim} \tag{15}$$

The loss function L_{BPR} used for learning user and item embeddings aims to assign higher prediction scores to items that users have interacted with compared to those they have not interacted with, as specified in Equation (16).

$$L_{BPR} = \sum_{(u,i,j) \in O} -\ln \sigma\left(\hat{y}_{ui} - \hat{y}_{uj}\right) \tag{16}$$

In Equation (16), $\hat{y}_{ui}$ denotes the set of interaction records that have occurred, $\hat{y}_{uj}$ denotes those that have not occurred, O denotes the entire training interaction set, and σ denotes the activation function. Combining the independence loss function of user intent, the complete loss function of the KGEGNN model is obtained as shown in Equation (17):

$$L_{KGEGNN} = L_{BPR} + \lambda_1 L_{IND} + \lambda_2 \|\theta\|_2^2 \tag{17}$$

In Equation (17), θ includes regularization terms for $e_u^{(0)}, e_v^{(0)}, e_r, e_k$, λ_1 balances the loss function for independent intent, and λ_2 balances the regularization terms.

Finally, based on the prediction results, personalized music teaching recommendations and feedback are provided, including recommending suitable practice content and teaching resources, as well as offering specific improvement suggestions. The specific pseudocode of this model is shown in Figure 3.

```
Start
Input: User behavior input in music teaching
Output:Personalized recommendation feedback results
# Data preprocessing
   data = load_data()
   preprocessed_data = preprocess_data(data)
# Knowledge Graph construction
   kg_data = extract_kg_data(preprocessed_data)
   kg = build_knowledge_graph(kg_data)
# Intent embedding
   intents = define_intents()
   relations = define_relations()
   weights = initialize_weights(intents, relations)
   intent_vectors = intent_embedding(kg, intents, relations, weights)
# Minimum association loss function
   loss = minimum_association_loss(intent_vectors)
# Indirect feedback layer
   users = load_users()
   interactions = load_interactions()
   feedback_weights = initialize_feedback_weights(users)
   feedback = indirect_feedback(users, interactions, feedback_weights)
# Feature fusion layer
   user_embeddings = initialize_user_embeddings(users)
   item_embeddings = initialize_item_embeddings()
   l = define_embedding_layers()
   user_embeddings_l, item_embeddings_l = feature_fusion(user_embeddings, item_embeddings, l)
# Model training and recommendation
# Output recommendations
   output_recommendations(recommendations)
End
```

Figure 3. Pseudocode Flow of the IPTRFS based on KGEGNN.

Analysis of Cross-Course Setting Optimization Strategies Supported by the IPTRFS

Under the support of the IPTRFS, strategies for optimizing cross-course settings are proposed. These include evaluating course effectiveness, personalized course recommendations, course content optimization, teaching method improvements, and interdisciplinary collaborative teaching. The system not only quantifies the teaching effectiveness of different cross-course settings but also provides real-time feedback and targeted teaching suggestions for teachers. The optimization strategies for cross-course settings are depicted in Figure 4.

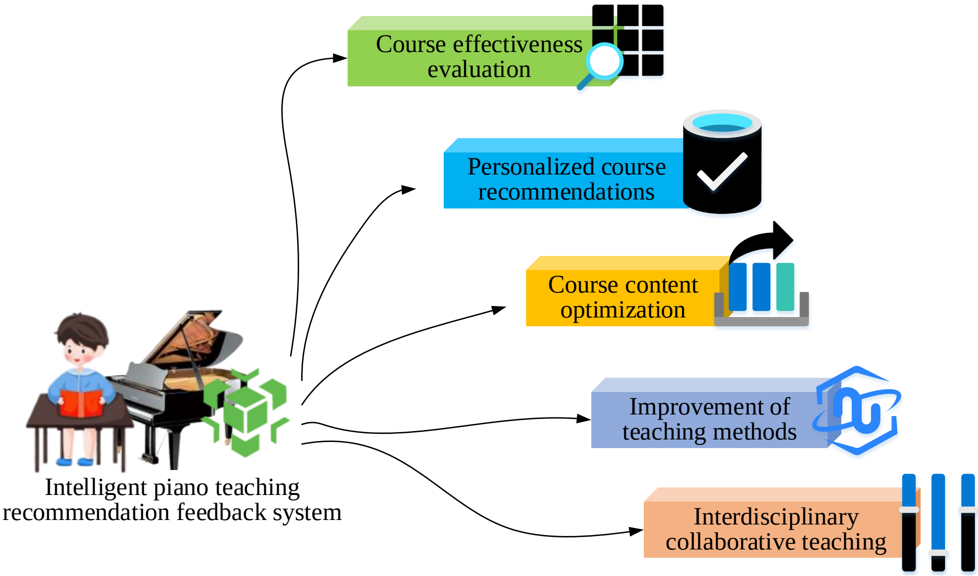

Figure 4. Illustration of Cross-Course Setting Optimization Strategies.

In Figure 4, through scientific data analysis and personalized teaching suggestions, the system not only enhances students' learning outcomes but also provides robust support for optimizing curriculum systems, driving innovation and development in music education.

EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

Datasets Collection

To validate the performance of the proposed model in this study, experimental data is sourced from the Last.fm music recommendation dataset (https://grouplens.org/datasets/hetrec-2011/), encompassing social network, tagging, and consumption of resources (web bookmarks and music artist listening) information from approximately 2,000 user sets. Subsequently, detailed preprocessing steps are applied to the acquired raw data, including data cleaning, outlier handling, and normalization, to ensure data quality and consistency. Feature engineering is also performed to transform the raw data into a format suitable for model training. Finally, the data is split into training (80%) and testing sets (20%) for model training and performance evaluation.

Experimental Environment

The hardware setup includes high-performance GPU accelerators crucial for handling large-scale data and complex models. Specifically, a 12th Gen Intel(R) Core (TM) i5-12400E GPU with graphics processing capabilities optimized for deep learning computations is used. The operating system selected is Windows 10, tailored for scientific computing, complemented with 64GB DDR4 RAM and 2TB NVMe SSD storage to ensure efficiency and stability in data processing and model training.

Software utilizes Python 3.6 as the primary programming language, TensorFlow 2.2 for implementing required algorithms and models in deep learning frameworks. Additionally, data processing libraries such as Pandas 1.3.3, NumPy 1.21.2, and Matplotlib are employed for visualization and input-output interfaces.

Parameters Setting

In this study, the Adaptive Moment Estimation (Adam) optimization algorithm is employed to optimize network model parameters. The choice of batch size accelerates the training process, while the embedding dimension affects the model's data representation capabilities. Regularization coefficients control model complexity, and parameters such as intent loss coefficient, node failure rate, and message aggregation failure rate directly influence the efficiency and accuracy of the model in handling knowledge graphs and user behavioral data processing, as detailed in Table 1.

Table 1. Accuracy Results of Personalized Solution Generation Predictions under Different Algorithms

Parameter name	Value	Parameter name	Value
batch size	1024	Message aggregation failure rate	0.1
embedding vector dimension	64	Number of hidden layer channels	32
regularization coefficient	0.00002	Number of intent nodes	6
learning rate	0.0001	Information aggregation order	3
intention loss term coefficient	0.0001	User enhancement factor	0.2
node failure rate	0.2	Item enhancement factor	0.2
iteration cycle	80		

Performance Evaluation

To evaluate the performance of the model constructed in this study, the algorithms proposed are compared with GCN [41], STGCN [42], KGCN [43], and the model algorithms proposed by Ahmadian Yazdi et al. (2024) in related fields using metrics such as Top1-Accuracy, Top1-F1 score, Top5-Accuracy, and Top5-F1 score.

Firstly, the results of the comparison between the algorithm and other models in terms of Top1-Accuracy and Top1-F1 score are analyzed, as shown in Figures 5 and 6.

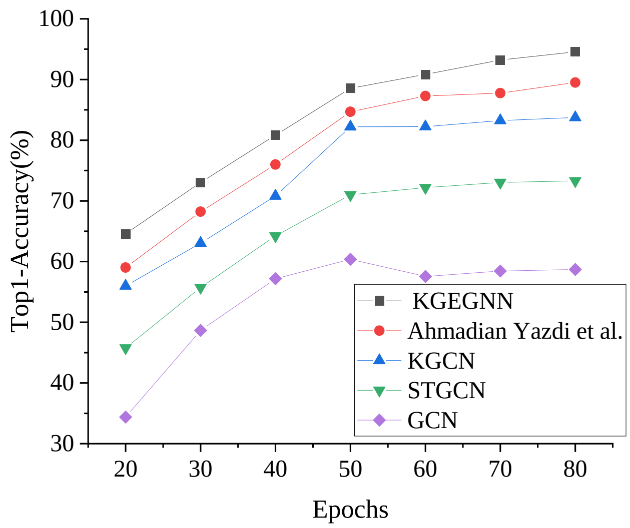

Figure 5. Top1-Accuracy Results of Recommendation Feedback System under Different Algorithms.

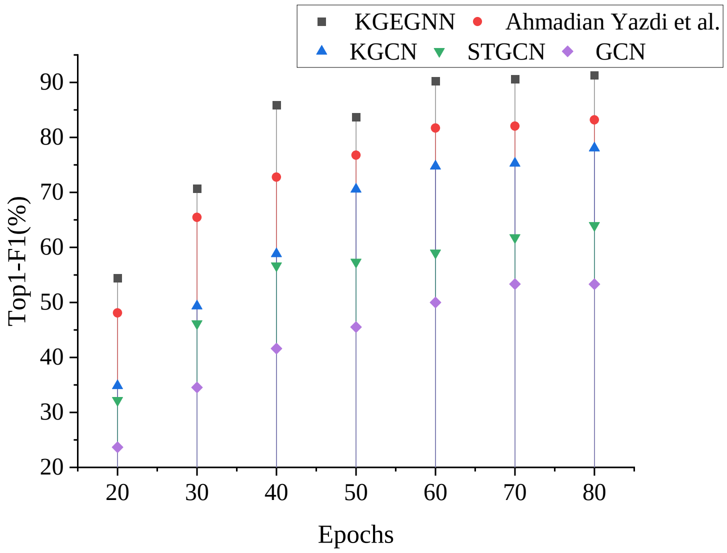

Figure 6. Top1-F1 Results of the Recommendation Feedback System under Different Algorithms.

In Figures 5 and 6, by comparing the Top1-Accuracy and Top1-F1 results of the recommendation feedback system under different algorithms, it can be observed that with an increase in iteration cycles, the Accuracy and F1 results of each algorithm show an initial increase followed by stabilization. In this study, the proposed KGEGNN algorithm model achieves an Accuracy of 94.58% and an F1 score of 91.29%, which is at least 6% higher than other model algorithms. The predictive accuracy of the recommendation feedback system under different algorithms ranks in descending order as follows: this study's model algorithm > algorithm proposed by Ahmadian Yazdi et al. (2024) > KGCN > STGCN > GCN. Therefore, the KGEGNN algorithm constructed in this study demonstrates superior predictive accuracy when applied to intelligent piano teaching recommendation feedback.

The analysis of Top5-Accuracy and Top5-F1 values comparing the algorithm with other models is presented in Figures 7 and 8.

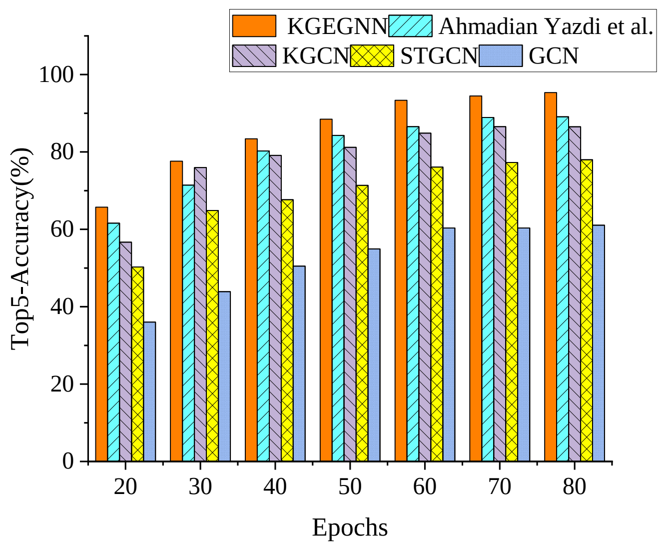

Figure 7. Top5-Accuracy Results of Recommendation Feedback System under Different Algorithms.

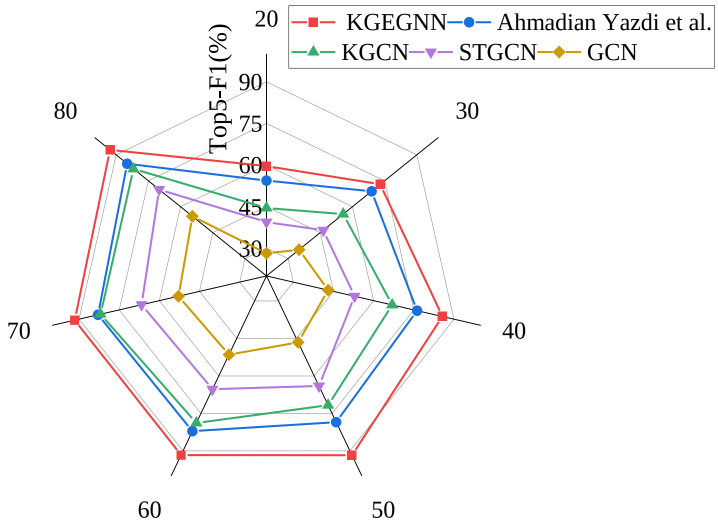

Figure 8. Top5-F1 Results of the Recommendation Feedback System under Different Algorithms.

In Figures 7 and 8, by comparing the Top5-Accuracy and Top5-F1 results of the recommendation feedback system under different algorithms, it can be observed that with an increase in iteration cycles, the Accuracy and F1 results of each algorithm exhibit an initial increase followed by stabilization. In this study, the proposed KGEGNN algorithm model achieves an Accuracy of 95.36% and an F1 score of 92.81%, which is at least 6% higher than other model algorithms. Compared to the Top1-Accuracy and Top1-F1 metrics, the accuracy significantly improves. This improvement may be attributed to Top5 allowing the model to correctly predict among a few candidate options, not just the single best choice (Top1). Therefore, the results further demonstrate that the KGEGNN algorithm constructed in this study, when applied to intelligent piano teaching recommendation feedback, can recommend superior choices to users with better predictive accuracy.

Discussion

This study introduces the KGEGNN algorithm into an IPTRFS and comprehensively compares it with other relevant models. Firstly, from the analysis of Top1-Accuracy and Top1-F1 score comparisons, the KGEGNN algorithm achieves an Accuracy of 94.58% and an F1 score of 91.29%, significantly outperforming other models such as the algorithm proposed by Ahmadian Yazdi et al. (2024) and traditional GCN, STGCN, and KGCN models. The data indicate that KGEGNN exhibits higher accuracy and comprehensiveness in single predictions, effectively enhancing the prediction accuracy of the recommendation system. This finding aligns with the viewpoints of Chang et al. and Zhang et al. [44,45]. Further comparing Top5-Accuracy and Top5-F1 scores, the KGEGNN algorithm also excels under Top5 conditions, achieving an Accuracy of 95.36% and an F1 score of 92.81%, at least 6% higher than other models. This correlation is consistent with the perspectives of Sheng et al. [46]. This reflects KGEGNN's predictive capability among multiple candidate options, enabling more comprehensive recommendations for users. Compared to traditional models, its application in complex tasks shows more significant effects.

Therefore, this study achieves personalized design and optimization of courses through an intelligent teaching recommendation feedback system. The application of the KGEGNN algorithm enhances the precision of educational recommendations, allowing personalized recommendations based on individual student learning data and preferences. This enhancement improves learning motivation and outcomes, providing scientific basis and technical support for teaching innovation in music education. It helps optimize course settings and teaching content, thereby enhancing overall educational quality and student learning experience.

CONCLUSION

Research Contribution

This study designs and implements an IPTRFS based on the KGEGNN algorithm, aiming to optimize cross-course settings in piano courses for Chinese university music students. By integrating deep learning and knowledge graph technologies, the experiment not only successfully achieves personalized course recommendations but also provides opportunities for interdisciplinary learning, expanding students' boundaries of knowledge and abilities. Results show that the KGEGNN algorithm achieves prediction accuracies exceeding 90% for both Top1 and Top5 scenarios, providing crucial experimental support for innovation in teaching models in music education.

Future Works and Research Limitations

Despite achieving positive outcomes, this study faces several challenges and limitations. Firstly, further optimization is needed in data acquisition and processing for the intelligent recommendation system, especially concerning data privacy and security considerations. Secondly, the scalability and generalization capability of the model need further validation and improvement to meet the diverse needs of different learning environments and individual students. Future study could focus on enhancing algorithm efficiency, optimizing model structures, and exploring integration of more advanced technologies such as reinforcement learning and natural language processing, to further advance the development and application of intelligent education systems.

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