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Article

Research on the Application of Shortest Path Algorithm in the Optimization of Higher Education Curriculum System

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Abstract: Traditional higher education course recommendation methods mostly rely on static rules or simple associations, making it difficult to dynamically generate optimal learning paths that match learners' characteristics. In this study, we propose a framework for optimizing higher education course system that integrates knowledge graph and shortest path algorithm. The framework first constructs a knowledge map of higher education courses oriented to knowledge points, which formally represents the complex logical relationships of the courses. The learning path planning problem is then converted into a problem of finding the optimal path on the knowledge graph, and an ant colony algorithm is introduced to solve the problem, which describes pheromones, heuristic functions, and other major objects, and dynamically plans the shortest learning path for the learners. The superiority of the algorithm in learning path planning rationality and personalization is verified through parameter optimization experiments and algorithm simulation experiments. The system can effectively help learners to carry out informative and high-quality learning, which provides important help to the Ministry of Education to cultivate high-quality talents.

Keywords: curriculum system optimization; ant colony algorithm; knowledge graph construction; learning path planning

1. Introduction

Since the twentieth century, international political, economic and cultural ties have been increasingly strengthened, cultures have intermingled and promoted each other, the pace of social change has accelerated, and new things, new ideas and new concepts have emerged. The development of science and technology is advancing by leaps and bounds, both highly differentiated and highly integrated, especially with the rapid development of information technology and the advent of knowledge-based economy, science and technology has become the most active factor in the productive forces, and plays a more and more critical role in the development of human society [1-3]. The rapid development of science and technology has led to a dramatic expansion of the total amount of human knowledge, with relatively independent disciplines reaching more than 2400 [4]. In this case, the contradiction between the infinity of knowledge and the limited carrying capacity of school curriculum is exposed unprecedentedly. At the same time, the restructuring of the relationship between the various fields of knowledge requires schools to reconsider the relationship between the different curricula. The problems facing education include not only the question of how the curriculum should be selected, but also the question of how it should be organized and optimized [5]. The infinite growth and accumulation of human knowledge, the rise of higher professional and technical education, the commercialization of curricula, and the massification of higher education have led to the rapid expansion of the curriculum system of modern higher education [6-9]. The university classroom has clearly appeared the image and characteristics of “knowledge supermarket” [10]. Therefore, combined with the development of society and higher education, the study of undergraduate curriculum system



optimization will help colleges and universities to improve the existing curriculum system and improve the quality of talent cultivation.

In the 1990s, the curriculum system model gradually developed into a model that strengthens and broadens the basic knowledge of disciplines, increases and strengthens the practical links, and cultivates and improves the comprehensive quality of students, and presents the characteristics of gradually realizing the modernization and synthesis of the curriculum, and strengthening the wholeness and scientificity of the curriculum structure [11-13]. Literature [14] regards the university curriculum system as a complex network system, the whole system is regarded as being divided into numerous isolated course groups, and different courses play different roles in the organization such as information source, hub and bridge, etc. The theory provides a new perspective for guiding the reform and optimization of the curriculum. Literature [15] points out that the arrangement and optimization of the college curriculum system is a complex and important routine work in the teaching management of colleges and universities, and is also the core part of teaching management, which is the basis for guaranteeing the normal operation of teaching. Literature [16] that the construction of high-level teacher team is the key to optimize the course system, while the reform and innovation of teaching content and teaching methods is the core of the optimization of the course system, and has been the "principle of automatic control" course system to build a specific practice. Literature [17] on the university "civil engineering construction" course system reform and innovation, proposed by building "double platform (course teaching platform and virtual simulation platform)", in order to expand the way of learning; and the establishment of "three Education (on-site education, classroom education and mental health education)" mode, in order to improve the comprehensive quality of students. The construction of the curriculum system pays more attention to the scientificization of the entire curriculum structure, the rationality of the integration and articulation of the curriculum content and the wholeness of the knowledge structure, the consistency between the wholeness of the various links of the curriculum system and the overall requirements of the talent cultivation objectives, the flexibility of the curriculum system and the curriculum system's self-regulation mechanism [18-21]. Literature [22] takes the teaching of "steel structure" course in colleges and universities as an example, and puts forward the methods to optimize the teaching effect of the curriculum system and improve the quality of teaching from the dimensions of precise course positioning, reconstructing teaching content, innovative teaching mode and strengthening the guarantee conditions. The arrangement of the courses is also basic, practical, personalized and internationalized, which can reflect the ever-changing social demands at any time.

Scheduling optimization is a very complex task in the management of university education curriculum system. First of all, there are a lot of constraints in the process of scheduling optimization, which requires that time, students, classrooms, teachers and related courses can be reasonably allocated to avoid "conflict" [23-25]. With the increasing scale of enrollment in recent years, as well as the expansion of the university professional curriculum system leads to a shortage of teaching resources, which increases the complexity and difficulty of scheduling. In this regard, the literature [26] proposed to improve the genetic algorithm by the method of co-evolution for the continuous expansion of teachers, students, and the number of course systems, and applied it to solve the problem of course scheduling in universities. Literature [27] considered the course scheduling problem to be an NP problem subject to multiple constraints, for which a novel heuristic algorithm based on Particle Swarm Optimization (PSO) was proposed, aiming to maximize the instructor's course scheduling and class scheduling needs. Literature [28] considers the university course scheduling problem, which is subject to multiple constraints such as courses, teachers, students, and classrooms, for which a hybrid approach (POGA-DP) combining genetic algorithms and dynamic programming is designed to further improve the utilization of teaching resources. None of the methods mentioned above can produce an optimal solution that satisfies all the constraints, and there are many soft constraints in the problem of optimizing the curriculum system of higher education. The shortest path algorithm, which can find a path with the smallest sum of total weights between two given nodes in the network, however, there is a lack of research on the application of the shortest path algorithm in the optimization of college education courses, so further in-depth research is needed.

Existing online course resources are difficult to meet the personalized learning needs of diversified learners, and the core challenge of reforming the higher education curriculum system is to reasonably plan an efficient learning path for students that conforms to the knowledge logic of the course and has personal characteristics. In this study, we introduce the ant colony algorithm in the shortest path algorithm, deeply integrate it with educational knowledge mapping, and construct an adaptive learning path planning algorithm for higher education courses. The transfer probability function of pheromone and multidimensional heuristic information in the ant colony algorithm is designed in detail to enable it to intelligently search and recommend the learning paths with the greatest learning benefit and the

smallest cognitive load in a large-scale course network. Simulation experiments and questionnaire research methods are used to confirm the path planning and assisted learning effects of the algorithm.

2. Knowledge mapping of higher education curricula for knowledge points

This chapter describes the process of constructing knowledge graphs [29] for higher education courses oriented to knowledge points, firstly, it explains the overall construction framework of knowledge graphs, and then describes each construction step in detail, including: ontology construction, data acquisition, knowledge extraction [30], knowledge fusion, knowledge graph storage and visualization.

2.1. Overall construction framework

Knowledge graph can be divided into ontology layer and data layer. In this paper, the knowledge graph is constructed in the domain, the knowledge scope is clear and the concept is clear, so it is constructed in a top-down way. The overall construction framework of higher education course knowledge graph is shown in Figure 1.

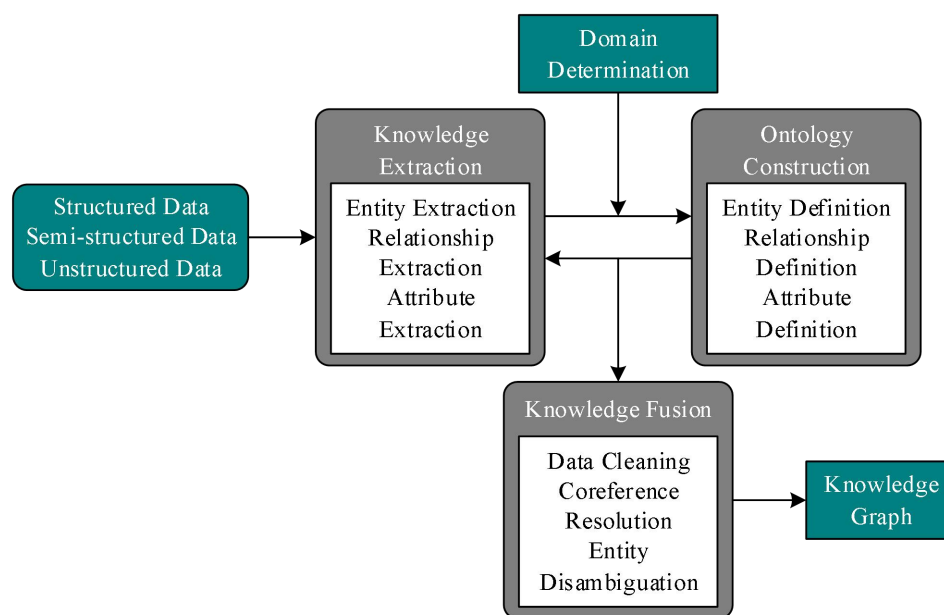


Figure 1. Framework of knowledge map of higher education course

The construction of knowledge map for higher education courses oriented to knowledge points in this paper mainly includes the following steps:

(1) Knowledge mapping ontology modeling, which mainly includes the analysis and determination of conceptual classes, data attributes, and object attributes.

(2) Obtaining structured, semi-structured, and unstructured data from the dataset and performing knowledge extraction, and depositing it into the database.

(3) Knowledge fusion of a large number of named entities identified in the knowledge extraction phase, which mainly includes data cleaning, co-reference disambiguation, entity disambiguation, to improve the quality of the knowledge graph.

(4) Use Neo4j graph database to store and visualize the fine-grained subject domain knowledge graph.

2.2. Knowledge Graph Ontology Construction

Knowledge graph ontology accurately describes the framework of concept classes, data attributes, and object attributes in the domain in a formalized way, which is the cornerstone of the whole knowledge graph construction. In this paper, the construction of knowledge graph ontology mainly includes the following steps: firstly, we clarify the goal of constructing the knowledge graph of the subject domain and extract the concept classes in the domain accordingly, then we analyze and define the data attributes and object attributes of the concept classes, and finally, we use the ontology

modeling tool to realize the knowledge graph ontology. The following section describes in detail the process of constructing knowledge map ontology for higher education courses oriented to knowledge points.

Decoupling the ontology construction work from the ontology description language (OWL) makes it unnecessary for developers to consider the syntax of the underlying ontology description language, which improves the efficiency of knowledge graph construction by developers. The knowledge graph ontology is shown in Figure 2, which shows the structure of the knowledge point-oriented higher education course knowledge graph ontology constructed using Protégé modeling tool in this paper.

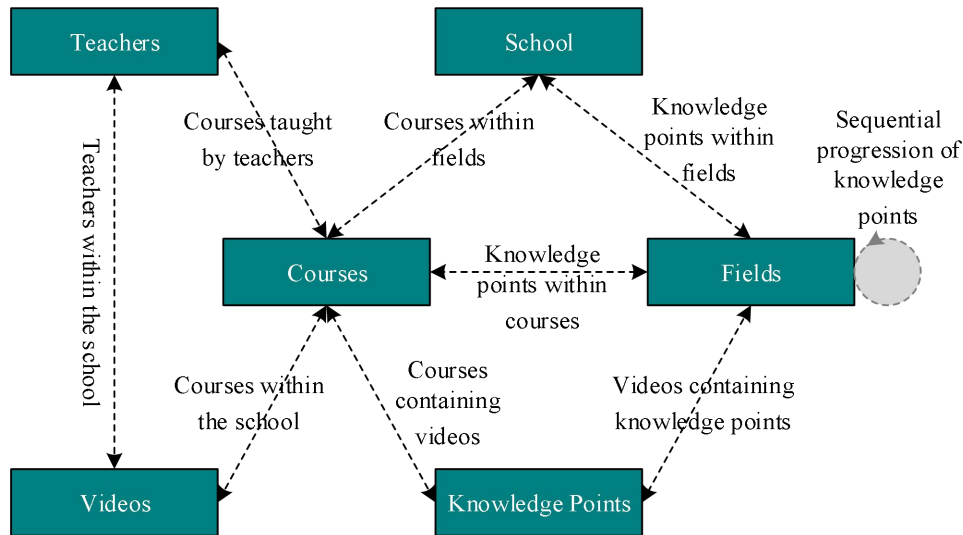


Figure 2. Knowledge map body

2.3. Data Acquisition and Knowledge Extraction

The experimental data in this paper is obtained from the open source MOOCube dataset. The open source MOOCube dataset has massive user records and teaching resources in MOOC platform. The dataset includes entity files and relationship files, both stored in JSON format.

Knowledge extraction is the process of collecting knowledge from structured, semi-structured and unstructured data from various data sources, including entity extraction, relationship extraction and attribute extraction. The realization methods of knowledge extraction mainly include the following three: methods based on traditional rules and templates, methods based on machine learning, and methods based on deep learning. In this paper, the traditional rule and template based knowledge extraction method is adopted, and Python scripts are used to write the recognition rules for each entity, attribute and relationship, and the extracted results are stored in the MySQL database.

The final MySQL database obtained contains a total of entity data tables: knowledge point, course, school, teacher, domain, student, video, and relational data tables: domain-course, course-knowledge point, school-course, domain-knowledge point, teacher-course, school-teacher, student-course, student-video, and knowledge point successively.

2.4. Knowledge integration

After knowledge extraction, the data obtained is in a more disorganized form, and there may be entities with repeated meanings and confusing structures. Therefore, knowledge fusion is needed. Knowledge fusion takes a large number of named entities identified in the knowledge extraction phase and performs data cleaning, entity alignment and other steps to improve the quality of the knowledge graph. This section describes the process of data cleaning and entity alignment respectively.

2.4.1. Data cleansing

Data cleaning is the process of removing redundant, erroneous, and useless data from the knowledge graph. Given that the results of data extraction are stored in a MySQL database, data cleaning is done using Structured Query Language (SQL). In order to make the knowledge graph semantic information more complete, generic courses from other domains also need to be queried and retained. Then useless data tables need to be deleted and only the entity tables corresponding to the

knowledge graph ontology need to be retained. Finally, each entity, attribute and relationship is analyzed and erroneous, redundant data is removed. At this point, data cleansing is complete, followed by the work related to entity alignment.

2.4.2. Entity alignment

Entity alignment is divided into two aspects: entity disambiguation and co-reference disambiguation. This paper constructs a domain-specific knowledge graph, in the case of ontology determination, there will not be the case of the same description pointing to different entities, so there is no need to carry out entity disambiguation. Co-index disambiguation aims at solving the situation where different descriptions point to the same entity, which will unify the entities with repeated meanings in the knowledge graph, and the commonly used methods for co-index disambiguation can be classified into those based on probabilistic models and those based on machine learning.

2.5. Knowledge graph storage and visualization

Knowledge graphs usually use graph databases to store, manage and visualize graph information. Graph databases do not contain table structures, and directly store individual nodes, node attributes and relationships between nodes, which can reach the billion level of storage, and have the functions of visualization, query, and reasoning. Current graph databases mainly include Neo4j, titan and OrientDB, etc. In this paper, Neo4j is used to store fine-grained subject area knowledge graphs and visualize them.

After storing the subject domain knowledge graph of higher education courses in Neo4j graph database, we can also use Cypher graph query language to perform the operations of inserting, deleting, updating, and querying the entities or relationships in the subject domain knowledge graph.

3. Learning path recommendation based on knowledge graph and ant colony algorithm

Knowledge graph provides a structured knowledge base for learning path planning, and combined with the ant colony algorithm, an efficient shortest path planning algorithm, personalized learning paths adapted to learners' styles and cognitive levels can be dynamically generated. Due to the sequential path problem of learning activities, the planning of learning paths is different from the recommendation of commodities, different learners have different knowledge levels and behavioral preferences, in order to be able to personalize the recommendation of learning paths suitable for the learner's current state of learning, this chapter combines the similarity between the characteristics of the learner's learning activities and the ants' activities of searching for food, and searches for the optimal path suitable for the learner's learning.

3.1. Knowledge graph-based learning path construction

3.1.1. Learner characterization

Learners are in the main position in the whole learning process, and the learning paths recommended by the learning system can only reflect their personalized characteristics if they meet the learning needs of different learners. Due to the differences in learning styles, cognitive levels and learning methods, different learners will choose different learning paths, so it is necessary to provide suitable learning paths through in-depth study of the characteristics of learners, and finally realize the personalized recommendation of learning paths.

(1) Learning style description

Learning style is a relatively consistent and long-lasting learning tendency of learners, which reflects the consistent way learners habitually process information in the learning situation. It is a complex composed of four parts: the learner's view of learning, learning orientation, cognitive processing strategies and management strategies, and will remain relatively stable for a certain period of time.

At present, there are already a variety of classifications about learning styles, which are divided into the following four categories by integrating various considerations: aggregation type, which pays more attention to the practical value of the learning content, processes the information through thinking, summarizes the main content of the information, is good at combining theory and practice and verifies the correctness of the theory through experiments; assimilation type, which collects explanatory information such as pages, extracurricular teaching resources, notes, and so on, and understands the different information based on abstract ideas for thought processing; Divergent, good at examining the

problems faced from multiple perspectives and finding solutions to problems through continuous observation, like to participate in a variety of group activities and online lectures, etc.; Conformist, like challenging content, and come to continuous learning in the process of problem solving issues.

Learning styles have diverse characteristics, different learners have different degrees of tendency in various learning styles, and the same learner will show a variety of learning styles tendency, so we can't use the principle of either/or for simple categorization. Therefore, we use the vector K^s to describe the learning style of the learner K :

$$K^s = \{k_i^s \mid k_i^s = (s_i^1, s_i^2, s_i^3, s_i^4), i = 1, 2, \dots, n\} \text{ And } s^1 + s^2 + s^3 + s^4 = 1 \quad (1)$$

(2) Cognitive level description

The learning paths of learners with different cognitive levels will have large differences, while learners with similar knowledge levels have smaller gaps in comprehension and literacy, etc., and tend to adopt similar learning paths.

According to the learners' learning progress and the breadth and depth of the acquired knowledge, the learners' knowledge level is assessed by means of post-course quizzes, synchronized quizzes, and summary tests, and the results are quantitatively represented by K^l ($0 \leq K^l \leq 1$), and $K^l = f(k_i)$,

K^l closer to 1 means that the learner is close to the expert level, and closer to 0 means the beginner level, and when it is greater than a certain value φ ($0 \leq \varphi \leq 1$), it means that the learner can pass the test and move on to the next stage of learning.

3.1.2. Learning Object Characterization

1) Description of knowledge structure

The study of personalized learning paths necessarily involves an in-depth analysis of the structure of the learning object, i.e., the knowledge learnt by the learner, the relationship between knowledge points and the state of knowledge. In the field of cognitive science, the learning object is represented by a set, and the elements of the set are the contents that learners need to learn. The learning object is divided into a series of knowledge points, which can be categorized into meta-knowledge points and composite knowledge points according to the division granularity.

In the field of knowledge teaching, the knowledge points are interconnected and have certain associative relationships, which can be mainly divided into organizational and dependency (support) relationships.

There can be no circular reasoning in the formation process of the knowledge system, and it is impossible to form a closed loop in the support relationship of knowledge points, so the knowledge structure graph is a directed acyclic graph. The nodes in the knowledge structure graph correspond to each knowledge point and are connected by hyperarcs, pointing from the supporting knowledge point to the supported point. A knowledge structure graph with a finite number of nodes needs to satisfy the following three conditions:

- (1) There is exactly one node a with no arc in the graph that shoots to node a .
- (2) There is a non-empty set B of nodes, and no arcs are shot from any node in B .
- (3) There are no loops.

A directed graph $G(Q, A)$ describing the association relationship of each knowledge point is built based on the above description, where $Q = \{q_1, q_2, q_3, q_4, \dots, q_n\}$ is the collection of knowledge points and $A = \{(q_i, q_j) : i \neq j\}$ is the set of vertex arcs:

$$A = \begin{cases} 1, & \text{If the learner studies } j \text{ after learning } i \\ 0, & \text{Else} \end{cases} \quad (2)$$

2) Knowledge expression characteristics

The online teaching system contains many knowledge points, and the multimedia digital resources that describe the knowledge points and are used for learners' learning constitute the basic teaching resources of the teaching system. These multimedia resources include text resources, image resources, video resources, audio resources, example resources, practice resources, etc., and for a particular knowledge point can be expressed in a variety of ways, but also has different attributes or personalized

labels, the author uses the vector Q^e to describe the expression of the knowledge point q :

$$Q^e = \{q_i^e \mid q_i^e = (e_i^1, e_i^2, e_i^3, e_i^4, e_i^5, e_i^6), i = 1, 2, \dots, m\}$$

$$\text{And } e^1 + e^2 + e^3 + e^4 + e^5 + e^6 = 1 \quad (3)$$

3) Knowledge Difficulty Coefficient

In the process of providing teaching resources, the manager of the teaching system is given a corresponding difficulty coefficient $Q^l (0 \leq Q^l \leq 1)$ according to the different depths and breadths of the knowledge expressed in the knowledge point, and the closer Q^l is to 1, it means that the knowledge point is more suitable for expert learning, and the closer it is to 0, it means that the knowledge point is more suitable for beginners to learn.

3.1.3. Learning path descriptions

According to the relevant definition of knowledge space theory, the learning path based on knowledge space theory is a path from the initial knowledge state to the target knowledge state in the knowledge space graph. In hypertext knowledge space we define a learning path as follows: select a set of learning object combinations $Q_i = (q_1, q_2, \dots, q_n)$ in the directed graph G in a forward and backward order. In order to complete the learning task, the learner needs to complete the learning of all learning objects on the learning path in sequence. The structure of the knowledge network is shown in Figure 3.

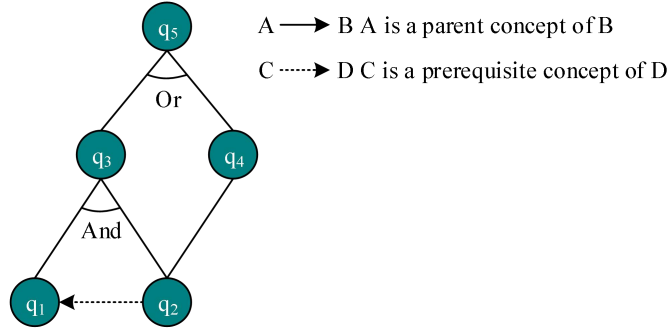


Figure 3. Learning knowledge network diagram

The solid line indicates the parent-child relationship and the dashed line indicates the prior learning relationship. Node q_1, q_2 is with node, must complete the learning of the two children nodes at the same time to carry out the learning of the parent node q_3 , and q_2 is the prior knowledge point of q_1 ; q_3, q_4 is or node, complete the learning of any of these knowledge points can be carried out to the learning of the knowledge point q_5 , and finally complete the learning task. From this figure, we can see that there are two learning paths, $Q_1 = (q_2, q_1, q_3, q_5)$ and $Q_2 = (q_2, q_4, q_5)$, the path Q_2 can accomplish the learning task with fewer nodes than Q_1 .

3.2. Ant Colony Algorithm

Ant Colony Algorithm (ACO) [31], also known as ant algorithm. The ant $k = (1, 2, \dots, m)$ in the process of searching for food, will be based on the residual pheromone on the path to guide it to the direction it will want to go, here we use the taboo table $tabu_k (k = 1, 2, \dots, m)$ in the record content to represent the city it is currently walking through. The city it has traveled through, meanwhile, the record of the taboo table will change as it moves, and during the movement in search of food, it will calculate the state transfer probability by referring to the pheromone with volatility and the amount of heuristic pheromone on the path, respectively. The state transfer probability of ant k moving from element (path node) i to element j is expressed in the following equation.

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^k \cdot [\eta_{ik}(t)]^\beta}{\sum_{scallowed} [\tau_{is}(t)]^\alpha \cdot [\eta_{is}(t)]^\beta}, & \text{If } j \in allowed_k \\ 0, & \text{Else} \end{cases} \quad (4)$$

The heuristic function is denoted as $\eta_{ij}(t)$ and its expression is shown in the following equation:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (5)$$

In order to avoid too much residual information, so that the amount of residual information overwhelms the amount of inspired information, it is necessary to make the amount of residual information be updated after each ant moves one step or completes traversing all n path nodes (the end of a path loop), so we adjust the amount of information on the node's path (i, j) at the moment of $t+n$ according to the following rule.

$$\tau_{ij}(t+n) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (6)$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k(t) \quad (7)$$

3.3. Modeling of Ant Colony Algorithm in Learning Path Systems

In order to apply the ant colony algorithm to the context of personalized learning path recommendation, the process of learner's activity of searching for learning path objects is viewed as the process of ants searching for food, therefore, the following hypotheses are proposed:

- (1) The learners are regarded as ants in the recommender system, and the ants communicate with each other through pheromones.
- (2) The target learning path object in the personalized recommendation system is regarded as the "food" that the ants are looking for.
- (3) There are many non-target learning path objects between the ants and the food, and they are regarded as nodes on the foraging path of the ants, and the learner browsing the learning path objects is similar to the ants passing by the node elements of these paths, and leaving pheromones on the path elements. Here the pheromone is the learner's rating of the learning path object, and in this paper, it is considered that the higher the rating, the better the learning effect of the learning path object, and the easier it is to be recommended.

3.4. Predictive scoring

- (1) Learners have graded learned learning path objects
- (2) The learner has not graded the learned learning path object.

In the following, we mainly discuss in detail the second case belonging to the unrated after learning, i.e., the learner has not rated the learned learning path, for which we can predict the rating by the similar neighbors of the target learner, and ultimately fill in the default rating value based on the predicted rating, and then adjust the recommendation of the learned learning path object in many aspects according to the background of the ant colony algorithm. Assuming that the set of nearest neighbor customers of learner u is denoted as U , the formula for the predicted score $P_{u,i}$ of this learner for learning path object i is as follows:

$$P_{u,i} = \bar{S}_u + \frac{\sum_{v \in U} (Sim(u,v) \times (S_{v,i} - \bar{S}_v))}{\sum_{v \in U} (Sim(u,v))} \quad (8)$$

where $Sim(u,v)$ denotes the measure of similarity between learner u and v , \bar{S}_u and \bar{S}_v

denote the average of the scores given by learner u and learner v to the learning path objects, respectively, and $S_{v,i}$ denotes the scores given by learner v to resource object i .

3.5. Establishment of the transfer probability function

In the process of searching for food, ants determine the next node to be traveled based on the pheromone concentration on the path. In the recommendation algorithm of this paper, the learner decides the next learning path object to be learned based on the magnitude of the scoring score of the learning path object during the learning process.

The visibility can be determined based on some heuristic function, the exact form of which will be presented below.

3.5.1. Pheromone settings

Learners will refer to the strength of the pheromone on the learning path when selecting a learning path object to decide the next learning path object to be learned. In order to adjust the context of ACO algorithm to the context of learning path recommendation, in this personalized learning path recommendation service platform, we set the size of pheromone as the learner's rating or predicted rating of the learning path object, and we notate the pheromone that is left behind by the learner u on the learning path object node i in the moment of t as $\tau_{ui}(t)$, which is computed by the following formula:

$$\tau_{ui}(t) = \begin{cases} S_{u,i}, & \text{Items already rated} \\ P_{u,i}, & \text{Items not yet rated} \end{cases} \quad (9)$$

3.5.2. Heuristic function design

The $\eta_{ik}(t)$ is denoted as a heuristic function expressed as the expected degree of the learner's transfer from the learning path object i to the learning path object k , and in this personalized recommender system we measure the similarity between the learning path objects from two parts, one part comes from the cosine value between the scoring values of the learning path objects, and one part comes from the labeling attributes between the learning paths themselves. The Euclidean distance value, is denoted as:

$$\eta_{ik}(t) = \begin{cases} \frac{\cos(i,k)}{d(i,k)}, & d(i,k) \neq 0 \\ \cos(i,k), & d(i,k) = 0 \end{cases} \quad (10)$$

A larger value of $\eta_{ik}(t)$ indicates a greater degree of expectation for the learner to move from learning path object i to choosing learning path object k , and vice versa. Where:

$$\cos(i,k) = \frac{\sum_{l=1}^M s_{li}s_{lk}}{\sqrt{\sum_{l=1}^M (s_{li})^2} \sqrt{\sum_{l=1}^M (s_{lk})^2}} \quad (11)$$

This part belongs to the rating situation of different learners on the same learning path object, the rating vector of item i is $S_i = \{s_{1i}, s_{2i}, \dots, s_{Mi}\}$, which is used to be denoted as the value of the item's evaluation attribute. Let the label vector of learning path object i be $\{c_{i1}, c_{i2}, \dots, c_{il}\}$, then the distance similarity formula between learning path object i and learning path object k is:

$$d(i,k) = \sqrt{\sum_{l=0}^{l-1} (c_{il} - c_{kl})^2} \quad (12)$$

That is, the smaller $d(i,k)$ is, the greater the similarity from learning path object i to learning path object k .

3.6. Pheromone update rules

When the learner u has not accessed the learning path object o_i for a long time, it is considered that the learner u 's interests and preferences have changed. As time goes by, the pheromones continuously evaporate, and the pheromones originally left on the learning path object o_i may have completely evaporated. This has led to the learning path object o_i being abandoned by the learner u in this system, thus causing the system to recommend another learning path object suitable for the learner u to him again. In addition, during the recommendation process of this system, when all the learning path objects o_i are traversed or a recommendation is completed, the pheromones should be updated based on the learners' responses, that is, the scores should be updated. In this paper, after learner u completes the learning of each section $o_i \rightarrow o_k$, the pheromone concentration of that learning section is updated in a timely manner, that is, the evaluation of $o_i \rightarrow o_k$. The pheromone adjustment of this section can be calculated by the following formula.

$$\tau_{ik}(t+1) = (1-\rho) \times \tau_{ik}(t) + \Delta\tau_{ik}^u(t) \quad (13)$$

3.7. Algorithm Design and Description

After the analysis and research in the previous sections, the adapted ACO algorithm is applied to the context of learning path object recommendation, and the description of the thought process and flowchart of the algorithm design is as follows:

Input: pheromone intensity a , visibility b , information volatility p , raw rating matrix *matrix* of all learners for all learning path objects, target learner learning information *info* (location, time).

Output: N recommended learning path objects.

The recommendation process is shown in Figure 4:

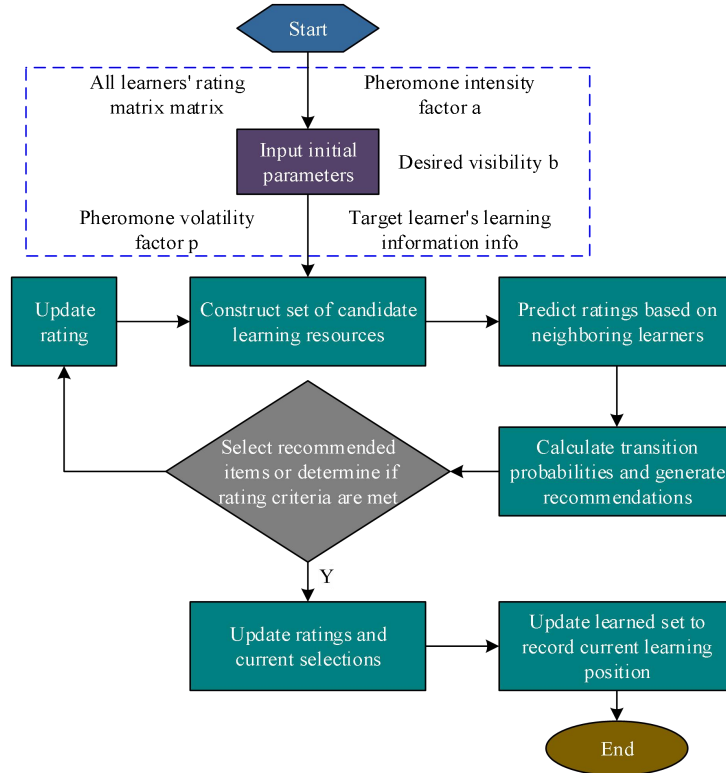


Figure 4. The study path recommendation process based on ant colony algorithm

4. Shortest learning path planning effects and their applications

4.1. Parameter optimization effect analysis

In order to verify the effectiveness of the recommended parameters using the ACO algorithm, this paper uses simulation experiments to compare the effects of two schemes for obtaining parameter combinations on the performance of the extended ACO algorithm. Scheme 1 is to randomly combine the parameters in the better interval of the parameters, and scheme 2 is to optimize the combination of parameters using the basic genetic algorithm. During the experimental simulation, the relevant parameters of the genetic algorithm are set as follows: population size $S=90$, evolutionary generation $G=160$, mutation probability is 0.002, crossover probability is 0.7, similar learner proximity thresholds are all 0.4, and the parameters of the ant colony algorithm are set as follows: the maximum number of iterations is 400. The 10 better results obtained by the ant colony algorithm using the strategy of randomly combining the parameters of each parameter are listed in the table, and the results are as shown in Table 1.

The optimal values obtained by using the basic genetic algorithm to optimize the parameter combination strategy of the ant colony algorithm are $\alpha=0.535$, $\beta=4.216$, $\rho=0.685$, and $m=50$, respectively. Applying this parameter combination to the ant colony algorithm, the results of the simulation experiments were obtained as shown in Fig. 5.

Table 1. The results of the random combination of the optimal parameter

N	α	β	ρ	m	Average preference matching	Average preference coverage	Average iteration times
1	0.7	7.0	0.70	68	0.654	0.735	95
2	0.5	4.5	0.65	55	0.712	0.782	105
3	0.8	3.0	0.60	74	0.610	0.710	85
4	0.7	6.0	0.80	50	0.755	0.815	160
5	0.8	3.2	0.85	45	0.625	0.722	90
6	0.6	3.2	0.75	65	0.630	0.725	102
7	0.6	8.5	0.90	64	0.675	0.736	120
8	0.8	2.5	0.75	45	0.588	0.665	103
9	0.5	8.0	0.60	42	0.690	0.762	188
10	0.4	2.5	0.65	74	0.605	0.698	130

As can be seen in Fig. 5, during the evolution of the solution, the evaluation mean of the learning path by similar learners shows an increasing trend. After evolving to the 70th generation, the evaluation mean is basically stable around 0.876. The average preference matching degree obtained after applying the parameter combinations optimized by the genetic algorithm to the ACO algorithm is 0.783, the average preference coverage is 0.835, and the average number of iterations is 80. Comparing the data in Table 1, it can be seen that, although the value of each parameter in the better interval is a good solution, the random combinations of each parameter do not necessarily lead to the best performance of the algorithm, and it may produce problems such as the algorithm falling into the local optimization, taking too long, and other problems. In contrast, the solution obtained by using the basic genetic algorithm to optimize the combination of parameters of the ACO algorithm can make the algorithm perform better.

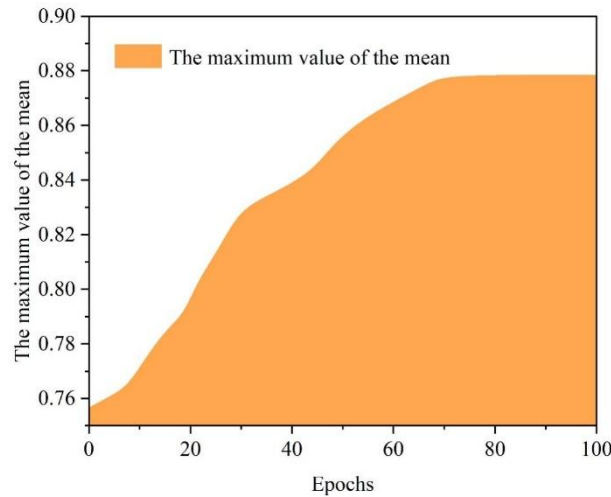


Figure 5. Experimental results

4.2. Analysis of the Effectiveness of Teaching Pathway Planning for Personalized Courses in Higher Education

In this study, data from 1500 students were simulated to generate data as training data for teaching pathway planning for personalized courses in higher education, in which the learner characteristic data were simulated to generate learner characteristic data conforming to a standard normal distribution using the reliability coefficients of the relevant questionnaires as the correlation coefficients of the relevant same dimension question items. The learner's cognitive diagnostic data is programmed on the basis of pybkt's synthetic data module. The simulation data of the learning path is implemented by programming simulation based on the course knowledge graph. In order to verify the effectiveness of the teaching path planning method for higher education personalized courses based on the ant colony algorithm proposed in this study, this study analyzes the effect of learning path planning in terms of the quality of learning paths and a detailed analysis of the specific process of learning path generation.

In this study, the quality assessment index Val, which initially tests the teaching path of personalized courses in higher education, is designed to test the reasonableness of the order of knowledge points in the path at the pedagogical and cognitive levels. The larger the value of Val, the worse the pedagogical and cognitive reasonableness of the path is.

In this study, 10 learners in the simulated data were randomly selected to test the algorithm respectively, and the results are shown in Table 2. From Table 2, it can be seen that compared with the genetic algorithm, the path planning method for teaching higher education personalized courses that incorporates the ant colony algorithm can effectively improve the reasonableness of the learning paths with a maximum Val value of only 10. Moreover, the learning path planning results further analyzed found that all the learning paths generated by the path planning method for teaching personalized courses in higher education incorporating the ACO algorithm did not have paths that violated the rules of antecedents and successors among knowledge.

Table 2. The rationality test results of the learning path

learners	Quantity of knowledge	The Val minimum of the genetic algorithm	The Val minimum of ant colony algorithm	Val maximum
A1	6	7	1	20
A2	25	65	7	185
A3	14	53	5	143
A4	15	55	5	154
A5	18	58	6	205
A6	20	60	6	221
A7	30	75	8	265
A8	34	80	10	280
A9	28	70	8	225
A10	26	68	7	240

The cognitive state data of one learner was randomly simulated to verify the effectiveness of the personalized course teaching path for higher education proposed in this study by analyzing the specific process of its learning path generation. The simulated cognitive state data of a student is shown in Table 3.

Table 3. Cognitive status data for a learner

Knowledge point	Course type	Credit value	Curriculum model	Elements of the curriculum system	Course structure	Teaching process	Graduation requirements
Kg-id	275	278	785	799	280	741	758
Score	1.00	0.85	0.84	0.86	0.85	0.88	0.91
Knowledge point	Conceptual model of teaching scheme	Basic requirements of teaching scheme	Teaching target correlation model	Conceptual model use	Modular course model	Academic model	Ability oriented course model
Kg-id	350	744	765	751	854	751	258
Score	0.85	0.89	0.92	0.94	0.95	0.93	0.96
Knowledge point	Hierarchical curriculum model	Curriculum transformation	Design personalized training plan	Curriculum optimization	Higher education mode	Higher education system	Teaching operation instance
Kg-id	805	806	811	785	776	702	701
Score	0.95	0.94	0.89	0.89	0.96	0.99	1.00
Knowledge point	Credit value	Tertiary curriculum architecture	Core course system	Optional course module	Optional course module	Curriculum standards	Course mapping
Kg-id	745	768	794	286	285	284	245
Score	0.85	0.86	0.87	0.89	0.91	0.88	0.95
Knowledge point	Higher education features	Educational administrator	Teaching software platform	Programme designer	Student user	Teaching staff	Digital resources
Kg-id	845	784	774	736	256	251	215
Score	0.89	0.78	0.89	0.95	0.94	0.96	0.96

According to the higher education personalized course teaching path planning based on the fusion ant colony algorithm, the sequence of higher education personalized course teaching paths that meets the cognitive state of the target learner is calculated as shown in Figure 6, and the red numbers are the learned progress. By analyzing the above learning path, it can be found that first of all, the learning path follows the cognitive learning law of pedagogical logic hierarchical modeling and the cognitive order of knowledge points, and the student is in the initial stage of learning, and the learning progress of the basics and course selection strategy reaches more than 40%, which indicates that the learning path planning method proposed in this study can effectively follow the pedagogical and cognitive laws of learning. Moreover, the knowledge learning sequence in the path achieves relatively high results in the learning paths of similar learners, which indicates that the personalized course teaching path planning of higher education integrating ACO algorithm can realize the personalized course teaching path planning of higher education for the learners while taking into account the pedagogical nature of the path planning. The optimal path for learner planning is shown in Figure 7 (only one learning path is listed here).

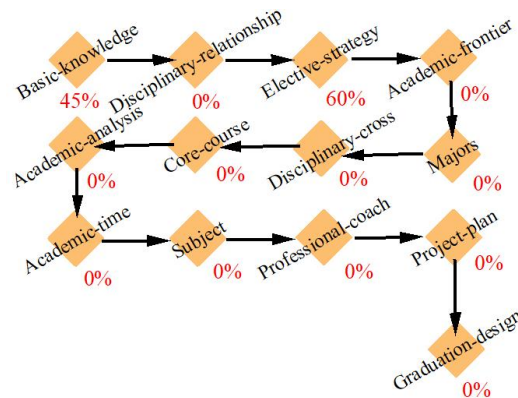


Figure 6. A learner's adaptive learning path planning sequence

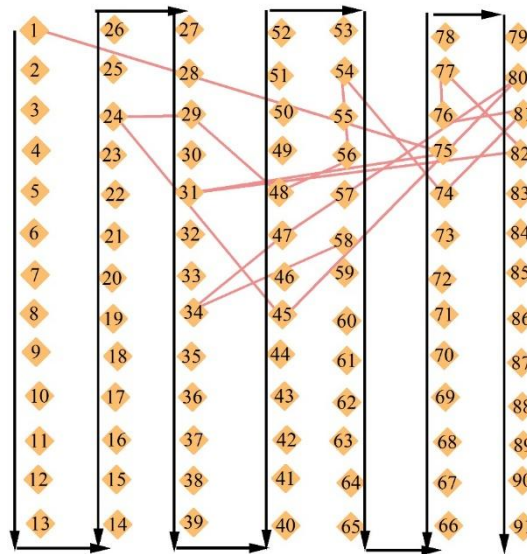


Figure 7. Learners plan to learn the optimal path

4.3. Effectiveness of the Application of Teaching Path Planning System for Personalized Courses in Higher Education

This study applies the learning path planning system of the previous paper to actual teaching, verifies the effectiveness and application value of the system in enhancing learning efficiency and adaptability by testing and analyzing it in teaching practice, and realizes the closed loop from theoretical construction to practical application.

4.3.1. Questionnaire design

Technology Acceptance Model (TAM), TAM model mainly includes four dimensions, namely, perceived ease of use, perceived usefulness, user attitude, and behavioral willingness, this model is widely used to determine the degree of user acceptance of computers, this paper designs evaluation indexes based on the TAM model as a means of determining the application effect of the personalized course teaching path planning system for higher education based on the knowledge graph and ant colony algorithm.

The questionnaire design of this paper is based on the evaluation indexes of the application effect of the personalized course teaching path planning system based on knowledge graph and ant colony algorithm in higher education, and incorporates a 5-point Likert scale, which is divided into 1 (strongly disagree) to 5 (strongly agree) levels, and the higher the level, the stronger the degree of agreement, i.e., the better the application effect of the system.

Table 4. System application effect evaluation index

Index	Index judgment	Metric
Learning resources	Knowledge organization method	The method of declarative knowledge is effective
	Knowledge organization visualization	It is useful to show the knowledge of knowledge
	Recommendation for learning resources	Learning resources are recommended
Learning companion	Peer group	Learning peer grouping is effective
	Recommendation for learning path	The learning path is recommended
Learning path	Learning path rendering	The learning path is clearer in the form of knowledge
Perceptual ease of use	System operability	The system works simple
Perceptual usefulness	The usefulness of the system	The system can help me learn
User attitude	Learners' satisfaction	I am willing to use the system to study

Behavior will	The use of learners	I often use the system to study
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4.3.2. Questionnaire collection and analysis

Questionnaires were randomly distributed online through Questionstar to investigate learners' feelings after using a path planning system for teaching personalized courses in higher education based on knowledge graph and ant colony algorithm, 40 questionnaires were distributed and 35 questionnaires were recovered.

Reliability, i.e. reliability, is the degree of consistency of the results obtained when the same object is measured repeatedly with the same method. Commonly used reliability analysis methods include retest reliability method, replica reliability method, folded half reliability method, alpha reliability coefficient method, etc., of which the reliability of alpha reliability coefficient method is called Cronbach's alpha coefficient, or alpha coefficient for short, which is the most commonly used reliability analysis method in social science research at present, so this paper adopts the alpha reliability coefficient method to validate the reliability of the questionnaire, in general. The value of α coefficient is between 0 and 1, where the value of α coefficient is above 0.8 means that the reliability of the questionnaire is very high, if the value of α coefficient is between 0.7-0.8, it means that the reliability of the questionnaire is relatively good, if the value of α coefficient is between 0.6-0.7, it means that the questionnaire's reliability is acceptable, and if the value of α coefficient is below 0.6, it means that the questionnaire's reliability is not good. The reliability analysis of the questionnaire in this paper is shown in Table 5. By analyzing the reliability of each dimension of the questionnaire, the minimum alpha coefficient value obtained is 0.755 and the maximum is 0.956, so the reliability of this questionnaire is good.

Table 5. Questionnaire reliability analysis

Index	Number of subjects	α coefficient
Learning resources	4	0.755
Learning companion	4	0.859
Learning path	4	0.889
Perceptual ease of use	4	0.867
Perceptual usefulness	4	0.954
User attitude	4	0.956
Behavior will	4	0.911

Validity, i.e. validity, is the extent to which a measurement tool or instrument can accurately measure the things to be measured, i.e. the extent to which the measurement result matches the problem to be explored, and the higher the degree of match between the two, the more effective the measurement tool or method is. Commonly used questionnaire validity analysis methods include single item and total correlation validity analysis, criterion validity analysis, structural validity analysis, etc., in which the method used for structural validity analysis is factor analysis, factor analysis is a statistical analysis method that uses a few factors to describe the connection between many indicators or factors, and reflects most of the information of the original data with a fewer number of factors, and the factors in factor analysis include KMO The factors in factor analysis include KMO value, common degree, variance explained rate value, factor loading coefficient value, etc. KMO value is used to judge the suitability of the questionnaire information extraction, if the KMO value is more than 0.8, it means that the data of the questionnaire is very suitable for extracting the information, and the validity of the questionnaire can be seen from the side that the questionnaire is better, if the value of KMO is between 0.7-0.8, it means that the data of the questionnaire is suitable for extracting the information, and the validity of the questionnaire can be seen from the side that the questionnaire is better. If the value of KMO is between 0.6-0.7, it means that the questionnaire data is more suitable for extracting information, and the validity can be seen from the side that the validity is average, if the value of KMO is less than 0.6, it means that the questionnaire data is not suitable for extracting information, and the validity can be seen from the side that the validity is not good. The Bartlett's sphericity test is used to indicate whether the questionnaire is suitable for factor analysis or not, when the p value is less than 0.05, it indicates that it is suitable for factor analysis and vice versa. The validity analysis of the questionnaire in this paper is shown in Table 6.

By analyzing the KMO value of the questionnaire and the Bartlett sphericity test, we get that the KMO value is 0.655 at the minimum and 0.789 at the maximum, and most of them are greater than 0.7, and the p-value is 0.000, which means that the data of the questionnaire is more suitable for extracting information, and it can be seen that the validity of the questionnaire is relatively good from the side.

Table 6. Questionnaire validity analysis

Index	Number of subjects	KMO	Bartlett metric test		
			Approximate card	df	p
Learning resources	4	0.655	25.443	4	0.000
Learning companion	4	0.710	40.512	4	0.000
Learning path	4	0.726	48.541	4	0.000
Perceptual ease of use	4	0.668	52.652	4	0.000
Perceptual usefulness	4	0.789	78.451	4	0.000
User attitude	4	0.758	75.459	4	0.000
Behavior will	4	0.716	58.698	4	0.000

Descriptive analysis was conducted on the recovered questionnaire data to illustrate the application effect of the higher education personalized course teaching path planning system based on knowledge graph and ant colony algorithm, where "X" represents the question number of the learning path indicator, "Y" represents the question number of the learning companion indicator, and "Z" represents the question number of the learning path indicator. "L" represents the question number of the perceived ease of use indicator, "M" represents the question number of the perceived usefulness indicator, "N" represents the question number of the user attitude indicator, and "O" represents the question number of the behavioral intention indicator.

In terms of learning paths, learning peers, learning paths, perceived ease of use, perceived usefulness, user attitudes and behavioral willingness, most learners chose the options of "agree" and "strongly agree", and 0 chose the option of "strongly disagree", indicating that learners think that the system is good for them from any point of view after using the knowledge graph and ACO algorithm based personalized teaching path planning system for higher education courses. The option of "strongly disagree" indicates that after using the personalized course teaching path planning system for higher education based on knowledge graph and ant colony algorithm, the learners think that this system is better for them no matter which way they look at it, and they are positive and supportive of the system, so it can be said that the system based on knowledge graph and ant colony algorithm constructed in this paper is very useful and useful. Knowledge Graph and Ant Colony Algorithm for teaching path planning system for personalized courses in higher education is better for the learners and is helpful for the learners. As shown in Table 7:

Table 7. System application results

Index	Topic	Options				
		Very different	Different meaning	General	Consent	Very agree
Learning resources	X1	0	1	4	14	16
	X2	0	0	5	15	15
	X3	0	1	6	13	15
	X4	0	0	4	12	19
Learning companion	Y1	0	0	5	14	16
	Y2	0	0	2	15	18
	Y3	0	0	3	16	16
	Y4	0	0	5	17	13
Learning path	Z1	0	0	1	15	19
	Z2	0	0	5	11	19
	Z3	0	0	5	13	17
	Z4	0	0	3	10	22
Perceptual ease of use	L1	0	0	5	12	18
	L2	0	0	3	13	19
	L3	0	0	4	13	18
	L4	0	0	1	14	20
Perceptual usefulness	M1	0	1	5	20	9
	M2	0	0	6	15	14
	M3	0	1	4	18	12
	M4	0	0	7	17	11
User attitude	N1	0	0	3	18	14
	N2	0	0	1	16	18

	N3	0	0	5	15	15
	N4	0	0	4	14	17
	O1	0	1	6	11	17
Behavior will	O2	0	0	6	12	17
	O3	0	0	1	13	21
	O4	0	0	5	14	16

5. Conclusion

In this paper, a course system optimization model based on course knowledge graph and shortest path algorithm is constructed.

The maximum value of the teaching path planning method for personalized higher education courses incorporating the ant colony algorithm in this paper is only 10, which confirms the reasonableness of the planning of learning paths, and the method effectively utilizes the structured information of higher education course knowledge graph to generate highly personalized learning paths for different types of learners with a coherent knowledge structure and following the learning rules. The higher education personalized course instructional path planning system has gained the affirmation of most users, and most people affirm the positive effects of the higher education personalized course instructional path planning system in terms of learning paths, learning peers, learning paths, perceived ease of use, perceived usefulness, user attitudes, and behavioral willingness.

This paper provides a method for modernizing teaching management that integrates data-driven and intelligent decision-making, and verifies the feasibility of applying knowledge graph and shortest path algorithm in higher education curriculum system. It provides data information for educational administrators to optimize the curriculum so as to achieve the optimal allocation of teaching resources and the overall improvement of talent cultivation quality.

Future research can explore balancing multiple objectives such as learning efficiency and knowledge breadth under the multi-objective optimization framework to further enhance the intelligence and practicality of the system.

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