Application of Knowledge Graph Technology in the Construction of University Physics Knowledge System and Learning Path Recommendation

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ABSTRACT With the advancement of new engineering education, university physics has become a core foundational course for science and engineering students, but its knowledge system is highly abstract, cross-branch, and dynamically evolving. Traditional knowledge organization methods cannot adequately support intelligent teaching or personalized learning, and problems such as fragmented knowledge points, unclear conceptual connections, and weak learning-path guidance increase students' cognitive load. To address these issues, this paper applies knowledge graph technology to construct a university physics knowledge system and develop personalized learning path recommendations. First, the core modules and knowledge associations of university physics, including mechanics, thermodynamics, and electromagnetics, are defined through ontology construction. Second, knowledge extraction, fusion, and graph visualization are implemented to clarify semantic dependencies such as the relation between Maxwell equations and electromagnetic wave propagation. Third, a personalized learning path recommendation algorithm is designed using student learning data and graph reasoning. A 16-week experiment involving 286 science and engineering students from three universities shows that the knowledge graph increases the knowledge-point mastery rate by 32.7%, while personalized path recommendation improves learning efficiency by 28.9% compared with traditional teaching.

INDEX TERMS knowledge graph, university physics, learning path recommendation, electromagnetics, personalized learning

I. INTRODUCTION

WITHIN the framework of new engineering disciplines, as the basic subject of natural sciences, the completeness of knowledge system and the pedagogical rigor of university physics teaching method are very important for training students' scientific literacy and innovation ability. At present, the problem of low knowledge transfer efficiency and lack of personalized guidance still exist in university physics teaching. The traditional linear knowledge organization method can't show the complex relationship between knowledge and can't meet the personalized learning needs of students. As an important technology that promotes education with artificial intelligence, knowledge graph can structure and network scattered knowledge, present the semantic relationship between knowledge clearly and provide a new way to reconstruct university physics knowledge system and optimize learning path. Taking the application of knowledge graph technology in university physics field as the research object, this study takes solving the problem of fragmented traditional knowledge system and lack of targeted learning path as the key to solve the problem. The research range is the core knowledge module of university physics and the learning needs of different basic students.

The significance of the project is to provide theoretical support and reference for the teaching reform of intelligent teaching in university physics and promote the improvement of teaching quality in basic subjects [1,2]. The main contributions of this study are summarized as follows: Firstly, the university physics knowledge graph meets the needs of teaching, breaks through the limitation of traditional knowledge organization, realizes the systematic integration of multiple branches of knowledge such as classical mechanics, electromagnetics, thermodynamics, etc., and clarifies the hierarchical relationship and association rules between knowledge points; Secondly, the personalized learning path recommendation algorithm based on knowledge graph and student learning data is proposed. It considers the differences in students' knowledge foundation and learning goals, and achieves "teaching according to students' aptitude"; Thirdly, the effectiveness of knowledge graph in construction of knowledge system and recommendation of learning path is verified by empirical research, and the scalable teaching application model is formed [3,4].

The rest of this article is organized as follows: Firstly, the problem and challenge in construction of current university physics knowledge system and recommendation of learning path are analyzed in detail. Secondly, the research method and technical implementation process are explained in detail. Then, the experimental results are presented and discussed in detail. Finally, the research conclusions, shortcomings and future research direction are drawn.

II. PROBLEMS AND CHALLENGES

The most prominent problem in building the knowledge system in university physics lies in the confusion and vague correlation of knowledge, which makes it hard to construct the systematic knowledge network. At present, physics teaching in universities is mainly carried out according to the chapters in the textbook, and knowledge is divided into different teaching modules. In addition, the deep correlation of knowledge is not explored and presented either. For example, there is a certain correlation between the Maxwell equations in electromagnetism and the concept of field theory in classical mechanics. But in the traditional teaching, the correlation of these two contents cannot be well organized, and it is difficult for students to construct the complete knowledge network. Besides, university physics knowledge involves multiple dimensions such as concepts, formulas, experiments and theories. The integration of knowledge from different dimensions is not enough, and the update of knowledge is delayed compared with the rapid development of new technologies. It is difficult to incorporate new experimental discoveries and theoretical achievements in time, which further aggravates the confusion of knowledge system and increases the burden of students in understanding knowledge. Meanwhile, the modeling of knowledge is difficult, and there is no unified ontology specification. Therefore, it is difficult to present the same knowledge representation in different teaching scenarios, which makes it difficult to achieve the sharing and reuse of knowledge [5,6].

The main problems existing in the current learning path recommendation are concentrated in two aspects: insufficient personalization and poor adaptability. On the one hand, most of the traditional learning paths adopt a uniform, undifferentiated instruction model in the learning process, and do not consider the differences in students' knowledge foundation, learning ability and learning goal. For example, for the students with poor mathematics foundation, the same learning path as the students with good mathematics foundation is recommended, which results in reduced pedagogical engagement for underprepared students and insufficient cognitive challenge for advanced learners. On the other hand, the recommendation of learning path lacks a dynamic adjustment mechanism, which makes it difficult to adjust the path in time according to the realtime learning data of students (such as knowledge mastery, learning process, distribution of wrong questions), and it is difficult to achieve the teaching goal of remediating specific knowledge deficits through targeted intervention. At the same time, the current recommendation method is based on single learning data, and it cannot combine the semantic association of knowledge graph for accurate recommendation. Therefore, it is difficult to make logical and systematic recommendation path based on knowledge graph, and it is impossible to guide students to construct knowledge system efficiently. Meanwhile, there is a lack of high-quality learning data and single data modality, which makes the accuracy and practicability of recommendation algorithm worse [7,8].

III. METHOD

A. CONSTRUCTION OF UNIVERSITY PHYSICS KNOWLEDGE ONTOLOGY

According to "Basic Requirements for Teaching Physics Courses in Science and Engineering Universities", take university physics textbooks, teaching syllabi and latest research results as the basis, construct the knowledge ontology framework of university physics, clarify the hierarchical structure and semantic relationship of knowledge. Firstly, define the basic categories of ontology. There are five top-level categories in ontology, namely, physical concept, physical quantity, physical law, experimental project and theoretical module. Each of top-level category is divided into two subcategories. For example, the category of physical concept includes physical concept of mechanics, physical concept of electromagnetic, etc. The category of physical law includes classical mechanical laws, electromagnetic laws, etc. Secondly, define the attributes and relationships of class. The attributes include difficulty of knowledge point, requirement of mastery, resource, etc. The relationships include "inclusion", "dependence", "derivation", "application", etc. For example, there is relationship of "dependency" between "Newton's Second Law" and "acceleration". There is relationship of "derivation" between "Maxwell's equations" and "electromagnetic wave propagation". Finally, use OWL language to formalize the ontology. Make the knowledge representation standardized and unified, which lays the basis for constructing knowledge graphs [9,10].

B. CONSTRUCTION OF UNIVERSITY PHYSICS KNOWLEDGE GRAPH

Based on the constructed knowledge ontology, a university physics knowledge graph is constructed using the process of "multi-source data collection knowledge extraction knowledge fusion graph storage". Multi-source data collection covers structured, semi-structured, and unstructured data such as university physics textbooks, academic papers, teaching courseware, and exercise sets. To bridge the gap from single-modality data to a comprehensive knowledge network, a multi-modal preprocessing pipeline was implemented: structured exercise data was parsed into knowledge-attribute pairs, semi-structured courseware was processed via XML metadata extraction, and unstructured textbook text underwent semantic segmentation. This pipeline ensures that disparate data formats are normalized into a unified relational schema before the extraction phase. Knowledge extraction then adopts a combination of deep learning and rules to extract entities, relationships, and attributes from these processed streams. The training corpus consists of 15,000 manually annotated sentence pairs derived from core textbooks and syllabi, split into an 8:1:1 ratio for training, validation, and testing. The BERT model is used for entity recognition, fine-tuned over 10 epochs with a learning rate of 2×10^{-5}, and the CNN-LSTM model is used for relationship extraction. To enhance precision, a rule-based postprocessing layer is applied, utilizing regular expression templates to capture high-frequency physical formulas and predefined linguistic patterns (e.g., 'is defined as', 'consists of') that denote semantic dependencies; Knowledge fusion solves problems such as knowledge duplication and ambiguity in different data sources through operations such as entity disambiguation and redundancy elimination, achieving unified integration of knowledge; The graph storage adopts Neo4j attribute graph database to achieve efficient storage of knowledge and complex relationship queries. Finally, a university physics knowledge graph containing more than 250 knowledge points and 260 knowledge relationships is constructed and visualized, presenting the association network between knowledge points clearly [11,12].

C. DESIGN OF PERSONALIZED LEARNING PATH RECOMMENDATION ALGORITHM

This article constructs a personalized learning path recommendation algorithm based on knowledge graphs and student learning data, as shown in Figure 1, to achieve accurate and dynamic learning paths. Firstly, by collecting pre class preview data, classroom interaction data, post class test data, etc., establish student profiles, excavate students' knowledge foundation, learning ability, learning interest, learning goals, and quantify students' mastery of various knowledge points; Secondly, based on the semantic associations and hierarchical relationships of knowledge points in the knowledge graph, constraint rules for learning paths are constructed to clarify the learning order and dependency relationships of knowledge points; Finally, using collaborative filtering and knowledge graph reasoning methods, personalized learning paths are generated and dynamically adjusted. The adjustment logic follows a threshold-based transition: if a student's mastery score (M_k) for a prerequisite knowledge point k falls below 0.6, the system triggers a 'Recovery Path.' This path is formally selected using a shortest-path algorithm within the graph to identify foundational nodes. For example, if a student fails an electromagnetics quiz, the system identifies the 'Low Mastery' state and executes the following logic:

$$\begin{aligned} \text{IF} \quad & M_{\text{electromagnetics}} < 0.6 \\ \text{THEN} \quad & \text{Recommend}(\\ & \qquad \text{Preview}_{\substack{\text{vector}\\ \text{calculus}}} + \text{Exercise}_{\substack{\text{basic field}\\ \text{theory}}}). \end{aligned}$$

This ensures that the transition from assessment to recommendation is governed by the structural dependencies defined in the ontology. Recommend advanced knowledge points related to those with a high level of mastery, and achieve personalized teaching [13].

IV. RESULTS AND DISCUSSION

A. VERIFICATION OF THE EFFECTIVENESS OF KNOWLEDGE GRAPH CONSTRUCTION

To verify the practicality and scientificity of the constructed university physics knowledge graph, and ensure that it can effectively solve the problems of fragmented and fuzzy traditional knowledge systems, this study selected 10 university physics teachers (including 3 professors, 4 associate professors, and 3 lecturers with more than 5 years of university physics teaching experience) and 50 science and engineering students (covering physics, electronic information engineering, and mechanical engineering majors, with 25 freshmen and 25 sophomores each) from 3 different levels of universities (including 1 Double First Class university, 1 ordinary undergraduate university, and 1 applied undergraduate university) as the evaluation subjects to comprehensively evaluate the construction effect of the proposed knowledge graph. The evaluation adopts a 100 point scale, and the evaluation indicators are clearly defined as four core dimensions: knowledge completeness, correlation accuracy, visualization effect, and teaching applicability. Among them, knowledge completeness mainly evaluates the coverage of the core knowledge points of university physics by the visualized graph, correlation accuracy evaluates the correctness of the dependencies, derivations, and other relationships between knowledge points, visualization effect evaluates the clarity and intuitiveness of the presentation of the evaluation map, and teaching applicability evaluates the adaptability of the evaluation map in classroom teaching, self-directed learning, and other scenarios. During the evaluation process, the evaluation subject independently scores each indicator, and then takes the average score of all evaluators as the final evaluation result. At the same time, the standard deviation of the scores is calculated to verify the consistency of the evaluation results. The specific evaluation data is shown in Table 1 below:

TABLE 1. Verification of the effectiveness of knowledge graph construction

Evaluation metric	Average rating (points)	Rating standard deviation	Rating Level
Integrity of knowledge	89.6	2.3	Excellent
Correlation accuracy	91.2	1.8	Excellent
Visualization effect	87.8	2.5	Good
Applicability of teaching	88.5	2.1	Good

The constructed knowledge graph of university physics performs excellently on the four core evaluation indicators, with an average score of over 85 points and a standard deviation of $\leq$ 2.5 for each indicator. The cognitive consistency of the evaluation subjects is strong, and the results are reliable. The average score for knowledge

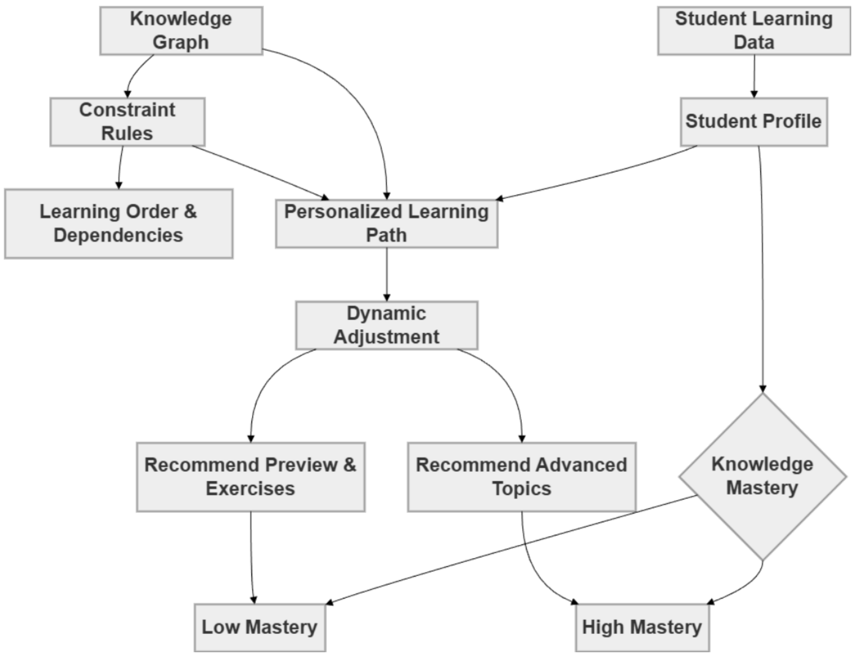

FIGURE 1. Design of Personalized Learning Path Recommendation Algorithm

completeness is 89.6, with a standard deviation of 2.3. It comprehensively covers core modules such as classical mechanics and electromagnetics, with only a few cutting-edge extended knowledge points missed, meeting the needs of daily teaching and self-learning. The average accuracy of association is 91.2 points, with a standard deviation of 1.8, which is the highest among the four items. Through ontology construction and knowledge fusion, the relationships between knowledge points such as "inclusion" and "dependence" are accurately sorted out, solving the problem of traditional association ambiguity and helping teachers and students grasp the internal logic. The average visual effect is 87.8 points, with a standard deviation of 2.5. The presentation is concise and intuitive, clearly showing the knowledge hierarchy and related networks, reducing the difficulty of understanding, and facilitating teachers and students to locate knowledge points and organize the context. The average teaching applicability score is 88.5, with a standard deviation of 2.1. It is suitable for different levels of university teaching scenarios, providing support for teachers' teaching design, helping to optimize processes, sort out key and difficult points, and also providing guidance for students' self-directed learning, helping to build knowledge networks. In summary, the knowledge graph has achieved the expected goals, effectively solving the problems of traditional knowledge systems, providing support for the systematic construction of knowledge systems, and laying the foundation for personalized learning path recommendations.

B. ANALYSIS OF THE EFFECTIVENESS OF PERSONALIZED LEARNING PATH RECOMMENDATION

To further validate the effectiveness of the personalized learning path recommendation algorithm based on knowledge graph and clarify its differences in teaching effectiveness compared to traditional learning paths, this study conducted a 16 week teaching control experiment. The experimental subjects selected 286 first-year students majoring in science and engineering from three universities, covering four majors: physics, electronic information engineering, mechanical engineering, and computer science and technology. All students had completed the basic stage of university physics. To account for the diverse academic backgrounds across the three institutional tiers (Double First Class, ordinary undergraduate, and applied undergraduate), a stratified random sampling approach was employed. Students were grouped by institutional tier before being randomly assigned to the experimental or control groups, ensuring that both groups maintained a proportional representation of each university level. A subsequent analysis of the baseline unified test scores confirmed that there were no statistically significant differences in foundational knowledge between the experimental and control groups within each specific tier ($P > 0.05$), thereby validating the comparative framework. Informed consent was obtained from all participants. Randomly divide the experimental subjects into two groups, with 143 participants in the experimental group. Adopt a personalized learning path based on knowledge graph for learning, that is, construct student profiles based on students' knowledge foundation and learning ability, combine the semantic association and knowledge point hierarchical relationship of the knowledge graph to generate personalized learning paths for each student, and dynamically adjust the learning content and pace based on students' real-time learning data (post class test scores, distribution of wrong questions, learning progress); The control group consisted of 143 individuals who followed a traditional learning path, where the teacher arranged the learning content and progress uniformly according to the order of the textbook chapters, without personalized adjustments. During the experiment, the teaching staff, duration, content, and assessment standards of the two groups of students remained consistent, with only the recommendation method for the learning path being different. After the experiment, a comprehensive comparative analysis was conducted on the learning outcomes of the two groups of students from the three core dimensions of knowledge mastery rate, learning efficiency, and learning satisfaction. The specific experimental data is shown in Table 2 below:

TABLE 2. Analysis of the effectiveness of personalized learning path recommendation

Evaluation metric	Experimental group (n=143)	Control group (n=143)	difference value	P value
Mastery rate of knowledge points (%)	86.3±4.2	65.6±5.8	+20.7	< 0.05
Average learning duration (hours/week)	6.8±1.3	9.5±1.5	-2.7	< 0.05
Learning satisfaction (score)	89.3±3.1	72.6±4.5	+16.7	< 0.05

The experimental data showed significant differences ($P < 0.05$) between the experimental group and the control group in various evaluation indicators, proving that personalized learning path recommendation algorithms based on knowledge graphs can effectively improve learning effectiveness. In terms of mastery rate of knowledge points, the experimental group had an average of 86.3% $\pm$ 4.2%, while the control group had an average of 65.6% $\pm$ 5.8%. The experimental group improved by 20.7 percentage points. Personalized paths accurately adapt to students' knowledge foundation, recommend targeted resources to help them identify weaknesses and fill in gaps, and push advanced content for those who have mastered them well, avoiding ineffective repetition and achieving efficient mastery. In terms of learning efficiency, the experimental group had an average weekly learning time of 6.8 $\pm$ 1.3 hours, while the control group had 9.5 $\pm$ 1.5 hours, a reduction of 2.7 hours. Personalized path sorting of knowledge point dependencies, guiding students to learn in a reasonable order, reducing ineffective learning time waste caused by unclear knowledge associations, and enabling students to grasp core knowledge in a short period of time. In terms of learning satisfaction, the experimental group scored an average of 89.3 $\pm$ 3.1 points, while the control group scored 72.6 $\pm$ 4.5 points, an increase of 16.7 points. Personalized paths consider students' learning differences, adapt to students with different foundations and abilities, solve the traditional "one size fits all" problem, and enhance learning initiative and sense of achievement. In summary, the algorithm accurately adapts to learning needs, improves learning effectiveness, and verifies its effectiveness and practicality.

C. DISCUSSION ON PROBLEMS AND OPTIMIZATION DIRECTIONS

Based on the experimental results and teaching scenarios, this research method has shortcomings in the construction of the university physics knowledge system and the recommendation of learning paths. In terms of knowledge graph construction, the knowledge update mechanism is not perfect, mainly based on existing textbooks, and the inclusion of cutting-edge knowledge and new teaching reform content is not timely. There is a lack of automated update processes, and manual supplementation and adjustment costs are high and difficult to adapt to rapid knowledge updates. In terms of personalized learning path recommendation, recommendation algorithms lack consideration for students' interests and mainly construct paths based on knowledge foundations, ignoring differences in interests. Some recommended content does not match students' interests, which affects learning initiative and effectiveness improvement. The automation level of the knowledge extraction process needs to be improved. Although the model combination method is used, the accuracy of extracting unstructured data is low, and complex knowledge points need to be manually corrected, which increases the workload of construction. There are three optimization directions to address the shortcomings: firstly, designing a dynamic knowledge update algorithm that combines cutting-edge achievements, reform trends, and feedback from teachers and students to achieve automated and real-time updates of the graph, reduce costs, and improve timeliness; Secondly, introducing learning interest factors, analyzing learning behavior data to mine interests, optimizing recommendation algorithms, and combining interests with content to enhance path attractiveness; The third is to improve deep learning models, introduce attention mechanisms and domain pre training models, optimize extraction algorithms, improve the accuracy of unstructured data extraction, and enhance the efficiency and quality of graph construction.

V. CONCLUSION

This article focuses on the application of knowledge graph technology in the construction of university physics knowledge system and learning path recommendation, effectively solving the problems of fragmented and fuzzy association of traditional university physics knowledge system, as well as the lack of pertinence and poor adaptability of learning paths. The research has constructed a standardized and complete ontology and knowledge graph of university physics, achieving systematic integration and visual display of multi branch knowledge; Designed a personalized learning path recommendation algorithm based on knowledge graph and student profile, achieving precise and dynamic learning paths. Experimental verification shows that this method can significantly improve students' mastery rate of knowledge points and learning efficiency, and enhance the learning experience. The theoretical value of this study lies in enriching the application theory of knowledge graph in basic subject teaching, and providing new ideas for the reform of university physics digitization teaching; The actual value lies in providing a scalable practical model for college physics teaching, helping to improve the quality of basic subject teaching. This study still has shortcomings such as untimely knowledge updates and incomplete recommendation algorithms. In the future, we will focus on optimizing these issues to further promote the deep integration of knowledge graphs and university physics teaching.

AUTHOR CONTRIBUTIONS

Conceptualization –Fu Meiqin and Wei Meiling; methodology – Fu Meiqin and Wei Meiling; investigation – Fu Meiqin and Wei Meiling; writing-original draft preparation – Fu Meiqin and Wei Meiling. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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