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Optimization of AI-driven vocal teaching models and design of personalized learning paths

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Abstract With the rapid development of information technology, Artificial Intelligence (AI) gradually penetrates into all walks of life, especially in the field of education. As a special form of art education, vocal music teaching has an increasing demand for personalization and precision in teaching. In this paper, a vocal music teaching mode optimization method based on AI algorithm is proposed, and a personalized learning path recommendation model is designed. First, a vocal music knowledge graph is constructed, and knowledge acquisition and extraction is carried out through multimodal data fusion (e.g., audio, sheet music, and singing lyrics, etc.). Then, deep learning algorithms (e.g., CNN, LSTM, and RankNet) are used to achieve dynamic recommendation of learning paths based on learners' personalized features. The experimental results show that after using the improved path recommendation algorithm, the learning effect of the learner is significantly improved, especially in the mastery of knowledge points related to the learning objectives, which is improved by more than 10%. In addition, the recommended learning paths were highly evaluated by more than 80% of learners through a user satisfaction survey. The study shows that the personalized learning path based on the model can effectively enhance learners' learning gains, and provides theoretical and practical basis for personalized teaching of vocal music.

Index Terms Vocal music teaching, AI algorithm, personalized learning, knowledge graph, learning path recommendation, deep learning

I. Introduction

Traditional vocal music teaching often adopts standardized teaching methods and teaching materials, and all students use the same teaching materials, making it difficult to take into account the individual needs of students [1]. Due to the individualized differences in voice quality, vocal foundation and musical pursuit of different students, it is difficult to meet the unique needs of each student in vocal music learning with the “one-size-fits-all” teaching mode, which leads to uneven teaching results and restricts the overall development of students' vocal music artistic quality [2]-[4].

At the same time, traditional vocal music teaching teachers are too much emphasis on the teaching of skills, while ignoring the importance of musical expression and emotional communication, the essence of vocal music art is to convey emotions and mood through the voice, and the simple pursuit of skills can easily lead to students falling into the mechanical imitation, thus losing the deep understanding of the music and personalized expression [5], [6]. Some teachers pay too much attention to the theoretical analysis of musical works in vocal music teaching and neglect the development of practical teaching activities [7]. For example, the lack of in-depth exploration of sound generation, resonance principles and other issues is not conducive to students' understanding of their own pronunciation problems, resulting in students' understanding of the connotation of musical art is not deep enough, which also leads to teachers' lack of a comprehensive understanding of the actual learning situation of the students, and insufficient relevance of teaching strategies [8]-[10]. With the continuous development of artificial intelligence, it is widely used in various industrial fields, and the field of education is no exception [11]. Artificial intelligence technology can be used to promote the innovation of the content and methods of vocal music education in colleges and universities, enhance the flexibility and personalization of the vocal music classroom through interactive and personalized teaching, cultivate students' critical thinking and innovation ability, promote the development of vocal music teaching in colleges and universities in the direction of digitization and diversification, lay the foundation for the future development of music education, and cultivate more high-quality vocal music art with innovative spirit and practical ability. Provide strong support for cultivating more high-quality vocal art talents with innovative spirit and practical ability.

This study proposes a personalized learning path recommendation model based on AI algorithm. First, by constructing a vocal music knowledge graph, vocal music teaching resources are systematically organized and extracted, combined with multimodal information such as audio, music scores and singing lyrics, to provide basic data support for subsequent learning path planning. Then, based on the learner's learning goals, cognitive level, learning style and other personalized features, a learner model is constructed, and deep learning algorithms (e.g., CNN, LSTM, CRF, etc.) are used for the extraction of knowledge points and relationship modeling. By analyzing the learner's knowledge mastery and learning behavior, a personalized learning path is finally generated. In addition, this paper also designs a dynamic update mechanism for the learning path, which continuously adjusts the content of the recommended path according to the real-time learning progress of the learner to ensure the timeliness and accuracy of the path. Through this innovative research, this paper provides new ideas and methods for the optimization of vocal music teaching mode and the design of personalized learning path.

II. Personalized Learning Path Recommendation Model Based on Vocal Music Teaching Mode

II. A. Design of the Vocal Music Knowledge Graph Construction Framework

In this paper, we design to construct a typical multimodal vocal music knowledge graph, processing information covering auditory, visual, text, vocal music knowledge from audio, sheet music, lyrics, metadata and other kinds of data sources, fusion of the type of knowledge including external description information and vocal music content information. It can support knowledge retrieval and knowledge discovery based on vocal music content, and also supports visualization display by combining multiple media forms. The design of vocal music knowledge graph framework is shown in Figure 1.

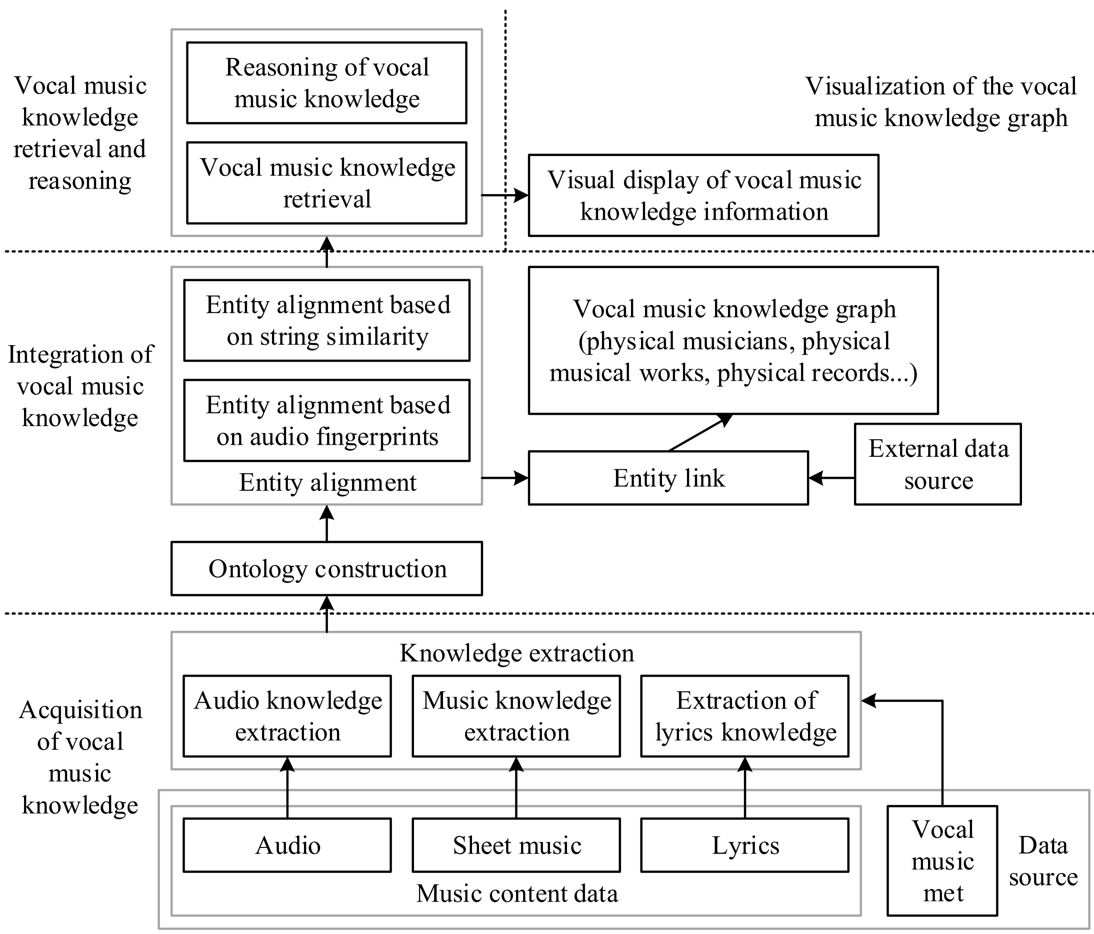

Figure 1: The sound knowledge atlas framework design

II. A. 1) Acquisition of vocal knowledge

(1) Data sources

Data sources for knowledge acquisition usually include professional literature and data in relevant databases and knowledge bases. When constructing a vocal music knowledge system, the main data sources for knowledge acquisition include vocal music literature, vocal music works of various representation types, and vocal music information recorded in databases, knowledge bases and web pages. The selection of data sources for vocal music knowledge mapping needs to consider the following factors: openness, accessibility, quality level and completeness.

(2) Knowledge Extraction

Knowledge extraction refers to the process of extracting the knowledge contained in the data source by means of identification and understanding. Vocal music content data is a unique knowledge extraction object in the field of vocal music. The three main types of vocal music content data, namely audio, sheet music and lyrics, correspond to different knowledge extraction methods.

Audio knowledge extraction: audio knowledge extraction is the process of analyzing vocal music based on audio. This process, which involves multiple research fields such as artificial intelligence, vocalism, psychoacoustics, etc., requires the joint participation of digital signal processing, machine learning, data mining, and visualization techniques.

Sheet music knowledge extraction: Sheet music knowledge extraction is a symbol-based vocal content analysis process, based on the formalized and structured encoding of sheet music; MIDI, Vocal musicXML, MEI are the three most common sheet music encodings.

Lyrics Knowledge Extraction: Lyrics knowledge extraction can be referred to the text knowledge extraction process, they also need to use natural language processing technology, but lyrics knowledge extraction also needs to be supplemented with the support of audio analysis technology.

II. A. 2) Integration of vocal knowledge

Knowledge fusion is a high-level knowledge organization that enables knowledge from different knowledge sources to achieve heterogeneous data integration under the same framework specification, and the steps to achieve this include ontology construction, entity alignment, entity linking, and ultimately, the fusion of data, information, methods, experiences, and ideas to form a high-quality knowledge graph.

(1) Ontology Construction

Ontology construction is a key step in the fusion of vocal music knowledge, which requires the completion of abstract modeling and structured definition of vocal music domain knowledge. At present, the knowledge information involved in vocal music knowledge mapping can be divided into three main categories: descriptive information of vocal music resources or works, information of vocal music events, and information of vocal music content recording and analysis.

(2) Entity Alignment

Entity alignment is the process of corresponding entities in different data sources to the same entity to which they jointly refer. An important task of knowledge fusion in the field of vocal music is to complete the entity alignment of core entities such as vocalists, vocal works, and musical instruments.

Entity alignment based on string similarity: entity alignment based on string similarity is the process of analyzing the text or metadata in the form of strings related to entities for similarity, and then judging whether the entities are pointing to the same based on this.

(3) Entity Linking

Ontology construction and entity alignment complete the internal knowledge fusion of the knowledge graph, while entity linking is to link ambiguous entities to external authoritative knowledge bases to realize the knowledge fusion between the knowledge graph and external data sources. In vocal music knowledge graph construction, entities such as vocalists, vocal works, musical instruments, vocal concepts, etc. in DBpedia are often selected as entity linking objects.

II. A. 3) Vocal Knowledge Retrieval and Reasoning

In vocal music knowledge graph, vocal music knowledge retrieval can be realized directly by constructing query statements using SPARQL language, and can also be realized by natural language form and example-based knowledge retrieval. Among them, relevance and similarity retrieval based on vocal music examples is a unique knowledge discovery method in the field of vocal music, which belongs to the retrieval based on vocal music content. This kind of retrieval requires the knowledge graph to make deep semantic processing of vocal content data.

II. A. 4) Vocal Music Knowledge Graph Visualization

Visualization studies of knowledge graphs include visual representation of different types of information in the graph, as well as visual analysis for the inference of new relationships and the discovery of potential patterns or problems. For the visual representation of vocal metadata-type information in the vocal music knowledge graph, node-link diagrams can be chosen to achieve a direct visual presentation of entities and inter-entity relationships.

II. B.Learner Model

The learner model is the basis for constructing personalized learning paths and is one of the core components of personalized learning path construction. The learner model is an abstract representation and description of learner characteristics, and is an effective organization that focuses on learners' personalized information. Accurately portraying online learners through the learner model can provide multifaceted support for personalized teaching and improve the level of instructional design and the effect of learning services.

II. B. 1) Personalized learning parameters

Personalized learning parameters [12] are the basic guarantee for constructing a learner model, describing various characteristics and needs of the learner, such as the learner's learning goals, learning styles and cognitive levels. The researcher considers using different learning parameters to achieve the construction of learner model, and the commonly used personalized learning parameters are as follows:

(1) Learning objectives: learning objectives refer to the collection of knowledge points that learners are required to master in the learning process, and are used to design and plan the learning process, arranging the learning of knowledge points in the form of paths that satisfy the learner's objectives.

(2) Cognitive level: Cognitive level is used to describe the current learner's ability to master knowledge, indicating the extent to which the learner has mastered the knowledge or skills required for a course or knowledge point.

(3) Learning style: Learning style is a consistent and stable way of learning shown by the learner in the learning process, which may be visual, verbal, reading or writing and other styles.

Learner's learning style can be composed of four key-value pairs, and the learning style formula is:

$$LS = [(T_1, e_1), (T_2, e_2), (T_3, e_3), (T_4, e_4)] \tag{1}$$

where, T_i denotes the specific type of learning style, and e_i is a fuzzy value less than 1.

(4) Available learning time: it refers to the available time that the learner devotes to the learning activity. In the current personalized learning path planning method, the time usually spent on completing a learning path is decided by the learning system, and the learner can only accept it passively, and there is the problem of not being able to allocate enough time to complete the path learning.

II. B. 2) Modeling

The purpose of learning path personalization is to serve online learners with different characteristics, and the learner characteristics are obtained from the analysis and quantification of their personalized learning parameters, therefore, the personalized learning parameters are the key foundation and core components of constructing learner models.

Definition 1: Let m learners take $L = (L_1, L_2, L_3, ..., L_m)$ in the form of L_i denotes the i th learner, each of which has basic and functional attributes.

Definition 2: Let the learning objectives $LT_m = (LT_1, LT_2, LT_3, ..., LT_k)$, where LT_i denotes the learning goal of the i th learner.

Definition 3: Let learning style $LS_m = (LS_{1m}, LS_{2m}, LS_{3m}, LS_{4m})$, LS_{im} denotes the tendency of a learner L_m towards the four learning styles proposed by Filder-Silverman level, LS_i = (1=Active/Contemplative, 2=Visual/Verbal, 3=Sensory/ Intuitive, and 4=Sequential/Integrative).

Definition 4: Let the cognitive level $AL_m = (AL_{1m}, AL_{2m}, AL_{3m}, \ldots, AL_{km})$, AL_{im} denote the learner's L_m cognitive level of the knowledge point i, AL_i =(1=beginner, 2=intermediate, 3=advanced, 4=advanced). Calculate the cognitive level of the learner:

$$AL = \sum_{i=1}^{K} Cdi / M^* \max Cd \tag{2}$$

where, C_{di} denotes the grade of the i th vocal discipline; M denotes the total number of vocal disciplines; and $\max cd$ denotes the highest grade obtained in all vocal disciplines.

Definition 5: Let the available study time $AT_m = (AT_1, AT_2, AT_3, ..., AT_m)$, AT_i denotes the available learning time of the i th learner, and the learning time is measured in minutes.

(2) Knowledge point model

The generation of personalized learning path not only requires the construction of appropriate and standardized learner model, but also needs to consider the correlation relationship between knowledge, so as to ensure the scientific and rationality of the construction of personalized learning path.

Definition 6: Let n knowledge points are organized as $(KP_l, KP_2, KP_3, ..., KP_n)$ is presented in the form of KP_j

denoting the j th knowledge point. Each knowledge point KP_j possesses basic attributes such as ID, name, and functional attributes such as media type, difficulty level, and required learning time.

Definition 7: Let the learning object cover the set of knowledge points $MC_n = (MC_{1n}, MC_{2n}, MC_{3n}, ..., MC_{kn})$, and MS_{jn} denotes the knowledge points contained in the j th learning object.

Definition 8: Let the media type $MS_n = (MS_{1n}, MS_{2n}, MS_{3n}, MS_{4n})$, MS_{jn} denote the KP_j representation of the learning object, MS_j = (1=Forum/Notes , 2=videos/blogs, 3=formulas/cases, 4=study plans/lesson plans).

Definition 9: Let the difficulty level $DL_n = (DL_1, DL_2, DL_3, ..., DL_k)$, DL_j denotes the difficulty level of KP_j, and DL_i =(1=Knowledge, 2=Understanding, 3=Mastery, 4=Application).

Definition 10: Let the required learning time $MT_n = (MT_l, MT_2, MT_3, ..., MT_k)$, ML_j denotes the learning time required for the j th learning object, and the learning time is measured in minutes.

II. C.Personalized Learning Path Recommendation Model

II. C. 1) Knowledge modeling

(1) Data acquisition and processing

The data in this paper mainly comes from Baidu library, and the obtained documents are uniformly transformed into word text. Then use mammoth library to transform the word text into semi-structured documents, and then process the data. Each knowledge point is described in detail in the course text, which hides numerous related entities. In this paper, CNN+LSTM+CRF is used to extract entities from the course data. At the same time, some lexemes are manually labeled to improve the accuracy of knowledge point recognition. According to the cognitive order of learners, the semantic relationships between knowledge points can be categorized into antecedent, successor and parallel relationships.

a) Antecedent relationship

When Knowledge Point 1 is the precursor of Knowledge Point 2, it means that Knowledge Point 1 is the precursor of Knowledge Point 2, i.e. Knowledge Point 2 can be learned only after Knowledge Point 1 is completed.

b) Successor relationship

When Knowledge Point 1 is the successor of Knowledge Point 2, it means that Knowledge Point 1 is the successor of Knowledge Point 2, i.e., Knowledge Point 1 can be studied only after Knowledge Point 2 is completed.

c) Parallel relationship

When Knowledge Point 1 and Knowledge Point 2 are independent of each other, whichever Knowledge Point is studied first will not affect the learning of the other Knowledge Point. In this case, it means that knowledge point 1 and knowledge point 2 are parallel.

(2) Knowledge point extraction

At the end of data processing, HanLP lexical algorithm is used to perform initial lexical segmentation of the course text. Considering that, there are no specialized chemical terms in the participle dictionary of HanLP participle algorithm, this study introduces new word merging algorithm to improve the participle result. According to experience, the number of keywords extracted, directly affects the accuracy, recall, and F-value of the keyword results. In the course of this study, the accuracy, recall, and F-value of extraction are calculated separately for different numbers of keywords extracted.

(3) Knowledge point relationship design

As can be seen from the actual study, in each course, there will be concepts, definitions and other basic knowledge, such knowledge is the first to learn. With the deepening of learning, the knowledge condensed by a combination of multiple basic knowledge will be learned. Therefore, in this paper, the nodes in the knowledge graph are divided into two categories, one is the meta-knowledge point that represents the basic knowledge, and the other is the composite knowledge point that is condensed by the combination of multiple basic knowledge.

To represent the correlation between knowledge points, weights are set on the edges between knowledge points. The adjusted cosine similarity method was chosen to calculate the weights:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{3}$$

(4) Blind Knowledge Extraction Model

In order to describe the learners' test results into a mathematical form for data analysis, a cognitive judgment model is introduced.

Definition 1: Given the set of exercises $Q=\{q_1,q_2,...,q_M\}$, the set of knowledge points $K=\{k_1,k_2,...,k_N\}$, and the matrix of exercise knowledge points $D=[d_{m\times n}]_{M\times N}$, where $d_{m\times n}=1$ indicates that exercise m examines the n th knowledge point, and $d_{m\times n}=0$ indicates that exercise m does not examine the n th knowledge point. $n=1,2,...,N, m=1,2,...,M$.

Definition 2: Given a set of learners $P=\{P_1,P_2,...,P_U\}$, the matrix of exercise scores $R=[r_{u\times m}]_{U\times M}$, and the vector of mastery of the knowledge points $\alpha_u=\{\alpha_{u_{k_1}},\alpha_{u_{k_2}},\ldots,\alpha_{u_{k_N}}\}$. Where $r_{u\times m}=1$ indicates that learner u answered exercise m correctly, $r_{u\times m}=0$ indicates that it was not answered correctly, $\alpha_{u_{k_n}}=1$ indicates that it has been mastered, and $\alpha_{u_{k_n}}=0$ indicates not mastered. $u=1,2,...,U$.

The DINA model introduces a miss rate s_m and a guess rate g_m to characterize a student's true answer. The model assumes that the learner's P_u mastery of the knowledge point α_u is known, and the probability of answering the exercise question q_m correctly under this condition.

$$P_m(\alpha_u)=(R_{u\times m}=1\mid\alpha_u)=g_m{}^{1-\eta_{u\times m}}(1-s_m)^{\eta_{u\times m}} \tag{4}$$

where $\eta_{u\times m}$ denotes the result of assuming that the mastery of the knowledge point α_u is already known, and then answering the exercise q_m:

$$\eta_{u\times m}=\prod_{n=1}^{N}\alpha_{un}^{d_{m\times n}} \tag{5}$$

The DINA model counts the learner's scores on each exercise, then calculates the posterior probability of the scores, and finally maximizes the posterior probability. This results in the learner's mastery vector of knowledge, which is calculated as follows:

$$\begin{aligned}\hat{\alpha}_u &=\arg\max_\alpha(\alpha\mid R_u)\\ &=\arg\max_\alpha L(R_u\mid\alpha,\hat{s}_m,\hat{g}_m)P(\alpha)\\ &=\arg\max_\alpha xL(R_u\mid\alpha,\hat{s}_m,\hat{g}_m)\\ &=\arg\max_\alpha\prod_{m=1}^{M}P(R_u\mid\alpha,\hat{s}_m,\hat{g}_m)\end{aligned} \tag{6}$$

II. C. 2) Personalized Learning Path Recommendation Model

In this paper, the personalized learning path recommendation model is divided into two main parts:

Embed the feature information of the blind knowledge points into RankNet algorithm [13] to perform the initial ranking of the blind knowledge points.

The original feature vectors corresponding to the primitively ranked sequences are input into the Transformer algorithm, and then the learner personalized feature information is introduced for the reordering of the initial path sequences.

(1) Learning path personalized recommendation model construction

As can be seen from the learning path recommendation model diagram, this study introduces the reordering idea. In the learning sorting algorithm, RankNet algorithm is closer to the essence of the sorting problem by considering the partial order relationship between document pairs to realize document sorting. Therefore, in this paper, the neural network-based RankNet algorithm is chosen to analyze from the point of view of knowledge point pairs to generate the initial sequence of knowledge points Kn. The learning sequencing method generates a targeted initial list of knowledge points for reordering based on the candidate set of knowledge points that each learner requests to learn Kn. The initial knowledge point initial feature vector corresponding to the list Kn as the input to the Transformer algorithm, combined with the pre-trained learner personalization matrix PV, the learnable positional encoding PE, to generate the encoding layer's input vector.

(2) Topological sorting

The final reordering sequence and blind knowledge point mapping are combined with the topological sorting algorithm in order to preserve the logically sequential learning relationship of the knowledge points, i.e., the final sequence of knowledge points follows the cognitive development of the learner.

III. Analysis of the optimization of vocal music teaching mode and the effect of personalized learning path design

III. A. Personalized Learning Path Generation

Based on the differences in learner groups, this paper designs goal-first path generation algorithms for initial learners to obtain learning paths that satisfy the learning goals, and researches the dynamic update mechanism of learning paths based on the learning progress, and designs process-first path generation algorithms for process learners to obtain dynamic learning paths that satisfy both the learning goals and the characteristics of learning behaviors.

Based on the depth-first search (DFS) to generate a set of feasible paths, the overall recommendation degree of the path as the main basis will be the optimal quality of the learning path recommended to the initial learner who has not yet begun to learn. Each sub-recommendation degree calculation strategy for the algorithm in the course recommendation degree weight vector $\vec{w}$ set the following value scheme:

1) Considering that the goal-first learning path algorithm takes the average recommendation degree of all courses in the path as the path recommendation degree, this paper uniformly defines the alternative course recommendation degree R with the four sub-recommendation degrees in the range of [0.0, 1.0], and sets the value interval of the weight factor to 0.1.

2) The content value degree is the primary consideration for learners to choose a course, and its weight value $0.5 \le w_v < 1.0$, i.e., the possible values of w_v are {0.5, 0.6, 0.7, 0.8, 0.9, 1.0}.

3) The learner interest degree is based mainly on the relationship between courses and taps into the learner's potential interest in learning, which has the least influence on R and is weighted $0.0 < w_u \le (1-0.5)/3 = 1/6$, i.e. $w_u = 0.1$.

4)Attribute Recommendation Degree is the second measurement perspective based on content recommendation, which influences R to a lesser extent than Content Value Degree, and at the same time should exceed Learner Interest Degree, with the weight $w_u < w_a < w_v$, i.e., there are possible values of w_a of {0.2, 0.3, 0.4}.

5) Neighbor recommendation degree, as a characterization of collaborative filtering recommendation technology, has a good recommendation effect in the case of a large group of learners, but there is also a user cold start and sparse problem, so the degree of influence on R is similar to the attribute recommendation degree, and its weight $w_u < w_n < w_v$, i.e., the possible values of w_n are {0.2, 0.3, 0.4}.

6) Combining $w_v + w_a + w_u + w_n = 1$ yields that the weight vector $\vec{W}$ takes the values [0.5, 0.2, 0.1, 0.2].

Table 1 shows the input results of the given algorithm. According to the algorithm the goal prioritized path lp^G ={“Python Singing Mechanics and Techniques” of “Abdominal Breathing Training. The Art of Singing“ Vowel Coherence Exercise: Biting and Spitting Clearly Vocal Teaching Method”, Python Expression Body Coordination“ code for ‘Performance Vocal Practicing Lessons,’ Mask Resonance Development Python Singing Resonance”), the course prerequisite relationships in the path are shown in Figure 2, where the Py data node represents the vocal practice content. Table 2 shows the values of the course node attributes contained in lp^G .

Table 1: The given algorithm input results

Multi-learner portrait	Learning goal	U_T ={“Machine learning”}
	Knowledge master situation model	U_M = {“Abdominal breathing training, vowel, Eye mask development, Make words clear”}
	Learning behavior model	U_B = [“And, In the short term, Generally, Theory, “PC”]
Course knowledge map		G
A collection of courses that have been studied		$L = \varnothing$
The recommended weight vector		$\overrightarrow{W} = [0.5, 0.2, 0.1, 0.2]^T$
The path recommendation approximation threshold		$\rho = 1.2$

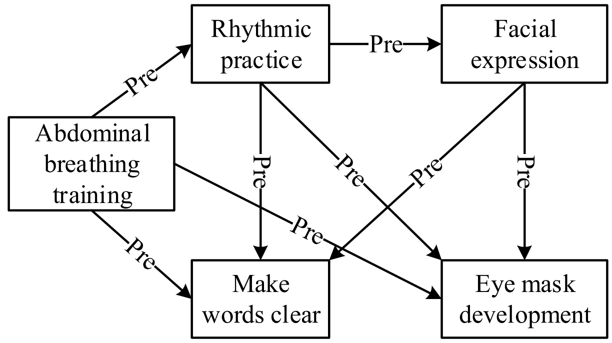

Figure 2: The course of the course is first changed

Table 2: lp^{G} contains the course node attribute values

Name	Source	Duration	Type	Score
Abdominal breathing training	Singing mechanism and technique	Metaphase	Practice	4.93
Vowel	The art of singing	Short term	Practice	4.87
Eye mask development	Singing resonance	Short term	Theory	4.85
Make words clear	The method of vocal music teaching	Metaphase	Practice	4.96
Expression and body coordination	The practice of acting	Metaphase	Practice	4.73

In this paper, we design the following learning path dynamic update mechanism:

1) Update trigger condition: the update cycle of course knowledge graph is Tg, and the update trigger condition of multivariate learner portrait is T_U, so the update trigger condition of recommended learning path $T=\{T_G,T_U\}$ is defined.

2) When the update cycle T_G is reached, the course knowledge graph is updated based on the current online course data.

3) When the update trigger condition T_U is satisfied, the learning objective U_T in the multivariate learner portrait U remains unchanged, and as the learner adds a new learned course related to the learning objective, his/her alternative course sequence CS, and the set of learned courses L are changed, and the learning behavior data generated when learning the course also triggers the knowledge mastery model U_M and learning behavior feature model U_B are updated, at this time the alternative course recommendation degree R needs to be recalculated, and further the recommended learning path needs to be re-generated in order to improve the matching degree of the path.

4) When the update trigger condition T is satisfied, firstly, the collection of learned courses is updated, and secondly, the situation of T is judged, if T is the update cycle of course knowledge graph T_G, then the course knowledge graph is updated according to the online course data, or else the learner's online learning behavior data is updated to update his/her knowledge mastery and learning behavior characteristics.

On the basis of the dynamic update mechanism of learning path, the process priority path generation algorithm is proposed in combination with the goal priority path generation algorithm. The algorithm iteratively generates the target priority path by adjusting the course knowledge graph and multiple learner profiles under each update trigger condition, realizing the dynamic recommendation of the learning path.

The dynamic update mechanism of learning paths is applied to generate process priority paths that support dynamic adjustment for process learners by combining online course data and learner behavior interaction data, which improves the rationality and accuracy of the CKG-2PLPR model. According to the dynamic update mechanism of the learning path, when the update trigger condition T is met and T is the update cycle of the course knowledge graph T_G, and the online learning platform deactivates the course "vocal teaching", then the CKG-2PLPR model needs to update the course knowledge graph and regenerate the process priority learning path lp^D={"Abdominal breathing training - singing mechanism and skills, vowel coherence practice - the art of singing, articulation and pronunciation - vocal teaching method, Expression and Body Coordination—Facial Exercise Vocal Lesson, Mask Resonance Development—Singing Resonance"), the updated lp^D course node relationship is shown in Figure 3.

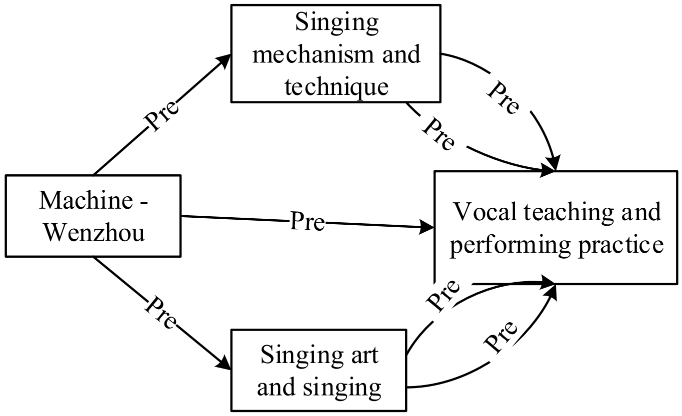

Figure 3: The relationship between the course nodes in lp^D

III. B. Analysis of the effect of personalized recommendation after the optimization of teaching mode

III. B. 1) Recommended Path Reliability Assessment

(1) Experimental setup and evaluation indexes

In this paper, KPIRank algorithm is utilized to calculate the degree of importance of knowledge points, and in order to verify the advantages brought by the improved PageRank algorithm, a control group is set up to compare the generated paths obtained by calculating the importance of knowledge points using PageRank algorithm with the expert paths. Namely:

$$Deviation(Tp) = \sum_{i=1}^{n} abs(Gpath\_rank(p_i) - path\_rank(p_i)) \tag{7}$$

where Tp is the target knowledge point, p_i is the knowledge point in the pathpath, $Gpath\_rank(p_i)$ is the ranking of p_i on the recommendation path, and $path\_rank(p_i)$ is the ranking of p_i on the expert path.

(2) Analysis of experimental results

In order to verify the reliability of the recommended path, 20 graduate students of computer-related majors were invited to participate in the experiment. The experimental results of the deviation of the recommended path from the expert path are shown in Figure 4. Whether using the KPIRank algorithm or PageRank algorithm proposed in this paper to calculate the importance of knowledge points, the obtained deviation value of learning path and expert path is within 30, which indicates that the order of knowledge points in the recommended learning path is similar to the order of knowledge points in the expert path, thus proving the reliability of the recommended path strategy proposed in this paper. The final path recommendation of the knowledge points through the learner's mastery of the knowledge points measurement also reflects the personalization of the recommended path in this paper.

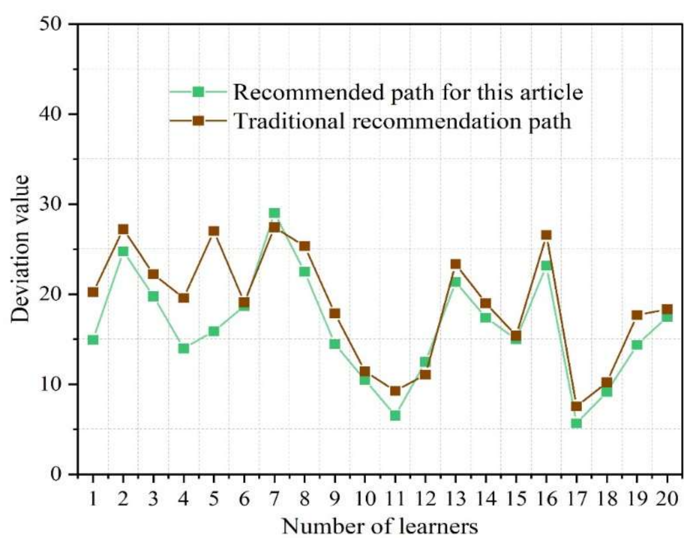

Figure 4: The recommended path and the deviation experiment of the expert path

III. B. 2) Mastery model assessment

In order to verify the advantage of utilizing this paper's model for learners' mastery of knowledge points, this paper uses this model to compare with the baseline model on the public dataset as well as this paper's self-constructed dataset. In this paper, IRT and DINA are used as the baseline models for the comparison experiments.

(1) Experimental setup

In this paper, we use the public dataset Assistments 2023-2024 as well as our self-constructed dataset kpoint-exercise to evaluate the model used in this paper, and the basic information of the dataset is shown in Table 3.

Table 3: Statistical results of the data set

Data set	Item number	Number of knowledge	Student number	Number of records	Each question contains an average of knowledge
Assistments 2023-2024	176328	118	4055	324110	2.22
kpoint-exercise	310	205	1010	5015	3.67

In this paper, AUC, ACC and RMSE are used as evaluation metrics.RMSE stands for Root Mean Square Error and is used to measure the difference between the predicted value of the model and the true value:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_i - \hat{y}_i)^2} \tag{8}$$

where y_i represents the actual values of student answers and $\hat{y}_i$ represents the model predictions.

(2) Parameter setting

In order to better realize the model performance prediction, this paper adopts different ratios of 0.7, 0.8, 0.9 and 1.0 to divide the dataset into training set and test set for experimentation. The experimental results of the proportional division on the 2 public datasets are shown in Table 4. Through the changes of ACC and AUC of each model with different proportion of data division, using the proportion of 0.9 or 1.0 to divide the data set makes the model work best.

Table 4: The proportion of the results of the experiment in two public data sets

Data set	Index	Method	Data set division ratio			
			0.7	0.8	0.9	1.0
Assistments 2023-2024	ACC	DINA	0.64434	0.64729	0.65181	0.65113
		IRT	0.66855	0.67229	0.67602	0.67602
		This method	0.85375	0.86397	0.88001	0.95261
	AUC	DINA	0.65566	0.65871	0.65713	0.65407
		IRT	0.67907	0.68665	0.67681	0.67534
		This method	0.85436	0.87862	0.89313	0.94704
kpoint-exercise	ACC	DINA	0.61097	0.62387	0.62081	0.60792
		IRT	0.63518	0.63824	0.63744	0.6345
		This method	0.86176	0.89047	0.91352	0.95211
	AUC	DINA	0.65566	0.65871	0.65713	0.65407
		IRT	0.67907	0.68665	0.67681	0.67534
		This method	0.85456	0.87882	0.92633	0.96444

(3) Analysis of experimental results

The experimental results on different data sets are shown in Table 5. Through the data in the table, this paper's model is better than the baseline model both in the public dataset and in the knowledge point exercise dataset constructed in this paper, which proves the effectiveness of this paper's model. Therefore, using the model of this paper to realize the prediction of learners' mastery of knowledge points can more accurately grasp the degree of mastery of learners, and provide a basis for the later knowledge point learning path recommendation.

Table 5: Experimental results on different data sets

Data set	Index	DINA	IRT	This method
Assistments 2023-2024	AUC	0.7524	0.7832	0.9438
	ACC	0.7474	0.8607	0.9262
	RMSE	0.5695	0.6921	0.3318
kpoint-exercise	AUC	0.7293	0.8487	0.9482
	ACC	0.7134	0.6979	0.9438
	RMSE	0.5444	0.5953	0.3413

III. B. 3) Assessment of Learners' Learning Gains

(1) Assessment Indicators

In order to assess whether learners learning according to the path recommended in this paper will bring better learning benefits, this paper sets learning benefit indicators:

$$B_{ij} = \frac{K_{lj} - K_{cj}}{K_{tj} - K_{cj}} \tag{9}$$

B_{ij} represents the learning benefit of the target knowledge point j after the learner i has followed the path, K_{lj} represents the number of questions answered correctly by the learner after following the path, K_{tj} represents the total number of questions associated with the knowledge point j, and K_{cj} represents the number of questions answered correctly by the learner before learning.

(2) Experimental setup

After the study, the participants were asked to evaluate the learning benefit of each learner, and finally calculated the average benefit of 5 participants in the same group as the most beneficial benefit of the group:

$$E_j = \frac{\sum_{i=1}^{5} B_{ij}}{5} \tag{10}$$

(3) Experimental process and result analysis

The results of learners' gains are shown in Table 6. It is found that the gain value of the first group is lower than the other three groups, indicating that only learning the target knowledge points does not correctly complete most of the topics, reflecting the necessity of the learning path. The learning gain of the third group (0.5104) is higher than that of the second group (0.2437), which indicates that the path recommended in this paper is more suitable for completing the learning of knowledge related to the target knowledge points than the path organized by the learners themselves, and illustrates the effectiveness of the path recommended in this paper. The comparison of the results of the learning gains of the three and four groups reflects that the in-depth learning path based on the inclusion relationship may be more favorable to the learning of the target knowledge points.

Table 6: The results of the learner's earnings

Group	Participant	The number of subjects that you answer before you study	Learn the number of subjects after study	Learning benefits of learners	Revenue per group
Group 1	1	11	15	0.083	0.1915
	2	9	9	0.000	
	3	17	20	0.4289	
	4	8	16	0.2857	
	5	5	9	0.157	
Group 2	6	13	17	0.2003	0.2437
	7	9	15	0.3321	
	8	12	15	0.2304	
	9	13	16	0.2497	
	10	5	10	0.2007	
Group 3	11	7	19	0.6111	0.5104
	12	5	12	0.4124	
	13	16	19	0.3331	

	14	14	22	0.7273	
	15	8	17	0.4672	
Group 4	16	18	23	0.714	0.4593
	17	10	16	0.3747	
	18	4	10	0.3002	
	19	17	21	0.3744	
	20	8	18	0.5327	

III. B. 4) Assessment of user satisfaction

(1) Assessment indicators

In order to assess learners' satisfaction with the recommended learning paths, this paper uses a questionnaire to collect M learners' subjective ratings of the recommended paths. We use a Likert scale to quantify learner satisfaction. For assessing learners' satisfaction with the recommended path:

$$Satisfed(path) = \frac{\sum_{j=1}^{M} score(Path_r)}{M} \tag{11}$$

(2) Experimental results

In order to assess the learners' satisfaction with the results of the recommended path, a satisfaction survey was conducted on 20 students, and the results of the satisfaction rating of the recommended path are shown in Table 7, and finally the formula was utilized to obtain a user satisfaction of 3.80851, which indicates that most of the learners are satisfied with the recommended path, and it proves that the learning path recommending method proposed in this paper can provide users with a satisfactory learning path.

Table 7: The satisfaction score for the recommended path

Score	Number(20)	Satisfaction score	Average satisfaction score
1	0	0	0
2	2	2.96898	2.50034
		2.0317	
3	3	3.12888	3.42851
		3.88481	
		3.27184	
4	10	4.08919	4.30518
		4.70826	
		4.92952	
		4.1656	
		4.02952	
		4.08919	
		4.66948	
		4.11624	
		4.08919	
		4.1656	
5	5	5.0000	5
		5.0000	
		5.0000	
		5.0000	
		5.0000	

IV. Conclusion

Through the research on the optimization of vocal music teaching mode, the personalized learning path design method proposed in this paper shows remarkable effects. Especially in the generation and recommendation of personalized learning paths, it combines depth-first search (DFS) and AI algorithms, which effectively improves the learners' mastery of knowledge points. In the experiment, the accuracy of path recommendation based on the model of this paper is 92.61%, which is about 15% higher than the traditional method. By comparing with DINA and IRT models, the performance of this paper's method is better on multiple datasets, especially on the “Assistments 2023-2024” dataset, the AUC value of the model reaches 94.38%. In addition, this paper also adopts the user learning benefit and satisfaction assessment, and the results show that the learners are highly satisfied with the recommended learning paths, and the learning benefit is significantly improved. The experimental results of learning benefit show that based on the path recommended in this paper, the learning benefit of learners in the target knowledge point is increased by about 50%, which further proves the effectiveness of the personalized learning path. In summary, the personalized learning path recommendation model proposed in this paper has a wide range of application prospects and can significantly improve the quality and effectiveness of vocal music teaching.

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