International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 5206-5218

https://doi.org/10.70517/ijhsa464361

Research on Intelligent Optimization Algorithms for Efficient Acquisition of Vocal Skills

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Abstract With the continuous development of vocal music education, traditional teaching methods have gradually failed to meet the needs of personalized and efficient learning. This study proposes a learning path recommendation model for vocal skills based on knowledge graph and Dijkstra's algorithm, which aims to provide a personalized learning path planning method for vocal education. First, the study constructed a knowledge graph of vocal music discipline containing 2245 knowledge points and 12 kinds of relationships, which covers the course content, knowledge points and their interrelationships. On this basis, Dijkstra's algorithm was used to solve the shortest learning path from the mastered knowledge points to the target knowledge points. The experimental results show that the learning path recommended based on the model can effectively improve students' learning efficiency. In the experimental group, the students' vocal skill scores increased from 5.56 to 8.14, with an improvement of 46.4%. Compared with the control group, the score of the experimental group was significantly higher, and the personalized features of the path recommendation significantly improved the learners' skill mastery. The study suggests that the learning path recommendation combining knowledge graph and Dijkstra's algorithm can provide students with more accurate and efficient learning guidance.

Index Terms Vocal skills, knowledge graph, Dijkstra's algorithm, learning path, personalized recommendation, skill mastery

I. Introduction

Vocal music teaching is an important part of music education, which is of great significance for cultivating talents with good music literacy and aesthetic ability [1], [2]. In vocal music teaching, good skill mastery is an important foundation for improving vocal music ability, but at present, in vocal music teaching, due to the backwardness of the school teaching strategy and the teachers' teaching ability can not keep up with the development of the times, resulting in vocal music teaching can not be well mastered vocal music skills [3]-[6]. Based on this, the only way to promote the mastery of skills in vocal music teaching is to innovate practical teaching [7].

In recent years, with the wide application of artificial intelligence in education. Among them, the shortest path problem, as a common teaching problem, not only has a wide range of application value in real life, but also occupies an important position in vocal music teaching [8]-[10]. The shortest path algorithm is an algorithm that calculates the shortest distance between two nodes in a graph, and in computer science, the shortest path algorithm is one of the most basic algorithms in graph theory [11], [12]. The most common application is in routing algorithms to find the shortest path between two network nodes [13]. It can optimize the process of skill mastery in acoustic teaching, which not only effectively reduces the time of learning, but also effectively improves the effect of acoustic skill mastery.

In this study, we first constructed a complete knowledge map of vocal music discipline, covering the core knowledge points and their interrelationships in vocal music teaching. Then, Dijkstra's algorithm was utilized to calculate the shortest path from the mastered knowledge points to the target knowledge points based on the current mastery of the students. This process not only takes into account the relationship between the knowledge points, but also combines the students' learning characteristics and mastered knowledge points to ensure that the recommended learning path is more accurate and practical. Finally, the effectiveness of the model in vocal skills learning is verified through comparison experiments with other recommendation methods.

II. A Knowledge Graph-based Recommendation Model for Vocal Skill Mastery Paths

This chapter constructs a path recommendation model for vocal skill mastery in practical teaching innovation based on subject knowledge mapping and uses Dijkstra's algorithm for shortest path solving.

II. A.Knowledge mapping

Knowledge graph, as a commonly used knowledge base, mainly adopts a graphical structure to visualize and intuitively present the relationships between real-world entities, events and other information. By applying knowledge graph, it can help machines to understand and process this knowledge with human thinking, and guide students to better learn and master the relevant knowledge in the real world. The knowledge graph representation is in the form of:

$$G = \{(h,r,t) \mid h \in E, r \in R, t \in E\} \tag{1}$$

In Eq. (1), E and R represent the vertex set and edge set of the knowledge graph, respectively.

During the construction of knowledge graph, it is necessary to collect and organize the required data sources, and when the data sources are organized, the following two methods are used to process the organized data sources:

(1) Top-down processing

In this way, experts in the relevant fields accurately define the concepts of top layer and edges, so as to make the knowledge graph structure more standardized and standardized, and at the same time, divide and define the sub-concepts, so as to promote the continuous expansion of the knowledge graph structure system.

(2) Bottom-up processing

Under this approach, relevant domain experts need to redefine and label the low-level concepts, so that the entire knowledge graph presents a higher coverage, thus further improving the accuracy of the knowledge graph. In this paper, during the construction of the knowledge graph, the bottom-up processing method is preferred, which can realize the accurate updating and construction of the knowledge graph, and reduce the cost of manpower, material and financial resources.

II. B.Construction of Knowledge Maps for Vocal Music Disciplines

II. B. 1) Constructive thinking

The process of knowledge graph construction can be understood as the extraction and refinement of relational data characterized by Resource Description Framework (RDF) triples. In this paper, the construction of the knowledge graph of vocal music disciplines integrates manual and automatic methods, combining both top-down and bottom-up approaches. As shown in Figure 1, firstly, based on the professional catalog of vocal discipline established by the Ministry of Education and the professional teaching standards issued by the teaching index committees, etc., for the professional cultivation specifications of different vocal disciplines, we refine the typical work tasks and vocational ability requirements corresponding to their core work areas, construct the curriculum system based on the work process, make clear the main teaching contents and requirements of the professional core courses, and form a logical framework of the knowledge system of vocal disciplines. On this basis, define the entity class, attribute class and relationship class of the professional core curriculum knowledge map, and complete the construction of the ontology structure from top to bottom, which requires the participation of experts in the field of vocal music. Secondly, using knowledge extraction, knowledge fusion and other technologies, a bottom-up approach is adopted to change multi-source heterogeneous data into structured knowledge triples, forming a specific instance data layer. Finally, the knowledge is stored in the graph database to realize the construction of the knowledge graph of vocal discipline. In the subsequent use of the knowledge graph in the process of updating the data layer, while the ontology structure is relatively stable and will not be updated frequently.

II. B. 2) Ontology construction of vocal music discipline

The main role of an ontology is to use a formal description language to provide a shared, consistent semantic model for defining and organizing concepts, attributes, and relationships within the domain, as a guide for subsequent knowledge extraction. Constructing a high-quality knowledge ontology for the discipline of vocal music is a prerequisite for building a complete and accurate knowledge map for the discipline of vocal music. The knowledge map for the discipline of vocal music has extremely stringent requirements for data quality, and focuses on consistency and standardization, scalability and updatability, and quality of knowledge and verifiability in the construction process. In this paper, we use manual construction to define the types of entity types, attributes and inter-entity relationships under the guidance of experts in the field of vocal music discipline, some of which are shown in Figure 2.

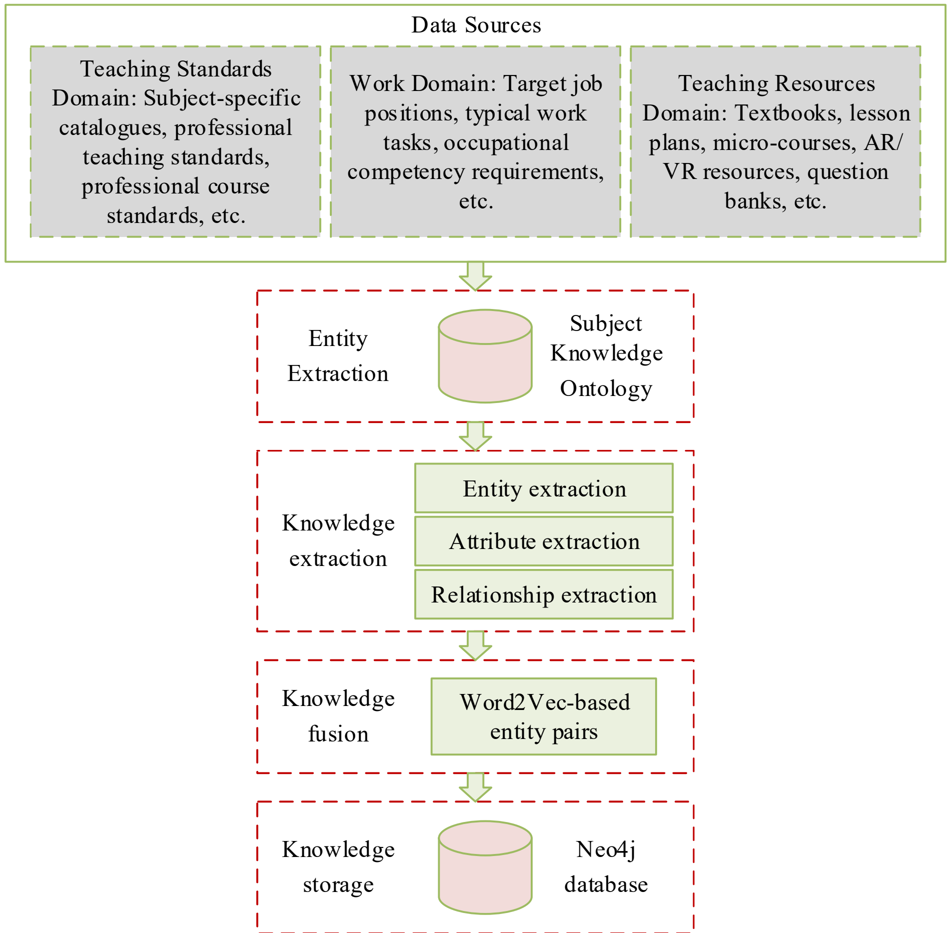

Figure 1: The construction process of the knowledge graph of vocal music discipline

II. B. 3) Vocal Subject Knowledge Extraction

Knowledge mapping data sources include semi-structured and unstructured data such as teaching text, video, audio, etc., which are divided into two parts: entity extraction and relationship extraction. Entity extraction is the process of extracting the knowledge and skills related to the topic from the data, and then mining the relationship between the entities to form the ternary representation of "entity-relationship-entity". The teaching program for vocal music majors contains a number of courses, and there is a relationship between the courses, and there are a number of different types of teaching resources in the courses, and the teaching resources are designed to explain the knowledge and skills, and there is a relationship between the knowledge points such as containment, juxtaposition, synonymy, antecedent, and so on, and the relationship between the entities is defined in this paper according to the actual needs, and some of the relationship definitions are shown in Table 1.

II. B. 4) Knowledge Integration and Storage of Vocal Disciplines

The overall task of knowledge fusion is to calculate the similarity between entities and delineate those entities whose similarity is within a certain threshold as the same entity. Data classification and cleaning and filtering are performed through the BERT model, and the alignment of entities is completed by using Word2Vec to determine the semantic similarity between them through the distance between words. Finally, the ternary knowledge obtained after information extraction and knowledge fusion is persistently stored in the non-relational graph database Neo4j using Cypher language to generate a structured knowledge semantic network, which helps the implementation of the subsequent functions and performance optimization. In this paper, we take the professional training program of vocal music, core work area, and curriculum standard of vocal music as the main data source, and the resources of network learning platform as the supplementary auxiliary data source to construct the knowledge mapping of vocal music discipline. After ontology construction, knowledge extraction, knowledge fusion and storage in the Neo4j graph database, the knowledge mapping of the vocal music professional part is shown in Figure 3.

Table 1: Definitions of relationships among some entities

Entity type	Relationship	Relational value range
Profession	Contain	Course
Course	Front-facing	Course
Course	Follow-on	Course
Course	Contain	Teaching plans, courseware, exercises, micro-lessons, virtual simulations, etc
Course	Contain	Knowledge and skill points
Knowledge and skill points	Front-facing	Knowledge and skill points
	Follow-on	
	Contain	
	Synonymous	
Teaching plans, courseware, exercises, micro-lessons, virtual simulations, etc	Contain	Knowledge and skill points

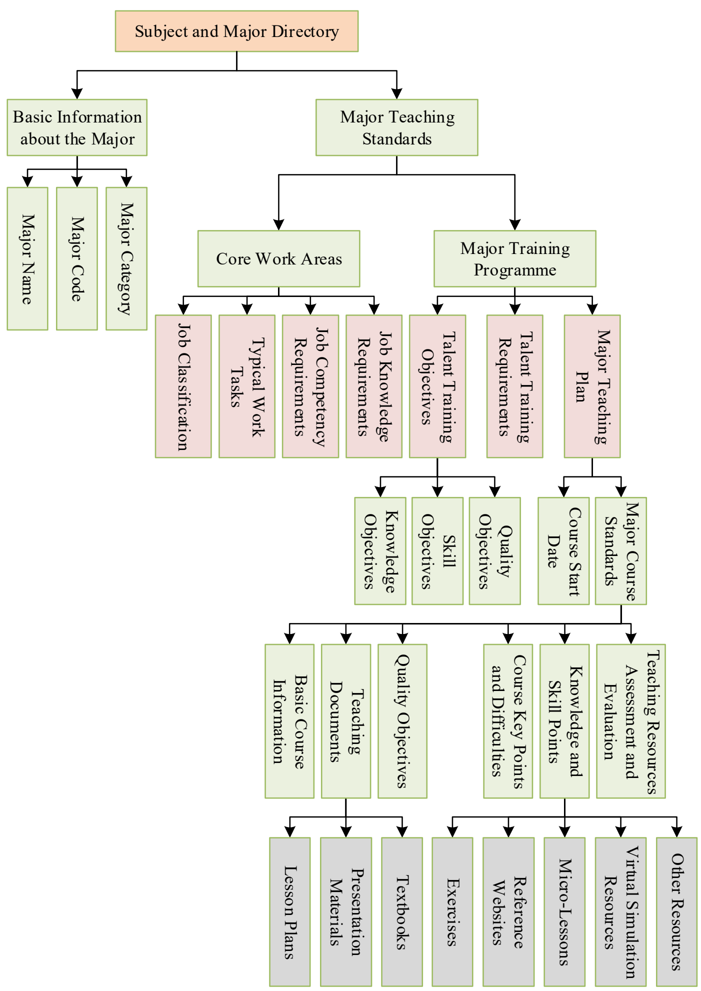

Figure 2: The logical framework of the knowledge system constructed manually

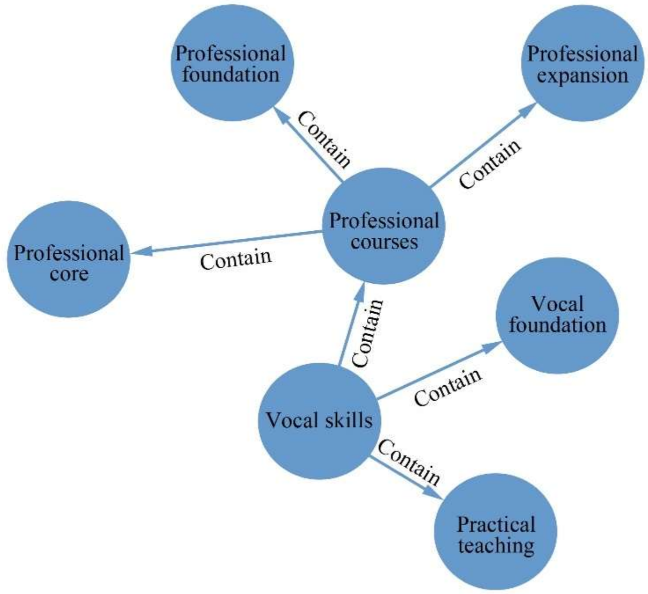

Figure 3: Partial knowledge map of the vocal music major

II. C.Vocal Skills Learning Path Analysis

The learning path represents a complete learning process, and a reasonable learning process itself has continuity, that is, relevant knowledge points cannot be omitted in the learning path. In addition, the learning path represents the sequence of knowledge learning, and the sequence of learning is closely related to the antecedent relationship and inclusion relationship in the knowledge graph, so when the learning path is recommended, it cannot violate the educational relationship of the knowledge points themselves. The formation of learning paths is related to the order of knowledge recommendation, and different recommendation strategies will form different learning paths. No matter how to form learning paths, the knowledge points are linked together through some kind of relationship, and the formation of learning paths depends on the educational relationship of the knowledge in the map. Because of the complex relationship between the knowledge points, the learning paths formed are multiple.

In this paper, several principles are considered in the recommendation of learning paths for vocal skills:

First, for the target knowledge points, in order to enable learners to carry out more in-depth learning as much as possible, as much as possible to explore the sub-knowledge of the target knowledge points for the recommendation of learning paths.

The second is to trace the root of the knowledge point and explore the source node of the target knowledge point, which is conducive to the learner's deep understanding of the knowledge point.

A reasonable learning path can show the organizational structure of the nodes in the knowledge graph and help learners learn sequentially. In order to better realize the vocal skill learning path recommendation, this paper proposes the knowledge model of vocal music course based on educational knowledge graph and the vocal skill learning path recommendation strategy. The framework of vocal skills learning path recommendation is shown in Figure 4.

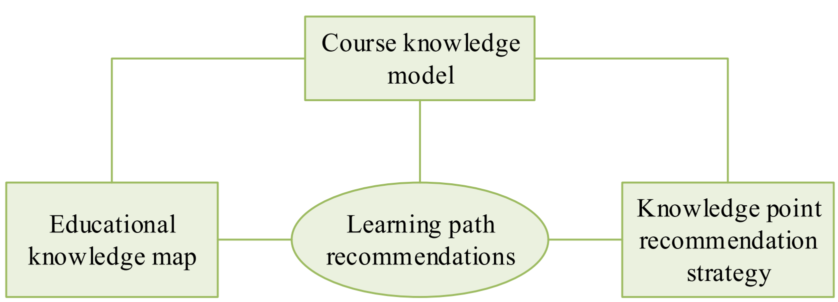

Figure 4: The framework for recommending learning paths of vocal music skills

II. D.Knowledge Modeling of Vocal Music Curriculum

The vocal curriculum knowledge model is designed to better utilize the vocal education knowledge graph for later vocal skill learning path recommendation efforts.

Definition 1: Existence of Learning Paths

The vocal music education knowledge graph EduKG consists of vocal music education entities and vocal music education relationships. Assuming that any two educational entities $EduEntity_i$ and $EduEntity_j$ in the knowledge graph, when there is a relationship between them, it is regarded as the existence of a learning path between these two educational entities, which is recorded as 1. Otherwise, the non-existence of a learning path is recorded as 0, which can be described by the following expression:

$$\begin{cases} (EduEntity_i, EduEntity_j) = 1 & EduEntity_i, EduEntity_j \in EduKG \\ (EduEntity_i, EduEntity_j) = 0 & EduEntity_i, EduEntity_j \in EduKG \end{cases} \tag{2}$$

Definition 2: Knowledge point association types

According to the data schema layer involved in the vocal music education knowledge graph, there are five types of educational relationships in the graph: containment relationship, antecedent relationship, brotherhood relationship, same relationship, and correlation relationship, and in this paper, $EduRe$ is used to represent the type of knowledge point association, defining $EduRe = \{1,2,3,4,5\}$ corresponds to these five types of educational relationships, for example, $EduRe = 1$, which indicates that the entity pair relationship between them is a containment relationship.

Definition 3: Degree of Knowledge Point Relevance

There will be many associated knowledge points around the target knowledge point, and the degree of knowledge point association is the distance $Distance$ between these knowledge points and the target knowledge point. In addition to this, define the distance n from the target knowledge point is called N-order neighboring knowledge points, so the degree of association between a knowledge point and the target knowledge point can be expressed as:

$$Distance = n \tag{3}$$

The degree of association of a knowledge point indicates the importance of the knowledge point to the target knowledge point, i.e., the smaller the value of $Distance$, the more closely the knowledge point is connected to the target knowledge point, and it needs to be prioritized in the recommendation.

Definition 4: Knowledge Point Association Number

Similar to the degree of knowledge point association, the number of knowledge point associations is another measure of the importance of a knowledge point. There are many knowledge points with different relationships around the target knowledge point, when the more knowledge points and relationships around the knowledge point, the more important the knowledge point is in the knowledge graph, in this paper, we use $Connect$ to represent the number of knowledge point associations, when the number of knowledge points around the number of 1, $Connect = 1$, and so on, can be defined by the following formula:

$$Connect = \sum_{Edu\mathrm{Re}=1}^{5} Num(Edu\,\mathrm{Re}) \tag{4}$$

where $Num(EduRe)$ represents the number of knowledge point associations for each educational relation.

Definition 5: Knowledge point incidence

According to vocal education knowledge mapping, educational relationships are bidirectional, i.e., arrows can be bidirectional in the mapping. Knowledge point incidence refers to the direction of the arrow between other knowledge points and that knowledge point from other knowledge points to that knowledge point, i.e., that knowledge point is the first-order antecedent knowledge point of other knowledge points. In this paper, we denote the knowledge point in-degree as In.

Definition 6: Knowledge point out degree

The opposite of the knowledge point in degree is the knowledge point out degree, the knowledge point out degree refers to the other knowledge points and the knowledge point between the arrow direction from the knowledge point outward, pointing to the surrounding other neighboring knowledge points, that is, the knowledge point for the other knowledge points of the first-order successor knowledge point. In this paper, we denote the knowledge point out degree as Out.

Definition 7: Knowledge point learning cost

For the nodes in the knowledge graph of vocal music education, each node is a more important knowledge point in the vocal music course, and learning each knowledge point requires the learner to spend a certain amount of learning time, which can be called the learning cost of the knowledge point. In this paper, the learning cost of a knowledge point is denoted as $Time(EduEntity_i)$, which represents the cost of learning time needed to learn the knowledge point $EduEntity_i$.

In this paper, we propose different recommendation strategies for vocal skill learning paths based on vocal education knowledge graph and vocal curriculum knowledge model, targeting containment relations and other educational relations in vocal knowledge graph. The goal of deep recommendation based on containment relationship is to recommend its contained knowledge points around the target knowledge point as much as possible, which is equivalent to mastering the target knowledge point when there is some mastery of all the knowledge points. The goal of hybrid recommendation based on other relations is to define its recommendation priority for the other four types of educational relations and recommend a vocal skill learning path to the target knowledge point based on the vocal course knowledge model.

II. E. Generation of Knowledge Point Paths

The goal of this phase is to order the knowledge points to be sequenced to ensure that learners master all of the a priori knowledge points of a particular vocal skill before learning it, and to rank the knowledge points in descending order of importance to minimize the overall learning cost.

II. E. 1) Mathematical Modeling of Recommended Learning Paths for Vocal Skills

Define the objective function of this problem as the knowledge point path connectivity (KPC):

$$KPC = \sum_{i \neq j} x_{ij} d_{ij} \tag{5}$$

where X denotes the knowledge point learning path selection matrix and is set:

$$x_{ij} = \begin{cases} 1 & k_i \text{ to } k_j \text{ on the optimal path} \\ 0 & \text{others} \end{cases} \tag{6}$$

D_K denotes the knowledge point relationship matrix. The matrix element d_{ij} denotes the degree of connectivity between knowledge points k_i and k_j and its value is defined as:

$$d_{ij} = \frac{Degree\left|k_j\right|}{ShortestPath\left(k_i, k_j\right)} \tag{7}$$

The shortest path distance from knowledge point k_i to k_j is $ShortestPath\left(k_i, k_j\right)$, and the shorter the distance, the closer the connection between the two knowledge points. If two knowledge points are subordinate to the same knowledge surface, it is considered that there is no sequential order between the two knowledge points, and their shortest path distance is set to 1. If there is no path between the two knowledge points or the two knowledge points are tautologically related, their shortest paths are assigned to the penalty parameter. The formula is defined as follows:

$$ShortestPath\left(k_i, k_j\right) = \begin{cases} ShortestPath\left(k_i, k_j\right) \\ 1 \quad \left(if \ k_i \in KS_n \ and \ k_j \in KS_n\right) \\ A \quad \begin{pmatrix} Penalty\ parameter, if \ k_i = k_j \ or \\ There\ is\ no\ path\ between\ k_i \ and \ k_j \end{pmatrix} \end{cases} \tag{8}$$

The degree of a knowledge point $Degree\left|k_j\right| = in\left|k_i\right| + out\left|k_i\right|$, where $in\left|k_i\right|$ denotes the in-degree of knowledge point k_i and $out\left|k_i\right|$ denotes the out-degree of knowledge point k_i, with a higher degree indicating that the knowledge point is more important in the graph.

II. E. 2) Model solving based on Dijkstra's algorithm

The steps for solving the learning path of knowledge points are as follows: first, according to the cognitive level in the learner's model, mark the set of mastered knowledge points as the starting point of the path in the knowledge atlas of the vocal music discipline, take the target knowledge points as the end point of the path, add the knowledge points for which there exists a connecting path between the starting point and the end point set into the solution space, and the algorithm searches for the optimal path in the solution space. In this paper, Dijkstra's algorithm [14] is used to solve the optimal path.

Dijkstra is a method that searches for the shortest path in the reverse order of increasing path length, as can be seen from the central concept of the method described in Chapter 2, the first step is to find the nearest node to the source, and then the source and the labeled nodes are compared iteratively to obtain an optimal route.

The steps of Dijkstra's algorithm are as follows:

(1) Label the start node with P, denoting the shortest route distance from V_S to V_S itself with $P(V_S)=0$, and label the remaining nodes with T, $T(V_i)=+\infty(i=2,3,\cdots,n)$.

(2) Assume that the v_i node has been labeled with P, and next label the v_j node, knowing that $(v_i,v_j)\in E$ and that v_j is labeled with T. The formula for modifying the T labeling of v_j is as follows:

$$T(v_j)=\min[T(v_j),P(v_j)+l_{ij}] \tag{9}$$

Compare all the nodes that get the T labeling and modify the one with the smallest value to the P labeling:

$$P(v_k)=\min[T(v_i)] \tag{10}$$

When two or more nodes are minimal, they can all be changed to P marking. The algorithm is terminated if all nodes get P-marked, and conversely, the v_k nodes are replaced with v_i and the previous step is continued.

From the basic idea of Dijkstra, it can be seen that this method is a global traversal method, which needs to be performed across nodes, thus giving the method a high degree of confidence and avoiding the pitfalls of local optimization.

III. Experiment on the recommended path of vocal skill mastery and analysis of results

This chapter provides a practical application of the proposed vocal skill mastery path recommendation model, compares it with other recommendation algorithms, and further validates the effectiveness of the recommendation model through a controlled teaching experiment.

III. A. Path recommendation comparison experiment

III. A. 1) Experimental environment

The hardware and software environments used for the experiments in this paper are shown in Table 2.

Table 2: Experimental environment data

Software/hardware environment	Explanation
Operating system	Windows 11 Pro
Memory	32GB
Hard disk	512GB
Processor	AMD Ryzen 5 4600U with Radeon Graphics
Database	MySQL
Development tool	IntelliJ IDEA 2024.2
Development language	Java, Python

III. A. 2) Experimental data sets

The knowledge map of vocal music discipline in colleges and universities utilized in this paper is derived from a total of 2,245 knowledge point entities, 12 kinds of correspondence between knowledge point entities, knowledge point entities and their correspondence, etc., stored in the My SQL base database.

In order to measure the rationality and feasibility of the learning path of vocal skills knowledge points proposed in this paper, the vocal knowledge answer data in the online learning system of a tutoring institution is selected for experimentation. The dataset contains the basic information of students and the data generated by students in the learning activities. A total of 800 students answered 80 vocal music knowledge questions, and a total of 80 knowledge points were examined, with the total number of students' answers being 3364 and the average number of answers being 10.

III. A. 3) Analysis of experimental results

Taking vocal skill p as the target, running PageRank algorithm [15] and CKT model to calculate the *Pagerank* value and *Probability* value of each knowledge point are shown in Table 3.

Table 3: Illustration of *pagerank* value and *probability* value

Knowledge points	*Pagerank* value	*Probability* value
v_1	0.0164	1
v_2	0.009	1
v_3	0.0083	1
v_4	0.017	0.14
v_5	0.024	0.83
v_6	0.019	0.12
v_7	0.007	0.85
v_8	0.014	0.13
v_9	0.007	0.92
v_{10}	0.008	0.14

According to the recommendation process proposed in this paper, Dijkstra's algorithm is used to calculate all the weighted shortest reachable paths to reach the target knowledge point from the set of mastered knowledge points, and then the vocal skill learning path with the minimum cost is selected from the set of shortest reachable paths and recommended to the user. Taking Student A as an example, all the reachable paths from each mastered knowledge point of Student A to reach the target knowledge point are shown in Table 4.

The weighted shortest reachable path from knowledge point v_1 is $v_1 \rightarrow v_5 \rightarrow v_7 \rightarrow p$ (23.69245), the weighted shortest reachable path from knowledge point v_2 is $v_2 \rightarrow v_8 \rightarrow v_6 \rightarrow p$ (94.06835), and the weighted shortest reachable path from knowledge point v_3 is $v_3 \rightarrow v_5 \rightarrow v_7 \rightarrow p$ (23.69245), because the learning path $v_5 \rightarrow v_7 \rightarrow p$ has the lowest cost among all weighted shortest learning paths has the smallest path cost, it is the recommended knowledge point learning path in this paper.

Table 4: Illustration of the learning path

Knowledge point path	Path cost
$v_1 \rightarrow v_5 \rightarrow v_7 \rightarrow p$	23.69245
$v_1 \rightarrow v_5 \rightarrow v_6 \rightarrow p$	51.73826
$v_1 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$	87.64053
$v_1 \rightarrow v_6 \rightarrow p$	42.71654
$v_1 \rightarrow v_6 \rightarrow v_5 \rightarrow v_7 \rightarrow p$	63.92538
$v_1 \rightarrow v_6 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$	128.12903
$v_2 \rightarrow v_8 \rightarrow v_6 \rightarrow p$	94.06835
$v_2 \rightarrow v_8 \rightarrow v_6 \rightarrow v_5 \rightarrow v_7 \rightarrow p$	115.82941
$v_2 \rightarrow v_8 \rightarrow v_6 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$	180.54676
$v_3 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$	87.59231
$v_3 \rightarrow v_5 \rightarrow v_7 \rightarrow p$	23.69245
$v_3 \rightarrow v_5 \rightarrow v_6 \rightarrow p$	51.73826

In this paper, a manual judgment is adopted to distinguish the good and bad results of the recommended paths. The learning path comparison recommendation strategies for student A to learn the target knowledge point p from the mastered knowledge point are shown in Table 5. Among them, Comparison Method 1 is a personalized path recommendation method that combines knowledge graph, PageRank algorithm and Dijkstra algorithm, and Comparison Method 2 is also based on knowledge graph for path recommendation, which proposes a vertical joint strategy based on knowledge graph inclusion relationship and a backtracking search strategy based on knowledge graph antecedent relationship.

The path recommended by Method 1 is: $v_6 \rightarrow p$, and its core idea is to advocate learning as few knowledge points as possible to reduce the consumption of time and energy, so that learners can quickly reach the target knowledge points. However, using the CKT model to predict the probability of Student A answering the exercises related to knowledge point v_6 correctly is 0.12, which indicates that Student A has almost never been exposed to knowledge point v_6. If the learning task of the target knowledge point is to be accomplished, Student A will need to spend more time learning to master knowledge point v_6, which is contrary to the task of quickly reaching the learning of the target knowledge point.

The path recommended by Method 2 is: $v_8 \rightarrow v_6 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$. The centrality of knowledge point v_8, knowledge point v_6 and knowledge point v_5 in this learning path is 0.014, 0.019 and 0.027 respectively, which is of high learning value in the whole knowledge graph, but the probability of acquisition of knowledge point v_8 and knowledge point straight v_6 by the students is 0.13 and 0.12 respectively, which indicates that Student A lacks the reserve of prior knowledge related to these two knowledge points and needs to consume a lot of time to acquire them. The centrality of knowledge point v_{10} is 0.008, and the probability of student A answering the questions related to this knowledge point is 0.14, and this knowledge point is the penultimate knowledge point on the learning path, if student A chooses this path for learning, when arriving at this knowledge point, student A's concentration and interest in learning are reduced, and at this moment, consuming more energy to acquire knowledge points of lower learning value is not conducive to the rapid achievement of his learning goals. It is not conducive to the rapid achievement of the learning objectives. Method 2 advocates as deep as possible, fine, more to traverse the knowledge points, so as to lay the foundation for subsequent learning and rapid mastery of knowledge points, but in the early learning, always recommend a large number of students do not know the knowledge points, it is easy to hit the students' confidence and interest, and the learning time is too long and easy to cause fatigue and thus lead to inefficiencies.

In this paper, the recommended learning path for student A: $v_5 \rightarrow v_7 \rightarrow p$, in which the centrality value of knowledge point v_5 is 0.024, which occupies a higher position in the knowledge graph, and the priority learning of this knowledge point can lay the foundation for the learning of other knowledge points in the subsequent period, and the *Probability* values of the two knowledge points v_5 and v_7 are 0.83 and 0.85 respectively, which can be inferred that the students are almost about to master these two knowledge points. It can be inferred that students are almost close to mastering these two knowledge points, and can spend less time to fully master and achieve the learning of the target knowledge points. From this, it is easy to see that the learning path of knowledge points recommended in this paper fully takes into account the personalized learning behavior of student A, i.e., the personalized learning rate, knowledge mastery and the logical correlation between the knowledge points, which can help student A to quickly achieve the learning of the target knowledge points.

Table 5: Learning Path Recommendation Comparison

Learning path recommendation method	Knowledge point path
This article	$v_5 \rightarrow v_7 \rightarrow p$
Comparison method 1	$v_6 \rightarrow p$
Comparison method 2	$v_8 \rightarrow v_6 \rightarrow v_5 \rightarrow v_9 \rightarrow v_{10} \rightarrow p$

III. B. Controlled Experiment on Vocal Music Practice Teaching

III. B. 1) Experimental design

A total of 100 second-year undergraduate students from a music college who have mastered basic vocal skills were invited to participate in this experiment to compare the changes in vocal skill mastery ability after learners followed the path recommended by the recommendation algorithm. The learners were divided into four groups of 25 learners each with different skill levels according to their pre-test scores, and group A was the experimental group, in which the learning paths were recommended to the students according to Dijkstra's algorithm for solving the path-planning model, while groups B, C, and D were the control groups, in which the experiments were conducted according to the learner-directed learning, the knowledge-based recommendation, and the content-based recommendation, respectively.

III. B. 2) Comparative experiments and analysis of results

(1) Box-and-line diagram

The distribution of the pre-test and post-test scores of the four groups of learners is plotted in a box-and-line diagram as shown in Figure 5.

It can be seen that in the pre-test stage, the average scores of each group are similar, and there are learners with different levels of vocal skill mastery. After the recommended stage of learning, the learners' vocal skill mastery improved to different degrees. Among them, when comparing the post-test and pre-test of group A, the mean score increases from 5.56 to 8.14, and the median score increases from 5.56 to 8.82, which is the most obvious improvement among the four groups, indicating that this paper's path recommendation model based on the Knowledge Graph and the Dijkstra algorithm can effectively improve the learners' vocal skill mastery ability in personalized recommendation. Meanwhile, in the post-test stage, the average score of Group A is 2.33, 2.09 and 2.39 points higher than that of Groups B, C and D respectively, indicating that the effect of improving the overall vocal skill mastery ability of the learners in the experimental group is the most obvious, and that the personalized learning path recommender model in this group has the most prominent effect on the overall vocal skill mastery status of the learners.

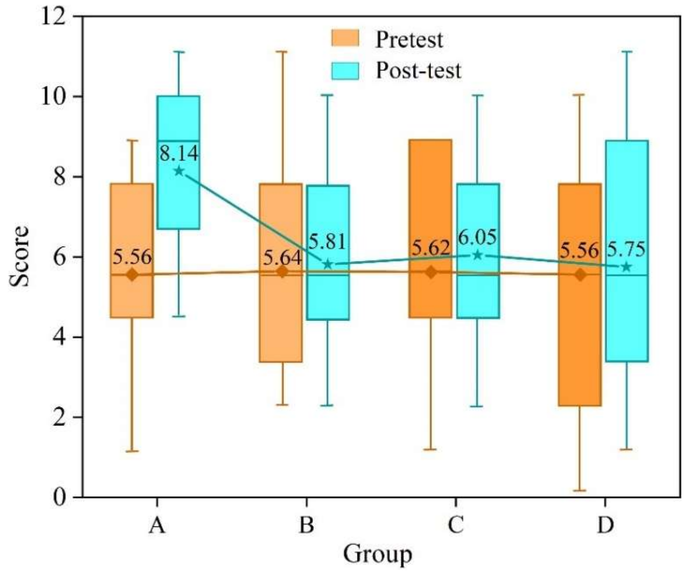

Figure 5: Comparison of learners' pre-test and post-test scores

(2) Independent samples t-test [16].

First of all, W-test was done on the pre- and post-test scores of the four groups of learners, and the results of W-test are shown in Table 6. From the experimental results, it can be seen that the p-value of the pre- and post-test stages of each group in this experiment is greater than 0.05, the original hypothesis is accepted, and the achievement data are all approximately in line with the normal distribution. Therefore, independent samples t-test can be used to verify whether the differences between the scores of different groups in the pre-test stage and post-test stage are significant.

Table 6: W test

Group	Pre-test stage		Post-test stage	
	W	p	W	p
A	0.964	0.729	0.941	0.423
B	0.953	0.602	0.940	0.431
C	0.968	0.745	0.864	0.058
D	0.972	0.836	0.957	0.627

The results of the independent samples t-test are shown in Table 7. The results show that in the pre-test stage, p>0.05 between the groups, accept H_0, there is no significant difference in scores between each group. It indicates that in the pre-test stage, the experiment controlled for the scoring variable and the distribution of learners' abilities was similar in each group. However, at the posttest stage, p<0.05 and rejection of H_0 indicated that there was a significant difference in scores between Group A and each control group at the posttest stage. In addition, the magnitude of difference d are more than 0.9, indicating that the learning path recommendation model adopted by the experimental group can effectively improve the learners' vocal skill mastery level compared with the recommendation algorithm of the control group.

Combined with Figure 5, it can be seen that Group A has the highest score in the post-test stage, and the scores of the rest of the groups also have a certain increase compared with the pre-test. Groups B, C and D compare with each other, p>0.05, accepting H_0, with a non-significant difference in the scores, all of which are lower than those of Group A. The difference in the scores of Group B, C and D is not significant. This indicates that using the recommendation algorithm of the control group, although it can improve learners' scores to some extent, it is not as large as the enhancement of group A, and the enhancement is not obvious.

Further analyze the reasons for the large difference in scores between the control group and group A in the posttest stage. Group B may be the adoption of learner self-selection, learners are difficult to find a suitable learning path for themselves, and the process of browsing and selecting learning resources wastes a lot of time and reduces the efficiency and motivation of learning. group C may be the adoption of knowledge-based recommendation, learners can only learn the knowledge contained in the resources of the answering error , but cannot master the knowledge of the solution, and this approach does not take into account the learner's current level of development.Group D adopts content-based recommendation, and the lack of diversity in the resources with similar textual semantics may only allow the learners to master the way of thinking in a specific condition, and is unable to adapt to the situation where the semantics have undergone a large change.

Table 7: Independent sample t-test

Group	Pre-test stage				Post-test stage			
	t	df	p	d	t	df	p	d
B-A	0.097	48	0.934	0.043	2.412	48	0.031	0.979
C-A	0.091	48	0.942	0.041	2.374	48	0.032	0.968
D-A	0	48	1.0	0	2.250	48	0.041	0.924
C-B	0	48	1.0	0	0.099	48	0.935	0.045
D-B	0.082	48	0.945	0.032	0.173	48	0.882	0.083
D-C	0.080	48	0.947	0.031	0.265	48	0.814	0.114

IV. Conclusion

The learning path recommendation model based on vocal subject knowledge graph and Dijkstra's algorithm has achieved significant results in the experiments. The experimental results showed that the learners using the model showed significant improvement in vocal skill mastery, and the average score of Group A increased from 5.56 to 8.14, which was an average improvement of 2.33 to 2.39 points over the other groups. In addition, Group A had the smallest learning path cost, indicating that the model optimized the learners' time and energy allocation while ensuring the learning effect. In the control experiments, the learning path recommendation methods in Groups B, C, and D were improved, but the effect was more limited in comparison, indicating that the recommendation methods based on the knowledge graph and Dijkstra's algorithm have higher effectiveness and accuracy in the generation of personalized learning paths. Therefore, this model not only can effectively improve learners' vocal skills mastery, but also provides new ideas and methods for personalized education path recommendation.

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