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*Research Article*

# A Personalized Learning Path for French Study in Colleges Based on a Big Data Knowledge Map

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The education industry is gradually improving with the rapid development of information technology. The learners use networks and computers to alter the traditional instructional framework based on educational information technology and achieve personalized learning. This teaching method emphasizes each learner's identity and autonomy. However, due to the huge number of learning resources available on the Internet, students lack relevant courses, clear learning tasks, and the connection between various knowledge points, resulting in an unsatisfactory effect on the learning process. Knowledge maps for different learner types are created using historical learners' conceptual knowledge and the segmentation and correlation technique of big data knowledge maps. Using a big data method in this process will automatically generate a set of weak conceptual learning pathways. For this problem, in the era of big data, people put forward the concept of knowledge map and used the algorithm based on the big data knowledge map to study the personalized learning path for college French. The content, structure, and relationship of college French knowledge points can be accurately expressed using this method, which is preferred by college administrators and teachers. This paper aims to investigate the personalized learning path for college French using a big data knowledge map, starting with the characteristics of a college French field of study. This study provides technical support in the establishment of a big data knowledge map based on a learning path recommendation framework. So, after the performance of several commonly used learning path recommendation algorithms, three French students have been selected at random for learning path planning. The results show that personalized learning path planning can be realized based on a knowledge map pre-repair relationship and objective attributes. In the analysis, not only the proposed technique is compared with the conventional optimization approach, but also a comparison study on the benefits of several learning effect prediction models is also performed. The results of this study suggest that this algorithm has a high learning efficiency and that the effective implementation of recommendations produced using our proposed strategy has a significant advantage.

## 1. Introduction

Education is the process of memorizing information in the human memory for later use in presenting important information or a part of a mental process to fully comprehend everything. The process of acquiring knowledge and skills that can be used to improve consciousness and intelligence is referred to as learning. Learning must be beneficial, pertinent, purposeful, and cumulative and carried out at the appropriate stages to be effective and successful [1]. The feedback learning is one of the significant learning behaviors produced by the learner's e-learning process. The historical response records can be used to determine the learner's conceptual knowledge, and knowledge gaps in the learning process can be precisely identified. A student's understanding of a subject may be lacking if, for comparison purposes, their past response archives reveal a higher exercise error rate for that concept. Because ideas are interdependent, a learning path must be planned to ensure that the learner fully understands the deficient concepts [2]. When performing activities, learners have more difficulties comprehending their conceptual knowledge and making judgments about the efficacy of their operations. Additionally, they could have a hard time analyzing and assimilating important and targeted concepts. The learner's response data may thus be utilized to automatically determine the connections between ideas, identify weak concepts, and provide individualized learning path assistance in real-world environments [3]. It can enable the students to bridge gaps in knowledge and perhaps grow into important competence in difficult concepts. The basis for the recommended path is built by automatically identifying challenging topics based on learner reaction data and providing future students with a successful introduction to the same concepts, to determine when concepts interact with one another to create tailored weak conceptual learning pathways for the targeted learners and to produce the intended learning outcome [4]. According to the following previous work on personalizing learning path, we build a personalized learning path for college French based on a big data knowledge map using the genetic algorithm.

A large number of them are now based on the previously established knowledge base, which, while occasionally useful, did not fully contribute to each learner's unique knowledge level. To address these issues, Liu proposed a knowledge structure improvement framework of learning approaches. It approaches the path recommendation procedure as a probabilistic decision-making method, keeping in view all personal variables of the learners and using the knowledge base as a framework. This demonstrates that when the learning pathway was designed, the standard learners were assumed to have completed the material, but this was not the case. Most students struggle to comprehend the material they have just learned [5]. Cai developed a knowledge mapping and reinforcement learning-based technique for designing learning paths. The algorithm can effectively predict students' learning progress, model learners' knowledge levels over time, and define students' learning conceptual frameworks [6]. Zhu proposed using long-term and short-term virtual memory (LSTM) to resolve this issue and select a unique learning path from among the suggested solutions. The use of genetic algorithms to design learning paths is one of the most exciting areas of research right now. An improved genetic algorithm based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used in order to facilitate the search for the nearly perfect learning route. TOPSIS, which is analogous to the perfect solution, is utilized to find the roughly optimal learning path solution [7]. The problem of establishing a learning path is described as a multiobjective optimization statement. The features of teaching and learning resources are used to generate a learner-centered knowledge map using a genetic algorithm, and a linear learning sequence is formed from the conceptual model using a traversal algorithm [8].

This study aims to create an algorithm that can automatically generate individualized learning paths based on the learners' current learning stages. Similar to the previous analysis, this one analyzes and comprehends behaviors as important factors in determining the knowledge levels of learners. This research is so much more comprehensive than the previous research, which required teachers to manually evaluate the difficulties in the knowledge points. The complexity of knowledge points for larger classes was automatically determined in this study using an information processing platform. This strategy reduces stress and time spent by instructors with the knowledge map learning resources on the Internet [2]. Personalized learning has become widely used in the field of learning due to the rapid development of the Internet, network technology, and computers in recent years, enabling people to share network learning resources [9]. However, there are a massive number of data learning resources on the Internet, and there are issues with lost knowledge and knowledge overload. The emergence of artificial intelligence technology effectively improves the way learners obtain learning resources, but learners are still unable to quickly obtain a huge number of knowledge points in the network resource environment. When college students study French, they are faced with the problem that numerous teaching resources on the network cannot be effectively used. The knowledge map algorithm solves this problem by combining a knowledge map and a personalized learning path. College students can fully grasp each knowledge point in the French personalized learning process and develop a personalized learning path for college French based on a big data knowledge map. Firstly, based on the entity recognition and the link of the knowledge map, the knowledge map between entities and relationships is established, and the map database is used to store and realize data visualization [10, 11]. The personalized learning path model is then built based on the learning path recommendation algorithm to determine the importance of each knowledge point in the knowledge map, allowing the importance of each knowledge point to be evaluated.

The main innovations in the research process of this paper are the following:

(i) This paper focuses on the analysis of the basic concept, storage mode, and basic architecture of the knowledge map algorithm

(ii) We build a personalized learning path for college French based on a big data knowledge map through text similarity calculation and establish a personalized learning path model

(iii) Using the personalized learning path model, college French students are randomly selected to test the learning path planning results, which are added to the prerequisite relationship map and objective

(iv) College students' attributes to personalized learning path planning based on a big data knowledge map can obtain the best personalized learning path and high learning efficiency

The remaining sections of the paper are organized as follows: Section 2 presents related work of the paper; Section 3 presents knowledge mapping algorithms for large data; Section 4 presents the personalized learning path for university French based on big data mapping; Section 5 presents the analysis of the application results of personalized learning path for college French; and finally, Section 6 concludes the research work.

## 2. Related Work

Due to the rapid development of network technology, e-learning resources will continue to iterate and be updated. Currently, recommending the best learning paths to students is the future development trend in e-education. At the same time, more and more experts at home and abroad are beginning to study personalized learning based on a knowledge map [12]. Wan et al. represent the data acquisition layer, the information visualization layer, the behavior layer, and the knowledge ontology layer, and then combine the layers to form a knowledge map learning model [13]. Golpardaz et al. proposed the conditional random field (CRF) model, which is the most typical statistical model for entity recognition and can transform entity recognition problems into sequence annotation problems [14]. LV produces a knowledge map of the medical field by statistically analyzing knowledge data in the field of medical education in order to increase students' enthusiasm for learning medical knowledge [15]. Lissa et al., the authors of this study, use the concept of a "knowledge map" in traditional education to express knowledge in the form of a map and display knowledge intuitively and powerfully to improve students' learning efficiency [16]. Tu used scientific knowledge in the knowledge map to show the relationship between various knowledge points in the way of the map. So, the students can visualize the difficulty of different knowledge points on the map, clearly understand the weaknesses of mastering knowledge, and better deal with problems [17]. Zhang and Ma proposed to establish an educational knowledge Atlas system based on a knowledge map in order to display educational knowledge in the form of a map [18]. Bazhukova and Afonina pointed out that the essence of applying a knowledge map to the field of education is to clarify the relationship between knowledge points and form a complete knowledge map [19]. Mohsin et al. use an ant colony algorithm to optimize the learning path and formulate the best algorithm to adapt to learning [20]. Saito and Watanobe enhanced learning path recommendation with a collaborative recommendation mechanism and used this new method in learning path recommendation [21]. Wang et al. used the experimental method to validate knowledge point ranking and selection. They arranged the knowledge points from the learning path based on the knowledge structure in the knowledge map and the reference index [22]. Zhang and Ye initiated with different learner styles and analyzed the similarity between different learners using data from the learning-style scale. It first creates a swarm intelligence learning recommendation model and then employs the improved ant colony algorithm to add the parameters that influence the learning style, because learners can present a common learning path and achieve their goals [23]. Zou, addressing the situation of the learners' questions, then marked the nodes and convoluted the questions with the classification map. It produces the learning path using the Prim minimum spanning tree algorithm and modifies it based on the current learning situation [24]. Aladwan suggested first to designing the learner model, then mining the learners' preferences in the association rules, obtaining the corresponding interactive data and learning results, and eventually having to feed the data into the ant colony algorithm to complete the path recommendation [25].

## 3. Knowledge Mapping Algorithms for Large Data

*3.1. Knowledge Map Algorithmic Concepts.* The technology of knowledge mapping covers two parts, namely, the construction of knowledge mapping and the application technology. At present, the main goal is to transform the knowledge that can be understood and calculated by computers on the Internet to form the knowledge that can be understood by people. Therefore, there is an urgent need to build a knowledge map for different industries because different industries require different data integration capabilities for vertical industries [26]. In recent years, knowledge mapping has played an advantage in organizing and displaying knowledge, starting from the field of education, to establish the ideal effect of the personalized learning path for college French based on big data knowledge. This paper develops a personalized learning path based on each student's learning speed, interest, and goal by analyzing knowledge maps and data from college students' French learning behaviors.

An entity is an important unit in the knowledge map, and the essence of entity recognition is named entity recognition in text. The purpose of entity link is to deal with the problem of diversity and ambiguity in entities. If the meaning of MAC is different in different fields, "MAC" has recently introduced a red slogan. In this case, the entity link system should correspond to the "MAC" mentioned in the corresponding text, not the three-tier architecture of MAC in the computer field. Because an object in a large amount of data can be expressed in many different ways, the complexity of large data is very high in the analysis of large amounts of text. So, it is necessary to identify entities and links first to reduce information overload. The technical architecture of knowledge mapping is depicted in Figure 1.

*3.2. Knowledge Map Storage.* At present, there are two methods for storing knowledge maps containing relational databases and graph databases. However, the amount of data continues to grow as information technology advances, and relational databases cause data redundancy, prompting some people to use graph databases [27]. A graph database is a new NoSQL database that uses a computer graph theory, which analyzes the internal relationships of data more intuitively and efficiently. Compared with relational databases, graph databases are suitable for the storage of this knowledge map. Most data types are semistructured or structured, and graphic databases store data information in a graph-structured sort of way. Users require a significant amount of time and effort to process data, but they will also easily find, modify, add, and delete data. The graph database can be used if the three attributes of nature, concept, and development in educational knowledge points are assumed. These relationships are directional and can be represented in a simple

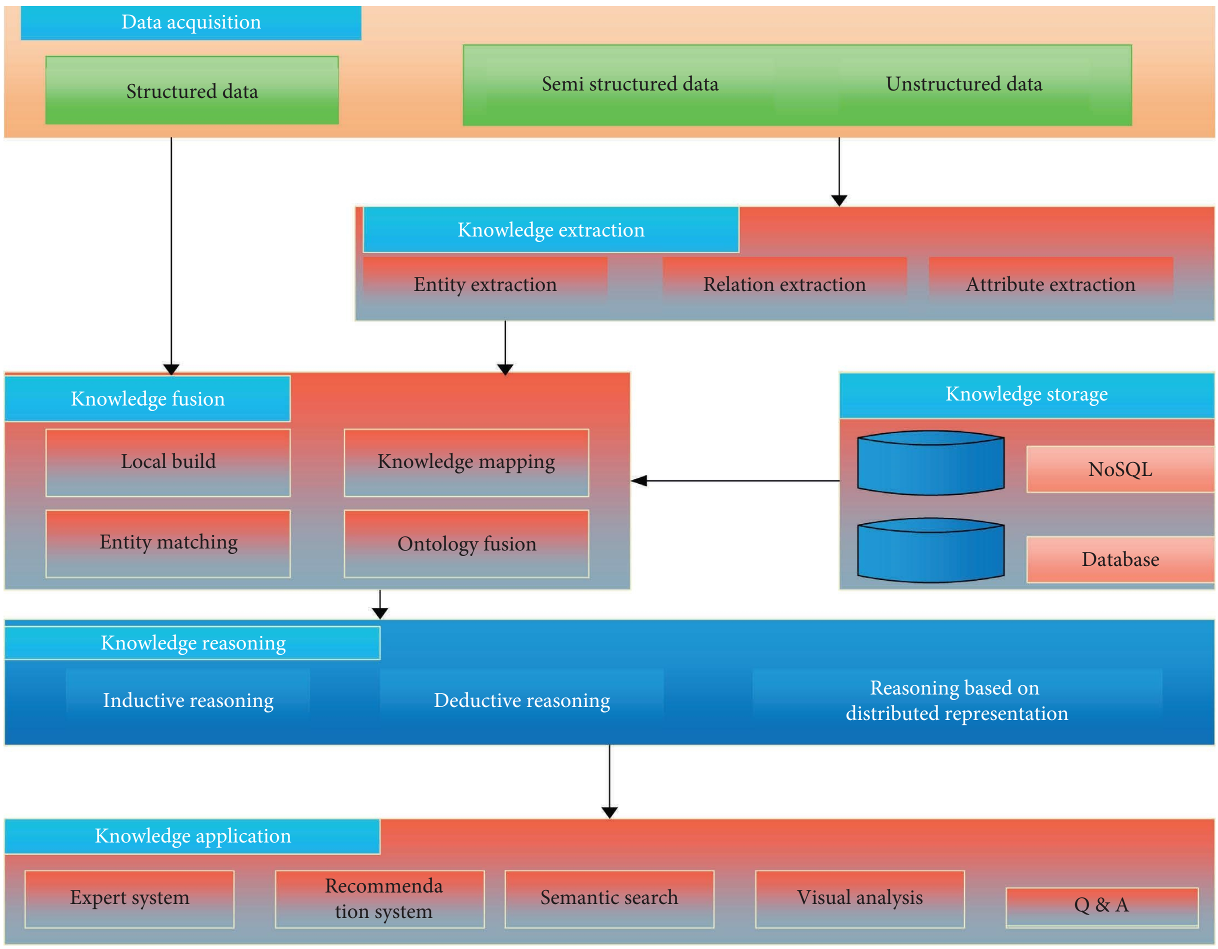


Figure 1: Knowledge map technology architecture.

form to show the connections among the knowledge points. As shown in Figure 2, graphic databases enable complex relationships between entities to be processed effectively.

This paper chooses the Neo4j diagram database and saves the data in the network instead of the traditional local database. The following are the significant advantages of the diagram database over the traditional database:

Step 1: Neo4j is highly compatible and supports popular programming languages such as Ruby and Python

Step 2: The Cypher database query language corresponds to the majority of people's thinking modes

Step 3: Neo4j processes data more quickly and has a very simple storage structure

Step 4: Using the import tool, it can import relational and entity data at the same time, as well as support large-volume data storage with less latency and significant real-time performance

Step 5: Data display page operation is simple

*3.3. Text Similarity Calculation.* In the personalized learning path for college French based on a big data map, more

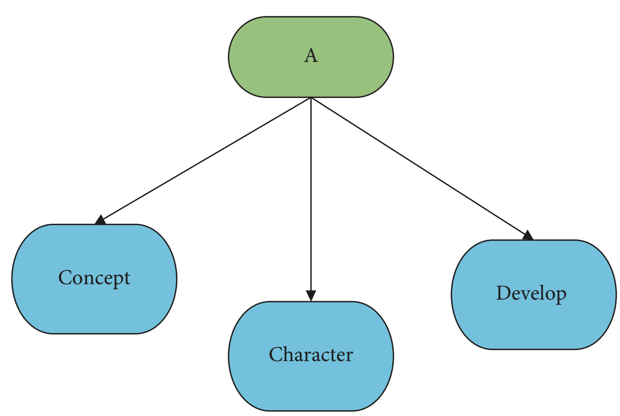


Figure 2: Knowledge map showing knowledge points.

algorithms are used for similarity calculation, which is also a basic technology in natural language processing (NLP). This paper calculates the similarity between different points of knowledge in college French courses, builds the connection between them based on the results of text similarity, and promotes the learners to achieve the rapid transfer and mastery of knowledge.

The following details describe several similar calculation methods currently used.

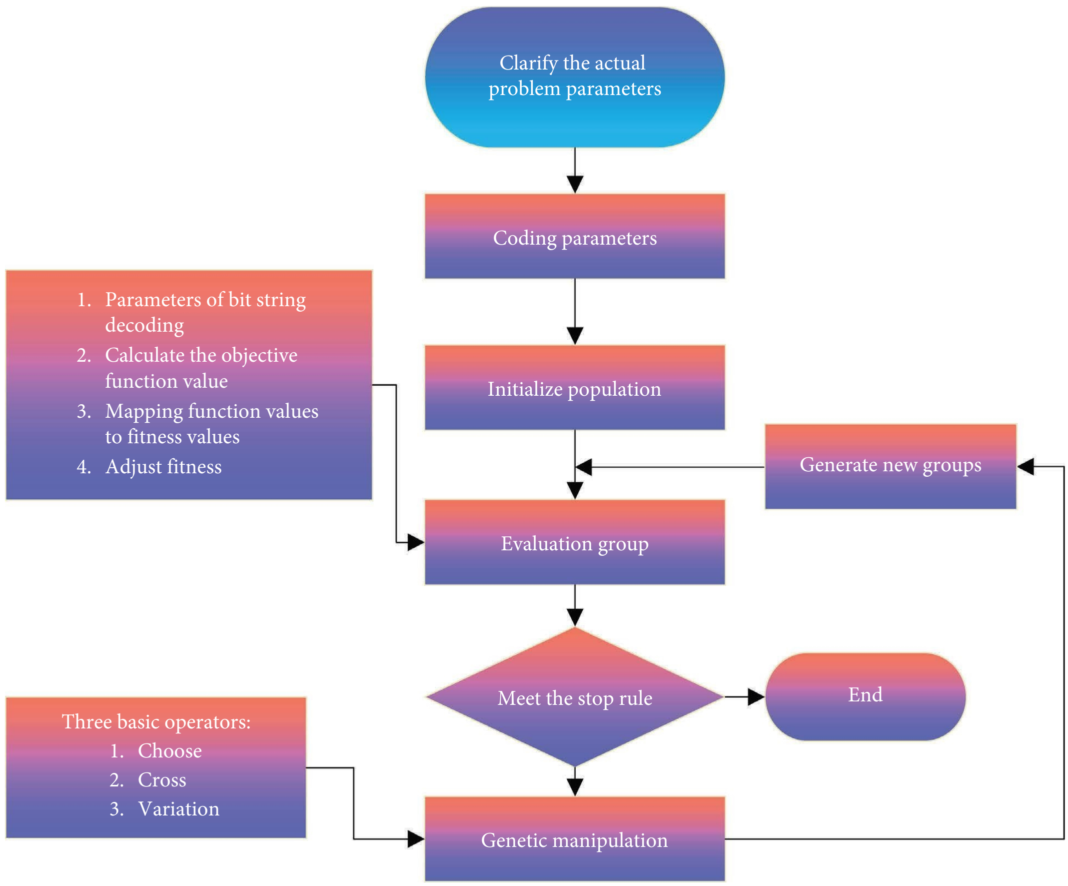


Figure 3: Schematic diagram of genetic algorithm learning path recommendation principles.

*3.3.1. Euclidean Distance.* When calculating text similarity, Euclidean distance can be used to judge the absolute distance in multidimensional space between two different knowledge points. For example, $x$ represents the word frequency of all words in two texts on knowledge point $A$. When $Y$ computes the word frequency at knowledge point $B$, the following results are obtained:

$$\begin{aligned} sim\,(A,B) &= \mathrm{dis}\,(A,B) \\ &= \sqrt{\sum_{i=1}^{n}(a_i-b_i)^2}. \end{aligned} \tag{1}$$

*3.3.2. Cosine Similarity.* By calculating the cosine angle through formulas, the similarity of two knowledge points in vector space is judged by the cosine of the angle between two vector points $A$ and $B$.

$$sim\,(a,b) = \frac{\vec{a}\cdot\vec{b}}{\vec{a} * \vec{b}} = \frac{\sum a_i b_i}{\sqrt{\sum a_i^2}\sqrt{\sum b_i^2}}. \tag{2}$$

*3.3.3. Jaccard's Similarity Factor.* The Jaccard similarity coefficient compares the similarity of two different knowledge points. Based on the number of knowledge points $A$ and $B$ intersect, the similarity between two knowledge points is calculated by the proportion of knowledge points $A$ and $B$ in the union. The formula is as follows:

$$sim\,(A,B) = \frac{|A\% \cap B|}{|A\cup B|}. \tag{3}$$

## 4. Personalized Learning Path for University French Based on Big Data Mapping

*4.1. Recommendation Algorithm for Learning Paths.* This paper studies personalized learning of college French based on a big data knowledge map. Here, two learning path algorithms, namely, the genetic algorithm and the ant colony algorithm, are described in detail.

*4.1.1. Genetic Algorithm.* The genetic algorithm does not need to compute all possible path solutions, but it needs to select the global optimal solution on the path. In the learning path recommendation algorithm, the genetic algorithm chromosome parameters are coded to find the $F(x)$ fitness value, and then, $P = F(x)\sum F(x)$ is selected randomly. The optimal learning path inheritance process is repeated by crossover, selection, compilation, and so on until the ideal learning path is found. Figure 3 illustrates the genetic algorithm learning path recommendation principles.

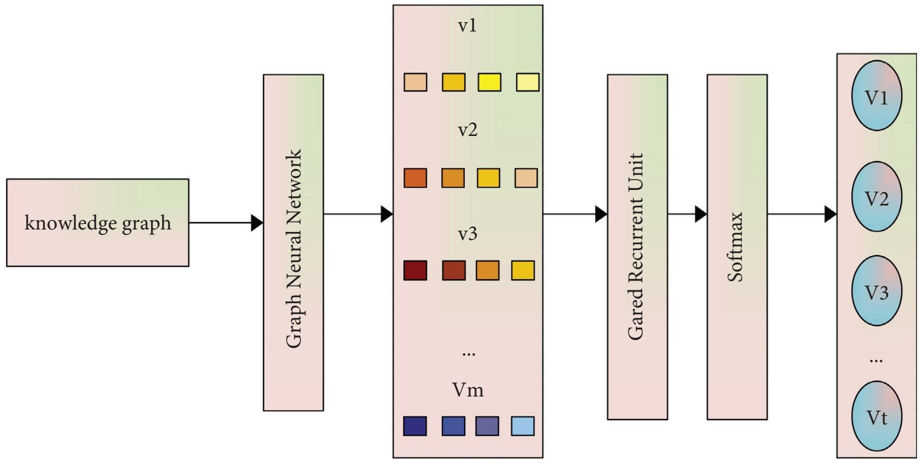


FIGURE 4: Framework for learning path recommendation based on a knowledge map.

*4.1.2. Ant Colony Algorithm.* Ant colony algorithm uses the learner's knowledge of French to leave a mark on the network, which is the pheromone to select the later learning path based on the concentration of the pheromone. Therefore, the pheromone is a key formula and path selection probability in the ant colony algorithm:

$$P(i,j) = \frac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum [\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}},$$
$$\tau(j) = (1-p)\cdot\tau(j) + p. \tag{4}$$

Upper form $\tau$ enlightens data for the amount of information that a pheromone can provide between Node 1 and other nodes at a given time. $\eta$ represents the expected value of the transfer node, and $p$ represents the pheromone play factor.

*4.2. The Learning Path Recommendation Algorithm Is Based on the Knowledge Map.* Based on a knowledge map, a graphical neural network can propagate and aggregate the characteristics of different knowledge points on the knowledge map to form a high-accuracy knowledge point embedded in the vector. The model establishes a reliable sequence based on the knowledge map to infer the importance of knowledge points at all levels. The knowledge point vector matrix is then combined as input to the graphical neural network after the corresponding knowledge point vectors from the knowledge map are first obtained. The selection coefficients related to each node are obtained using the gated graphical neural network. After that, the vector is processed using SoftMax to determine its centrality. A substantial number of datasets are used to test the efficacy of this algorithm after completion, and the probability judgment for choosing the following knowledge point is made. The framework for knowledge map-based learning path recommendation methods is shown in Figure 4.

*4.3. Building Personalized Learning Path Model.* The essence of planning a personalized learning path for college grammar is to arrange the learning objects in the set of candidate contents in regular order, and then show the sorting structure to the learners for reference. The system automatically recommends the learners listed in front as their next choice. The specific path planning is shown in Figure 5.

As learners enter the system, they can recommend the learning materials they need according to certain rules, or they can send the results of the recommendation to the learners for their own choice. Therefore, the most important thing is to identify the candidate learning set and calculate the weights.

Assuming that $T$ is a coarse-grained learning object with $n$ fine-grained learning objects and $M$ is required to learn, that is, $M_1, M_2, M_3, \ldots, M_n$, the learning object $T$ is defined by the following formula:

$$T = \{M_1, M_2, M_3, \ldots, M_n\}. \tag{5}$$

Based on the knowledge map that there is a preemptive relationship among the learning objects, the preemptive relationship $K_{ij}$ is defined by the following formula:

$$K_{ij} = \begin{cases} 1, & M_j \text{ prefix representing } M_i \text{ learning objects,} \\ 0, & \text{Other cases.} \end{cases} \tag{6}$$

The learner can only acquire and master the learning object after completely grasping all or most of the learning object's prelearning materials. $M_i$ means that the learner has mastered all the prerequisite points on $M$. Usually, this threshold is set to 0.6, which leads to the definition of $\mathrm{Pr}_i$, the set of prerequisite learning objects in the $M_j$ learning queue, as follows:

$$\mathrm{Pr}_j = \left\{M_i | \forall \quad M_i \in T, K_{ij} = 1\right\}. \tag{7}$$

Based on the calculations, the next set $C$ recommended to the learner can be achieved.

$$C = \left\{M_j | \forall \quad M_j \in T, M_j \in T', \forall \quad Mi \in \mathrm{Pr}_j, P_{M_i} \geq \alpha\right\}. \tag{8}$$

Topic $T'$ means that the learner has completed all of the learning objectives or that the initial learning is empty. When the learner completes a learning object $M$, a new $M$ is added to the $T'$.

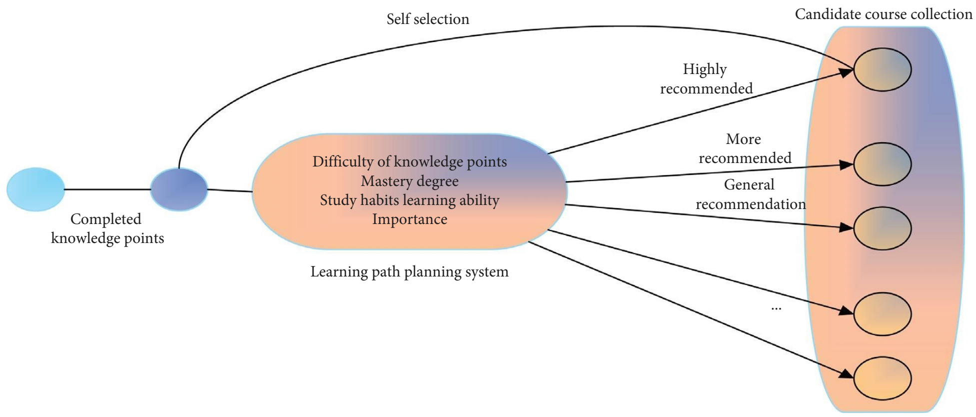


Figure 5: Route planning diagram.

According to the above formulas, the learning objects $C$ are all the prelearning objects that the learners have already mastered. However, some of the learning objects do not meet the learning requirements. They also need to review the prelearning objects further. Here is the formula $C$ for reviewing the set of learning objects:

$$C' = \{M_k | \forall \quad M_j \in T, M_j \in T', \forall \\ M_i \in \Pr_j, M_j \in T', \exists M_k \in \Pr_j, P_{M_k} < \alpha\}. \tag{9}$$

$C$ is the set of candidates learning objects, and $C'$ is the total number of learning objects awaiting review. The learning materials that must be retained after the review are maintained in this set. This algorithm arranges the candidate learning objects in a specified sequence according to predefined rules, after which the learner decides for themselves whether to learn next. The course and knowledge point weights are defined here in terms of different formulas, and the knowledge point weights are defined by these formulas:

$$B_M = \frac{\sum_{i=1}^{m} b_i}{m}, \\ W_M = \frac{e^{-(B_M - 0.5)^2/2} I_M(\overrightarrow{P})(1 - e^{-\mathrm{Imp}_M})}{\sqrt{2\pi}(1 + (1 + e^{-\mathrm{Imp}_M}))}. \tag{10}$$

$b_i$ indicates the difficulty of the title $i$, and $B_M$ indicates the difficulty of $M$ knowledge points. This algorithm calculates the average difficulty of each knowledge point on $M$. $I_M(\overrightarrow{P})$ denotes the benefits that $\overrightarrow{P}$ learning sequence learners have gained from learning $M$ knowledge points. $Im_{PM}$ represents the importance of $M$ knowledge points. $W_M$, $W_M$ represents the weight of $M$ knowledge points when planning a route. A high value indicates that this knowledge point is more suitable for the next learner to use as a learning object.

After clarifying that there are no courses to be materialized, one of them is selected for learning. The difference between the points of comparison is that before arranging the French courses, the restriction of the learner is analyzed. The following formula defines the weight $W_T$ of a French course $T$.

$$W_T = \frac{kI_T}{K}. \tag{11}$$

Top $I_T$ denotes the benefits that learners will receive from the $T$. French course and $K$ denote the number of students in the broad course that learners will receive from the $T$. Based on the weight of the course, the number of times a learner in the learning group has studied a course indicates that the learner has earned a high return from learning the course. Therefore, the course in this language will be preferred to other learners.

## 5. Analysis of the Application Results of Personalized Learning Path for College French

This paper builds a model of personalized learning path for college French based on a big data map because it studies the best personalized learning path for college French. Based on the data from XuetangX dataset, a knowledge map is built for the course of college French. There are 19 nodes, 19 edges, and 70 exercises in this knowledge map. Three of them are randomly selected to plan the personalized learning path for college French using the knowledge map algorithm based on large data, and the three learning paths listed in Table 1 are obtained:

According to the data in Table 1, the order of learning knowledge points of the three students is different. The results of the income obtained from the calculation of the learning knowledge of the three students are also different in that the differences among the three students are not significant even though their initial learning behaviors are different. Firstly, the knowledge sequence is planned from the learner's previous learning behavior. During the planning period, no new learning behavior occurs. As a result, students can only predict the sequence in a fixed learning style when answering questions. Because of data factor interference, no complete knowledge map has been established, the number of trainings is very minor, and the recorded course video is small, making this parameter ineffective.

Table 1: Learning path planning results.

| Learner number | 48504238 | 62834945 | 24850562 |
|---|---|---|---|
| Knowledge point sequence | 1–9–12–11<br>–10–14–13<br>–2–4–3–8<br>–7–6–5–15<br>–19–16–18–17 | 1–9–12–11<br>–10–14–2–8<br>–4–3–7–6<br>–5–13–15<br>–19–16–17–18 | 1–2–4–3<br>–8–7–6–5<br>–9–12–11–10<br>–14–13–15–19<br>–16–18–17 |

Table 2: Route planning data statistics excluding knowledge point benefit parameters.

| Learner number | 48504238 | 62834945 | 24850562 |
|---|---|---|---|
| Knowledge point sequence | 1–9–12–11<br>–10–14–13–2<br>–8–4–3–7<br>–6–5–15–19<br>–16–17–18 | 1–9–12–11<br>–10–14–13<br>–2–8–4–3<br>–7–6–5–15<br>–19–16–17–18 | 1–9–12–11<br>–10–14–13–2<br>–8–4–3–7<br>–6–5–15–1<br>9–16–17–18 |

Table 3: Route planning with all parameters removed.

| Learner number | 48504238 | 62834945 | 24850562 |
|---|---|---|---|
| Knowledge point sequence | 1–15–16–17<br>–18–19–9–10<br>–11–12–13–14<br>–2–3–4–5<br>–6–7–8 | 1–15–16–17<br>–18–19– 9–10<br>–11–12–13–14<br>–2–3–4–5<br>–6–7–8 | 1–15–16–17<br>–18–19–9–10<br>–11–12–13–14<br>–2–3–4–5<br>–6–7–8 |

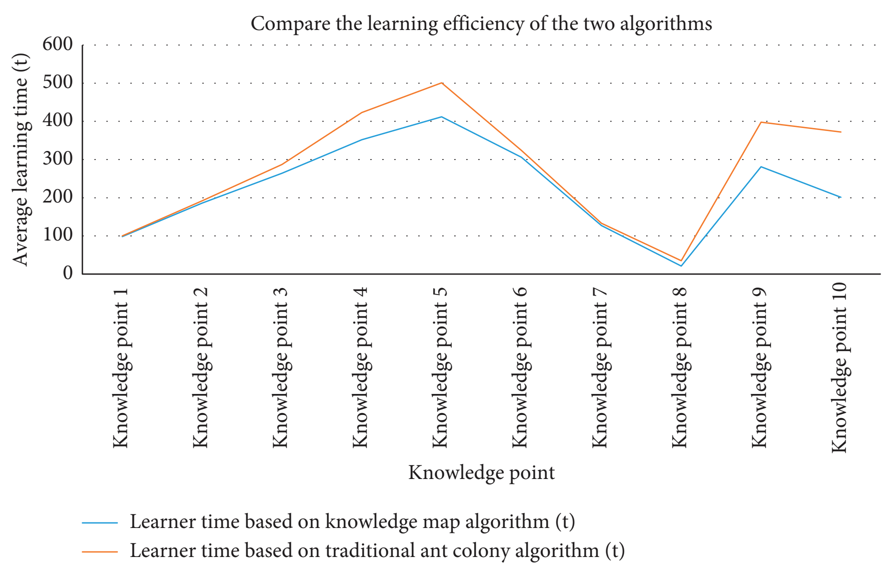


Figure 6: Comparison of learning efficiency between two algorithm learners.

*5.1. Analysis of Learning Accuracy.* In this study, the accuracy of the personalized learning path for college French based on the big data map is studied. According to the data in Table 1, the recommended accuracy of each learning path is 1.0, 0.947, and 0.842 calculated by substituting it into the formula above, which indicates that the learning planning path has a higher accuracy [28, 29]. Since the current dataset contains a complete French course for the learner, the lists at the time of knowledge point recommendation will cover the learner's learning.

The parameters in the knowledge point model are readjusted here to highlight the personalized learning path, and two additional groups of experiments are added to compare, that is, learning path planning with each parameter excluding the benefit of knowledge points. The results are presented in Tables 2 and 3.

Table 2 shows the corresponding learning path planning without taking into account the benefits from learning knowledge points. The three students get the same learning path planning because knowledge points are of the same importance and difficulty to the learners and do not show the personalized characteristics of different students. Table 3 is the initial learning path. It does not use the knowledge point parameters mentioned in the paper and does not take into account the prerequisite relationships in the knowledge map. It is the configuration of open knowledge points made during instruction by university professors. From the results of observations, it can be concluded that the only way to plan a path that differs from the initial learning path is to consider the knowledge map's objective attribute and precondition relationship constraints. The learning benefits from each learner can then be added together to create an individual learning path.

*5.2. Analysis of Learning Efficiency.* When proving the efficiency of this algorithm based on a big data knowledge map, this paper randomly extracts ten knowledge points from French college learners and compares them. The learning efficiency of this algorithm is obtained by individual learning paths based on the ant colony algorithm. The result is shown in Figure 6.

The learning efficiency of the algorithm based on the knowledge map of large data is significantly higher, as shown by the line graph in Figure 6. The individual learning path is then based on the traditional ant colony algorithm, with similar learning efficiency for each knowledge point. This demonstrates that a personalized college French learning path based on a big data map is more efficient, can fully utilize each student's personality, and can improve students' French learning efficiency.

## 6. Conclusions

The analysis of personalized learning is currently a hot topic in the educational era of big data and the Internet. When big data and the Internet play an important role in educational achievement, system design expands significantly. The explosion of e-learning websites has provided the education sector with a variety of new learning data. As a result, it is possible to identify the learner's knowledge point and mine the implicit relationships between learning. It aims to encourage different types of students to use appropriate teaching methods to maximize their benefits. However, in the era of big data, the rapid increase in data amount makes students unable to find a suitable learning path in the face of vast teaching resources, resulting in low learning efficiency and loss of motivation. This paper takes the personalized learning path for college French as the object and establishes the personalized learning path model for college French based on the big data knowledge map. Based on the knowledge map, it identifies the learning path algorithm in detail and develops the personalized learning path. Three French students from colleges and universities were chosen at random to compare the learning outcomes of various learning paths. According to the findings, the best results for personalized learning paths based on a big data knowledge map are those that can personalize course planning for students. When compared to students who follow a personalized learning path based on the ant colony algorithm, the algorithm mentioned in this paper has a higher learning efficiency. Several large college education datasets can be used to confirm the future, and more in-depth analyses can be performed in combination with learner behavioral aspects such as time spent answering questionnaires and frequency of reminders.

## Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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