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Retraction

Retracted: Research on the Strategy of Autonomous Learning under the Dual-Class Model of Ideological and Political Courses Based on the Knowledge Map Route

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] P. S. Shi, "Research on the Strategy of Autonomous Learning under the Dual-Class Model of Ideological and Political Courses Based on the Knowledge Map Route," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2854233, 11 pages, 2022.

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Research Article

Research on the Strategy of Autonomous Learning under the Dual-Class Model of Ideological and Political Courses Based on the Knowledge Map Route

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The two-part classroom teaching mode organically combines teachers' lectures with students' discussions, which can not only ensure the dominance of ideological and political teachers' classroom teaching but also give full play to students' autonomy in learning. The role of students' autonomous learning as a bridge between teachers' lectures and students' discussions cannot be ignored. Through the study of the knowledge map, the self-learning strategies of ideological and political courses calculated from the aspects of resource push and path planning, accurate learning resource search, in-depth reading, and answering robots will maximize the benefits of students' self-learning.

1. Introduction

1.1. Two-Part Classroom Model and Its Characteristics. The split classroom is a new model of classroom teaching reform proposed by Zhang Xuexin from the Department of Psychology of Fudan University. Its core concept is to allocate half of the class time to teachers for teaching and the other half to discuss with students and to stagger the teaching and discussion time so that students have one week after class to arrange their learning and conduct personalized internalization absorption, also known as P A D Courses, namely, Presentation, Assimilation, and Discussion, as shown in Figure 1.

In the two-part class [1], the teacher introduces the basic framework and basic concepts and focuses on the key points and difficulties but does not exhaust the content of the teaching materials. Leaving the simple, boring, monotonous, and unsuitable content for students to read, not only changes the current situation of teachers filling the classroom and improves the enthusiasm of students for theoretical learning but also reduces the teaching burden of teachers, allowing teachers to concentrate. The strength carefully creates difficult and difficult lectures, which helps to improve the professional ability of teachers. Through the teacher's teaching, the students grasped the basic content of the chapter, understood the key points and difficulties, and greatly reduced the difficulty of learning after class. During after-class study, students can learn theoretical knowledge through books according to their characteristics and specific conditions, think and study in combination with auxiliary reference materials, fully prepare for classroom discussions, complete the internalization and absorption process at their own pace, and complete a more comprehensive study and understanding of the content of the textbook.

After internalization and absorption, students return to the classroom, discuss in groups what they have learned, and then engage in in-depth interaction with the whole class and teachers. This method of discussion requires every student to participate in it, allowing students to actively discover problems, think about problems, and solve problems. Problems that cannot be solved are brought up in the classroom, and reasonable solutions can be found under the guidance of teachers.

Teaching, self-study, and discussion are not uncommon in the traditional classroom teaching process. The question-answering session gives full play to the classroom

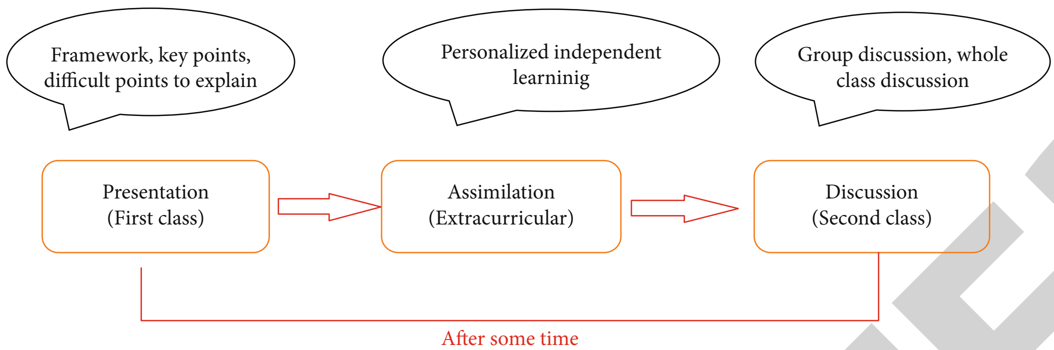

Figure 1: Split classroom.

dominance of ideological and political teachers' teaching, can grasp the main content, and can fully mobilize the enthusiasm and initiative of students' autonomous learning under the promotion of classroom discussions, ensuring the teacher-led teaching efficiency and efficiency. Internalized and absorbed personalized design can meet the learning needs of different students and stimulate the enthusiasm and initiative of learning. The split-class teaching mode reflects the characteristics of autonomous learning. China's higher education has made outstanding achievements in cultivating talents, but the cultivation of students' autonomous learning ability needs to be improved. The ideological and political courses of colleges and universities shoulder the mission of cultivating people by virtue. To make the course content enter the minds and hearts of students, it is also necessary to cultivate students' autonomous learning abilities. This requires "renewing the educational concept," "reforming the teaching mode," and " evaluation system," and these are well presented in the concept of split classrooms.

1.2. Self-Directed Learning and Its Importance

1.2.1. Self-Directed Learning Is Conscious, Active, and Independent Learning. Self-directed learning [2] means that learners can control their behavior and control their actions in the process of learning. Zheng Jinzhou believes that "autonomous learning refers to the way students actively cultivate autonomous learning under the guidance of teachers, using metacognitive methods, motivational strategies, and behavioral strategies." That is, students, as the main body of the learning process, must learn to independently question, self-analyze, explore, practice consciously, and achieve self-efficacy to achieve self-directed learning. The idea of self-study in old age has already emerged. For example, Zhu Xi said that "Tao cannot sit still and wait for it to come to itself, and only wait for others to pay attention to it and put it in one's mouth." Confucius said that "If you study without thinking, you will be useless; if you think without learning, you will be in danger; if you are not angry, you will not be enlightened; if you are not angry, you will not be able to express it." It reflects that learning must be independent and cannot rely on the thoughts of others. Self-directed learning is a long-lasting learning change in psychology, behavior, and aptitude that results from the accumulation of long-term experience and repeated exploration of learning patterns. Cheng Xiaotang pointed out that "Autonomous learning is A learning method or learning mode, which can be divided into self-independent learning, self-monitored learning, self-directed learning, and self-regulated learning." Self-directed learning is a combination of learners' attitudes, goals, abilities, and learning strategies that reflect student learning. The dominant factor of the internal mechanism of learning is also the learner's control of their learning ability and the use of autonomous methods for adjustment and guidance. Secondly, as a learning mode, autonomous learning is a learner's goal, interest, learning content, and learning materials for their learning; the learning method can be freely chosen and used independently.

1.2.2. Autonomous Learning Is an Active, Constructive, and Self-Regulated Learning Process. The famous American educational psychologists Sebastian Bonner and Robert Kovach pointed out that autonomous learning is an active, constructive, and self-regulating process. Active means that learners have a purposeful and interesting activity consciousness, and constructive means that learners become active constructors of autonomous learning by constructing knowledge based on their own experience. Self-regulation is that learners use and regulate their metacognitive level, motivation, and behavior independently and independently to improve the effectiveness of learning, achieve the goal of learning, and ensure the success of learning. Set your own learning goals, choose a learning method, regulate your learning behavior, and evaluate your learning results. As a learning method, autonomous learning is based on the internal mechanism that triggers the learner's learning, mobilizes the internal factors of the learner, and cultivates the learner's autonomous learning habit from content learning, strategy mastery, learning behavior, and evaluation.

1.2.3. Autonomous Learning Is an Application Cycle Process of Self-Monitoring, Self-Evaluation, and Learning Feedback. Through autonomous learning, learners can control their behavior, adjust their learning methods, and then feedback into their learning activities, evaluate their learning results, and achieve their expected learning goals. If learners can consciously choose and control their learning, effective adjustment is self-directed learning. That is to say, learners can self-determine their learning motivation, choose their learning materials, plan their own learning goals, arrange their own learning time, adjust their learning methods [3], and evaluate their learning results. Pang Weiguo, a Chinese educator, puts forward that "If students make pre-school preparations, establish learning goals, and formulate goal plans before their learning activities. During the learning process, adjust learning behaviors and change learning strategies. After learning activities, self-examination, summary, Self-evaluation, strategy modification for learning. This kind of learning is self-directed learning."

In short, autonomous learning is a high-level learning activity based on one's changes and development. Under the guidance and help of teachers, one should seek truth from facts and make one's own learning plans, goals, and learning tasks according to the individual's learning situation. Consciously adjust the learning method, monitor the learning situation from time to time, and evaluate your learning results. Self-directed learning requires students to be in " the process of taking various control measures to optimize their learning." At this time, it is particularly important to find appropriate control measures based on the advantages of knowledge graphs.

1.3. Knowledge Graph and Its Application Value. Knowledge graph [4] is a large-scale semantic network, which is a semantic representation of the real world. The entity is represented as a node; the attribute of the entity and the relationship between the entities are represented as an edge, which constitutes a meshed graph structure. This structured form is recognizable by humans, friendly to machines, and easy for machines to understand. The large-scale concepts, attributes, and relationships between entities in the graph make it rich in semantic information, rich in related information, and naturally have various characteristics of the graph, which can be used for graph-related operations and applications. After construction, it can also be used as background knowledge directly for downstream applications. It is just that the map was first proposed by Google, mainly used to improve the ability of search engines and improve search quality. Due to the unique characteristics of the knowledge graph, it can play important value in many aspects of artificial intelligence [5].

Since Google proposed the knowledge graph in 2012, with the vigorous development of data science and the widespread use of deep learning, artificial intelligence technology has also achieved rapid development. With the gradual maturity of the Internet, artificial intelligence, 5 g, and other technological applications, human society has begun to enter the era of intelligence. Intelligence puts forward requirements on the intelligence level of machines, including computational intelligence, perceptual intelligence, and cognitive intelligence of machines, as shown in Figure 2.Cognitive intelligence is a higher level of intelligence, and enabling machines to have cognitive intelligence means enabling machines to think like humans. This kind of thinking ability is embodied in the machine's ability to understand data, understand language, and then understand the real world; in the machine's ability to interpret data, explain the process and then explain the phenomenon, in a series of reasoning, planning, etc., unique to humans. Compared with perception ability, cognitive ability is more difficult and valuable to realize. The realization of machine cognitive intelligence relies on knowledge graph technology, and a series of technologies of knowledge engineering represented by knowledge graph play a very key role in the realization of cognitive intelligence.

The value of the knowledge graph is mainly reflected as follows.

1.3.1. Data Governance. Structure the heterogeneous knowledge in the field and build the relationship between knowledge. It mainly solves the application scenarios where the data in the field is scattered in multiple systems; the data is diverse, complex, and isolated; and the value of a single data is not high. Structured knowledge naturally makes domain knowledge explicit, precipitation, and association. A graph is constructed. The features of native graphs can be used to support data mining and analysis. For example, do community discovery, association analysis, source tracing, and other applications.

1.3.2. Enabling Machine Language Cognition. The knowledge graph has rich semantic relationships, concepts, attributes, relationships, etc. These semantic relationships can be well applied to NLP-related tasks, such as word segmentation, phrase understanding, text understanding, and other tasks. Through the knowledge graph, the machine can better understand natural language and further better understand the user's intention and the meaning of the text. In basic NLP tasks such as word segmentation, semantic understanding, and text mining, it has many functions in system-level applications such as user portraits, search, recommendation, and intelligent question answering.

1.3.3. Knowledge to Guide and Solve Problems. Provide industry background knowledge, provide knowledge guidance, and solve problems in the implementation of industry intelligence. In-depth applications in vertical fields, such as intelligent customer service systems and intelligent outbound call systems, can use knowledge graphs to accurately answer user questions and answer complex questions. Some traditional expert systems commonly used in vertical industries can improve the effect by giving them certain background knowledge.

1.3.4. Knowledge Graph Enables Explainable Artificial Intelligence. Interpretability is an important feature of strong artificial intelligence. The current artificial intelligence applications are based on deep learning models, although the results are not bad. However, the model itself is a black box and is not interpretable, which makes it impossible to use complex deep learning models in many industries that require interpretability, for example, in the judicial field, medical diagnosis field, and certain scenarios in the financial field. The application of interpretability will also improve users' trust in the system and improve user satisfaction. In the question and answer scenario, the explanation function can be added in the recommended scenario.

1.3.5. Knowledge Reasoning. Other applications are based on knowledge graph reasoning, which comprehensively utilizes conceptual subordinate relationships, attribute types and

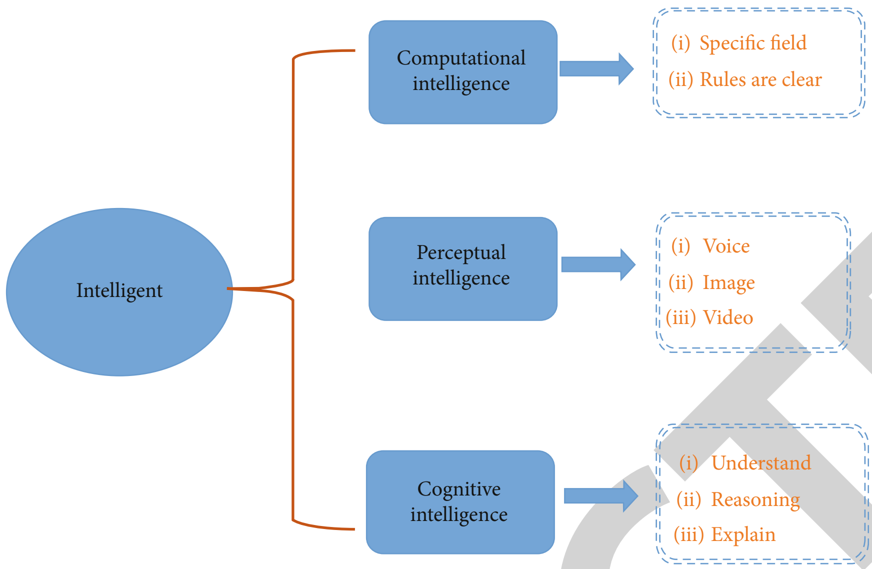

Figure 2: Cognitive intelligence, computational intelligence, and perceptual intelligence.

constraints in graphs, associations between entities in graph models, and relational reasoning rules defined in combination with business scenarios. It can be used for various reasoning applications such as inconsistency detection, inference completion, knowledge discovery, commodity traceability, and auxiliary reasoning decision-making.

The knowledge graph technology has now fully entered the stage of actual implementation and has already had quite surprising applications in many vertical industries.

1.3.6. Accurate Academic Analysis. The knowledge graph can be used for more accurate learning analysis. The learning diagnosis of traditional education experts (teacher experience) mainly relies on experience to evaluate the knowledge and ability status of learners, lacks the integration of educational measurement ideas, and has great contingency and subjectivity. Based on knowledge graphs, big data analysis [6], and other methods to mine the objective learning process of learners and analyze from various dimensions, the data can be mined in many dimensions, not limited to test scores, error books, learning records, and other behaviors. The dominant features of knowledge mastery and weak knowledge excavated in the trajectory can also tap some deep-level learning speed, learning preference, cognitive level, and other invisible features and make the analysis results more personalized and objective.

For the learning goals that cannot be achieved, the knowledge graph can be used to analyze the reasons, find weak points and related knowledge points, and effectively check and fill the gaps. The diagnostic process is more adaptive and personalized.

The first chapter of this paper introduces the significance of ideological and political courses and autonomous learning and the concept and value of knowledge graphs, the second chapter introduces the construction of knowledge graphs, the third chapter describes the research on autonomous learning strategies based on knowledge graphs, and the fourth chapter summarizes the relationship between autonomous learning and knowledge graphs.

2. Design Program

Education and knowledge have a natural connection because education is essentially the creation, transmission, reception, and processing of knowledge. As the key technical foundation of cognitive intelligence, knowledge graph plays a decisive role in the more advanced stage of educational intelligence moving towards "cognitive intelligence." Based on the educational knowledge graph [7], intelligent applications in scenarios such as precise teaching and adaptive learning can be realized.

2.1. Application Logic of Educational Knowledge Graph. Educational knowledge map, with subject knowledge as the core, establishes the concept of knowledge points in each discipline to establish hierarchical relationships, the correlation between knowledge points and knowledge points, and the sequence relationship between different knowledge points to form a subject knowledge map. As shown in Figure 3, using this map, the relationship between knowledge points can be displayed to students in a visual form. It is clear at a glance and can be used to help students build a knowledge system, check knowledge points, discover the relationship between knowledge points, and help students make summaries and precipitations to eliminate knowledge blind spots.

After the subject knowledge map is constructed, it can be associated with teaching resources (teaching materials, test questions, handouts, teaching videos, test papers, etc.) and then established the association between knowledge points and users through user information and learning records. Through the knowledge map, the knowledge mastery of students can be more accurately depicted, and resources can be more accurately depicted. In this way, it can realize accurate research and judgment of users [8], learning path planning, and personalized recommendation of learning resources.

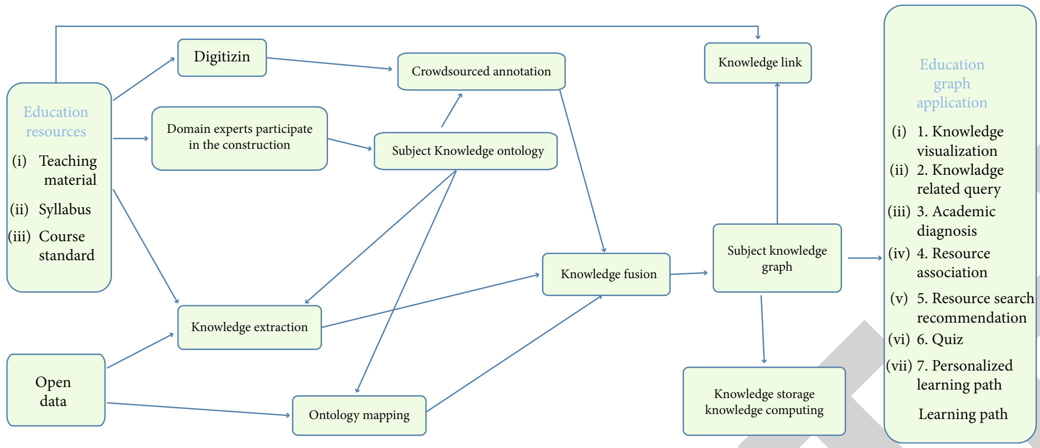

Figure 3: The overall process of building a subject knowledge map.

It can also help teachers better understand students' learning situations, optimize teaching methods, and adjust teaching strategies. It can improve the efficiency and quality of teaching and research preparation for teachers by linking with teaching and research materials and actively recommending teaching and researching. Satisfy the students' needs. Based on these application scenarios and application logic, the following is the specific design and construction of the graph.

2.2. The Construction of Educational Knowledge Resources with Subject Knowledge Map as the Core. The educational knowledge graph has some characteristics of its own. The points in the education map are diverse. The points in the map include knowledge points, various learning resources, and attribute values of knowledge points. The relationship includes the relationship between knowledge points and the relationship between knowledge points and learning resources can be a dynamic change [9]. The knowledge map in the education field has very high-quality requirements, and the accuracy rate must reach nearly 100%. Therefore, the audit and verification stage requires the participation of many business personnel. This is also a challenge for the implementation of educational maps. The educational knowledge graph has a strong demand for multimodal knowledge. Knowledge points can be expressed in various forms such as pictures, videos, and voices. This is also in line with people's habit of understanding things. In addition to text descriptions, some concrete perception is also required.

The construction of educational knowledge resources with knowledge map as the core uses knowledge map to establish the relationship between domain knowledge and establishes the relationship between knowledge points and different versions of teaching materials, teaching aids, handouts, videos, test questions, and other educational resources, forming an overall network. Use these associated networks to support upper-layer applications.

The core is the definition of the schema, which requires a deep understanding of the domain business. Therefore, this part is currently mainly based on the sorting of domain experts and is supplemented by certain technical means. Domain experts can sort out the domain knowledge system in a way they are familiar with and like. For example, using ontology modeling tools, mind or even excel can be used. Refer to the course standards and textbooks to sort out the knowledge system covering core semantic concepts and basic relationships. The core of this step is to express a general framework of knowledge in the current field. Then, the map engineer, according to the sorting out of business experts, makes adjustments according to the modeling principles of the knowledge map. After several iterations, business experts cooperate with graph engineers to construct a suitable schema. When building a schema, you can also infer what knowledge is needed by analyzing the problems of actual application scenarios.

There are also problems with the way top-down experts sort out schemas. First, it will be a lot of work to use experts to sort out, and if there is a lot of domain knowledge, a lot of it may be missed. Second, domain experts may have different understandings of the knowledge system, and the descriptions of concepts and relationships in the actual corpus may be somewhat different from those defined by experts. Third, the concepts and relationships defined by experts are often inconsistent with the descriptions in the actual corpus, resulting in inaccurate extraction in subsequent extractions. Based on these problems, we can actively dig out candidate concepts and relationships from the corpus by using the method of OpenID first, which will be more complete from the bottom up. The candidate concepts and relationships are given to business experts for reference, and business experts are asked to do "true and false questions" and "multiple-choice questions," which greatly improves the modeling efficiency. Moreover, different representations of the same concept, the same attribute, and relationships in the corpus can be mined.

In the subject knowledge map in the field of education, the relationship between knowledge mainly includes upper and lower relationships, mainly between parent and child concepts and between concepts and entities. Concept maps express the relationships between concepts in the educational domain. In the field of education, there will be more conceptual content and the relationship between these concepts in the context of the entire knowledge, several specific test points under the knowledge point, the relationship between the whole and the part. The sequence relationship can be used to make study planning. There are also some special relationships in different disciplines, such as mutual exclusion and causality, which need to be sorted out and refined by domain experts and knowledge engineers when actually building map resources.

Knowledge in the educational map also has rich attributes, such as common attributes such as "test sites," "difficulties," "error-prone points," and "test syllabus requirements." There are specific fine-grained attributes in different disciplines, such as "definition," "property," "area formula," and "perimeter formula" in mathematics.

After the schema construction is completed, the subsequent triple extraction and knowledge fusion tasks are clarified, and multiple methods can be flexibly selected for extraction. It is worth noting that the landing in the vertical field cannot be solved by a few cool deep learning models. The field data itself is much smaller than that of general fields such as the Internet and e-commerce, and there is less labeled data. This leads to the model using supervised learning; the applicability of the domain data becomes much worse. Therefore, when it is actually implemented, it will comprehensively apply a variety of methods and a combination of strategies to solve practical problems. First of all, in terms of data sources, high-quality data such as structured and semistructured and easy-to-extract relationships are preferred to quickly build a preliminary version. Then, gradually add knowledge from unstructured data and crowdsourced annotation data.

Knowledge extraction is mainly domain entity recognition and relationship extraction (to be precise, relationship classification). There are two methods: the pipeline method and the joint model method. If you have enough labeled data, you can consider using the joint model method. When the amount of labeled data is not enough, the pipeline method is still the main method. At present, the pipeline method is still used more.

3. Results and Discussion

3.1. Resource Push and Path Planning. Based on knowledge map and data analysis technology, it can quickly detect and locate students' learning status and weak points. Based on the more accurate judgment of students' learning situation, using the correlation between knowledge points, including the pre- and postsequence relationship, can reasonably target students for students. Accurate detection, content push, path planning, and the entire process are used as a dynamic closed-loop to steadily improve students' knowledge. Through the automatic analysis of students' procedural dynamic learning data, it can detect students' learning levels, accurately diagnose students' learning situations, and analyze students' weak knowledge points.

Although online teaching has obvious advantages, it also exposes many problems. Practical problems such as cognitive loss, information overload, and incompatibility of learning styles will trouble learners, make learners feel tired of learning, and lead to a decline in learning efficiency and transfer of learning interest, the negative impact of system disapproval. There is no way to develop the ability of the learner. In this case, a learning path recommendation strategy is proposed, which can provide an appropriate learning path according to the learner's learning characteristics and learning goals, reduce the learning cost, and promote the construction of the learner's knowledge structure. Therefore, it is of great practical significance to provide learners with a personalized learning path. An intelligent optimization algorithm, also known as a heuristic algorithm, is an optimization algorithm proposed by scholars inspired by natural biological groups. Different from the optimal solution algorithm, the intelligent optimization algorithm can generally give the optimal solution when solving the problem, also known as the optimal solution, but it does not only provide the optimal solution. Several types of intelligent optimization algorithms such as genetic algorithm, ant colony algorithm, particle swarm algorithm, and coordinated filtering recommendation are often used in the field of personalized learning path recommendation. Table 1 shows the dimensional comparison of the factors that the four algorithms need to consider when recommending learning paths, where "1" represents the factor considered by the algorithm and "0" represents the factor not considered.

Content push, graph-based recommendation, and a combination of content-based and collaborative filtering and other recommendation technologies make recommendations more accurate. Recommend more targeted content to students. Provide students with personalized learning resources that recommend high-quality learning resources, realize the inference of wrong questions and free students from the tactics of the sea of questions, and greatly reduce the time and schoolwork burden of students' repeated practice. Recommendations based on knowledge graphs can also explain the recommendation results from the dimensions of the concept, pre- and postorder, and attributes.

The learning path is mainly the orderly arrangement of knowledge point objects, and the path to the target object is not unique. This paper proposes Vertical Joint Strategy Based on the Inclusion Relationship of Knowledge Map (VJSBIRKM) according to the principle of coarse-grained proximity. According to the principle of fine-grained pan-learning, Backtracking Search Strategy Based on the Antecedent Relationship of Knowledge Map (BSSARKM) is propose. VJSBIRKM recommends the knowledge point object set contained in the target knowledge point object (targetobjectkp) for learning, that is, mastering all the knowledge points contained in the targetobjectkp, which is equivalent to mastering the targetobjectkp; BSSARKM believes that there is a sequential relationship between the learning points and is obtained according to the precursor relationship. The precursor knowledge point of the target knowledge point object is up to the meta node. After derivation, reverse backtracking is performed to form a learning path. After learning the precursor knowledge point object set of targetobjectkp, it is equivalent to mastering targetobjectkp. To measure the rationality and feasibility of the strategy proposed in this paper, the data set used in the experiment comes from the online smart operation system that the team has developed. The sequence of knowledge points learned by the user is

Table 1: Considerations for four algorithms in learning path recommendation.

Algorithm name	Learner factor				Learning object factor			
	Learning style	Behavioral preferences	Cognitive level	Group reference	Learning object difficulty	Constraints between objects	Media representation	Environmental facilities
Genetic algorithm	0	0	1	0	1	1	0	0
Ant colony algorithm	1	0	1	1	1	1	1	0
Particle swarm algorithm	0	0	1	0	1	1	0	0
Coordinated filtering algorithm	1	1	1	1	1	1	0	0

compared with the learning path recommended by the system, to judge the rationality of the learning path recommendation strategy. The learning objectives of the learners are not consistent. Record the sequence of knowledge points that the learners have learned under different learning objectives. If the learning sequence of the learners is consistent with the recommended path sequence, the matching frequency is recorded as P_1; otherwise, it is recorded as P_2, among which the same path is recorded as P_1. The frequency of using the VJSBIRKM strategy is LP_1, the number of using the BSSARKM strategy is BP_1, the recommended learning path usage frequency is $L_P = P_1/(P_1 + P_2)$, the adoption rate of the VJSBIRKM strategy is $L_{\mathrm{LP}} = \mathrm{LP}_1/P_1$, and the adoption rate of the BSSARKM strategy is $L_{\mathrm{BP}} = \mathrm{BP}_1/P_1$; the specific operation steps are as follows:

Step 1. Track and obtain the learning data of the learners for some time, classify them according to the learner ID, and arrange the learning records in the ascending order of learning time in the classification to obtain the learning sequence of the learners.

Step 2. Take the learning objectives as the basis for division, select only the first one for the same learning record information in continuous time, and finally obtain the actual learning sequences of learners under different learning objectives.

Step 3. Select the learning path sequence recommended by the system according to different strategies under the same learning objective.

Step 4. Contrast the actual learning sequence of the learner with the learning path recommended by the system under the same learning objective in turn.

Whether the sequence of diameters matches, if they match, $P_1 = P_1 + 1$; otherwise, $P_2 = P_2 + 1$.

Step 5. Compare P_1 with the path recommended by the VJSBIRKM strategy one by one, if they are the same, then $\mathrm{LP}_1 = \mathrm{LP}_1 + 1$; compare P_1 with the route recommended by the BSSARKM strategy, if they are the same, then $\mathrm{BP}_1 = \mathrm{BP}_1 + 1$.

Table 2: Comparison of detailed parameters of the three strategies.

Strategy	Number of successes	Success rate	Average build time/s	Mean path length
VJSBIRKM	188	94.5%	0.874	4
BSSARKM	170	87%	0.882	7
LIU	165	84.5%	0.903	5

Step 6. Traverse the next learning objectives in sequence, and repeat the above steps until all the learning objectives that have been learned are compared and completed.

Step 7. Calculate and obtain according to the formulas $L_p = P_{1/}(P_1 + P_2)$, $L_{\mathrm{Lp}} = \mathrm{LP}_1/P_1$, and $L_{\mathrm{BP}} = \mathrm{BP}_1/P_1$, respectively, and values of L_p, L_{LP}, and L_{BP}.

Experiments are carried out on the knowledge point of "law basis" in ideological and political disciplines. The frequency of learners' adoption of learning paths is $L_p \approx 80\%$, $L_{\mathrm{LP}} \approx 53\%$, and $L_{\mathrm{BP}} \approx 47\%$, which indirectly indicates that the systematic learning path recommendation is reasonable. Compare the relationship between path adoption rate and learner's mastery of knowledge points. Students with a high adoption rate of the learning paths recommended by the VJSBIRKM strategy are mostly students with good grades and a good grasp of knowledge points and usually like to study at the teacher's pace; students with a high adoption rate of the learning paths recommended by the BSSARKM strategy are mostly graded students who are average and have an average level of mastery of knowledge points choose the general learning from the shallower to the deeper and usually like to learn at the teacher's pace. This part of the students with excellent grades is more inclined to learn independently and will not learn completely according to the given path. At the same time, it also shows that the learning path recommendation strategy for this part of students needs to be improved, and different learning strategies need to be proposed according to the different needs of learners, to improve the rationality of the overall recommendation.

The meta node is the minimum granularity of the knowledge graph, and the composite node is the node larger than the

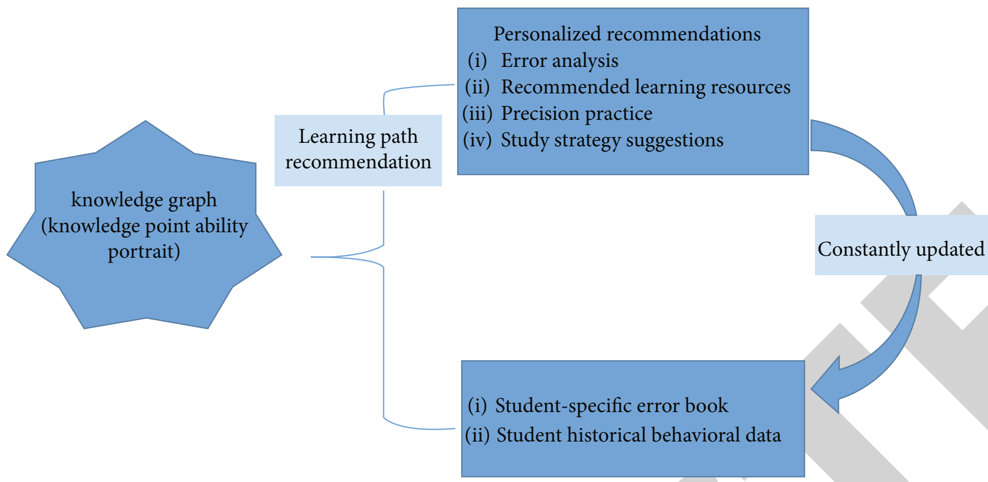

Figure 4: Automatic recommendation of learning resources and exam questions.

minimum granularity. LIU proposes a strategy method for calculating the knowledge centrality [10] and finally recommends the learning path according to the centrality value. Based on the VJSBIRKM strategy and BSSARKM strategy, the path generation test is performed on 200 compound node learning objectives, the number of successful path generations is recorded, and the success rate, the average path generation time, and the average length of the generated learning path are calculated, as shown in Table 2.

It can be seen from Table 2 that when the running data and running times of VJSBIRKM, BSSARKM, and LIU are equal, the path generation success rate of VJSBIRKM and BSSARKM is higher than that proposed by LIU. Among them, the VJSBIRKM strategy generates a complete path. The success rate is 7.5% higher than that of the path generated by the BSSARKM strategy and 10% higher than that of the LIU recommended path, indicating that the two recommendation strategies based on knowledge graphs proposed in this paper have certain feasibility. The average time of the path generated by VJSBIRKM is 0.008 s less than that of BSSARKM and 0.029 s less than that of LIU. These data show that the route recommendation strategy proposed in this paper has certain efficiency; the average length of the path generated by VJSBIRKM is 4. Most of them are composite nodes, which conform to the principle of coarse-grained proximity. The average length of the paths generated by BSSARKM is 7, and the generated paths include the most fine-grained meta nodes, which conform to the principle of fine-grained pan-science.

As shown in Figure 4, based on the relationship between knowledge points, students' own learning preferences, learning ability, and other dimensions, a personalized learning plan is tailored for students, so that students can learn from the original surface knowledge and gradually deepen to deep learning.

3.2. Precise Search for Learning Resources. Based on the knowledge map, the teaching resources can be labeled, the knowledge points involved in the learning resources can be understood, and the test sites and test questions can be related. A deep understanding of the search content input by the user can well implement semantic search and accurately search for the required resources. In addition, using the knowledge graph, when the user searches for a related entity [11], the graph subgraphs related to the entity can be displayed at the same time. It enables users to discover more knowledge related to the knowledge and helps users to carry out knowledge association and divergent learning. As shown in Figure 5, in the study of ideological and political courses, by tagging resources and searching with keywords, ideology, ideology, and politics, and ideological construction, semantic search, and related search are realized.

3.3. Deep Reading. Deep reading based on knowledge graph [12], the main goal is to realize the correlation between knowledge, intelligence, and comprehensive knowledge. Using entity linking technology to identify and connect entities to electronic publications, the current knowledge information can be displayed in the form of knowledge cards. It can also be associated with other related knowledge, and recommend related knowledge to help users connect knowledge. This can greatly promote the user's comprehensive understanding of knowledge. Deep reading can be used not only in education but also in knowledge management and publishing.

The core technology of deep reading is entity linking technology. At present, the entity understanding service developed by our knowledge workshop enables machines to understand the entities in the text, making entity search and semantic search possible, with 90% + accuracy and recall rate in general fields.

3.4. Answering Robot. The NLPCC2016-KBQA dataset is a dataset released by Natural Language Processing and Chinese Computing, a KBQA question answering system evaluation proposed by NLPCC in 2016. The training set in the dataset contains 14,609 question-answer pairs, and the test set contains 9,870 question-answer pairs and provides a knowledge base with 6,502,738 entities, 587,875 attribute relationships, and 43,063,796 triples. The NLPCC2016

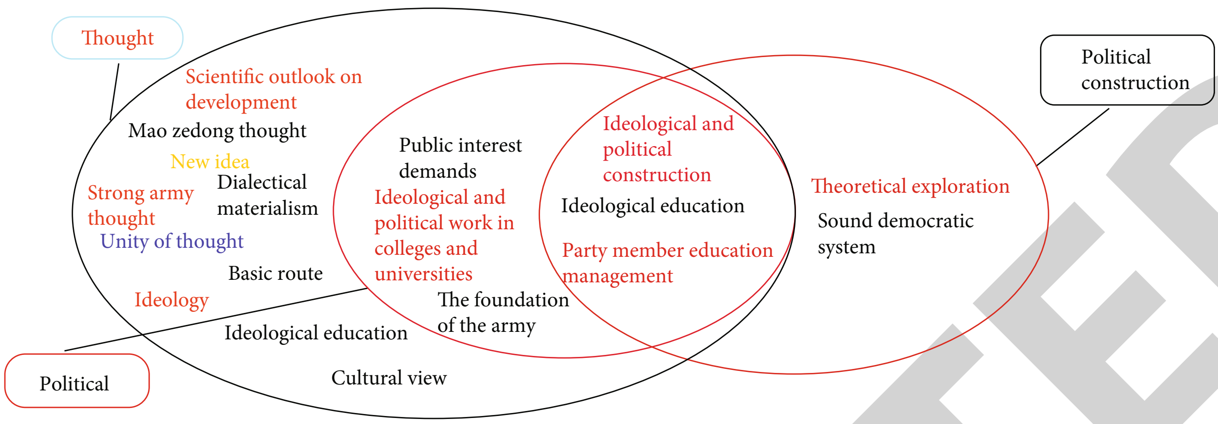

Figure 5: Example of tag tree and keywords.

dataset only contains the knowledge base and question-answer pairs and does not directly provide the training data required for each module of the question-answering system, so we can only construct the relevant datasets from the knowledge base and question-answer pairs.

We use Python language and PyTorch deep learning framework to write the experimental code. For the entity recognition module, we mark the question and answer pairs. According to the entity labeling problem in the triplet, we use the BIO labeling method to obtain the NLPCC2016-NER dataset. For the entity disambiguation module, we annotate the candidate entity set of each entity to obtain the NLPCC2016-DISAM dataset.

For the attribute prediction model, we use the entities of the triples in the question-and-answer pair to get their related attributes, label the attributes in the triples as positive and other candidate attributes as negative, and get the NLPCC2016-REL dataset. For the input sentence classification model, we construct some negative feedback sentences and, at the same time, mark the questions and answers in the question-and-answer pair as datasets to obtain the NLPCC2016-CLS dataset.

In the experiment, to simulate the question-and-answer scenario, we regard a question text in the test set as a question from the user. For the knowledge base-based question answering system (CL-KBQA) proposed in this section, if the question answering system gives the correct answer, the question and answer are over; if the question answering system gives the wrong answer or the question answering system asks the user, then we assume that the user has the probability of Pu to give the correct answer; that is, the answer entity is directly given, and then, the question answering system processes the answer fed back by the user, and the question and answer end. For the BERT-based question answering system (BB-KBQA) [13], after the system answers, no matter whether the answer is correct or not, question and answer are over. To be able to verify the effect of continuous learning, we randomly select 10% of the question-answer pairs from the test set and delete the knowledge triples involved in them from the knowledge base. Then, after testing on the test set according to the setting of the above simulated question-and-answer scenario, test it again on the test set, and record the test data twice, which can illustrate the effect of continuous learning. The system conducts experiments on different values of the user's answer probability Pu, and the specific experimental data are shown in Table 3.

As can be seen from Table 3, the performance of BB-KBQA does not change in the two tests. After adding a continuous learning structure to it, the second test of CL-KBQA is improved compared to the first test. The improvement of CL-KBQA is proportional to the interaction probability of the user. The higher the probability of the user giving the correct answer, the more improvement of CL-KBQA in the second test. This experiment shows that the continuous learning question answering system proposed in this section can continuously improve its performance by using the answers given by users. This section proposes a continuous learning knowledge base-based question answering system architecture. Firstly, a knowledge base question answering system based on the BERT model is constructed, and then, a knowledge base question answering system of continuous learning is proposed for the feature that the knowledge base question answering system can use the knowledge base to store knowledge. The system continuously learns knowledge by interacting with users and stores the knowledge in the knowledge base. It includes modules such as a static question answering system, question generation, and triple structure. If the confidence of the answer given by the system is low or the user is dissatisfied, it will ask the user for the answer, use the user's answer to construct a triplet, store it in the knowledge base, and generate samples for model training, to achieve the effect of continuous learning. Experiments on the NLPCC2016-KBQA question answering dataset verify the effectiveness of the continuous learning question answering system proposed in this section.

Educational robots [14] have become an important application in the field of education. Using the educational robot with the question answering system as the core, a series of teaching tasks such as course answering, knowledge retrieval, recommendation, and teaching management can be realized. It not only reduces the burden and pressure of

Table 3: Experimental results on NLPCC2016 dataset.

Method	Accuracy (%)
BB-KBQA (first test)	73.5
BB-KBQA (second test)	73.5
CL-KBQA (first test)	73.5
CL-KBQA (second test, Pu = 0.0)	73.5
CL-KBQA (second test, Pu = 0.2)	75.6
CL-KBQA (second test, Pu = 0.5)	77.3
CL-KBQA (second test, Pu = 1.0)	80.2

teachers but also solves the practical problems of students. An excellent and comprehensive teaching robot is a combination of multiple system modules such as task-based question answering, Chatbot, knowledge-based question answering, and search recommendation system and has the ability of multiple rounds of question and answer. Knowledge graph plays an important role in query understanding and knowledge-guided language generation and is also the core of KBQA.

The language understanding module is a core module of all kinds of intelligent products with question answering as the core. It mainly uses natural language understanding related technologies to enable machines to understand human language and user queries like humans. The input is the ASR-transformed text, and the output is the text that has been "understood" by the machine. To understand language is not simply from the level of grammar rules but understanding the knowledge behind it. Domain knowledge graphs can help machines understand the language intent of users.

Entity recognition and entity linking, the identified entities are correctly linked to the entities corresponding to the knowledge graph through disambiguation and other processing. Use predefined roles to label keywords or entities to identify the intent of sentences. For multiround question answering, multiround session management is also required.

4. Conclusion

Students' autonomous learning needs to have internal and external necessary conditions. From an internal point of view, students' autonomous learning is inseparable from "self-awareness, intrinsic learning motivation, learning strategies, will control and other internal components." Specifically, students should have the basis of a certain level of psychological development, and they should "be able to learn"; the premise that students have intrinsic learning motivation, they should "want to learn"; the guarantee that students master the corresponding learning strategies, they should "learn"; certain conditions of will control must be "persistently learned." From the perspective of external conditions, students' autonomous learning is also inseparable from external components such as the external educational environment and teacher guidance. The split-class teaching model gives students "the right to self-study," "sufficient self-study time," and "rich self-study course resources." Therefore, in addition to the internal conditions of the students, the external conditions are also very important for students' autonomous learning. The establishment of knowledge maps is from resource pushing, path planning, accurate learning resource searching, in-depth reading, and so on. In terms of self-study, students can achieve more with half the effort. Through the mutual promotion of internal and external factors, the effective combination of the two can play a better role in educational practice.

Data Availability

The experimental data used to support the findings of this study are available on request from the corresponding authors.

Conflicts of Interest

The author declares that there no conflicts of interest to report on this study.

References

[1] Y. Zhou, C. Jin, K. Peng et al., "Application of" PAD classroom" teaching mode in professional basic courses and its research," *Advances in Social Science, Education and Humanities Research*, vol. 283, pp. 64–67, 2018.

[2] W. Yuan and C. H. O. W. Tong Wooi, "Overview of mobile autonomous learning in Chinese higher education," *Curriculum and Teaching Methodology*, vol. 4, no. 5, pp. 76–78, 2021.

[3] B. Liu, D. Xu, and Y. Xu, "Analysis of college students' multimodal autonomous learning strategies in the context of Internet plus," *International Journal of Education and Economics*, vol. 4, no. 3, 2021.

[4] S. Cui, "Study of the knowledge atlas," *World Scientific Research Journal*, vol. 7, no. 12, pp. 225–228, 2021.

[5] S. Panda and R. Chakravarty, "Adapting intelligent information services in libraries: a case of smart AI chatbots," *Library Hi Tech News*, vol. 39, no. 1, pp. 12–15, 2022.

[6] M. I. Khalil, R. Kim, and C. Seo, "Challenges and opportunities of big data," *Journal of Platform Technology*, vol. 8, no. 2, pp. 3–9, 2020.

[7] W. Lei, "Research on innovative education thoughts and teaching methods for China universities," in *2009 International Conference on Information Management, Innovation Management and Industrial Engineering*, pp. 379–382, Xi'an, China, 2009.

[8] H. Fan, Y. Zhong, G. Zeng, and C. Ge, "Improving recommender system via knowledge graph based exploring user preference," *Applied Intelligence*, no. 4, pp. 1–13, 2022.

[9] D. F. Rong, T. J. Tao, P. K. Yuan, T. Wang, L. S. Sha, and L. Xiao, "Constructing an educational knowledge graph with concepts linked to Wikipedia," *Journal of Computer Science and Technology*, vol. 36, no. 5, pp. 1200–1211, 2021.

[10] L. Yuliang, *Research on Personalized Learning Resource Recommendation Based on Knowledge Graph*, Henan Normal University, 2018.

[11] Z. Haixia and L. Lei, "Knowledge graph oriented information extraction," *Data Mining*, vol. 10, no. 4, pp. 282–302, 2020.

[12] C. Juan, W. Zhuowei, and C. Lianglun, "Named entity recognition algorithm based on deep learning," *Computer Science and Applications*, vol. 11, no. 3, pp. 628–634, 2021.

[13] A. Liu, Z. Huang, H. Lu, X. Wang, and C. Yuan, "BB-KBQA: BERT-based knowledge base question answering," in *China National Conference on Chinese Computational Linguistics*, pp. 81–92, Kunming, China, 2019.

[14] Y.-W. Cheng, P.-C. Sun, and N.-S. Chen, "The essential applications of educational robot: requirement analysis from the perspectives of experts, researchers and instructors," *Computers & Education*, vol. 126, pp. 399–416, 2018.