International Journal of Information and Communication Technology Education
Volume 19 • Issue 1

Design of a Learning Path Recommendation System Based on a Knowledge Graph

Chunhong Liu, College of Computer and Information Engineering, Henan Normal University, China*
Haoyang Zhang, College of Computer and Information Engineering, Henan Normal University, China
Jieyu Zhang, College of Computer and Information Engineering, Henan Normal University, China
Zhengling Zhang, College of Computer and Information Engineering, Henan Normal University, China
Peiyan Yuan, College of Software, Henan Normal University, China
https://orcid.org/0000-0003-0023-1194

ABSTRACT

Current learning platforms generally have problems such as fragmented knowledge, redundant information, and chaotic learning routes, which cannot meet learners' autonomous learning requirements. This paper designs a learning path recommendation system based on knowledge graphs by using the characteristics of knowledge graphs to structurally represent subject knowledge. The system uses the node centrality and node weight to expand the knowledge graph system, which can better express the structural relationship among knowledge. It applies the particle swarm fusion algorithm of multiple rounds of iterative simulated annealing to achieve the recommendation of learning paths. Furthermore, the system feeds back the students' learning situation to the teachers. Teachers check and fill in the gaps according to the performance of the learners in the teaching activities. Aiming at the weak links of students' knowledge points, the particle swarm intelligence algorithm is used to recommend learning paths and learning resources to fill in the gaps in a targeted manner.

KEYWORDS

Knowledge Graph, Learning Path, Learning Recommendation System, Node Centrality

INTRODUCTION

With the development of information technology, China's education has entered the stage of intelligence (Qinghua et al., 2019), demonstrated by knowledge, openness, and synergy. The Implementation Plan for Accelerating Educational Modernization (2018 – 2022) (Xinhua News Agency., 2019) pointed out that educational development relies on the promotion of the informatization of education, speeding

DOI: 10.4018/IJICTE.319962
*Corresponding Author

up smart education, encouraging learners to conduct autonomous learning, and taking feedback on teaching. The New Generation Artificial Intelligence Development Plan noted that the construction of a knowledge graph is the key analysis and reasoning technology. Thus, the learner-centered education platform should be built through a knowledge graph.

Current learning platforms tend to have problems related to resource overload, redundant information, and chaotic learning routes. These cannot meet individualized learning requirements, fail to provide timely feedback between teachers and students, and leave learners and teachers dissatisfied with self-learning methods. There is, therefore, a need for structured teaching and learning. Thus, the use of knowledge graphs for reasonable learning path recommendation has become an urgent problem.

The learning knowledge and nation system designed via the knowledge graph can accurately identify learning paths, eliminate knowledge fragmentation and information redundancy, form structured knowledge, and clarify the relationship between predecessors and successors of knowledge. Therefore, recommending learning paths can make students' learning more scientific and reasonable.

The concept of a knowledge graph was first proposed by Google in 2012 as it accelerated and optimized its search engine capabilities. In 2013, it was popularized in academia, becoming a key technology in the field of artificial intelligence (AI). Zhen et al. (2019) proposed the construction method of a knowledge graph in the adaptive learning system of human-computer collaboration, which expresses the application of a knowledge graph in an adaptive learning system from the dimensions of resource integration and adaptive learning. Hang (Hang Z.,2020) proposed using a knowledge graph to evaluate the mathematics lesson plan, reduce the complexity, obtain key indicators, and supplement the evaluation of knowledge points, abnormal knowledge points, and knowledge point spans. Ye et al. (2021) proposed the basic concept and construction of a multimodal knowledge graph, analyzing key technologies and related application scenarios. Ang et al. (2022) used reinforcement learning to solve the problems of data labeling, noise, and reasoning interpretability and reliability. They introduced its application to practical fields like intelligent recommendation. Aidan et al. (2021) illustrated how to represent and extract knowledge in knowledge graphs using a combination of deductive and inductive techniques. Padia et al. (2019) proposed a method for embedding knowledge graphs into real-valued tensors and a linear tensor decomposition algorithm with provable convergence. These proved the effectiveness of the proposed model on knowledge graph prediction. Kwa et al. (2020) proposed a schema-based iterative knowledge graph completion method, solving the problem of consistency of the ontology schema between the extended knowledge graph and initial knowledge graph.

Learning path recommendation aims to recommend reasonable paths to learners in support of comprehensive, reliable learning. Guangquan (2018) designed and proposed a method for recommending learning resources and exercise resources according to learners' personalities. Yue (2019) proposed improving the binary particle swarm algorithm to improve the efficiency and accuracy of personalized learning path recommendation. Menghua (2020) achieved personalized learning path recommendation by constructing a course knowledge graph and showing the relationship between knowledge points. Zhuang Chen (Zhuang., 2020) proposed a learning path generation algorithm based on clustering and an improved learning path recommendation algorithm based on a long short-term memory network, realizing a better adaptive and more accurate path recommendation scheme. Hanlin (2021) proposed an effective scheme to transform learning resources into learning paths by using learner portrait technology in the environment of semi-supervised learning. Ronghai and Changdong (2021) proposed a hin-def model that combined tensor decomposition, a heterogeneous information network, and deep learning triple technology. They solved the problem of sparse data and improved the accuracy of the recommendation system. Seghroucheni et al. (2014) proposed an adaptive learning system model based on a recommender system, helping learners who encounter difficulties in learning evaluation to correct the learning path. Nguyen and Tran (2021) proposed embedding career goals into knowledge graphs to form a new knowledge graph architecture to achieve specific classification of learners and make the semantic relationship between subjects clearer and more relevant. Niknam and Thulasiraman (2020) proposed a bionic intelligent learning path recommendation scheme based on learning theory. This enables the system to adjust itself and provides different learning support for learners. Thus, they can overcome the one-size-fits-all learning recommendation form. Shi et al. (2020) designed a multidimensional knowledge mapping framework, proposing six semantic relationships among learning objects in the knowledge map. It can generate and recommend customized learning paths based on the target learning objects of e-learners. Fiqri and Nurjanah (2017) proposed a Dijkstra algorithm applicable to the improvement of graph-based domain models. It recommends dynamic learning paths to students based on the success likelihood score to accommodate their progress. Wang et al. (2021) proposed a new model, the knowledge graph-based intent network (KGIN). The network aims to improve the capability and interpretability of the model. A new information aggregation scheme is designed, which recursively integrates long-distance connected relational sequences (relational paths). KGIN provides interpretable explanations for predictions.

This article proposes a learning path recommendation system based on a knowledge graph. This helps learners recommend reasonable learning paths, as well as provides feedback between teachers and students. Learners learn by combining scientific guidance and advice from teachers. The system builds a knowledge graph of the chapters learned according to the relationship between knowledge points and the analysis of important or difficult points. It then uses related technologies to recommend reasonable learning paths, which is convenient for learners to conduct systematic and structured learning. Learners can use the feedback function to communicate with teachers. It also helps learners control their learning direction and progress. In turn, teachers can grasp the learning situation of students and adjust the teaching progress in a timely manner.

The recommended learning path differs from the course structure in that the course knowledge graph is made up of knowledge entities and relationships between knowledge entities connected to each other. The learning path recommendation realized by using the knowledge graph reflects the knowledge points directly related to the surface phenomenon of students' learning activities. More importantly, it can identify the key knowledge points logically related to students' learning activities in the whole learning process. The learning path based on the knowledge graph guides students' learning direction. It also improves the structure of the knowledge system for students' learning, allowing students to clearly recognize the precursor and successor relationships of knowledge points. The system effectively improves the quality and efficiency of teaching and learning, providing an idea for the development of learning path recommendation research under the new teaching mode.

The remainder of this article is organized as follows. The second section introduces key technologies and related concepts in the system design process through a description of the exact steps of the algorithm. The third section introduces the design ideas and related analysis of the learning path recommendation system based on a knowledge graph. The fourth section carries out the system implementation and performance and application effect verification. Finally, the article provides a summary and outlook.

PRELIMINARY

Node Centrality Theory

Node centrality is a common concept and an important indicator in network analysis. It is used to measure the importance of a node element in the entire network. The numerical value expresses the importance of the centrality of the node. The importance of the node is often determined by the topological properties, structural characteristics of the network, and specific meaning of the node in the network (Sizhu et al., 2010).

In existing research, the concept of node centrality is often used in the analysis of complex networks, such as social networks and biological protein networks. It is rarely used in the field of education. This article explores the chapter, "Fundamentals of Information Technology in Senior High School," and the knowledge points in the "Expression of Information" of the course as the research object. The importance of knowledge nodes in the graph is calculated through the difficulty and order of knowledge points in the chapter. Its importance level is used to describe the centrality of knowledge nodes.

From the perspective of teachers and students, learning is a directional process (simple to complex). Therefore, the centrality of the knowledge point entity in the knowledge graph of this article is approximately equivalent to the weight of the node in the graph. The quantification of the centrality is also based on the directed network structure. Node centrality, in the narrow sense, is regarded as the geometric center in the knowledge graph. In contrast, generalized node centrality refers to the relative importance of knowledge nodes in the knowledge graph. Both demonstrate the degree of concentration of knowledge.

Regarding the information technology knowledge graph in this article, if part of the first-level node is key knowledge, the weight of the content of the second-level node will occupy a higher weight in this layer. The teacher can use the teaching experience to adjust the weight flexibly and dynamically.

According to the characteristics of the relationship between knowledge points, this article selects the PageRank algorithm proposed by Google founders Larry Pagekin and Sergey Brin in 1997. The idea of the algorithm is that the importance of a web page is determined by the number of links to the pages and the importance of the page to judge. Regarding the idea of the original algorithm, the dependence and importance between knowledge points are considered according to the teacher's teaching experience. Thus, the obtained node centrality is more in line with the node centrality of the knowledge graph in the teaching field without deviating from the centrality of the network structure.

Simulated Annealing Particle Swarm Fusion Algorithm for Multiple Iterations

Aiming at the problems of fast convergence speed and lack of diversity in particle swarm optimization, Haiping et al. (2012) adopted the introduction of a simulated annealing strategy to adaptively adjust the proportion of particle self-learning and social learning, as well as propose an adaptive particle swarm optimization algorithm based on simulated annealing. The algorithm continues to use the PSO algorithm to obtain a higher optimization speed before iteration. It then introduces the idea of simulated annealing after the iteration to balance the convergence of global optimization and local optimization. This algorithm proceeds with the idea of simulated annealing, using the particle swarm algorithm (Limiao., 2019) that integrates simulated annealing, processing the node information population according to multiple rounds of loop iteration, and obtaining the optimal knowledge point for each round within the range of knowledge points. Then, the learning paths are formed by the weight.

In this article, the algorithm is improved to obtain a simulated annealing particle swarm fusion algorithm (MI-SA-PSO). This is suitable for multiple rounds of iterations in the case of forming a learning path based on a knowledge graph. The basic idea of applying this method in path recommendation is as follows. The first-level nodes (or knowledge blocks) are obtained by dividing the weights into high and low levels. The global situation uses the simulated annealing particle swarm fusion algorithm with multiple iterations. Thus, the individual optimal pbest is found as the global optimal instead of the real optimal solution to preserve the diversity of the population and avoid the local optimal situation. After obtaining a global optimum, it updates the population to perform a new round of algorithm to realize the learning path of the knowledge block part, form the learning path of different knowledge blocks according to the weight of different knowledge blocks cyclic iteration, and merge to obtain the overall learning path. The detailed execution of the algorithm is shown in Table 1.

DESIGN OF A LEARNING PATH RECOMMENDATION SYSTEM BASED ON A KNOWLEDGE GRAPH

Construction of Knowledge Graph

Learners can grasp the direction of learning to improve learning efficiency and learning quality in autonomous learning. Therefore, the authors recommend learning paths, introduce the subject

Table 1.
Algorithm description

Algorithm: MI-SA-PSO **Input:** A test module **Output:** Learning Path for the Test Module
1. **Setting parameters.** The parameters of the particle swarm algorithm, including the population size m, inertia weight w, maximum interval speed v_{max}, learning factors η1 and η2, and parameters of the simulated annealing algorithm, including heating chain length L, temperature drop rate ζ, solidification temperature T_{end}, etc. 2. **Initialize the population:** Randomly generate m particles in the search space. The most initial position is set to a random number between [0,1] times the interval width. The initial speed is set to a random number between 0-1 times the maximum interval speed. 3. **Calculate the fitness of the particle:** Take the current position of each particle as the optimal value pbest of the individual particle. Select the optimal position from the generated individual optimal value as the global optimal value gbest. The respective optimal value pbest is compared with the current global optimal value gbset. Then, the node with the largest optimal value is selected as the global optimal value gbest. Its initial value is between the maximum and minimum values of pbest. 4. **Rounds of iteration:** A neighborhood search is performed on each particle using a simulated annealing strategy. 5. **Optimization update function:** According to the function, the new fitness of each particle is obtained. The individual optimal value and global optimal value of the particle are determined. 6. **Obtain new speed:** Obtain the new speed and position according to the speed update formula (1) and position update formula (2). $v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 \left(pbest_{id}^{k} - x_{id}^{k} \right) + c_2 r_2 \left(gbest' - x_{id}^{k} \right)$ (1) $x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}$ (2) 7. **Heating and annealing:** Preheat before annealing. The value after heating was taken as the initial temperature during annealing. 8. **Determine if the smallest global optimal value:** Continue if the conditions are met. Go to *step4* if not. 9. **Update the particle population:** The obtained global optimum is excluded from the population. The new population is used as the new population for the next round. Then, the algorithm goes to the next iteration. 10. **Terminate judgment:** The particles number in the population is 1. Then, output the result. Otherwise, skip to *step 3.*

knowledge graph, and expand its system. They also arrange the weight of node information, use this weight to represent the predecessor-successor relationship of nodes, carry out efficient and high-quality learning, and use the feedback between teachers and students in the system for learning. Data acquisition and entity relationship extraction are top priorities in the construction of subject knowledge graphs.

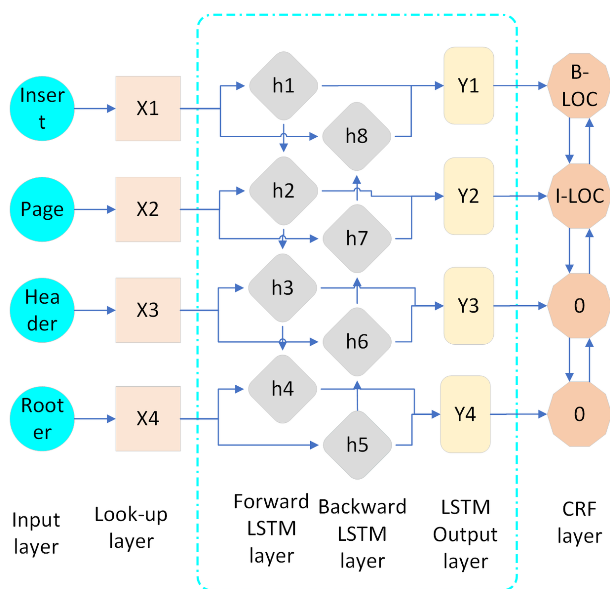
Data acquisition is the premise of the construction of a subject knowledge graph. The quality of the collected data has an important impact on the graph's construction (Yuan., 2021) . The knowledge graph in this article is based on the chapter "Information Processing and Processing" in the course "Information Technology Fundamentals in Senior High Schools." The knowledge graph is a chapter knowledge graph mastered by teachers. Follow-up functions are carried out based on the graph. To get high school students to study this course, specific data information is collected and acquired according to the content of the textbook. It is preprocessed according to manual labor, allowing the obtained knowledge to be more accurate and of high quality.

Entity extraction is the link in which knowledge nodes in knowledge graphs can be acquired and realized. Huang et al. (2015) introduced and proposed LSTM, bidirectional LSTM, LSTM+CRF, and BiLSTM+CRF models. The experimental results showed that the BiLSTM+CRF model has less dependence on word vectors and is more robust. The entity extraction and recognition in this article uses the BiLSTM+CRF model, which consists of three layers. The specific framework is as follows. The first layer of the model, the look-up input layer, converts the sentences obtained by preprocessing into word vectors. The second layer is a bidirectional LSTM layer, inputting the word vector in the BiLSTM of this layer and according to the score value of all labels of each word in the output sentence. The third layer is the sequence labeling layer. This is based on the output of the second layer as input, obtaining the probability of reaching the label sequence. The specific model structure is shown in Figure 1. In this article, a series of entity data are obtained by processing the text information in the textbook of the course chapter.

The whole BiLSTM+CRF model is suitable for use in the education domain in the step of entity extraction of the curriculum knowledge graph. It uses the curriculum-related labeled pre-training dataset for training adjustment. The model first awards the input into the look-up layer, which is mapped into word vectors using the model. The word vector enters the BiLSTM layer, which outputs the score probability of each word corresponding to each tag by learning the information of the context. The score probabilities of the tags are used as the unnormalized firing probabilities in the CRF model. The output of all the BiLSTMs will be used as the input of the CRF layer to obtain the final prediction result by learning the order dependence information among the tags.

Relation extraction is used to determine whether there is a defined relationship type between entities (Yuan., 2021). In the existing research, there are rule-based methods and deep learning methods for the extraction of relations between entities. According to the characteristics of the information technology discipline, that is, the combination of theory and practice, and the specific scenario applied to this course in high school education, this article uses a rule-based method to define the relationship between entities and conducts similar operations in the data set. The comparison and search are performed using manual intervention to ensure the accuracy of relational entities and weights.

Figure 1.
BiLSTM+CRF model framework

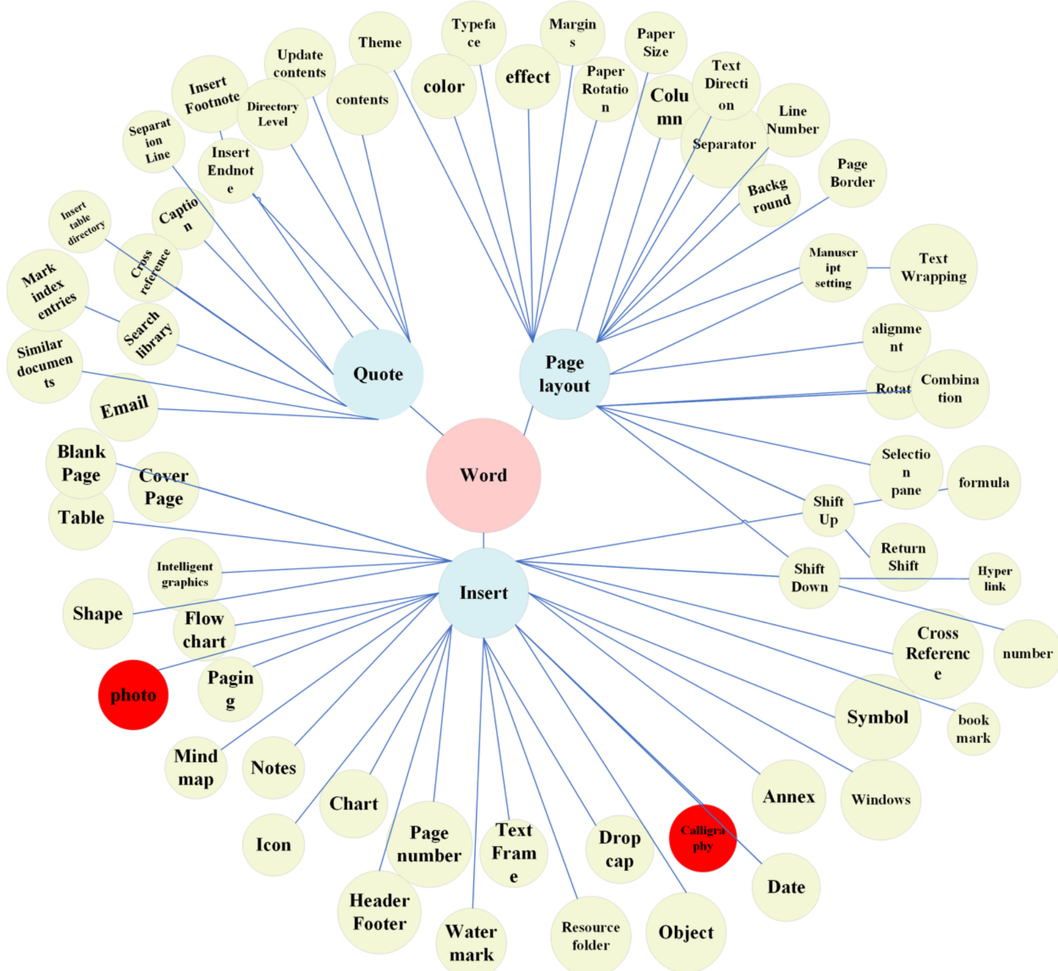


Graph Storage and Node Representation

Knowledge Graph Storage

The storage of knowledge is described in the form of RDF triples (*s, p, o*), which means there is a relationship *p* between resource *s* and resource *o* or that resource *s* has attribute *p* and takes the value *o*. With the rapid development of knowledge graphs, the database field has developed a graph database for the storage and data management of knowledge graphs. For the storage of the knowledge graph, triples are obtained after entity and relation extraction. The graph constructed in this article belongs to the knowledge graph in the education field. Therefore, its accuracy and quality are highly needed. After human intervention and processing, the repeated information in the triplet is merged; the redundant information is corrected to ensure the accuracy of the relationship between the nodes and the nodes of the knowledge graph. Finally, the obtained knowledge point entities and the predecessor-successor relationship layers, hierarchical relationships, and weights existing between the entities are stored in the graph database. Here, the graph database instance in the "Word" part of this chapter is used as a display. The instance knowledge graph is shown in Figure 2.

Figure 2.
Chapter knowledge graph



Knowledge Graph Node Representation

In the implementation graph, nodes are represented according to their attributes, such as relationships, features, and uses. This article adopts the following representation method (Yuan., 2021), as shown in Table 2:

$$Knowledge_i=\{ID_i,Name_i,Definition_i,Contain_i,Level_i,Centrality_i,Parents_i,Children_i,Offspring_i,Brothers_i\}$$

Design and Analysis of the Learning Path Recommendation System

Requirements Analysis

The use of learning path recommendation systems (LPRS) is aimed at groups of learners and teachers. Therefore, it is analyzed from the perspective of learners and teachers. From the perspective of learners' needs, the system should provide learners with the recommendation of the learning path of the learning chapter. In doing so, the learner can obtain the correct and objective guidance of the learning path when learning. On the other hand, learners participate in combined project-based learning through group cooperation. They can see the knowledge graph formed by the group and between groups according to the learners' cognitive learning situation. Learners can provide teachers with feedback about their learning situation and difficulties through the feedback function. They can also view feedback of the teachers.

From the perspective of teachers' needs, the system should provide teachers with a grasp of the knowledge graph between groups, as well as a view of the knowledge graph of chapters. Moreover,

Table 2.
Knowledge node description

Attributes	Meaning
ID_i	An identifier that uniquely identifies a knowledge point.
$Name_i$	Indicating the name of the knowledge node.
$Definition_i$	Relevant information about the knowledge node, such as definition, etc.
$Contain_i$	Inclusion relationships of knowledge nodes at different levels.
$Level_i$	The hierarchical level where the knowledge node is located.
$Centrality_i$	The node centrality of the knowledge node is the importance degree.
$Parents_i$	The set of elements of the predecessor nodes contained in the knowledge node.
$Children_i$	The set of elements of the immediate successor nodes contained in the knowledge node
$Offspring_i$	In the same hierarchical level, any knowledge node contained in a subtree rooted at a node.
$Brothers_i$	The set of all sibling node elements of the target knowledge node, that is, the set of nodes that have the same predecessor as the target knowledge node.

Table 3.
Development Environment

Hardware Environment	Software Environment	Key Technology
Os: Windows 10 64-bit system	Java-environment: JDK12.02	Backstage: Java
CPU: AMD Ryzen 5 3550H 2.10 Hz	Eclipse 2020.09 Tomcat 8.0	Front-end: Bootstrap JSP
RAM:16.0GB	Mysql Server 5.7	Framework: SSM

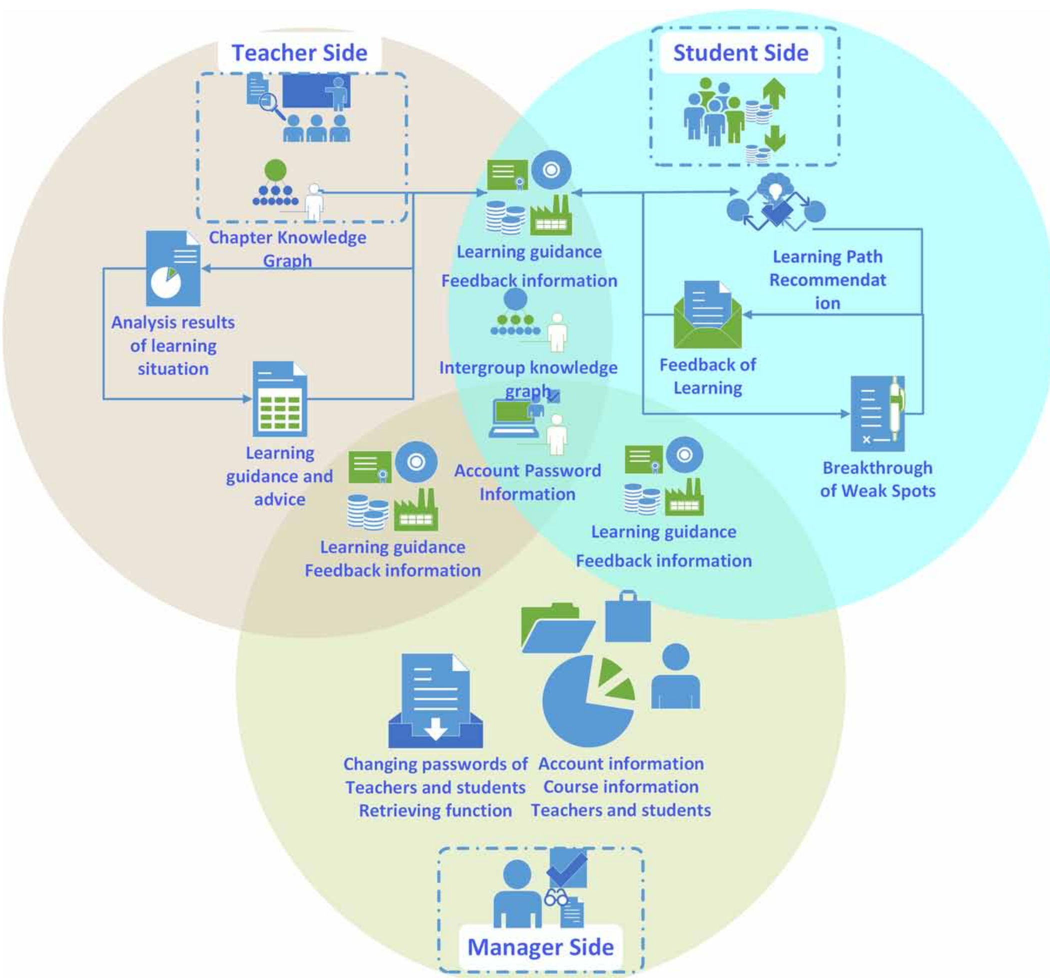
it is necessary to understand the group situation of students and the completion and mastery of the course knowledge in the project-driven course. In doing so, they can give corresponding feedback and suggestions. From the perspective of the designed system model, it realizes different functions according to users. It also realizes information feedback between learners and teachers. The functional framework of the learning path recommendation system is shown in Figure 3.

Overall System Design

Based on the analysis of requirements, the system design and analysis are carried out. The analysis of the system shows that the core of the system consists of the learning path recommendation supported by the teacher-side chapter knowledge graph and the learning situation feedback between teachers and students. On this basis, according to the differences in the functions of teachers, learners, and administrators, its design can be composed of the web client layer, core layer, and database layer.

The first layer, the web client, is also called the system browser interface. Its main function is to present the corresponding resources to the user in an interfaced form according to the user's identity. This helps to facilitate the user's operation and interaction. The authenticated user identity information

Figure 3.
Functional framework of the learning path recommendation system



provides different functional modules. The visualization functions of all users in the Web layer are centrally stored and called by identity modules.

The second layer, the core layer or service interaction layer,connects the web client layer and database layer through the server. First, the login information of the Web client layer is compared with the database. Then, it calls the identity functions that correspond to different identity modules to display the corresponding interface information after determining the identity. For teachers, this is the interface of learning guidance and learning situation details. It is also the viewing of chapter knowledge graphs. For students, it recommends learning paths, offers feedback for learning situation information, and gives a view of teachers' suggestions. It also provides interfaces, such as the knowledge graph, for individual groups and between groups in the project-based lessons.

The third layer, the database layer, stores and manages data (like a data warehouse). This stores learners' personal information and feedback information, teachers' personal information and feedback information, interaction data, and knowledge graph of the learning path recommendation system based on knowledge graph.

Modular Design

The system takes the high school information technology basic course as an example. Two senior students are used as the research object. The system function design is based on the role-based division module according to the many functions of personnel. The rational design and development of the system are carried out. The final functional module design is divided into the teacher side, student side, and administrator side. The focus is on the design of the teacher and student sides. The administrator side is used for the management of personnel information.

The three modules include submodules. All have different functions. Among them, the teacher terminal grasps the progress and learning situation of each student based on information feedback from the student terminal. The student side recommends paths and conducts related learning based on the chapter knowledge graph of the teacher side. The student side performs learning based on feedback from the teacher, filling gaps and strengthening exercises. The functions of the learning path recommendation system are shown in Figure 4. Next, the two major functions of learning path recommendation and teacher-student learning guidance information feedback are introduced.

The learning path recommendation function module is first. The recommendation of the learning path requires the reading and expansion of the chapter knowledge graph on the teacher side. The process is carried out according to the first-level center point in this knowledge block and the multi-round iterative simulated annealing particle swarm fusion algorithm in this article. The result of the learning path recommendation is obtained through analysis. The result is presented on the interface of the corresponding function module on the student side.

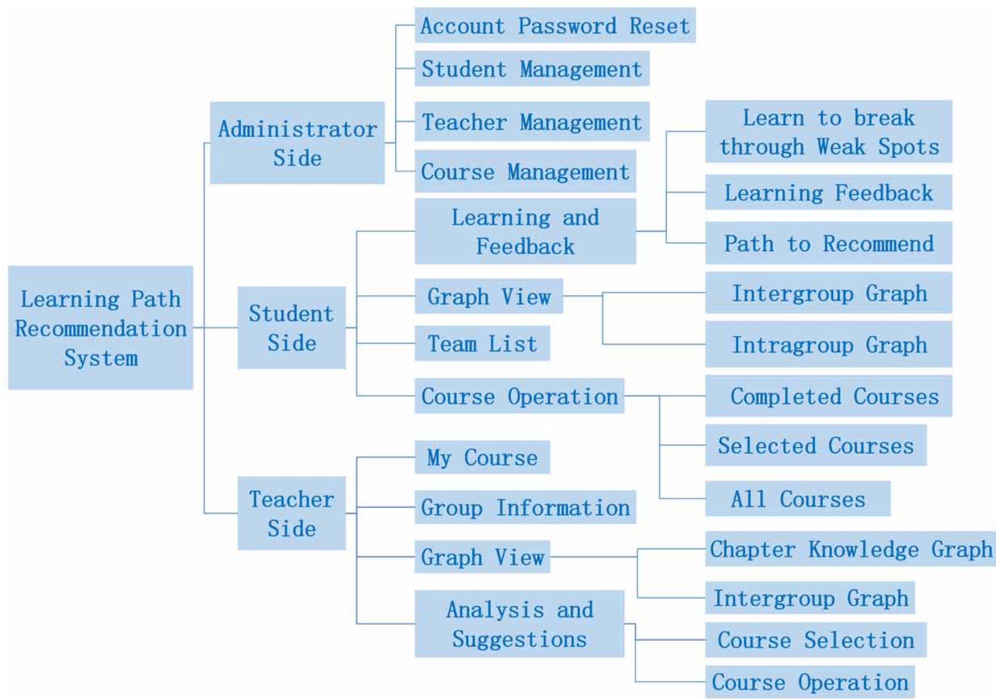
A module for feedback on learning information between teachers and students is second. In the project-based course, students submit their details to teachers through the feedback function module according to their learning results, usual homework, and test information. After receiving the learning information from the students, the teacher puts forward follow-up study suggestions that grasp the students' weak points and guides them to break through and carry out self-intensive learning. Students can also give feedback to teachers on other occasions according to their internal conditions. The information obtained by teachers and students is presented in an interface.

SYSTEM FUNCTION REALIZATION AND PERFORMANCE TEST

Development Environment

The learning path recommendation system includes modules like personnel login, path learning on the student side, group information, chapter knowledge graphs, and information feedback on the teacher side. It also includes a series of management functions on the administrator side.

Figure 4.
System function



The system uses eclipse 2020.09 as the compilation environment during development. The system also uses the ssm framework for development. The back end uses Java language to write logic content and the database uses the relational database Mysql. Front-end development uses the unified method in the bootstrap framework for reasonable layout. The ORM framework of Mybatis is used to describe the details of object-relational mapping in the form of metadata. It adopts the Web framework of SpringMVC and uses the IOC (inversion of control) of Spring container instantiates objects, locates, configures objects in the application, and establishes dependencies between these objects, uses the Shiro security framework to perform authentication, authorization, password and session management, and uses the C3P0 data source, which is an open source JDBC connection pool that implements data source and JNDI binding and supports a variety of open-source frameworks at the same time. Using log4j, its destination of the log information delivery through the configuration file system is the console, file, and GUI components. Even the socket server, NT event recorder, UNIX Syslog daemon, etc., can control the output format of each log. The log generation process is controlled by defining the level of each log information control.

Function Module Implementation

The system adopts the idea of modularization. Its overall functional module diagram is shown in Figure 4. The following introduction describes and displays the functions and implementation of the core modules of the learning path recommendation system in this article.

Login and Identity Verification

The function module uses the Shiro authority management framework to realize login verification and storage of login information. It identifies authority roles according to different login accounts.

It also sets roles for different URLs. When logging in, the user needs to fill in the account password and select the identity category information. The specific interface is shown in Figure 5.

Chapter Knowledge Graph

The chapter knowledge graph module is a teacher-side module. Teachers can enter this functional module to view the knowledge graph formed by the chapter of the course and the related processing of text information. It can then perform node query and search. The specific situation is shown in Figure 5.

Learning Path Recommendation

The main functional module of learning path recommendation is implemented according to the chapter knowledge graph on the teacher side. By using the simulated annealing particle swarm fusion algorithm of multiple rounds of iterations, the recommendation of the learning path for the chapter "Information Processing" is realized. This also looks at the connection between knowledge and the relevant weight ratio to show the level and order to use. The learning path obtained from the knowledge graph recommendation contains a sequence of the big steps of the module formed by the recommendation and the small steps within it. Each big step is labeled with a color block to show its contents. This guides students' learning to be holistic and structured according to the recommended path. The knowledge learned by students presents a more perfect connection of antecedents and successors. The effect is shown in Figure 5.

Knowledge Graph Between Groups

The knowledge graph between groups is an important part of project-based course learning through group cooperation. Students improve the graph through learning. Teachers can master the teaching by viewing the graph between groups. At the same time, the knowledge graph between groups is an important part of the group students' mutual checking and filling. It is also one of the means for teachers to carry out targeted teaching and improve teaching plans. Finally, the intergroup knowledge graph is displayed between teachers and students with visual technology.

Information Feedback on Learning Situation

The learning information feedback module is a functional submodule on the student side. Students submit their knowledge, usual homework, test information, and personal completion evaluation to teachers through a course study. This allows the teachers to understand the students' knowledge mastery and the weaknesses of each student. The specific interface is shown in Figure 5.

Teacher Guidance and Feedback

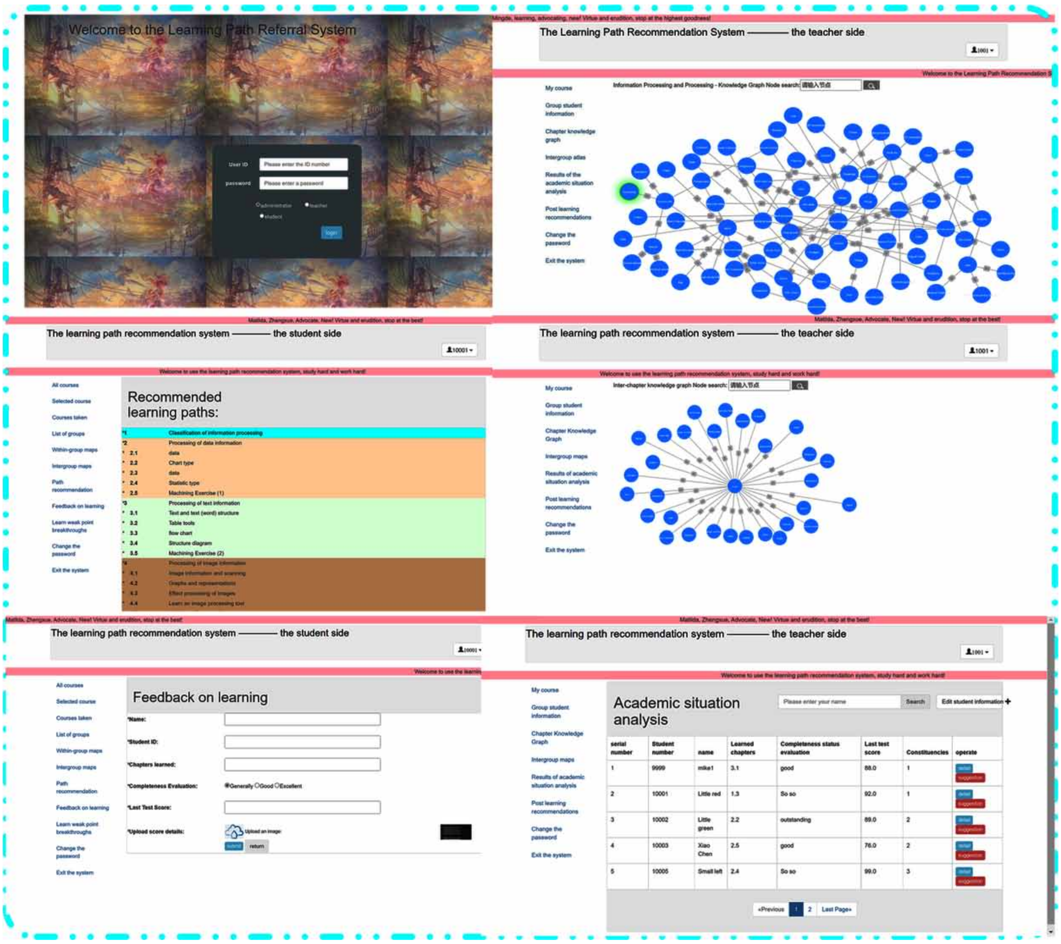
Teacher guidance feedback depends on the information submitted by students in the learning information feedback module. Teachers can intuitively see the specific information of students. According to the content of the module and through the interface prompts of this module, the teachers can make targeted learning suggestions or offer guidance and help. Students overcome weak points and implement reinforcement learning programs. The specific implementation is shown in Figure 5.

System Test

Function Test

The functional testing of the learning path recommendation system checks whether the system satisfies the goals of its development and whether the relevant functions are realized. It also verifies the functional modules of the detection system. The operation of data information is normal. The functional modules meet the software engineering requirements of "high cohesion and low coupling."

Figure 5.
Learning path recommender system function implementation



The black box test is used to study the function of the system and whether the corresponding functions of each identity end of the learning path recommendation system can be implemented normally according to the known functional requirements and check its normal use. Through this test, it is found that the functions of the software are not omitted. The interface is implemented normally, the data structure meets the requirements, and the initialization and termination meet the requirements. The system passes the functional test. Its performance test is described in the next part.

Performance Test

The learning path recommendation system is used in students and course teaching. The number of users is less than 100; therefore, the requirements for concurrent issuance are low. Feedback between teachers and students should be timely in project-based course learning. It should also have a low delay. The viewing and integration of knowledge graphs between groups puts forward higher requirements for delay. Therefore, the overall purpose of performance testing is more inclined to detect system delays or throughput and pay more attention to system efficiency. Due to space requirements, only the results of some performance tests are described.

Compatibility Test

The learning path recommendation system is used in teaching and the classroom. The computers used by teachers and learners are almost all Windows operating systems on the network within the school. Therefore, the compatibility of the operating system does not need to be considered. Considerations include different mainstream browsers, network environments, devices to test, applicable conditions of the network environment, browser, and device testing. The results obtained by testing these conditions are as follows.

First, tests are carried out on different network environments, specifically laptops with direct connection and WiFi networks. The test results show that the system can be used in two network environments. Both network conditions are relatively stable. For WiFi testing, the strength of the signal affects the fluency and response time of the system. Second, testing different browsers on the PC side, through the test results, shows that in the current mainstream browsers, the compatibility of the system has reached the goal of comfort and convenience. Finally, when testing the different devices, the results show that the use of the system is suitable for computers and tablets. The compatibility with the mobile phone interface is relatively low.

Use Effect Verification

Recommendation of learning paths for learners and feedback from teachers and students are the main functions of the system. These are important ways for learners to learn. It also improves learning quality and performance of the learners. To verify the application effect of the system, approximately 100 students in the first grade of the affiliated middle school of Henan Normal University were verified for a period of six weeks. The effect verification consists of the average stage weekly test scores.

Table 4.
Login and Learning Path Performance Test

Module function: Login, learning path recommendation
Test operation: 1. Access and log into multiple hosts. 2. Enter account and password. 3. Browser shows loading is complete. Path recommendation page is a normal display. 4. Record response timestamp. Test duration is one hour.
Result analysis: 1. Interfaces can be loaded normally without exception. 2. Page information is normal. Response time (t < 10s) is as expected.

Table 5.
Learning Feedback Performance Test

Module function: Feedback on learning situation – student side
Test operation: 1. Submit learning feedback of multiple accounts. 2. Enter login and feedback interface. 3. Browser shows loading is complete and the page is normal display. 4. Record upload time of submitted learning situation information. 5. Each user repeats feedback detection five times.
Result analysis: 1. Interfaces can be loaded normally. Abnormality does not appear. 2. Submit information upload time (t < 10s) as expected. 3. Page information is normal. Response time (t < 10s) is as expected.

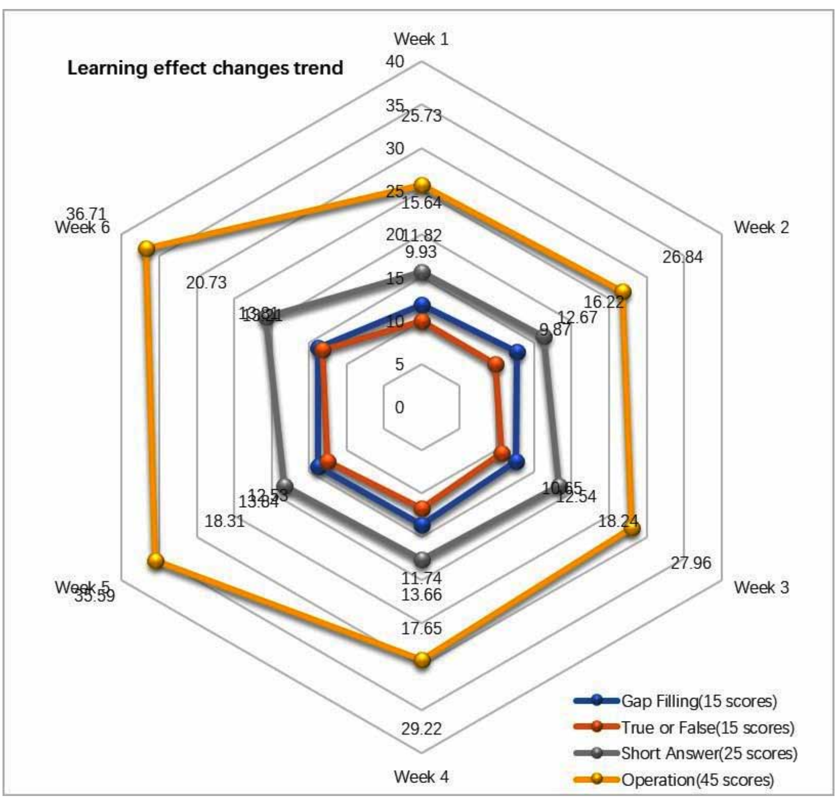
Table 6.
Study Guide Performance Test

Module function: Learning guidance feedback - teacher side
Test operation: 1. Log into system and enter the student learning situation analysis. 2. Provide five guidance and suggestion feedbacks to 20 learners. 3. Record time spent uploading guidance and suggested systems
Result analysis: 1. Interfaces can be loaded normally. Abnormalities do not appear. 2. Submit information upload time (t < 10s) as expected. 3. Page information is normal. Response time (t < 10s) is as expected.

The average phase weekly test score, which can be combined with the other trends, can reveal whether students have improved or where they have improved. On the one hand, it reflects the overall level of mastery of the different topics. On the other hand, it is possible to verify the manifestation of learner progress because the dependence on the system increases. The average weekly grades of the learners in the experiment are presented by topic type in Figure 6.

The goals of a learning path recommendation system are to improve the learning efficiency of learners and enable teachers to obtain better feedback information. On this basis, learners can have an improved learning experience as they master a more structured knowledge network. The experimental

Figure 6.
Learning effect changes trend



results show that learners accept the system and become independent learners with the support of the system. From the stage results, learners' scores are improved with the use of the system. This shows that the system is effective and practical.

SUMMARY AND OUTLOOK

This article explores the background of educational informatization, the principle of knowledge structure, the direction of learners' learning, and the feedback of teachers and students as the auxiliary. Then, it designs and implements a learning path recommendation system based on a knowledge graph. The learning path recommendation system makes up for any learning confusion caused by knowledge overload in the existing education platform. It indicates a learning path for students, which can satisfy the information feedback communication between teachers and learners.

The system can help learners check knowledge points, make breakthroughs in weak points, strengthen learning in a timely manner, and help teachers grasp the learning situation of students in time to adjust the teaching progress and arrangements. It solves the disorder of the massive resource recommendation of the existing learning and education platform and adds the auxiliary guidance function that the existing education platform lacks. The recommendation of learning paths is implemented based on knowledge graphs and related algorithms. Therefore, there are strong logical connection requirements for the applicable disciplines. Additional research is needed on how to adapt the system to more disciplines and intelligently generate the educational knowledge graph.

ACKNOWLEDGMENT

Supported by research and practice project of higher education teaching reform in Henan Province (No 2021SJGLX355, 2021SJGLX106), New Engineering Research and Practice program (2020JGLX017), and Intelligent Teaching special research project of undergraduate universities in Henan Province (2021).

REFERENCES

Aidan, H., Eva, B., Michael, C. d'Amato, C., Gerardm de M., Claudiom G., … Antoine, Z. (2021). Knowledge Graphs. Morgan & Claypool Publishers.

Ang, M., Yanhua, Y., Shengli, Y., Ishikawa, J. L., & Xiuxiu, C. (2022). A review of knowledge graph research based on reinforcement learning. *Jisuanji Yanjiu Yu Fazhan*, 1–28.

Fiqri, M., & Nurjanah, D. (2017). Graph-based domain model for adaptive learning path recommendation. *IEEE Global Engineering Education Conference (EDUCON)*, 375–380. doi:10.1109/EDUCON.2017.7942875

Guangquan, L. (2018). *Research on educational resource recommendation service based on learner's personality* [Master's thesis]. Jiangxi University of Finance and Economics, Jiangxi Province, China.

Haiping, Y., Huichao, L., & Jianxiong, W. (2012). Improved strategy of adaptive particle swarm optimization algorithm based on simulated annealing. *Jisuanji Yingyong Yanjiu*, *29*(12), 4448–4450.

Hang, Z. (2020). *Research on the automatic evaluation method of junior high school mathematics lesson plans based on knowledge graph* [Master's thesis]. Huazhong Normal University, Wuhan, Hubei Province, China.

Hanlin, W. (2021). *Design and research of learning path recommendation based on learner portrait* [Master's thesis]. Zhejiang Normal University, Wuhan Province, China.

Huang, Z., Wei, X., & Kai, Y. (2015). Bidirectional lstm-crf models for sequence tagging. *Computer Science*.

Kwa, B., Jzp, A., & Mjk, A. (2020). Schema aware iterative knowledge graph completion. *Journal of Web Semantics*.

Limiao, X. (2019). *Recommendation algorithm and application research based on particle swarm optimization* [Master's thesis]. Minzu University of China, Beijing, China.

Menghua, C. (2020). *Personalized learning path recommendation based on knowledge graph* [Master's thesis]. National University of Defense Technology, Hunan Province, China.

Nguyen, T. T. M., & Tran, T. P. Q. (2021). A knowledge graph embedding based approach for learning path recommendation for career goals. In *International Conference on Computational Collective Intelligence*. Springer. doi:10.1007/978-3-030-88081-1_6

Niknam, M., & Thulasiraman, P. (2020). Lpr: A bio-inspired intelligent learning path recommendation system based on meaningful learning theory. *Education and Information Technologies*, *25*(5), 3797–3819. doi:10.1007/s10639-020-10133-3

Padia, A., Kalpakis, K., Ferraro, F., & Finin, T. (2019). Knowledge graph fact prediction via knowledge-enriched tensor factorization. *Journal of Web Semantics*, *59*, 100497. doi:10.1016/j.websem.2019.01.004

Qinghua, Z., Bo, D., Buyue, Q., Feng, T., Bifan, W., Weizhan, Z., & Jun, L. (2019). Research status and development trend of smart education. *Jisuanji Yanjiu Yu Fazhan*, *01*, 209–224.

Ronghai, X., & Changdong, W. (2021). Deep learning recommendation system based on tensor decomposition of heterogeneous information network meta-paths. *Journal of Information Security*, *6*(05), 77–87.

Seghroucheni, Y. Z., Mohammed, A. A., & Mohajir, B. (2014). Exploitation of the recommendation systems in the calculation of the learning path. *International Conference on Information & Communication Systems*, 1–6. doi:10.1109/IACS.2014.6841985

Shi, D., Wang, T., Xing, H., & Xu, H. (2020). A learning path recommendation model based on a multidimensional knowledge graph framework for e-learning. *Knowledge-Based Systems*, *195*, 105618. doi:10.1016/j.knosys.2020.105618

Sizhu, W., & Zhixiong, Z. (2010). A survey of research on network centrality calculation methods. *Library and Information Work, 54*(18), 107–110, 148.

Wang, X., Huang, T., Wang, D., Yuan, Y., Liu, Z., He, X., & Chua, T. S. (2021). Learning intents behind interactions with knowledge graph for recommendation. *Proceedings of the Web Conference*, 878–887. doi:10.1145/3442381.3450133

Xinhua News Agency. (2019). *The General Office of the CPC Central Committee and the General Office of the State Council issued the Implementation Plan for Accelerating the Modernization of Education (2018-2022).* http://www.gov.cn/zhengce /2019-02/23/content_5367988.htm

Ye, C., Gang, Z., & Cang, J. L. (2021). A review of research on the construction and application of multimodal knowledge graphs. *Research in Computer Applications*, 3535–3543.

Yuan, M. (2021). *Research and application of adaptive learning path recommendation method based on knowledge graph* [Master's thesis]. Xi'an University of Technology, Xi'an, Shanxi Province, China.

Yue, W. (2019). *Research on personalized learning path recommendation based on improved binary particle swarm optimization* [Master's thesis]. Zhejiang University of Technology, Zhejiang Province, China.

Zhen, L., Xiaoxiao, D., Dongdai, Z., & Tingting, T. (2019). Human-machine collaborative construction method and application of knowledge graph in adaptive learning system. *Modern Educational Technology*, *29*(10), 80–86.

Zhuang, C. (2020). *Research on online learning path recommendation algorithm* [Master's thesis]. Huazhong Normal University, China.

Peiyan Yuan received the B.S., the M.S. and Ph.D. degrees from Henan Normal University, Xinxiang, China, Wuhan University of Technology, Wuhan, China, and Beijing University of Posts and Telecommunications, Beijing, China, respectively, all in computer science. He is a Professor of Computer Science at the Henan Normal University. He also worked as a post-doctoral researcher at the University of Texas at Dallas, USA. His research interests include future networks and distributed systems, and he authored or coauthored more than fifty papers and one book in these fields. He won the national scholarship for Ph. D students from Ministry of Education of the P. R. China in 2012, and he received the Best Paper Award of IEEE CSE in 2014. He is a senior member of CCF and a member of ACM and IEEE.