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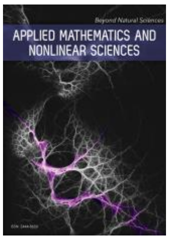

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Construction of Piano Performing Arts Talent Cultivation and Creative Thinking Based on the Constant Differential Error Approximation Method

Xiao Yang[1,†], Yanyan Lu[2]

1. College of Art, Department of Piano, Zhejiang Normal University, Jinhua, Zhejiang, 321000, China.
2. School of Music and Dance, Department of Piano, Nanjing Normal University of Special Education, Nanjing, Jiangsu, 210038, China.

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Abstract

Piano talent cultivation mostly focuses on repetitive training only, and lacks a clear cultivation program for theoretical knowledge and skill points. In this paper, we adopt the curriculum knowledge graph to extract the knowledge point subgraph of piano learning and provide an initialized knowledge graph structure for the learning path under the cultivation scheme. A multi-objective optimization model of the path containing constraints such as the difficulty and mastery of knowledge points is set, and the relevant parameters of the model are defined and calculated to establish a multi-optimization objective function. A solution method that uses constant differential error approximation is proposed as a means of approaching the Pareto optimal solution. To develop the LSPIA algorithm with reciprocal weights, the adjustment vectors are modified using a least squares asymptotic iterative approximation with minimum squares values. Following the discovery of the most suitable route, a teaching experiment was carried out. The results show that the posttest P-value of the total creative thinking score of the experimental and control classes is 0.022 less than 0.05, which indicates that there is a significant difference between the creative thinking of the students in the two classes in terms of affective characteristics. The experimental group achieved a mean score of 122.69 on the post-test, which was a significant improvement from the mean score on the pre-test. An innovative approach to cultivating piano playing talents involves optimizing learning paths.

Keywords: Knowledge mapping; Multi-objective optimization; Constant differential error approximation; Pareto optimal solution; LSPIA algorithm; Piano talent.
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†Corresponding author.
Email address: 13366625026@163.com

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1 Introduction

Piano playing is an elegant artistic activity of pure technique and complexity [1]. With the development of China's economy and the continuous improvement of people's living standards, the piano has been widely popularized, and more and more people are learning the piano in society [2-3]. The significance and function of piano learning are multi-level, it can not only cultivate performers, intellectual function, and aesthetic function, but there is also a very important under-explored deeper function - the function of creative thinking.

As a key teaching course in art colleges and universities, the piano major should conform to the development trend of the times, adjust and innovate the teaching system of the piano major, to lay a solid foundation for students to become high-quality composite talents in line with the standard of social talent demand [4-6]. At present, there are still many deficiencies in the piano education offered by colleges and universities in China. In the learning process of piano playing, many people fall into a kind of misunderstanding [7]. Many people think that as long as they understand the piano score and master the skills of playing, they can present a piece of music perfectly, which is a very wrong kind of understanding [8-9]. Lacking creative thinking ability, players will find it difficult to achieve a deep understanding of the connotation of the work, which will greatly reduce the impact of their performance. Piano performance is largely dependent on the ability to think creatively.

The piano professional course's overall teaching approach still involves cultivating students as the entrance point. Literature [10] analysis of the differences in dropout behavior in children's piano education, through a follow-up study of 14 beginner piano students, concluded that grades or teacher appreciation is an important factor in adherence to piano learning. Literature [11] assessed the consistency between expected learning levels and physical acquisition of different piano playing skills with the help of music educators' ratings to provide feedback on the teaching of piano skills in higher music education. Literature [12] collected records of information related to one-on-one teaching gestures from three piano teachers and analyzed the data processing to point out the significant correlation of musical gestures on the language of piano music and to make inferences about gesture differences between different teaching behaviors.

The development of students' creative thinking abilities is crucial in piano teaching. Literature [13], to explore the mediating role of creative thinking between autonomy support and self-efficacy, constructed a structural equation model based on covariance, and verified the mediating effect of creative thinking in teaching behavior through statistical analysis. Literature [14] proposed a hypothetical model oriented towards the utility played by creative thinking in music composition and creation, combining data collection from audio files and semi-structured interviews, and argued that the hypothesis was valid using statistical methods. Literature [15] invited participants to conduct two experiments with creative thinking and visual attention, measured subjects' visual attention, and assessed how divergent thinking works in terms of goal setting and attention deficit positive and negative.

In this paper, course knowledge mapping is introduced to capture the knowledge points contained in the initial learning path, and inter-entity relationships are used to represent the backward and forward sequential relationships between knowledge points. The difficulty of knowledge points and learners' mastery, the balance of the importance of knowledge points, the cost of learning, and the evaluation of learning experience are taken as the multi-objectives of learning path optimization, and different parameter constraints are set to derive the calculation method. The optimization objective function can be constructed through the combination of multi-objective and constraints. According to the relationship between Pareto optimal solution set and Pareto optimal frontier, the learning path optimization problem in piano teaching is transformed into solving the Pareto optimal solution of the multi-objective optimization model. The descent rate of the problem where the adjustment vectors cannot be adequately expressed is enhanced by adding reciprocal weights when fitting using the least squares asymptotic iterative approximation algorithm. School Z conducted a teaching experiment after determining the optimal learning path. The controlled class opted for the previous learning path while the experimental class utilized the optimized learning path for piano learning. The effect of creative thinking was verified through the use of pre- and post-tests.

2 Learning Path Modeling for Piano Performer Cultivation

The process of piano learning is more tedious, requiring long hours of repetitive practice and repeated cultivation, and most students are not interested enough in piano learning and find it more difficult to persist. Most students struggle to improve their skills and level during piano lessons due to their lack of spontaneity and initiative. For cultivating piano-playing talents and developing creative thinking, it is crucial to plan a reasonable learning path.

2.1 Knowledge point subgraph extraction

In piano teaching, to refine the real knowledge needs of learners, this paper obtains the knowledge points contained in the initial learning path by introducing a curriculum knowledge map.

A curriculum knowledge graph is a graph structure that contains a large number of knowledge entities and relationships [16], which can be represented as $G=\{N,R\}$, where $N=(h,t)$ denotes the set of knowledge entities contained in the graph and $R=\{<h,t>|\,h,t\in N\}$ denotes the set of relationships between nodes.

In this paper, the knowledge point subgraph extracted from the knowledge graph G_K, which is mainly the graph structure composed of the knowledge points contained in the resources in the initial learning path, and the relationship between the entities indicates the forward and backward sequence relationship between the two. Assuming that the initial learning path derived in this paper is denoted as $RLP=\left\{r_1,r_2,\ldots,r_{|RLP|}\right\}$, for each node r_i in the path contains multiple knowledge points, which is denoted as $r_i=\left\{k_1,k_2,\ldots,k_{|r_i|}\right\}$. Therefore, the steps of knowledge point subgraph extraction in this paper are as follows:

1) For each node r_i in the initial learning path RLP, search for a knowledge point entity in the course knowledge graph G, and if $k_i\in r_i$, store k_i in the knowledge point subgraph G_K.

2) For knowledge point entities k_i and k_j in G_K, if a ternary relationship such as $\left(k_i,relation,k_j\right)$ exists in the knowledge graph G, add that $relation$ to G_K.

3) Repeat steps (1) and (2) until all nodes in the initial learning path RLP are traversed.

4) Output the extracted knowledge point subgraph $G_K=\{K,\mathrm{Rel}\}$, where $K=\left\{k_1,k_2,\ldots,k_{|K|}\right\}$ and $K\in N$ denote the set of entities of the extracted knowledge points, and $Rel=\left\{relation_1,relation_2,\ldots,relation_{|Rel|}\right\}$ and $Rel\in R$ denote the set of relationships between the extracted knowledge points.

The knowledge point subgraph extraction process is shown in Fig. 1, where the upper layer represents the learning resource entity layer in the knowledge graph G and the lower layer represents the knowledge point entity layer. Assuming that the initial learning path is $RLP=\{r_1,r_2,r_6\}$, it can be seen from the figure that node r_1 contains five knowledge points $\{k_1,k_2,k_3,k_4,k_6\}$, r_2 contains three knowledge points $\{k_5,k_7,k_8\}$, and r_3 contains four knowledge points $\{k_9,k_{10},k_{11},k_{12}\}$, so the extracted knowledge point subgraph G_K contains a total of 12 knowledge points, which is the knowledge point layer in the figure.

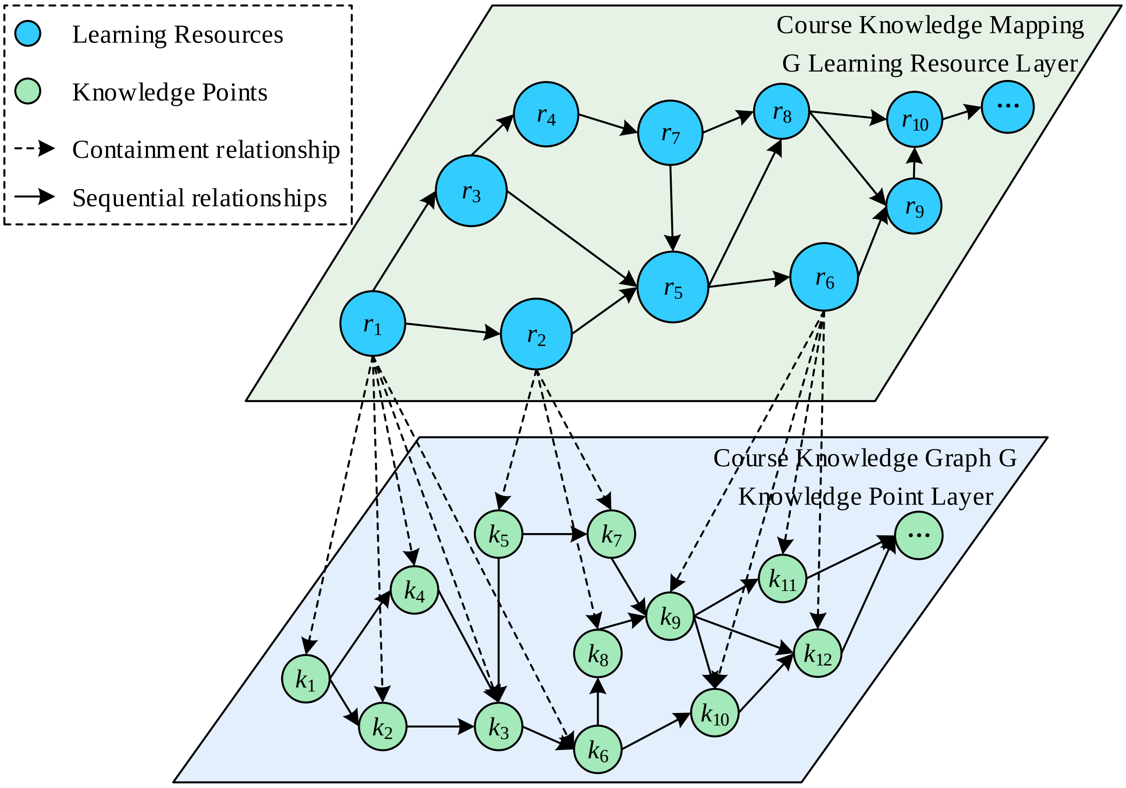

Figure 1. Example of Knowledge Point Subgraph Extraction

2.2 Learning path optimization objective analysis

In this paper, the model is analyzed from four aspects: the difficulty of knowledge points and learners' mastery, the balance of the importance of knowledge points, the cost of learning, and the evaluation of learning experience.

Let the difficulty of the knowledge point be denoted as D in the knowledge point subgraph G_K, and the learner's mastery of the knowledge point be denoted as A. Then the relative learning difficulty of the nodes in the ultimately generated learning path KLP should satisfy the gradual increment of the nodes, i.e., for the neighboring node k_i,k_j,k_l in KLP, the following formula should be satisfied:

$$f_1\left(g\left(D_i,A_i\right),g\left(D_j,A_j\right)\right)\leq f_1\left(g\left(D_j,A_j\right),g\left(D_l,A_l\right)\right) \tag{1}$$

Where function $g(D, A)$ represents the gap between the difficulty of a knowledge point and the learner's mastery level, and function $f_1\left(g_i, g_j\right)$ represents the relative learning difficulty between nodes.

Let the importance of the knowledge point be denoted as I, then the learning path KLP should satisfy the decreasing relative importance of the nodes, i.e., for the consecutively neighboring node k_i, k_j, k_l in KLP, the following equation should be satisfied:

$$f_2\left(I_i, I_j\right) \leq f_2\left(I_j, I_l\right) \tag{2}$$

where the function $f_2\left(I_i, I_j\right)$ represents the importance gap between neighboring knowledge points.

Let the learning cost of a knowledge point be denoted as S, then the learning path KLP should satisfy the gradual increment of the relative learning cost between nodes, i.e., for the consecutive neighboring nodes k_i, k_j, k_l in KLP, the following equation should be satisfied:

$$f_3\left(S_{ij}\right) \leq f_3\left(S_{jl}\right) \tag{3}$$

Where function $f_3\left(S_{ij}\right)$ represents the learning cost between neighboring knowledge points.

The learning experience is to reflect the learner's satisfaction with the overall learning situation in the learning process. Let the learning experience evaluation of transferring between knowledge points be H, then the learning path KLP should satisfy the relative learning cost of nodes gradually increasing, that is, for the consecutive neighboring nodes k_i, k_j, k_l in KLP, the following formula should be satisfied:

$$f_4\left(H_{ij}\right) \leq f_4\left(H_{jl}\right) \tag{4}$$

where the function $f_4\left(H_{ij}\right)$ represents the learning experience evaluation of transferring between neighboring knowledge points.

The learning path optimization problem in this paper ultimately generates a learning path KLP with knowledge points as nodes that should satisfy the conditions including the most appropriate learning difficulty of the knowledge points, a relatively balanced degree of importance of the knowledge points, the minimum total cost of learning, and the maximum evaluation of the overall learning experience.

2.3 Learning Path Parameter Setting and Calculation

Learning path optimization is to enable teachers to rationalize the ordering of knowledge points to be learned based on learners' mastery of course knowledge and learning objectives, and then serve as learners' personalized learning paths. To better construct the model and use it for quantitative calculation, the parameters of the multi-objective learning path optimization model MLPOM in this paper are first set as follows:

Define the structure of the knowledge point subgraph as $G_K = \{K, Rel\}$, where $K = \{k_1, k_2, \ldots, k_{|K|}\}$ represents all the knowledge points contained in the knowledge point subgraph, k_i represents the i th knowledge point, and $1 \le i \le |K|$. $Rel = relation_1, relation_2, \ldots, relation_{|Rel|}$ represents the relationship between the knowledge points.

Learners' correct or incorrect answers to the test questions corresponding to the knowledge points can intuitively reflect the learning difficulty level of the knowledge points, so the difficulty value D_i for knowledge point k_i is calculated as follows:

$$D_i = \frac{N_{i\_right}}{N_{i\_All}} \tag{5}$$

Where N_{i_right} indicates the number of learners who gave correct answers to the test questions corresponding to knowledge point k_i, and N_{i_All} indicates the number of all learners who have done the test questions corresponding to knowledge point k_i.

The learners' mastery of knowledge point 5 is quantified by using the scores of the test questions containing the knowledge point in the learners' historical learning behavior data, and the learners' mastery of knowledge point k_i is calculated by the formula of A_i:

$$A_i = \frac{\sum_{q=1}^{Q} Score_{i\_q}}{\sum_{q=1}^{Q} All\_Score_{i\_q}} \tag{6}$$

where $Score_{i\_q}$ denotes the learner's score for test question q containing knowledge point k_i and $All\_Score_{i\_q}$ denotes the total score for test question q.

In this paper, it is argued that the higher the level of importance, the more space and time needs to be used to teach the knowledge point. Therefore, the importance level I_i of knowledge point k_i is calculated by the formula:

$$I_i = \frac{L_i}{L_{All}}\left(1 + \lg\frac{N_{i\_s}}{N_{i\_1}}\right) \tag{7}$$

Where L_i represents the total duration of the course resources containing knowledge point k_i, L_{All} represents the total duration of all learning resources of the course, N_{i_s} represents the total number of learners who have viewed the learning resources related to the knowledge point at least once, and N_{i_1} represents the total number of learners who have viewed the learning resources related to the knowledge point only once.

$S_{ij} = 1$ if there is a first-order sequential relationship between knowledge points k_i and k_j, and $S_{ji} = 2S_{ij}$ if there is an inverse-order relationship between the two. If multiple transitions are required between the two, the learning cost is the minimum of the sum of the learning costs on the transfer path, which can be expressed as follows:

$$S_{ij} = \min_{1 \le p \le lp} S_p \tag{8}$$

where lp denotes the total number of paths between knowledge points k_i and k_j, and S_p denotes the sum of learning costs on path p.

The learning experience evaluation value between knowledge points k_i and k_j is calculated as:

$$H_{ij} = \frac{h_{ij}}{h_{ij} + h_{ji}} \tag{9}$$

where h_{ij} denotes the number of learning sessions transferred from KM k_i to KM k_j in all data.

2.4 Learning path multi-optimization objective function design

According to the above derivation and calculation, the conditions satisfied by the multi-objective learning path optimization model MLPOM in this paper can be transformed into four objective functions $F_1 \sim F_4$, whose mapping relations F are shown in Eq:

$$F\begin{cases} F_1(X) = \sqrt{\sum_{j=1}^{|K|} \left| \frac{\sum_{i=1}^{|K|}\left[x_{ij}\left(D_i - A_i\right) + X_{ij}\left(D_j - A_j\right)\right]}{2\sum_{i=1}^{|K|} x_{ij}} \right|^2} \\ F_2(X) = \frac{\sum_{j=1}^{|K|}\sum_{i=1}^{|K|} x_{ij}\left|I_i - I_j\right|}{\sum_{j=1}^{|K|}\sum_{i=1}^{|K|} x_{ij}} \\ F_3(X) = \sum_{j=1}^{|K|}\sum_{i=1}^{|K|} x_{ij} S_{ij} \\ F_4(X) = \sum_{j=1}^{|K|}\sum_{i=1}^{|K|} X_{ij} H_{ij} \end{cases} \tag{10}$$

Where $F_i(X)$ represents the four objective functions, $F_1(X)$ represents the difference between the difficulty level of the knowledge points on the learning path and the knowledge mastery of the learners. $F_2(X)$ denotes the balance of importance of knowledge points on the learning path. $F_3(X)$ represents the total learning cost of the knowledge points on the recommended learning path. $F_4(X)$ denotes the total learning experience evaluation of the recommended learning path.

3 Learning path optimization solution based on constant differential error approximation method

3.1 Optimal Solution and Error Approximation for Multi-Objective Optimization

In Chapter 2, the focus is on modeling the learning path planning to cultivate piano playing talent and construct creative thinking, and it turns the learning path optimization into a multi-objective optimization problem. For a multi-objective optimization problem, when all the objective functions are considered at the same time, there usually exists a solution that is a better solution for a certain part of the objective function, but a worse solution for the other objective functions, so the multi-objective optimization problem usually exists a collection of solutions, called the Pareto optimal solution.

In general, there is more than one Pareto-optimal solution, and the set of all Pareto-optimal solutions is called the Pareto-optimal solution set PS. The image of the Pareto-optimal solution set in the objective function space is called the Pareto-optimal frontier PF.

Figure 2 illustrates the relationship between the Pareto optimal solution set and the Pareto optimal frontier, which graphically shows the dominance relationship in a multi-objective optimization problem as well as the optimal solution set PS in the decision space and the optimal frontier PF in the objective space. F denotes the mapping relationship from PS to PF, D denotes the decision space, and $F(D)$ denotes the objective space. The upper left region in front of the Pareto is called the feasible solution set. It can be seen that $F(C)$ dominates $F(B)$, and there is a non-dominating relationship between $F(A)$ and $F(C)$.

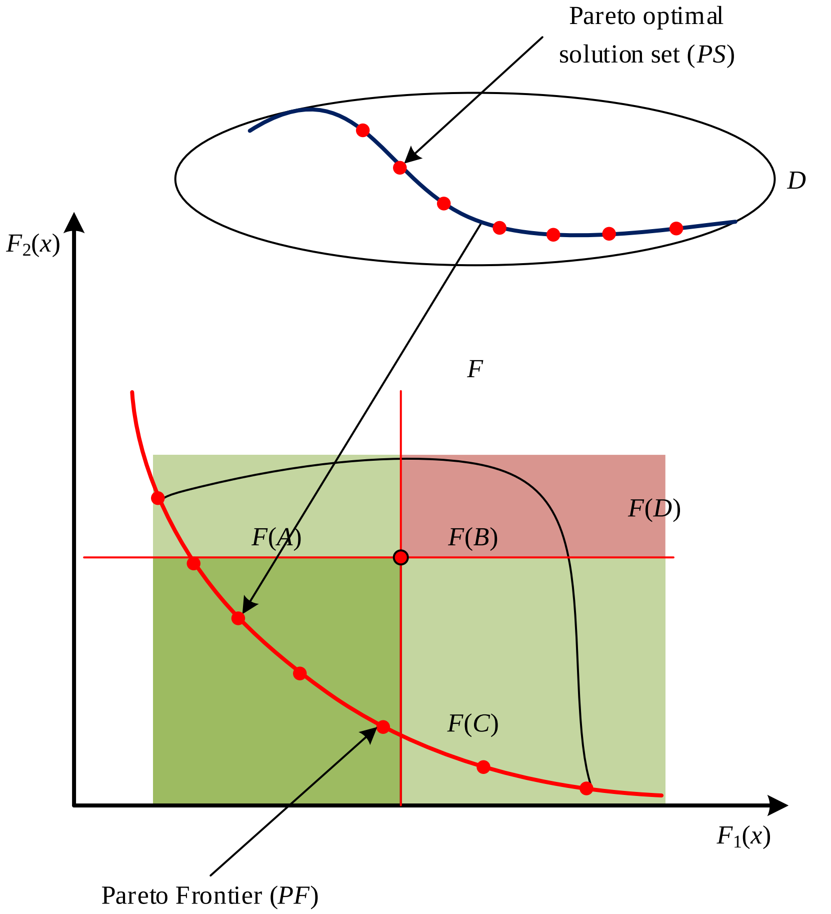

Figure 2. The pareto optimal solution is associated with pareto's optimal frontier

The multi-objective optimization problem is to find a set of Pareto optimal solutions and make the corresponding non-dominated set as close as possible to the real Pareto front, and at the same time to be uniformly distributed on the Pareto front, which can well represent the whole Pareto front. Based on the above derivation, the learning path optimization problem in piano teaching can be transformed into solving the Pareto optimal solution of the multi-objective optimization model, i.e., it can be solved by continuously reducing the error with the real Pareto frontier and approximating the Pareto frontier. In this paper, a solution method based on constant differential error approximation is given.

3.2 Asymptotic Iterative Approximation Combined with Least Squares

3.2.1 Least Squares Fitting

The Least Squares Asymptotic Iterative Approximation Algorithm (LSPIA) does not require that the objective function must pass through the data points during the fitting process, but only to the extent of approximating the discrete points, and uses the principle of minimizing the sum of squares of the errors to minimize the fitting error as much as possible.

Assuming that a set of data points $(x_i, y_i), i = 1, 2, \ldots, m$ is obtained experimentally, the least squares fitting procedure is to solve for a function $f(x)$ satisfying $\min \sum^{m} \left(y_i - f(x_i)\right)^2$. The curve is fitted by this method, and the form of the fitted function $f(x)$ is determined from the given image of the scattered data points. In general, it is assumed that the function to be solved $f(x)$ belongs to the space $\phi = span\{\phi_1, \phi_2, \ldots, \phi_n\}$, i.e., $f(x)$ can be linearly combined by the function $\phi_j, j = 1, 2, \ldots, n$.

Therefore, the solution process of $f(x)$ can be expressed as $\min \sum^{m} \left(y_i - \sum^{n} \beta_j \phi_j(x_i) \right)^2$. Order:

$$X = \begin{pmatrix} \phi_1(x_1) & \phi_2(x_1) & \cdots & \phi_n(x_1) \\ \phi_1(x_2) & \phi_2(x_2) & \cdots & \phi_n(x_2) \\ \cdots & \cdots & \ddots & \cdots \\ \phi_1(x_m) & \phi_2(x_m) & \cdots & \phi_n(x_m) \end{pmatrix}, \quad y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix} \tag{11}$$

Then the solution process for $f(x)$ can be expressed as $\min \|X\beta - y\|_2^2$, where $\|\cdot\|_2$ is the Euclidean paradigm.

When the function space satisfies $\phi = span\{1, x, x^2 \ldots, x^n\}$, which is the commonly used least squares polynomial fit.

3.2.2 LSPIA algorithm with reciprocal weights

Let $\{Q_j\}_{j=0}^{m}$ be a given ordered data point to be fitted and the sequence of nodes be $\{t_0 = t_1 = t_2 = t_3 = 0, t_4, \cdots, t_m, t_{m+1} = t_{m+2} = t_{m+3} = t_{m+4} = 1\}$. In this paper, $n+1$ points $\{P_i\}_{i=0}^{n}$ are selected from $\{Q_j\}_{j=0}^{m}$ as the initial control vertices, and the initial cubic homogeneous B-spline curve is:

$$P^0(t) = \sum_{i=0}^{n} B_i(t) P_i^0, t \in [t_0, t_m] \tag{12}$$

where $\{B_i(t); i = 0,1,\ldots,n\}$ is a cubic uniform B-spline basis function with a configuration matrix:

$$B = \begin{bmatrix} B_0(t_0) & B_1(t_0) & \cdots & B_n(t_0) \\ B_0(t_1) & B_1(t_1) & \cdots & B_n(t_1) \\ \cdots & \cdots & \cdots & \cdots \\ B_0(t_m) & B_1(t_m) & \cdots & B_n(t_m) \end{bmatrix} \tag{13}$$

Let the difference vector be:

$$\delta_j^0 = Q_j - P^0(t_j), j = 0,1,\ldots,m \tag{14}$$

and the first adjustment vector of the i st control vertex is:

$$\Delta_i^0 = \mu \sum_{j=0}^{m} B_i(t_j)\delta_j^0 \tag{15}$$

where the weights μ satisfy $0 < \mu < 2/\lambda_0$, λ_0 are the largest eigenvalues of matrix $B^T B$, from which the new control vertex is obtained as:

$$P_i^1 = P_i^0 + \Delta_i^0, i = 0,1,\ldots,n \tag{16}$$

The new curve is:

$$P^1(t) = \sum_{i=0}^{n} B_i(t)P_i^1, t \in [t_0, t_m] \tag{17}$$

Similarly, assume that curve $P^k(t)$ is obtained after the k st iteration, such that:

$$\delta_j^k = Q_j - P^k(t_j), j = 0,1,\ldots,m \tag{18}$$

$$\Delta_i^k = \mu \sum_{j=0}^{m} B_i(t_j)\delta_j^k, i = 0,1,\ldots,n \tag{19}$$

$$P_i^{k+1} = P_i^k + \Delta_i^k, i = 0,1,\ldots,n \tag{20}$$

The curve after the $k+1$ st iteration can be obtained as:

$$P^{k+1}(t) = \sum_{i=0}^{n} B_i(t)P_i^{k+1} \tag{21}$$

The original LSPIA algorithm has been improved by adding reciprocal weights to the LSPIA algorithm. In this algorithm, the expression form of the curve and difference vectors remains unchanged and the adjustment vector is changed. The constant μ in the LSPIA algorithm is given a different value, i.e., the adjustment vector is changed during the iteration:

$$\Delta_i^k = \mu_i \sum_{j=0}^{m} B_i\left(t_j\right)\delta_j^k, i = 0,1,\ldots,n \tag{22}$$

Suppose the curve after the k st iteration is known and the control vertex after the $k+1$ nd iteration is:

$$P_i^{k+1} = P_i^k + \Delta_i^k, i = 0,1,\ldots,n \tag{23}$$

The curve obtained after the $k+1$ rd iteration is:

$$P^{k+1}(t) = \sum_{i=0}^{n} B_i(t)P_i^{k+1} \tag{24}$$

This results in a series of iterative approximation curves $\left\{P^k(t), k = 0,1,\ldots\right\}$ (k is the number of iterations). The improved algorithm degenerates to the LSPIA algorithm when μ_i all take the same value and satisfy $0 < \mu < 2/\lambda_0$.

4 Piano learning path optimization effect analysis

4.1 Piano learning knowledge extraction results

In this paper, we take the piano course of School Z as a research sample and extract the knowledge sub-map of the piano course to mine the association of knowledge points, which lays the foundation for the optimization of the learning path.

4.1.1 Analysis of the number of knowledge points associated with the piano

In this paper, we establish a knowledge map of piano teaching through teaching resources such as lesson plans and assessments of piano courses in Z school. The correlation results of the knowledge points of the piano course are shown in Figure 3. Knowledge labeling resulted in the extraction of 156 knowledge points. The highest association density is knowledge point K62, with the number of associations reaching 59, and the degree centrality achieving 0.93. The knowledge map encompasses a broader spectrum of knowledge and encompasses the majority of the knowledge points in the course. The addition of sequential operations to knowledge content can effectively organize it and demonstrate the internal structure of knowledge and the connection between knowledge points to learners.

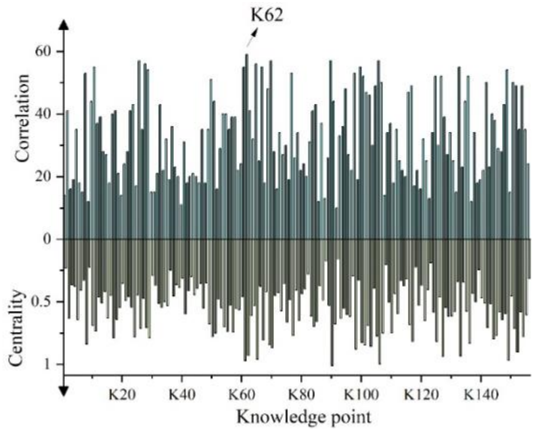

Figure 3. The relevant results of the piano course

A gradient is established for every 10 points depending on the number of knowledge associations, and 156 piano learning knowledge points are separated. The gradient separation of piano learning knowledge points is shown in Table 1. The average gradient mean value is 15.6, and the highest density interval is [15,20).

Table 1. The piano learns the gradient separation of the knowledge point

Range	Quantity of knowledge	Interval center	Cumulative percentage (%)	Symbolization
[10,15)	10	12.5	6.4103	R1
[15,20)	24	17.5	21.7949	R2
[20,25)	22	22.5	35.8974	R3
[25,30)	16	27.5	46.1538	R4
[30,35)	15	32.5	55.7692	R5
[35,40)	18	37.5	67.3077	R6
[40,45)	17	42.5	78.2051	R7
[45,50)	9	47.5	83.9744	R8
[50,55)	13	52.5	92.3077	R9
[55,60)	12	57.5	100	R10

4.1.2 Effectiveness of grading the mastery of knowledge points

Based on the above knowledge association and gradient separation results, combined with the learning habits of new piano majors, the predicted mastery level of students is shown in Figure 4. A group of learners whose actual mastery of each knowledge node is described as ‘novice’ is represented by each bar in the figure. According to the four different patterns in the bars, the learners are expected to have a mastery of knowledge that is high, medium, low, and novice. "The area of the pattern represents the area of the four categories of learners. By examining the area of the patterns, we can determine how many learners belong to each category in the group. The accuracy of predictions for the novice class can be determined by the area of the pattern corresponding to novice in the figure. From the figure, it can be seen that the correct prediction rate of each knowledge node is between [0.683,0.916], which is relatively high. Due to their lack of learning ability and poor mastery of individual knowledge nodes, learners with the mastery level of ‘novice’ tend to perform poorly. The mastery of the predecessor nodes will also be poor for the learners who have poor mastery of the successor nodes. Therefore, it is reasonable to predict their mastery level as "novice".

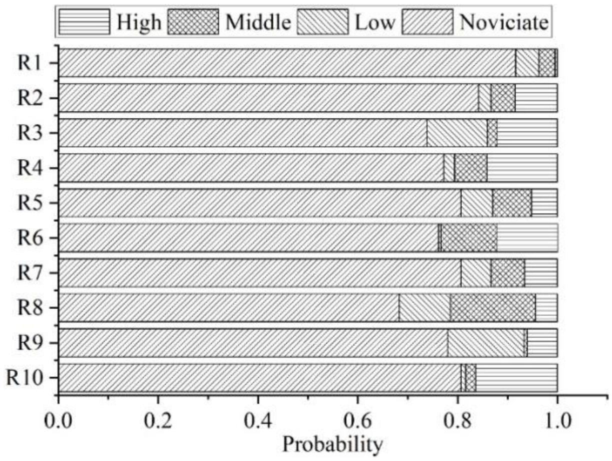

Figure 4. Students' mastery of knowledge points

4.2 Multi-objective optimization effect of piano learning paths

For the knowledge domain {R|R1~R10} after gradient separation, set the problem domain as {Q|a,b,c,d,e,f,g}. A multi-objective optimization model for learning paths is established and solved using the LSPIA algorithm with reciprocal weights to obtain the optimal paths. The background of knowledge points obtained from R-Q-oriented solving is shown in Table 2.

Learners can select any one of the learning paths to learn, and every time they learn a new knowledge point, their knowledge state will change. For example, if a student selects the learning path R1→R3→R5→R6→R2, initially his/her knowledge state is {∅}. After learning knowledge point R1, its knowledge state is {a}, at this time, the student has a preliminary understanding of the knowledge point and can answer the recognition-related questions. Further, learning knowledge point R3, its knowledge state changes to {a,c}. At this point, the student recognizes the knowledge point, masters the associated skills, and can practice skills to strengthen the knowledge point. The student follows this learning path step by step and eventually masters all knowledge points {a,b,c,d,e,f,g}.

At the same time, the learner can select a learning path suitable for him/her according to the individual's current knowledge state, if the student's current knowledge state is {a,d,f}, his/her corresponding knowledge point state is {R1,R3,R5}. At this time, the learning path R1→R3→R5→R4 or R1→R3→R5→R2 can be selected for learning. By learning according to different learning paths, students can gradually and effectively master the knowledge points until they master all the knowledge points.

Table 2. The knowledge point background for the analysis of the R-Q

R-Q	a	b	c	d	e	f	g
R1	1	1	1	0	0	0	1
R2	0	0	1	0	0	0	1
R3	1	1	0	0	0	1	1
R4	1	0	1	1	0	1	0
R5	0	1	1	1	0	0	0
R6	1	0	0	0	0	1	1
R7	0	0	1	1	0	0	0
R8	0	1	1	0	1	0	1

R9	1	0	1	1	1	0	0
R10	0	0	1	0	1	1	0

4.3 Learning path optimization for creative thinking

In this paper, creative thinking is categorized into four dimensions: risk-taking, curiosity, imagination, and challenge in terms of affective traits, according to the Creativity Measurement Scale (CMS). A teaching experiment was conducted in School Z. The control class opted for the previous learning path while the experimental class adopted the optimized learning path for piano learning. The pre-test and post-test of sexual thinking of the experimental and control classes were conducted, and the scores and independent samples t-test results are shown in Table 3. In terms of average scores, the average posttest score of creative thinking of the students in the experimental class was 122.69, which was significantly higher than the average score of the pretest (112.65). The mean score of the posttest of creative thinking of the students in the control class is 113.84, which is not significantly different from the mean score of the pretest (112.65). Secondly, the posttest p-value of the total score of the creative tendency of the experimental and control classes was 0.022, which is less than 0.05, which indicates that there is a significant difference between the creative thinking of the students in the two classes in terms of affective characteristics. The students in the experimental class experienced a significant improvement in their level of creative thinking before and after being taught based on learning path optimization. From the above analysis, it can be seen that the teaching method of optimizing learning paths has a more significant positive impact on the emotional characteristics of students' creative thinking. From the dimension of adventurousness, the P value of the independent sample t-test result of the post-test of the experimental class and the control class is 0.214, which is greater than 0.05, and there is no significant difference. From the mean value, the average score of students in the experimental class is 25.71, which is higher than the average score of the control class (23.74).

Table 3. Total score and independent sample t test results

Projects	Group		Mean±SD	P
Risk	Posttest	Experimental	25.71±3.65	0.214
		Control	23.74±3.10	
Curiosity		Experimental	36.53±3.47	0.054
		Control	33.17±3.85	
Imaginability		Experimental	30.53±3.23	0.035
		Control	28.02±4.10	
Challenge		Experimental	29.92±3.89	0.657
		Control	28.91±3.59	
Creative thinking	Pretest	Experimental	112.65±9.24	0.867
		Control	112.52±8.46	
	Posttest	Experimental	122.69±14.24	0.022
		Control	113.84±14.64	

5 Conclusion

This study focuses on optimizing piano teaching through the construction of learning paths. The process of cultivating piano playing talents is modeled as an optimization problem with multiple objectives, and the solution is achieved through the use of the LSPIA algorithm with reciprocal weights for error approximation. Following the discovery of the optimal path, it is examined how it affects the development of creative thinking, and the following conclusions are drawn:

1) Taking the piano course of School Z as the research sample, the knowledge map extracts 156 knowledge points, and the knowledge point K62 has the highest association density, the number of associations reaches 59, and the degree centrality achieves 0.93. The construction of the course knowledge map provides a precise description of the piano cultivation system and lays the foundation for the construction of the learning path.

2) Oriented to the knowledge domain after gradient separation, the multi-objective optimization model of the learning path in the knowledge domain-problem domain is constructed. A clearer learning path is achievable due to the faster solution speed of the LSPIA algorithm with reciprocal weights. Students can gradually and effectively master the knowledge points until they have completed all the knowledge points by learning according to different learning paths.

3) According to the acquired learning paths to carry out teaching control experiments, the average score of the post-test of creative thinking of the students in the experimental class is 10.04 higher than the average score of the pre-test, and the creative thinking of the students in the two classes appears to be significantly different in terms of affective characteristics.

The cultivation of piano-playing talents should be based on a good grasp of the current teaching objectives, and explore the key training programs at this stage to continuously improve the comprehensive quality of students and enhance their competitiveness.

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