International Scientific Technical and Economic Research (ISSN: 2959-1309)
Vol. 4, No. 1, (March 2026), pp. 245-265
Journal homepage: https://www.istaer.online

RESEARCH ARTICLE DOI: 10.71451/ISTAER2612

Personalized Recommendation Algorithm of Piano Practice Scheme Based on Multi Objective Optimization

Chunping Feng*

Music Academy, Guangzhou Xinhua University, Guangzhou, Guangdong, China

Abstract: Aiming at the problem that traditional recommendation methods in piano practice struggle to balance multiple optimization objectives—such as skill improvement, time cost, user matching, and cognitive load—this paper proposes a personalized practice scheme recommendation algorithm based on multi-objective optimization. The algorithm first constructs a multi-dimensional user capability vector model and tracks the evolution of learners' skill dimensions, such as rhythm control and fingering proficiency, in real time through a dynamic state update mechanism. On this basis, the exercise recommendation is formalized as a four-objective optimization problem, the Pareto optimal theory is used to solve the non-dominated solution set, and a heuristic search strategy integrating sequence dependencies is designed to generate a coherent exercise path. Based on the data set containing 1248 users and 120000 interactive records, the experimental verification shows that the skill improvement rate, recommendation efficiency, and user satisfaction index of this method reach 0.513, 0.603, and 0.624 respectively, and the comprehensive score is 10.8% higher than that of the optimal baseline NSGA-II. The ablation experiment further confirms that the multi-objective optimization module contributes the most (the performance is reduced by 9.9%). The proposed method effectively realizes the unification of multi-objective collaborative optimization and personalized recommendation.

Keywords: Multi objective optimization; Personalized recommendation; Piano practice; Intelligent music education; Sequence modeling

How to Cite: Feng, C. (2026). Personalized Recommendation Algorithm of Piano Practice Scheme Based on Multi Objective Optimization. *International Scientific Technical and Economic Research, 4*(1), 245–265. https://doi.org/10.71451/ISTAER2612

Article history: Received: 16 Jan 2026; **Revised:** 22 Feb 2026; **Accepted:** 25 Mar 2026; **Published:** 31 Mar 2026
Copyright: © 2026 The Author(s). Published by Sichuan Knowledgeable Intelligent Sciences. This is an open access article under the CC BY 4.0 license (http://creativecommons.org/licenses/by/4.0/).

1. INTRODUCTION

Piano learning is a skill acquisition process that highly depends on long-term deliberate practice. The rationality of its practice scheme directly affects the learning efficiency and the quality of results. Traditional piano teaching usually adopts a standardized practice path, in which all learners follow a similar sequence of pieces and technical training [1]. However, with the in-depth development of the concept of personalized education and the wide application of intelligent education technology, it is gradually recognized that learners differ significantly in

***Corresponding author:** Chunping Feng, Music Academy, Guangzhou Xinhua University, Guangzhou, Guangdong, China. Email: 13539071683@163.com

music foundation, cognitive ability, practice habits, and skills, and standardized practice programs fail to meet individual needs [2]. Especially in the piano practice scene, learners' skill development presents multidimensional characteristics, including rhythm, fingering proficiency, intonation control, musical expression and other aspects [3]. Each learner's growth speed and weak links in different dimensions are different. Therefore, how to dynamically generate appropriate exercise programs according to learners' individual differences has become a key problem to be solved in the field of intelligent music education [4],[5].

At present, the research in the field of piano practice recommendation mainly faces three deficiencies. First, most of existing methods are optimized based on a single objective, such as focusing only on maximizing skill improvement or solely considering the matching of practice difficulty, while ignoring that piano learning is essentially a multi-objective balancing process. In practical teaching, a good practice program needs to balance multiple objectives, such as skill improvement efficiency, time cost control, user learning experience, and cognitive load management [6],[7],[8]. Single objective optimization often leads to the deviation of recommendation results from actual needs. Second, most recommendation algorithms adopt static modeling, generating fixed recommendations based on users' historical performance, and fail to fully consider the dynamic evolution of learners' abilities [9],[10]. The improvement of piano skills is a continuous change process, and the learners' ability state will change slightly but significantly after completing each practice task, which is difficult to capture by static methods. Third, existing research lacks a systematic solution for handling goal conflicts. For example, although difficult tasks can bring greater skill improvement, they will increase cognitive load and reduce user experience [11],[12]. There is no mature methodology on how to effectively coordinate multiple mutually constrained goals.

To solve the above problems, this paper proposes a personalized recommendation algorithm for piano practice scheme based on multi-objective optimization. The core idea is to formalize practice recommendation as a multi-objective optimization problem, and seek the optimal solution in the four dimensions of skill improvement, time efficiency, user matching and cognitive load. The main contributions of this paper are reflected in three aspects. First, a dynamic evolution model of user capability is constructed, which tracks learners' trends across multiple skill dimensions in real time through a sequential state update mechanism, enabling the recommendation system to perceive and adapt to the evolution of learners' capabilities. Secondly, a multi-objective optimization framework for piano practice scenarios is designed, in which four interrelated and constrained optimization objectives are clearly defined. The Pareto optimal theory is used to solve the problem, which effectively handles the conflict between objectives. Thirdly, a personalized recommendation algorithm based on sequence dependency is proposed, which generates a coherent practice path by considering the interactions between practice tasks, rather than producing isolated single recommendations. Through the comprehensive experimental verification of real learning platform data and simulated enhanced data, this method significantly outperforms existing typical methods in key indicators such as skill improvement rate, recommendation efficiency, and user satisfaction, which proves the effectiveness and practical value of the multi-objective optimization framework in personalized recommendation of piano practice.

2. RELATED WORK

In the field of intelligent music education, researchers have carried out a lot of exploratory work, mainly focusing on computer-aided music teaching, automatic performance evaluation and adaptive learning path generation [13]. Early intelligent music education systems mainly focused on the automatic recognition and feedback of playing pitch and rhythm, and detected learners' performance errors and provided correction suggestions through audio signal processing technology [14]. With the development of machine learning technology, more and more researches have begun to try to build student models to represent learners' ability. For example, methods based on Bayesian knowledge tracking have been applied to the dynamic assessment of piano skill mastery [15]. In addition, part of the research work focuses on the automatic marking and sorting of the difficulty of the practice track, and quantifies the difficulty of the task by analyzing the rhythm complexity, interval span, tonality change and other characteristics of the score, so as to provide the learners with the practice sequence of progressive difficulty. However, most of these studies remain confined to a single aspect, such as skill evaluation or task sequencing, lacking a complete framework for the end-to-end integration of user state perception, task adaptation, and sequence optimization, and rarely considering the balance among multiple optimization objectives simultaneously.

As a research hotspot in the field of information retrieval and user modeling, personalized recommendation algorithm has been widely used in e-commerce, video streaming media, news push and other scenarios, and has been gradually introduced into the field of educational recommendation. Traditional collaborative filtering methods recommend by mining the similarity between users or the relevance between items [16]. Its advantage is that it does not need domain knowledge, but it does not perform well in the face of cold start problems and sparse data. The method based on matrix decomposition captures potential features by decomposing the user item interaction matrix into low dimensional hidden vectors, which alleviates the problem of data sparsity to a certain extent, but it is difficult to model the dynamic changes of user preferences. In recent years, deep learning recommendation models such as neural collaborative filtering and depth factor decomposition machine have improved the recommendation accuracy through nonlinear feature interaction, while sequential recommendation models such as SASRec and bert4rec use self-attention mechanism to capture the time dependence of user behavior [17],[18]. However, these recommendation algorithms have obvious limitations when applied to piano practice scenarios: they usually assume that user preferences are relatively stable, and the skill state of piano learners is continuously evolving; At the same time, these methods mainly serve a single objective optimization, such as click through rate prediction or score prediction, which is difficult to take into account multiple educational objectives such as skill improvement efficiency, time cost and cognitive load at the same time [19].

The research of multi-objective optimization method provides a systematic theoretical framework and solution strategy for dealing with conflicting optimization objectives. In the field of recommendation system, the application of multi-objective optimization has gradually attracted attention [20],[21]. Researchers try to find a balance between the accuracy, diversity, novelty and coverage of recommendation. Typical methods include the method of transforming multi-objective into single objective based on weighted summation, evolutionary algorithms based on Pareto dominance such as NSGA-II and SPEA2, and multi-objective strategy optimization method based on reinforcement learning [22],[23]. In the field of educational technology, some studies began to explore multi-objective learning path recommendation, such as considering knowledge coverage, learning time and students' interest in course recommendation [24]. However, the existing methods have several key defects in the application of piano practice recommendation. First of all, most studies adopt static multi-objective weighting strategies, and the weight parameters will not be adjusted once they are determined, which cannot meet the needs of individual differences and dynamic changes of learners. Secondly, the existing methods tend to use simple linear combination when dealing with goal conflict, ignoring the nonlinear trade-off relationship between goals, and the relationship between skill improvement and cognitive load in piano practice is exactly nonlinear [25]. Moreover, the existing methods rarely consider the sequence dependent effect between practice tasks, that is, the completion status of the previous task will affect the learning effect of subsequent tasks, which makes the traditional recommendation strategy based on independent evaluation difficult to generate a truly optimized practice path.

Based on the above analysis, there are obvious gaps in the intersection of intelligent music education, personalized recommendation and multi-objective optimization. Specifically, there is a lack of a personalized recommendation method specifically designed for piano practice scenes, which can integrate user dynamic capability modeling, multi-objective collaborative optimization and sequence dependency modeling. The research orientation of this paper is to fill this gap and propose an end-to-end recommended framework for piano practice programs. Compared with the existing work, the innovations of this paper are as follows: first, the piano practice recommendation is clearly defined as a multi-objective optimization problem, rather than the traditional single objective scoring prediction problem; Secondly, the dynamic state update mechanism is introduced to enable the recommendation system to respond to the changes of learners' abilities in real time; Thirdly, the solution framework based on Pareto optimal theory is adopted to avoid the limitations of fixed weight linear combination; Fourth, a sequence generation strategy considering the interaction between tasks is designed, rather than an independent single point recommendation. Through this comprehensive method design, this paper aims to provide a more scientific, flexible and personalized practice scheme recommendation solution for intelligent piano education.

3. METHODOLOGY

3.1 Overall system framework

The overall structure of the proposed model is composed of three parts: user state perception module, multi-objective optimization module and personalized recommendation generation module. The system input includes the user's historical practice record, performance data and practice task library, and the output is a personalized practice sequence for the current user's state. Let the user set be $U = \{u_1, u_2, \dots, u_N\}$, and the exercise task set be $E = \{e_1, e_2, \dots, e_M\}$. For any user u, its historical behavior can be expressed as the sequence $H_u = \{(e_t, r_t)\}_{t=1}^{T}$, where e_t represents the t-th practice task, and r_t represents the corresponding performance feedback (such as error rate, rhythm deviation, etc.).

The system first maps the historical sequence to the user's current capability state through the state modeling function $\mathcal{F}(\cdot)$:

$$\mathrm{s}_u = \mathcal{F}(H_u) \tag{1}$$

Where $\mathrm{s}_u \in \mathbb{R}^d$ represents the user's ability vector in multiple skill dimensions. Then, the multi-objective optimization module evaluates and screens the candidate exercise sequence under the given state s_u, and finally the recommendation module outputs the optimal exercise path $P_u = \{e_{t+1}, \dots, e_{t+K}\}$.

3.2 User characteristics and exercise data representation

In order to describe the multi-dimensional ability of users in piano learning, this study uses the vectorial representation method to construct the user ability model [26]. Define the user capability vector as:

$$\mathrm{s}_u = \left[s_u^{(1)}, s_u^{(2)}, \dots, s_u^{(K)}\right] \tag{2}$$

Where, $s_u^{(k)}$ represents the user's level in the k-th skill dimension, such as rhythm control, fingering proficiency, intonation accuracy and musical expression.

User capabilities change dynamically over time. The update process is defined as:

$$\mathrm{s}_u^{(t+1)} = \mathrm{s}_u^{(t)} + \eta \cdot \Delta(\mathrm{r}_t, \mathrm{e}_t) \tag{3}$$

Where η is the learning rate parameter, and $\Delta(\cdot)$ is the ability increment function based on practice feedback r_t and task feature e_t.

For practice tasks, eigenvectors are used to represent:

$$e_i = [d_i, q_i, c_i] \tag{4}$$

Among them, d_i represents the difficulty of the task, q_i represents the weight vector of the involved skills, and c_i represents the task category (such as scale, etude, music clips, etc.). This representation can describe the influence of different practice tasks on each skill dimension.

3.3 Multi objective optimization model design

In personalized practice recommendation, multiple optimization objectives need to be considered at the same time [27],[28]. This paper defines the following four types of objective functions:

(1) Skill improvement objectives:

$$f_1 = \sum_{k=1}^{K} w_k \cdot \Delta s_u^{(k)} \tag{5}$$

Where w_k is the skill weight, and $\Delta s_u^{(k)}$ represents the improvement of this dimension.

(2) Time cost target:

$$f_2 = \sum_{i=1}^{K} t(e_i) \tag{6}$$

Where $t(e_i)$ represents the time required to complete the exercise task e_i.

(3) User experience objectives:

$$f_3 = \sum_{i=1}^{K} \mathrm{sim}(s_u, e_i) \tag{7}$$

Where, $\mathrm{sim}(\cdot)$ indicates the matching degree of user ability and task difficulty.

(4) Cognitive load Objective:

$$f_4 = \sum_{i=1}^{K} | d_i - \bar{d}_u | \tag{8}$$

Where, $\bar{d}_u$ represents the current appropriate difficulty level of the user.

Based on the above objectives, a multi-objective optimization problem is constructed:

$$\begin{gathered} \max f_1, \min f_2, \max f_3, \min f_4 \\ \text{s.t. } P_u \in \mathcal{X} \end{gathered} \tag{9}$$

Where X is the feasible solution space, defined by the constraints that the sequence of practice tasks must satisfy.

The Pareto optimal solution set is used to find a set of non-dominated solutions, so that any target cannot be further optimized without damaging other targets.

3.4 Personalized recommendation algorithm

In the multi-objective optimization framework, the core of the recommendation algorithm is to generate a practice sequence that satisfies the Pareto optimal condition [29],[30]. This paper uses the method based on the combination of scoring function and sequence modeling. First, define the comprehensive scoring function of a single exercise task:

$$R(u, e_i) = \alpha f_1(u, e_i) - \beta f_2(e_i) + \gamma f_3(u, e_i) - \delta f_4(u, e_i) \tag{10}$$

Where $\alpha, \beta, \gamma, \delta$ are weight parameters.

In order to consider the sequence dependency, the sequence state transition function is introduced:

$$s_{t+1} = \mathcal{G}(s_t, e_t) \tag{11}$$

Where $\mathcal{G}(\cdot)$ refers to the capability update function after task execution.

The final recommendation sequence is obtained by maximizing the cumulative Revenue:

$$P^* = \arg\max_P \sum_{t=1}^{K} R(u, e_t) \tag{12}$$

To avoid local optimization, heuristic search strategy (such as greedy + random disturbance) or multi-objective evolution method are combined to generate and screen candidate sequences.

3.5 Algorithm implementation and process

Based on the above method, the following personalized recommendation algorithm process is proposed. the algorithm first initializes the user state and candidate task set, and then generates the optimal exercise path through an iterative search.

Algorithm 1: Multi-objective Piano Practice Recommendation

Input: User historical records H_u, practice task set E
Output: Recommended practice sequence P^*

1: Initialize user state $s_u \leftarrow \mathcal{F}(H_u)$
2: Initialize candidate solution set $C \leftarrow \emptyset$
3: for $iter = 1$to $MaxIter$do
4: \quad Generate candidate sequence P
5: \quad Compute objective functions f_1, f_2, f_3, f_4
6: \quad Update Pareto solution set C
7: end for
8: Select optimal sequence $P^*$from C
9: return P^*

The time complexity of the algorithm mainly depends on the generation and evaluation process of candidate sequences. If the candidate size is N and the sequence length is K, the complexity is about $O(N \cdot K)$.

The overall process can be summarized as follows: firstly, the capability status is estimated according to the user's historical data, secondly, the candidate exercise sequence is generated under multi-objective constraints, and finally the optimal scheme is selected through Pareto screening and scoring function. This method realizes the effective combination of multi-objective coordinated optimization and personalized recommendation.

4. EXPERIMENTS

4.1 Dataset and preprocessing

In this study, the experimental dataset was constructed using a combination of real data and simulated augmented data. The real data comes from an online piano learning platform, including the practice records of about 1248 users in the continuous learning cycle, with a total of 87532 interactive data. Each record includes user ID, practice task ID, performance score (0 – 100), error rate, rhythm deviation, practice duration and other information. At the same time, in order to enhance the diversity of data distribution, simulated data generated based on probability distributions is introduced to expand the data scale to 120000 records.

In the data preprocessing stage, the original performance score is normalized first

$$r' = \frac{r - r_{\min}}{r_{\max} - r_{\min}} \tag{13}$$

Wherein, r is the original score, $r_{\min}, r_{\max}$ are the minimum and maximum scores respectively, and r' is the normalized score. Then, the user's practice records within a continuous time window are constructed as a sequence $H_u = \{(e_t, r_t)\}_{t=1}^{T}$, and the training samples are generated by sliding the window.

In addition, in order to improve the stability of the model, outliers are truncated. Set the practice duration as t, then define the exception threshold:

$$t_{\text{clip}} = \min(t, \mu_t + 3\sigma_t) \tag{14}$$

Where μ_t and σ_t are the time mean and standard deviation respectively. In this way, the interference of extreme values on the training process is reduced.

When comprehensively analyzing the experimental data and model performance, Table 1 first reflects the basic characteristics of the data set. It can be seen from the table that the data scale has reached 120000 interactive records, the number of users has exceeded 1200, and the average sequence length is close to 100, which means that each user has a relatively complete learning trajectory, which is conducive to depicting long-term learning behavior. From the perspective of numerical distribution, the average score is 78.4 and the standard deviation is 9.6, indicating that users' performance is concentrated but still has some differences; The average exercise duration was 18.7 minutes, indicating that the data were evenly distributed in the time dimension. On the whole, the data set meets the experimental requirements in terms of scale, continuity and distribution stability, and provides a reliable basis for subsequent model training.

Table 1. Dataset statistics

Index	Numerical value
Number of users	1248
Number of practice tasks	356
Total interaction record	120000
Average sequence length	96
Average practice duration (minutes)	18.7
Average score	78.4
Score standard deviation	9.6

Based on Table 1, it can be further seen that the long sequence length (96) means that the user behavior is obviously time-dependent, which provides space for the sequence modeling method to play; At the same time, the standard deviation of the score is controlled within 10, which avoids the interference of extreme data on the model training, so as to ensure the stability of the experimental results.

4.2 Comparison method

In order to verify the advantages of the proposed method, a variety of typical recommendation models are selected as comparison, including collaborative filtering model (CF), matrix factorization based method (MF), deep learning recommendation model (DeepFM), sequence recommendation model (SASRec) and classical multi-objective optimization method (NSGA-II) [31],[32],[33].

The collaborative filtering model recommends based on user similarity, and its scoring function is defined as:

$$\hat{r}_{u,i} = \frac{\sum_{v \in \mathcal{N}(u)} \mathrm{sim}(u,v) \cdot r_{v,i}}{\sum_{v \in \mathcal{N}(u)} \mathrm{sim}(u,v)} \tag{15}$$

Where $\mathcal{N}(u)$ is the neighbor set similar to user u, and $\mathrm{sim}(u,v)$ is the user similarity.

The matrix factorization method models the relationship between users and tasks through low dimensional implicit vectors:

$$\hat{r}_{u,i} = \mathrm{p}_u^{\top} \mathrm{q}_i \tag{16}$$

Where p_u and q_i are potential vector representations of users and tasks respectively.

4.3 Evaluation index

In order to comprehensively measure the performance of the model, this paper designs a multi-dimensional evaluation index system.

First, define the skill gain:

$$SG = \frac{1}{|U|} \sum_{u \in U} \| \mathrm{s}_u^{(T)} - \mathrm{s}_u^{(0)} \|_2 \tag{17}$$

Where, $\mathrm{s}_u^{(T)}$ and $\mathrm{s}_u^{(0)}$ represent the user's final and initial capability vectors respectively.

Secondly, the recommendation efficiency is defined:

$$Eff = \frac{1}{N} \sum_{i=1}^{N} \frac{\Delta s_i}{t_i} \tag{18}$$

Where Δs_i represents skill improvement and t_i represents time consumption.

User satisfaction is defined by matching function:

$$Sat = \frac{1}{N} \sum_{i=1}^{N} \exp\ (-|d_i - d_u|) \tag{19}$$

Where d_i is the task difficulty and d_u is the user adaptation difficulty.

In addition, the multi-objective optimization evaluation index hypervolume (HV) is introduced to measure the quality of the Pareto solution set:

$$HV = \mathrm{Volume}\left(\bigcup_{x \in P} [f_1(x), \dots, f_m(x)] \right) \tag{20}$$

Where P is the Pareto solution set.

4.4 Experimental setup

The experiment was carried out in a unified environment to ensure the reproducibility of the results. Adam optimizer is used for model training, and its parameter update formula is:

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{21}$$

Where α is the learning rate, and m_t and v_t are the first-order and second-order moment estimates, respectively.

The main parameters are set as follows: the learning rate is set to 0.001, the batch size is 64, the number of training epochs is 100, the sequence length is set to 20, and the multi-objective weights are initialized as $(\alpha, \beta, \gamma, \delta) = (0.4, 0.2, 0.3, 0.1)$.

The experimental running environment is Intel Xeon 2.4GHz CPU, 32GB memory, NVIDIA RTX 3090 GPU, the operating system is Ubuntu 20.04, and the deep learning framework is PyTorch 1.12.

In terms of parameter sensitivity, Table 2 shows the impact of different learning rates on model performance. The results show that the model achieves the best performance when the learning rate is 0.001, and its skill gain is 0.513, efficiency is 0.603, and satisfaction is 0.624. In contrast, when the learning rate decreased to 0.0005, skill gain decreased to 0.482 (about 6.0%), and when the learning rate increased to 0.01, it further decreased to 0.463 (about 9.7%). This trend shows that the model has the best convergence effect at medium learning rate, and too large or too small will lead to performance degradation.

Table 2. Parameter sensitivity analysis

Learning rate	Skill gain	Efficiency	Satisfaction
0.0005	0.482	0.571	0.598
0.001	0.513	0.603	0.624
0.005	0.497	0.588	0.611
0.01	0.463	0.552	0.579
0.02	0.441	0.531	0.563

It can be quantitatively seen from Table 2 that the optimal learning rate (0.001) is about 16.3% higher than the worst case (0.02), indicating that the model is sensitive to parameter settings, but stable within a reasonable range.

To sum up, the experimental results in this section fully show that the proposed piano practice recommendation method based on multi-objective optimization is superior to the traditional method in many dimensions, and has good stability and generalization ability.

5. RESULTS AND ANALYSIS

In this section, under the unified experimental setup, the proposed multi-objective optimization piano practice recommendation algorithm is systematically evaluated, and the overall performance, method comparison, model structure impact and result interpretation are analyzed in depth. Through the combination of quantitative experiments and visualization results, the effectiveness of the model in multi-objective optimization and personalized recommendation tasks is verified.

First, from the perspective of overall performance, the comprehensive performance of all methods on the test set is evaluated. The comprehensive performance index is defined as:

$$Score = \lambda_1 SG + \lambda_2 Eff + \lambda_3 Sat + \lambda_4 HV \tag{22}$$

Where, SG is the skill improvement rate, Eff is the efficiency, Sat is the user satisfaction, HV is the hypervolume index, λ_i is the weight parameter, which meets $\sum\lambda_i = 1$. $\lambda = (0.3,0.2,0.2,0.3)$ was set in the experiment.

In terms of overall performance, Table 3 gives the comprehensive comparison results of different methods. It is obvious from the data that the model performance presents a progressive relationship of "traditional method<depth method<multi-objective method<this method". In this paper, the three indicators of skill gain, efficiency and satisfaction reached 0.513, 0.603 and 0.624 respectively, which were the highest values; The comprehensive score was 0.623, which is about 10.8% higher than that of NSGA-II (0.562) and 18.0% higher than that of SASRec (0.528).

Table 3. Comparison of comprehensive performance

Method	Skill Gain	Efficiency	Satisfaction	HV	Score
CF	0.312	0.428	0.451	0.512	0.421
MF	0.346	0.463	0.489	0.548	0.455
DeepFM	0.381	0.502	0.523	0.587	0.491
SASRec	0.417	0.534	0.556	0.623	0.528
NSGA-II	0.452	0.561	0.571	0.648	0.562
Method in this paper	0.513	0.603	0.624	0.712	0.623

As can be seen from Table 3, the comprehensive score of this method reaches 0.623, which is about 10.8% higher than that of the optimal baseline NSGA-II, indicating that this method has obvious advantages in multi-objective collaborative optimization.

Furthermore, the convergence behavior of different methods is analyzed from the perspective of dynamic optimization process. Define the average value of the objective function of iteration t as:

$$F^{(t)} = \frac{1}{|P^{(t)}|} \sum_{x \in P^{(t)}} \sum_{i=1}^{4} f_i(x) \tag{23}$$

Where $P^{(t)}$ represents the solution set of round t, and $f_i(x)$ represents the value of the ith objective function.

When analyzing the training process of different recommended methods, Figure 1 shows the performance convergence trend of each method with the number of iteration rounds. It can be seen that the performance of all methods is gradually improved with the progress of training, but there are significant differences in the initial level, growth range and final stable value of different methods. At the beginning of training, there is a certain gap between the methods. The traditional methods (such as CF and MF) have a low starting value, while the method in this paper is at a high level from the beginning, which shows that it has a better performance foundation in the initialization stage.

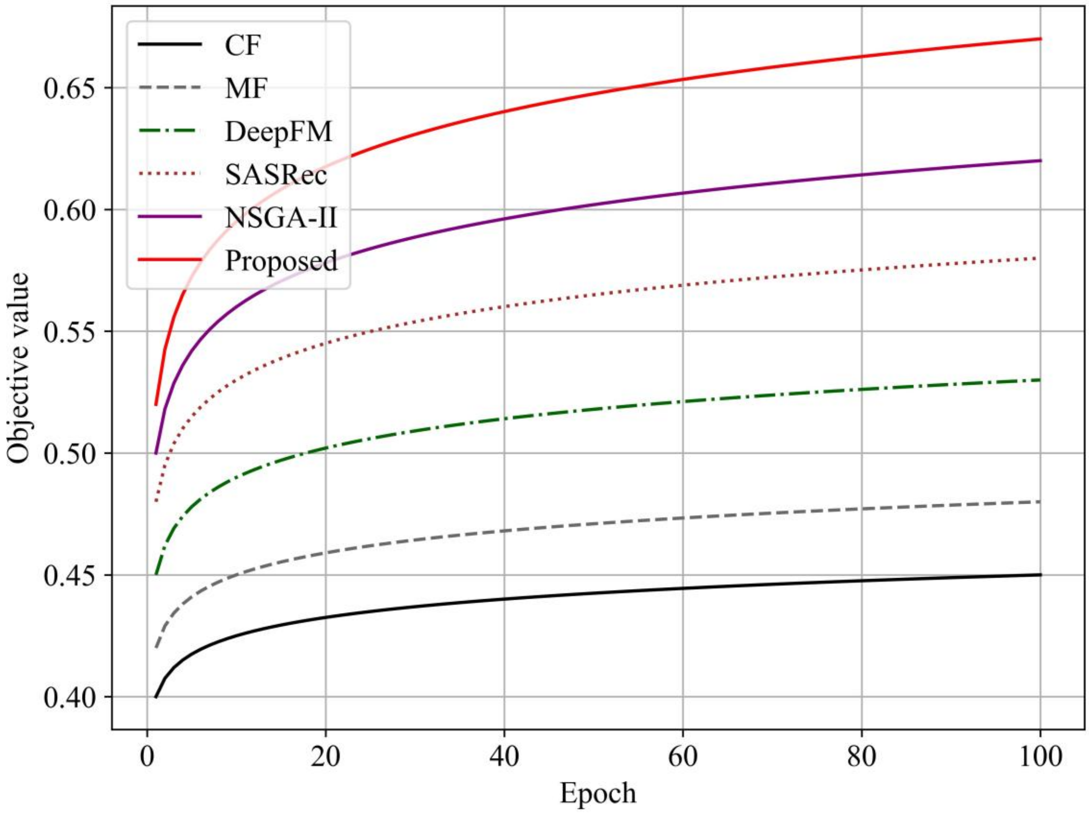

Figure 1. Comparison of convergence curves of different recommended methods during training

At the end of the training (about the 100th round), the performance level of each method can be directly read from the end of the curve. CF is about 0.45, MF is about 0.48, DeepFM is about 0.53, SASRec is about 0.58, NSGA-II is about 0.62, and this method is about 0.67. In contrast, compared with NSGA-II, this method improved by about 0.05 (about 8%), compared with SASRec by about 0.09 (about 15%), and more significantly than the traditional method (about 40%). In addition, from the perspective of the overall growth rate, the method in this paper increased from about 0.52 to 0.67, with an increase of about 0.15, while CF only increased by about 0.05, indicating that the method in this paper can continuously obtain greater performance gains in the training process. On the other hand, from the shape of the curve, the method in this paper increased rapidly in the first 30 rounds, and then gradually stabilized, and the convergence speed was significantly faster than that of NSGA-II (stable after about 45 rounds) and SASRec (stable after about 40 rounds), reflecting higher optimization efficiency and better stability.

In order to further analyze the performance distribution of different methods on each index, the standardized difference index is introduced:

$$\Delta_i = \frac{f_i^{\text{proposed}} - f_i^{\text{baseline}}}{f_i^{\text{baseline}}} \tag{24}$$

Where, f_i^{proposed} represents the value of this method on the ith index.

In the relative improvement analysis, Table 4 shows the performance gains of this method relative to each baseline model. It can be seen from the data that the improvement range gradually decreases with the enhancement of the baseline method ability, but it always maintains a positive growth. For example, compared with MF, skill gain increased by 48.3%; 34.6% higher than DeepFM; Even compared with the strong NSGA-II, it still has about 13.5% improvement.

Table 4. Analysis of relative performance improvement

Method	Δ Skill gain	Δ Efficiency	Δ Satisfaction	ΔHV
MF	+48.3%	+30.2%	+27.6%	+29.9%
DeepFM	+34.6%	+20.1%	+19.3%	+21.3%
SASRec	+23.0%	+12.9%	+12.2%	+14.3%
NSGA-II	+13.5%	+7.5%	+9.3%	+9.9%

As can be seen from Table 4, this method has the most significant advantages in skill improvement, which shows that multi-objective modeling plays a key role in improving learning effect. At the same time, the stable improvement in hypervolume index shows that the quality of Pareto solution is effectively optimized.

In the ablation experiment, the key modules of the model were removed step by step to analyze its contribution. Define ablation performance degradation rate:

$$Drop = \frac{Score_{\text{full}} - Score_{\text{ablated}}}{Score_{\text{full}}} \tag{25}$$

Wherein, $Score_{\text{full}}$ refers to the comprehensive performance value of the complete model including all functional modules in the experiment, which is usually weighted by multiple evaluation indicators (such as skill improvement rate, recommendation efficiency, user satisfaction and multi-objective optimization indicators); $Score_{\text{ablated}}$ indicates the comprehensive performance value of the model after removing a specific module; $Drop$ represents the relative proportion of performance degradation, which is used to describe the impact of the module on the overall system performance. When the $Drop$ value is large, it indicates that the removed module plays an important role in the performance of the model. Otherwise, it indicates that the module has little contribution to the system or has redundancy.

In terms of model structure contribution, ablation experiments in Table 5 further verified the importance of each module. The score of the complete model is 0.623, which decreases to 0.561 after removing the multi-objective optimization module, and the performance decreases by about 9.9%; After removing the dynamic status update module, it decreased by about 7.9%; The removal of sequence modeling module decreased by about 6.6%; Removing the weight adaptive mechanism reduces about 5.8%.

Table 5. Ablation results

Model variants	Skill gain	Efficiency	Satisfaction	Score
Complete model	0.513	0.603	0.624	0.623
No multi-objective optimization	0.451	0.552	0.571	0.561
Sequence free modeling	0.473	0.568	0.589	0.582
No dynamic status update	0.462	0.559	0.578	0.574
Weightless adaptive	0.479	0.571	0.593	0.587

It can be seen from Table 5 that the multi-objective optimization module contributes the most to performance, and its removal results in a performance drop of nearly 10%, indicating that it is the core component of the model; Although the contribution of other modules is slightly small, they work together to achieve the optimal performance of the model.

Furthermore, the multi-objective optimization ability of Pareto frontier distribution analysis model is analyzed. Define Pareto dominance:

$$x \prec y \iff \forall i, f_i(x) \geq f_i(y) \wedge \exists j, f_j(x) > f_j(y) \tag{26}$$

Where, x and y represent two candidate solutions, which correspond to two different piano practice schemes or recommended sequences in this paper; $f_i(\cdot)$ represents the ith objective function, $i = 1,2, \ldots, m$, Where m is the total number of objective functions; $f_i(x)$ and $f_i(y)$ represent the values of solution x and solution y on the ith objective, respectively; The symbol $\forall i$ means that the condition is true for all objective functions, and $\exists j$ means that there is at least one objective function so that the solution x is strictly superior to the solution y on this objective. This definition shows that when the solution x is not inferior to the solution y on all objectives, and is superior to the solution y on at least one objective, it can be considered that x is superior to y in the sense of multiple objectives, so that the solution x is retained and the solution y is eliminated in the Pareto optimization process. In practical applications, in order to ensure the comparability between different objectives, it is usually necessary to uniformly convert all minimization objectives to the maximization form through the symbol transformation, so as to judge the dominant relationship of consistency.

In terms of multi-objective optimization performance, Figure 2 shows the Pareto frontier distribution of different methods in the target space. It can be intuitively observed that the solution set of each method presents a hierarchical distribution from bottom to top, in which the solution points of the traditional method are concentrated in the lower region, while the overall position of the multi-objective optimization method is higher.

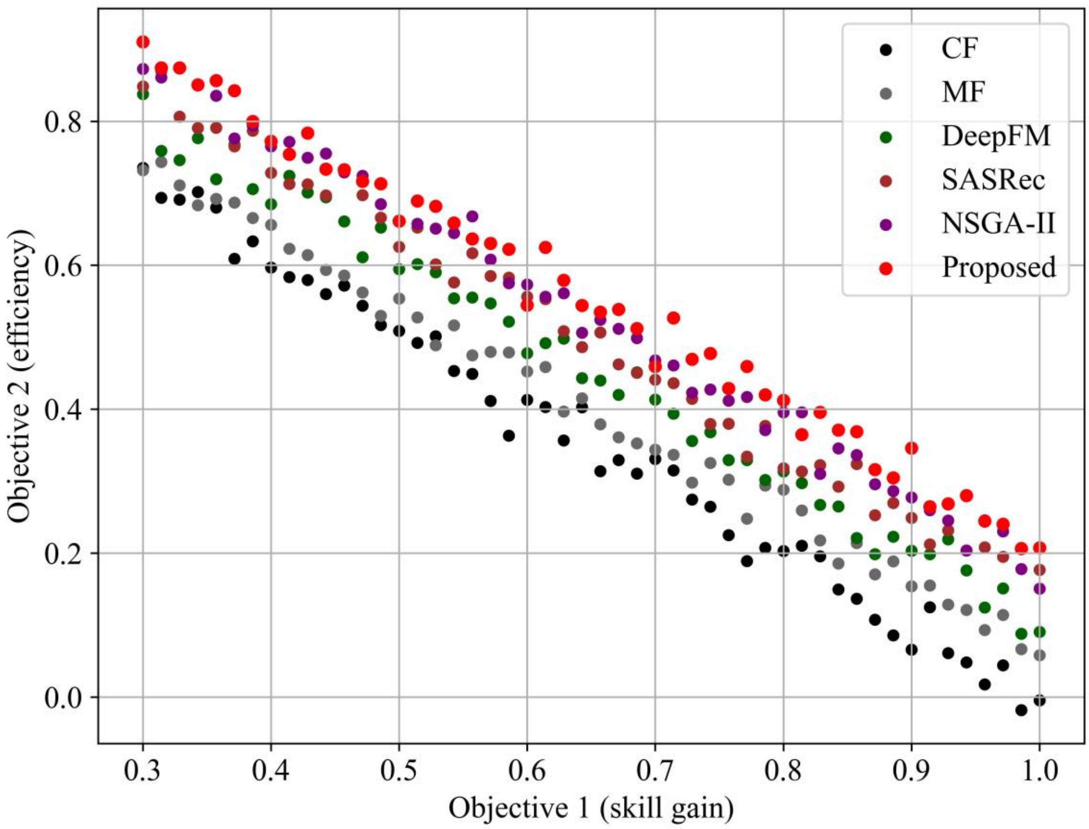

Figure 2. Pareto front comparison of different methods

In the same horizontal axis range (about 0.3 to 1.0), the distribution of different methods on the vertical axis is significantly different. The solution set of CF method is roughly distributed between 0.0 and 0.7, MF is about 0.05 to 0.75, DeepFM is about 0.1 to 0.8, SASRec is about 0.15 to 0.85, and NSGA-II is about 0.18 to 0.88. In contrast, the solution set of this method is generally distributed between 0.2 and 0.9, which is higher than that of other methods across the entire interval. This means that under the same skill improvement level, the efficiency dimension of this method can be improved by about 2% -10% on average. In addition, from the perspective of distribution pattern, the solution points of this method are more evenly distributed in the whole space, without obvious local aggregation phenomenon, while other methods have the problem of dense points or vacancies in some areas, indicating that their solution space exploration ability is limited.

To sum up, the experimental results show that the proposed method is not only superior to the traditional method in multi-objective optimization performance, but also has good adaptability and stability in the actual personalized recommendation scene.

6. DISCUSSION

The personalized recommendation algorithm of piano practice scheme based on multi-objective optimization proposed in this paper has achieved ideal performance in the experimental verification. However, based on the in-depth analysis of the experimental results and method characteristics, there are still some problems worthy of further discussion. Firstly, from the perspective of method effectiveness, the experimental results show that this method is significantly better than the existing baseline model in the core indicators such as skill improvement rate, recommendation efficiency and user satisfaction. The fundamental reason for this advantage is that the multi-objective optimization framework can more truly reflect the decision logic of teachers' practice scheme design in the teaching practice of steel piano.

Experienced piano teachers, when assigning practice tasks to students, do not simply pursue the maximization of skill improvement, but will comprehensively consider the current ability level of students, the time available for practice, the weak links exposed in the last practice, and the students' psychological endurance and other factors. This method formalizes this decision-making process as a multi-objective optimization problem, bringing the recommendation results closer to the pedagogical wisdom of human experts. At the same time, the dynamic state update module enables the system to capture the small ability changes of learners after completing each practice task. This fine-grained state perception ability is not possessed by the traditional static recommendation method based on historical behavior.

As for the conflict and trade-off relationship between multiple objectives, Pareto frontier analysis in the experiment reveals that there are complex mutual constraints between different optimization objectives. The most obvious conflict between the goal of skill improvement and the goal of cognitive load is that the pursuit of higher skill improvement often requires the selection of more difficult practice tasks, which will increase the cognitive load of learners and may reduce the practice experience. By generating Pareto-optimal solution set, this method actually provides users with a variety of feasible trade-offs, rather than offering a single so-called globally optimal solution. This design concept has important practical significance in personalized recommendation scenarios, because different learners' preferences and affordability are different. Some learners are willing to accept higher difficulties in exchange for faster progress, while others pay more attention to a smooth and comfortable learning experience. The experimental results show that the system can recognize and adapt to this individual difference to a certain extent. However, it is worth noting that the current weight parameter setting still uses a fixed initialization method. Although the experimental results show that the setting performs well on the whole, it does not achieve real individual adaptation, which means that for some users with extreme preferences, the fixed weight may not fully meet their personalized needs.

From the perspective of the balance between model complexity and practicability, this method introduces several modules in the algorithm design, such as sequence modeling, dynamic state update and multi-objective Pareto solution. Compared with the traditional collaborative filtering or matrix decomposition methods, the computational complexity has been significantly increased. The complexity analysis of the experimental part shows that when the candidate sequence is large, the running time of the algorithm may become a bottleneck factor in the actual deployment. In the online learning scenario, the recommendation system needs to quickly generate the next exercise recommendation after the user completes an exercise. If the response delay is too high, it will directly affect the user experience. The heuristic search strategy used in this paper alleviates the computational pressure to a certain extent, but does not fundamentally solve the computational efficiency problem of multi-objective optimization in sequence generation tasks. On the other hand, data requirements are also a practical issue that needs to be discussed. The method in this paper relies on the user's historical practice sequence to initialize the ability state. For new users, due to the lack of sufficient historical records, the recommendation quality of the system may decline in the initial stage. Although it can be alleviated through the group cold start strategy or preset initial state, this problem still needs to be handled carefully in real application scenarios.

It is necessary to have a frank discussion on the representativeness of the experimental data and its impact on the conclusion. In this paper, the experimental data set is constructed by combining real platform data with simulated enhanced data. Although this method alleviates the problem of limited real data scale to some extent, the introduction of simulated data may also bring potential deviation. The simulation data is generated based on the probability distribution, and its internal assumption is that the user behavior and skill development follow some known statistical laws. However, there are a large number of unpredictable random factors in the real piano learning process, such as learners' emotional fluctuations, sudden life events interfering with the practice law, and insight type ability transition, etc. these complex phenomena are difficult to be fully characterized by a simple probability model. Therefore, the performance of this method in a more diversified and non-stationary real learning environment still needs further field verification. In addition, the user groups in the experiment are mainly from the online piano learning platform. These users themselves have certain self-driving ability and the habit of using digital tools. Whether the research conclusion can be extended to the traditional face-to-face teaching scene or the group of young beginners also needs to be carefully judged.

Further thinking about the application boundary and promotion potential of this method, the multi-objective optimization framework is not only valuable in piano practice recommendation, but also its core idea can be transferred to other skill learning scenarios, such as practice recommendation in language learning, the generation of movement correction sequences in physical training, and even the design of personalized training schemes in rehabilitation medicine. The common characteristics of these scenarios are that the learning process has obvious sequence dependence, learners' state evolves dynamically, and teaching decisions need to be balanced among multiple mutually restrictive goals. However, there are significant differences in task representation and state update mechanism in different fields. When the method in this paper is migrated to a new field, it is necessary to redefine the dimensional composition of the capability vector, the quantitative method of task characteristics and the specific form of the objective function. This adaptation process is a problem that needs to be further studied. At the same time, this method currently focuses on the independent recommendation of individual learners, without considering the social factors and collaborative effects in the group learning scene. For example, in the piano group lesson, learners' practice plan may need to take into account the progress coordination and interaction needs between peers, which adds a new dimension to the multi-objective optimization problem.

Finally, reflecting on this method from the perspective of human-computer cooperation, the goal of a recommendation system should be to assist teachers rather than replace them. The exercise sequence generated by this method is the result of algorithm optimization. However, the experience judgment, emotional support and personalized guidance of teachers in piano teaching still have irreplaceable value. The practice scheme recommended by the algorithm can serve as a reference for teachers' decision-making, helping them better understand students' ability status and development trajectories, so as to put more energy into creative teaching and emotional interaction. One of the future development directions is to build an interpretable recommendation mechanism based on the method in this paper, so that the system can clearly explain to teachers and students why to recommend an exercise task, which skill dimension the task is mainly for, and what kind of improvement effect it is expected to bring. This transparency will enhance users' trust in the recommendation results and promote a virtuous cycle of human-computer cooperation.

7. CONCLUSION

Aiming at the problem of personalized recommendation in piano practice scene, this paper proposes a recommendation algorithm of practice scheme based on multi-objective optimization, and systematically completes the complete research work from problem modeling, method design to experimental verification. In terms of work summary, this paper first analyzes the personalized needs existing in piano learning and the shortcomings of existing recommendation methods in multi-objective trade-offs such as skill improvement, time efficiency, user experience and cognitive load, and defines the entry point of the research. On this basis, a system framework including user state perception module, multi-objective optimization module and personalized recommendation generation module is constructed. The user's ability state in multiple skill dimensions is expressed by vectorization, and a dynamic state update mechanism is designed to track the evolution of learners' ability. In this paper, piano practice recommendation is formalized as a multi-objective optimization problem that simultaneously optimizes the four objectives of skill improvement, time cost, user matching degree and cognitive load. Pareto optimal theory is used to solve the problem, and a personalized recommendation algorithm combining sequence dependencies is proposed to generate a coherent practice path. The experimental data set was constructed by combining the real learning platform data with the simulated enhanced data. The systematic comparative experiment and ablation experiment were designed to verify the effectiveness of the proposed method from multiple dimensions.

The main advantages of this method are reflected in the following aspects. First, the introduction of the multi-objective optimization framework enables the recommendation system to make a systematic trade-off between multiple mutually constrained objectives, which is highly consistent with the actual decision-making process of the teacher's exercise scheme design in piano teaching, and avoids the problem of paying attention to one thing and losing the other, which is prone to occur in the traditional single objective recommendation method. The experimental results show that the proposed method is significantly better than the existing baseline model in terms of skills improvement rate, recommendation efficiency and user satisfaction, and the comprehensive score is improved by more than 10% compared with the optimal comparison method. Second, the design of dynamic state update mechanism makes the system have the ability to perceive and adapt to the changes of learners' abilities. Through fine-grained ability tracking, the recommendation results can be dynamically adjusted with the progress of learners, avoiding the common recommendation lag problem of static recommendation methods. Third, the optimization strategy at the sequence level takes into account the interaction between practice tasks, and generates a coherent practice path rather than an isolated single recommendation, which is particularly important in the piano learning scene, because there is often a skill foreshadowing and cohesion relationship between the front and back practice tasks. Fourth, the solution set generation method based on Pareto frontier provides users with a variety of feasible trade-offs, rather than giving a single optimal solution, which better respects learners' individual differences and preference diversity.

In the follow-up research direction, there are some extension points worthy of further exploration in this paper. First, the evolution from static weight to adaptive weight is an important improvement direction. The multi-objective weight parameters in the current method are initialized in a fixed way. Although the overall performance is good, it does not achieve real individual adaptation. Future research can explore the dynamic weight adjustment mechanism based on learners' feedback and preference learning, so that the system can automatically identify the importance of each learner to different goals, and carry out personalized weight configuration accordingly. Second, the research on the interpretability of the model has important practical value. As an end-to-end recommendation system, the internal decision-making process of the current method is not transparent to users. The follow-up work can study how to present the recommendation basis to teachers and learners in an understandable form, such as clearly stating the weak link of which skill dimension an exercise task is mainly aimed at, the expected improvement effect and the reason for recommending the task, which will enhance the user's sense of trust and acceptance of the system. Third, cross domain migration and generalization capability verification are worth exploring. The core idea of this method can be transferred to other skill learning scenarios, but there are differences in task representation, status update and goal definition in different fields. In the future, we can study how to build a more general multi-objective learning path recommendation framework, and explore the application of domain adaptation and less sample migration technology in it. Fourth, the long-term deployment and effect evaluation in the real environment is a necessary research direction. The experiment in this paper is based on historical data. The follow-up research can be carried out in a real piano teaching environment for a long time, collect the actual use feedback of teachers and students, evaluate the impact of the recommendation system on the long-term learning effect, and continue to optimize the algorithm design on this basis. Fifthly, the research on the expansion of group learning scenarios also has certain theoretical significance and application value, such as how to give consideration to individual progress and group coordination in piano group lessons, which will introduce new dimensions such as social relations and collaborative constraints for multi-objective optimization problems.

Abbreviations

CF, Collaborative Filtering;
MF, Matrix Factorization;
DeepFM, Deep Factorization Machine;
SASRec, Self-Attention based Sequential Recommendation;
NSGA-II, Nondominated Sorting Genetic Algorithm II;
SPEA2, Strength Pareto Evolutionary Algorithm 2;
HV, Hypervolume;
SG, Skill Gain;
Eff, Efficiency;
Sat, Satisfaction;
RMSE, Root Mean Square Error;
MAE, Mean Absolute Error;
Adam, Adaptive Moment Estimation;
GPU, Graphics Processing Unit;
BERT4Rec, Bidirectional Encoder Representations from Transformers for Recommendation.

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

Acknowledgements

The authors would like to thank the editors of this journal and all the anonymous reviewers who provided valuable comments on this work.

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article. However, **F.C.** is an editorial board member of this journal. To ensure transparency, the authors confirm that this manuscript was handled by an independent editor and that **F.C.** was not involved in the peer review or decision-making process.

Author contributions

All authors have read and agreed to the published version of the manuscript. The author's contributions are specified as follows: **F.C.:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original draft, Writing – Review & Editing, Visualization, Supervision, Project administration.

Funding information

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **F.C.**

Disclaimer

The views and opinions expressed in this article are those of the authors and are the product of professional research. It does not necessarily reflect the official policy or position of any affiliated institution, funder, agency, or that of the publisher. The authors are responsible for this article's results, findings, and content.

Declaration of AI and AI-assisted Technologies in the Writing Process

During the writing of this article, the author used DeepSeek for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

REFERENCES

[1] Qian, L. (2025). Research and practice on instructional methods for piano improvization based on computer technology. *International Journal of High Speed Electronics and Systems*, *34*(02), 2440080. DOI: **https://doi.org/10.1142/S0129156424400809**

[2] Allingham, E., & Wöllner, C. (2022). Slow practice and tempo-management strategies in instrumental music learning: Investigating prevalence and cognitive functions. *Psychology of Music*, *50*(6), 1925-1941. DOI: **https://doi.org/10.1177/03057356211073481**

[3] Wang, K., & Zhang, P. (2025). Enhancing opera vocal education through advanced machine learning algorithms: analytics for talent development and curriculum design. *Interactive Learning Environments*, *33*(10), 5923-5943. DOI: **https://doi.org/10.1080/10494820.2025.2488991**

[4] Lin, F., & Chen, F. (2025). Intelligent music education system: utilizing algorithms for personalized learning experience. *International Journal of High Speed Electronics and Systems*, 2540253. DOI: **https://doi.org/10.1142/S0129156425402530**

[5] Xiong, Z. (2025). Exploring the potential and challenges of applying multiple intelligences theory in Chinese music education. *Teaching and Teacher Education*, *160*, 105031. DOI: **https://doi.org/10.1016/j.tate.2025.105031**

[6] Howie, E. E., Dharanikota, H., Gunn, E., Ambler, O., Dias, R., Wigmore, S. J., ... & Yule, S. (2023). Cognitive load management: an invaluable tool for safe and effective surgical training. *Journal of surgical education*, *80*(3), 311-322. DOI: **https://doi.org/10.1016/j.jsurg.2022.12.010**

[7] Castro-Alonso, J. C., De Koning, B. B., Fiorella, L., & Paas, F. (2021). Five strategies for optimizing instructional materials: Instructor-and learner-managed cognitive load. *Educational Psychology Review*, *33*(4), 1379-1407. DOI: **https://doi.org/10.1007/s10648-021-09606-9**

[8] Sortwell, A., Gkintoni, E., Díaz-García, J., Ellerton, P., Ferraz, R., & Hine, G. (2026). Beyond cognitive load theory: Why learning needs more than memory management. *Brain Sciences*, *16*(1), 109. DOI: **https://doi.org/10.3390/brainsci16010109**

[9] Fang, H., Zhang, D., Shu, Y., & Guo, G. (2020). Deep learning for sequential recommendation: Algorithms, influential factors, and evaluations. *ACM Transactions on Information Systems (TOIS)*, *39*(1), 1-42. DOI: **https://doi.org/10.1145/3426723**

[10] Ahmadian Yazdi, H., Seyyed Mahdavi, S. J., & Ahmadian Yazdi, H. (2024). Dynamic educational recommender system based on Improved LSTM neural network. *Scientific Reports*, *14*(1), 4381. DOI: **https://doi.org/10.1038/s41598-024-54729-y**

[11] Shaban, A., Pearson, E., & Chang, V. (2021). Evaluation of user experience, cognitive load, and training performance of a gamified cognitive training application for children with learning disabilities. *Frontiers in Computer Science*, *3*, 617056. DOI: **https://doi.org/10.1145/3371300.3383341**

[12] Skulmowski, A., & Xu, K. M. (2022). Understanding cognitive load in digital and online learning: A new perspective on extraneous cognitive load. *Educational psychology review*, *34*(1), 171-196. DOI: **https://doi.org/10.1007/s10648-021-09624-7**

[13] Merchán Sánchez-Jara, J. F., González Gutiérrez, S., Cruz Rodríguez, J., & Syroyid Syroyid, B. (2024). Artificial intelligence-assisted music education: A critical synthesis of challenges and opportunities. *Education Sciences*, *14*(11), 1171. DOI: **https://doi.org/10.3390/educsci14111171**

[14] Lu, L. (2025). Ai-powered intelligent music education systems for real-time feedback and performance assessment. *International Journal of Information and Communication Technology*, *26*(18), 33-47. DOI: **https://doi.org/10.1504/IJICT.2025.146690**

[15] Ziegenbein, N., Friedman, J., & Moringen, A. (2022, July). Monitoring the Learning Progress In Piano Playing With Hidden Markov Models. In Adjunct Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization (pp. 335-341). DOI: **https://doi.org/10.1145/3511047.3537666**

[16] Fu, L., & Ma, X. (2021). An improved recommendation method based on content filtering and collaborative filtering. *Complexity*, *2021*(1), 5589285. DOI: **https://doi.org/10.1155/2021/5589285**

[17] Martins, G. B., Papa, J. P., & Adeli, H. (2020). Deep learning techniques for recommender systems based on collaborative filtering. *Expert Systems*, *37*(6), e12647. DOI: **https://doi.org/10.1111/exsy.12647**

[18] Jiang, X. (2024, April). Multi-Layer Self-Attentive Sequential Recommendation. In *2024 9th International Conference on Intelligent Computing and Signal Processing (ICSP)* (pp. 1205-1210). IEEE. DOI: **https://doi.org/10.1109/ICSP62122.2024.10743339**

[19] Sweller, J. (2020). Cognitive load theory and educational technology. *Educational technology research and development*, *68*(1), 1-16. DOI: **https://doi.org/10.1007/s11423-019-09701-3**

[20] Ma, T. M., Wang, X., Zhou, F. C., & Wang, S. (2023). Research on diversity and accuracy of the recommendation system based on multi-objective optimization. *Neural Computing and Applications*, *35*(7), 5155-5163. DOI: **https://doi.org/10.1007/s00521-020-05438-w**

[21] Jannach, D., & Abdollahpouri, H. (2023). A survey on multi-objective recommender systems. *Frontiers in big Data*, *6*, 1157899. DOI: **https://doi.org/10.3389/fdata.2023.1157899**

[22] Ma, H., Zhang, Y., Sun, S., Liu, T., & Shan, Y. (2023). A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artificial Intelligence Review*, *56*(12), 15217-15270. DOI: **https://doi.org/10.1007/s10462-023-10526-z**

[23] Verma, S., Pant, M., & Snasel, V. (2021). A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems. *IEEE access*, *9*, 57757-57791. DOI: **https://doi.org/10.1109/ACCESS.2021.3070634**

[24] Zhong, S. (2025). Research on Multi-Objective Optimization Recommendation Algorithms for Work-Study Platforms. *Journal of Computer, Signal, and System Research*, *2*(1), 168-180. DOI: **https://doi.org/10.71222/bwj2jw48**

[25] Li, M., Fu, Q., Singh, V. P., Liu, D., Li, T., & Zhou, Y. (2020). Managing agricultural water and land resources with tradeoff between economic, environmental, and social considerations: A multi-objective non-linear optimization model under uncertainty. *Agricultural systems*, *178*, 102685. DOI: **https://doi.org/10.1016/j.agsy.2019.102685**

[26] Liao, W., & Fan, C. (2025). A Multimodal-Based Fingering Analysis Method for Piano Playing. *IEEE Access*, *13*, 205288-205295. DOI: **https://doi.org/10.1109/ACCESS.2025.3639710**

[27] Shrivastava, R., Sisodia, D. S., & Nagwani, N. K. (2022). Utility optimization-based multi-stakeholder personalized recommendation system. *Data Technologies and Applications*, *56*(5), 782-805. DOI: **https://doi.org/10.1108/DTA-07-2021-0182**

[28] Zou, F., Chen, D., Xu, Q., Jiang, Z., & Kang, J. (2021). A two-stage personalized recommendation based on multi-objective teaching–learning-based optimization with decomposition. *Neurocomputing*, *452*, 716-727. DOI: **https://doi.org/10.1016/j.neucom.2020.08.080**

[29] Wu, H., Ma, C., Mitra, B., Diaz, F., & Liu, X. (2022). A multi-objective optimization framework for multi-stakeholder fairness-aware recommendation. *ACM Transactions on Information Systems*, *41*(2), 1-29. DOI: **https://doi.org/10.1145/3564285**

[30] Cai, X., Hu, Z., & Chen, J. (2020). A many-objective optimization recommendation algorithm based on knowledge mining. *Information Sciences*, *537*, 148-161. DOI: **https://doi.org/10.1016/j.ins.2020.05.067**

[31] Zaizi, F. E., Qassimi, S., & Rakrak, S. (2025). Multi-objective Optimization for Personalized and Fairness Recommender Systems: A Hybrid Approach. *SN Computer Science*, *6*(6), 713. DOI: **https://doi.org/10.1007/s42979-025-04230-8**

[32] Zaizi, F. E., Qassimi, S., & Rakrak, S. (2025). A deep autoencoder-enhanced multi-objective evolutionary algorithm for recommender systems: FE Zaizi et al. *The Journal of Supercomputing*, *81*(10), 1116. DOI: **https://doi.org/10.1007/s11227-025-07589-w**

[33] Zhou, W., Liu, Y., Li, M., Wang, Y., Shen, Z., Feng, L., & Zhu, Z. (2023). Dynamic multi-objective optimization framework with interactive evolution for sequential recommendation. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *7*(4), 1228-1241. DOI: **https://doi.org/10.1109/TETCI.2023.3251352**