Cultivating College Students' Adaptive Learning Ability Based on LLM-Enhanced Knowledge Graph

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Abstracts: *With the rapid development of internet technology, the field of education is undergoing profound changes. As the main force of future society, college students' adaptive learning ability is particularly important. This article aims to explore how to enhance college students' adaptive learning ability by combining large-scale models and knowledge graph technologies. By constructing a knowledge graph system enhanced by large-scale models, it can be achieved in-depth mining of learning content and personalized recommendations, providing college students with more accurate and efficient learning paths, thereby cultivating their ability for autonomous and lifelong learning.*

***Keywords*：** *Knowledge graphs(KG)，Large language model(LLM), Adaptive Learning Ability, College Student*

1. Introduction

Adaptive learning, as a new teaching model, achieves personalized and intelligent learning processes through technological means and becomes an important development direction for future education. Adaptive learning refers to the use of technological means to dynamically adjust learning content and strategies according to the individual characteristics and learning behaviors of learners, in order to provide the most suitable learning path for each learner. Its core lies in personalized learning path planning, data-driven decision-making, timely feedback support, and personalized learning content.

Knowledge graphs(KG), as important tools for representing the relationships between knowledge, possess powerful knowledge representation and reasoning capabilities. LLMs, such as deep learning models, with their strong learning and data processing capabilities, provide new possibilities for the improvement and application of knowledge graphs. Knowledge graph shows the correlation and hierarchical structure of knowledge in a graphical way, which can clearly reflect the internal logic and system of subject knowledge. In the adaptive learning system, knowledge graph, as the basis of knowledge representation and reasoning, provides learners with structured knowledge query and deep mining functions for learners, thus supporting the generation and recommendation of personalized learning paths.

Large language model(LLM) can automatically extract knowledge and build or improve knowledge graph. At the same time, the LLM also has powerful reasoning and generation capabilities, and can realize more intelligent reasoning and recommendation systems based on the knowledge graph. Combining the LLM and the knowledge graph, the accuracy and personalization degree of the adaptive learning system can be significantly improved.

This article will combine LLM and KG technology to explore their application in the cultivation of adaptive learning abilities among university students.

2. Research status both at home and abroad

2.1 *Development of Adaptive Learning Systems*

In recent years, significant progress has been made in the research of adaptive learning systems both domestically and internationally[1]. Representative foreign institutions such as Duolingo Max and

Khan Academy have achieved highly personalized learning experiences by incorporating techniques like role-playing and probabilistic models. In China, many outstanding adaptive learning platforms have also emerged, such as Squirrel AI, which use technologies like knowledge graphs and recommendation systems to provide learners with precise learning path recommendations.

2.2 Application of the knowledge graph in adaptive learning

The application of knowledge graph in adaptive learning is mainly reflected in the following aspects[2-3,5,6]. First, build domain knowledge graph to provide structured knowledge query and reasoning. Second, design normalized recommendation algorithm based on knowledge graph to realize the recommendation of personalized learning content. Third, complete and expand the knowledge graph combined with the LLM to improve the intelligence level of the system.

A knowledge graph is a graph-based method for knowledge representation and reasoning, used to describe entities, concepts, attributes, and their relationships. In adaptive learning, constructing domain knowledge graphs can provide students with structured knowledge querying and reasoning services. Through knowledge graphs, students can intuitively understand the interconnections and hierarchical relationships between knowledge points, thereby better understanding and mastering knowledge. At the same time, teachers can also use knowledge graphs for curriculum design and instructional planning, ensuring the coherence and systematic nature of the teaching content.

Another important application of knowledge graphs in adaptive learning is designing personalized recommendation algorithms. By collecting information such as students' learning history, interests, and current learning status, knowledge graphs can analyze students' learning needs and preferences, thereby recommending suitable learning resources and paths. This personalized approach not only improves students' learning efficiency and interest but also helps them identify and address their knowledge gaps, promoting comprehensive development and progress. For example, some personalized learning resource recommendation systems based on knowledge graphs have been applied in actual teaching and have achieved good results.

With the continuous development of artificial intelligence technology, LLMs are playing an increasingly important role in the construction and completion of knowledge graphs. By combining LLMs, we can conduct more in-depth and comprehensive completion and expansion of knowledge graphs, thereby improving their accuracy and completeness. This not only can further enhance the intelligence level of adaptive learning systems but also provide students with richer and more diverse learning resources and experiences. For example, some researchers have proposed methods based on deep learning to complete and expand knowledge graphs and have achieved significant results.

2.3 Complementarity of Knowledge Graphs and LLMs

Knowledge graphs can provide rich background knowledge and structured information to LLMs, enhancing their interpretability and reasoning capabilities; conversely, LLMs can offer stronger computational power and data mining capabilities for the construction and refinement of knowledge graphs. The combination of the two facilitates the interconnectivity between different data modalities. Research progress in this field is mainly reflected in the following aspects.

2.3.1 Enhancement of LLMs by Knowledge Graph

Knowledge map of big model: knowledge map can provide real and reliable knowledge for big model, reduce big model illusion, provide means of explanation and reasoning knowledge, explore the big model internal complex working steps and reasoning process, can also be used as an external retrieval tool, help big model to solve the problems such as fairness, privacy and security.

Table 1 KG-enhanced LLM methods[4,7-8]

Categories	Name	Year	Mechanism
Standard Pretrained Corpus	KGTEXT	2020	LLMs as generators
	KELM	2021	LLMs as generators
	ANANLOGTKB	2023	LLMs as generators
KG-embedded LLM	K-BERT	2020	KG-injected LLM
	ERNIE3.0	2021	KG-embedded LLM
	SKILL	2022	KG-trained LLM
	Lu YJ	2022	KG-injected LLM

	KnowGPT	2023	KG-injected LLM
	Fang Y	2023	KG-trained LLM
Enhance LLM inference	JointLK	2021	GNN+KG
	DRAGON	2022	KG-trained LLM
Enhance LLM retrieve	RAG	2020	KG for LLM retrieval document
	LaMDA	2022	KG-trained LLM
	KaLMA	2023	KG for LLM retrieval document
Enhance the interpretability of LLMs	LMExplainer	2023	KG as a search engine
	XplainLLM	2023	Link LLM with KG

2.3.2 Enhancement of Knowledge Graphs by LLMs

In the training of zero sample and few sample, the LLM can cope with various challenges such as knowledge graph construction, completion, reasoning and question answering. For example, LLMs can use the information extraction ability learned with zero or few samples to complete entity extraction and relationship extraction tasks from text or other data sources, saving the time and cost of data annotation; and can also be used as an additional knowledge base to extract trusted knowledge and complete the completion of knowledge graph.

Table 2 LLM-enhanced KG methods[4,7-8]

Categories	Name	Year	Mechanism
Enhanced graph construction	ChatIE	2023	Extract information through prompt engineering
	ChatExtract	2023	Extract the hint question set through the hint engineering prompt
	AutoKG	2023	Extract keywords using pre-trained LLMs
	Tang R X	2023	Generate labeled samples using ChatGPT
Enhanced graph completion	KoPA	2023	LLM-embedded KG
	KICGPT	2024	LLMs as an additional knowledge base
	Wei Y	2024	LLMs as training data generators
Enhanced graph reasoning	LLM-ARK	2023	LLM-guided knowledge graph reasoning
	LARK	2023	
	ChatRule	2023	LLMs as rule generators
Enhanced Graph Q& A	Taffa TA	2023	Generate SPARQL queries through prompt engineering
	ChatKBQA	2023	Fine-tune LLMs to generate SPARQL queries
	KnowPAT	2023	Fine-tune the knowledge preference of the LLM
	BYOKG	2023	LLMs as a supplementary corpus

3. Design of Adaptive Learning Systems Based on LLM-Enhanced KG

3.1 System Architecture

The construction framework of an adaptive learning system based on LLM-enhanced knowledge graphs includes data acquisition, preprocessing, information extraction, knowledge storage, etc. By integrating the data from various sources, the natural language processing technology is used for entity recognition and relationship extraction, and the knowledge is stored in the Neo4j graph database, which finally realizes the efficient management and reasoning of knowledge. The technology of co-index resolution and entity disambiguation further improves the accuracy and consistency of the knowledge graph, and provides a solid foundation for the intelligent question and answer system. Each link in the construction framework is closely related to form a complete process of knowledge graph construction.

3.2 Data Collection and Processing

Data collection is the foundation for constructing knowledge graphs. The system needs to gather learning resources and learning behavior data from various channels, including text, images, videos, etc.

Then, through preprocessing and feature extraction steps, it converts unstructured data into structured data, providing data support for subsequent knowledge graph construction and recommendation algorithms.

This paper focuses on building a recommendation system to cultivate adaptive learning ability based on LLM enhanced knowledge graph, so as to meet the needs of students with different foundations for knowledge acquisition. To ensure the authority and standardization of the information provided by the system, core data sources such as textbooks, teaching plans, and online resources are selected by domain experts to support the construction of adaptive learning domain knowledge graphs. To further enhance the practicality and accuracy of the knowledge graph, this paper also obtains relevant data from CNKI (China National Knowledge Infrastructure) as an important supplementary data source.

In the preprocessing stage, the text data is first cleaned by removing irrelevant characters, such as punctuation marks, HTML tags, special symbols, and extra spaces. To further reduce noise data, stop words are removed—these are words that appear frequently but have low actual meaning, such as "of", "is" , "in", “at” , etc. After cleaning, tokenization is performed, dividing the Chinese text into individual words or phrases. This article uses the jieba tokenizer for segmentation, as it offers efficient and accurate tokenization capabilities and supports custom dictionaries, which significantly improves the recognition of domain-specific terms. These data can undergo subsequent knowledge extraction and relationship identification after preprocessing.

An adaptive learning recommendation system based on LLM-enhanced knowledge graphs involves various entities during its construction process. These entities play different roles within the system, collectively supporting the realization of adaptive learning recommendations. Considering the diversity, conceptual cross-over, and spatiotemporal dynamics of entities and relationships in the field of adaptive learning. In this study, five types of entity are involved, namely Learner entities, Learning Resource entities, Knowledge entities, Relationship entities, and System Component entities.

In the aforementioned knowledge graph-based adaptive learning recommendation system, the relationships between various entities are rich and diverse. These relationships not only reveal the inherent structure of subject knowledge but also reflect the dynamic interactions between learners and learning resources. The following are some of the main types of relationships: the relationship between learners and learning resources, the relationship between learners and knowledge, the relationship between knowledge and learning resources, the relationships among knowledge entities, and the relationships between system components.

3.3 Construction and Completion of Knowledge Graphs

The construction of a knowledge graph can indeed be divided into an expert-driven phase and a data-driven phase.

In the expert-driven phase, educational experts play a crucial role. Relying on their profound professional knowledge and teaching experience, they deeply deconstruct and analyze teaching content, thereby forming a preliminary knowledge graph.

Deconstruction of teaching content：Educational experts carefully study teaching objectives, content of teaching materials, and teaching syllabi to clarify the logical relationships and teaching sequence between various knowledge points. They break down the teaching content into individual knowledge points and determine the relationships and dependencies among these points.

Preliminary construction of the knowledge graph：Based on the results of the deconstruction of teaching content, educational experts begin to construct a preliminary knowledge graph. In this process, they use graphical methods to represent the knowledge points and their relationships, forming a clear knowledge structure diagram.

Expert review and correction：After the preliminary construction is completed, educational experts will review and correct the knowledge graph. They will check whether the knowledge points in the graph are accurate and complete, and whether the relationships are clear and reasonable. Based on the review results, experts will make corresponding adjustments and optimizations to the graph to ensure its accuracy and usability.

In the data-driven phase, the system utilizes the learning capabilities of LLMs and natural language processing techniques to automatically extract knowledge from vast amounts of data and fill in missing information in the knowledge graph. Additionally, the system can also achieve automatic annotation and verification of entities and relationships within the knowledge graph.

Knowledge Extraction and Completion：Leveraging the learning ability of LLMs, the system can automatically extract knowledge points and their relationships from text data. These extracted knowledge points and relationships are used to fill in missing information in the initially constructed knowledge graph. In this way, the knowledge graph can become more complete and rich.

Automatic Annotation and Verification of Entities and Relationships：The system uses natural language processing technology to automatically annotate entities and relationships in the knowledge graph. This helps to clarify the specific meanings of each element in the graph and the types of relationships between them. At the same time, the system also verifies these annotations to ensure their accuracy and consistency.

Continuous Optimization and Update：As data continues to accumulate and technology advances, the knowledge graph needs to be continuously optimized and updated. The system periodically re-runs knowledge extraction and relationship identification algorithms to discover new knowledge points and relationships, and updates them into the knowledge graph. In addition, educational experts will also regularly review and correct the graph to ensure that it always remains consistent with the teaching content.

3.4 Learning Path Generation and Recommendation

Based on knowledge graphs and learning behavior data, the system can generate personalized learning paths. The system standardizes students' learning behavior data, thereby forming an individual learning profile for each student, which is a complex yet crucial process. The system first collects students' learning behavior data through various technical means, such as online learning platforms, learning management systems, etc., including learning time, progress, completion of exercises, accuracy rate, number of discussions participated in, etc. Then, clean the data. Preprocess the collected data by removing invalid, duplicate, or abnormal data. Check the integrity of the data, and for missing data, the system may use methods such as mean imputation, interpolation, or others to fill in the gaps. And apply min-max normalization to standardize the data. Finally, classify and encode the standardized data, categorizing different types of learning behavior data, such as learning time, completion of exercises, etc. Encode the data under each category for subsequent analysis and processing.

It can be utilized to analyze the interrelations and hierarchical relationships between various knowledge points based on the existing knowledge graphs. We can determine students' mastery levels at each knowledge point, including fully mastered, partially mastered, and not mastered. Based on students' learning behavior data and knowledge point mastery, an individual learning paths can be constructed for students. The learning path should include the knowledge points the student currently needs to learn, recommended learning resources (such as video tutorials, reading materials, practice questions, etc.), and the learning sequence. The system can track students' learning progress in real-time, recording the time spent on each knowledge point and the completion of practice exercises. The learning path will be dynamically adjusted according to progress, and personalized learning suggestions and resource recommendations can be provided.

3.5 Learning feedback and adjustment

Learning feedback is an important part of adaptive learning systems. The system collects feedback data from students during the learning process, including their performance on questions, learning duration, and learning status, to evaluate their learning effectiveness and progress. Then, based on the feedback data, the system adjusts the learning path and recommendation strategies to ensure the continuous update and optimization of the learning content. Additionally, the system can provide personalized learning suggestions and resource recommendations to help students better master subject knowledge.

4. Empirical research

4.1 Experimental Design

To verify the effectiveness of the adaptive learning system enhanced by large-scale models and knowledge graphs, an empirical study was designed. A certain number of college students were selected as subjects and randomly assigned to an experimental group and a control group. The experimental group used the adaptive learning system enhanced by large-scale models and knowledge graphs for learning, while the control group used traditional online learning platforms.

4.2 Experimental Results

After a period of learning, we evaluated the learning outcomes of both the experimental group and the control group. The assessment indicators included academic performance, learning satisfaction, and learning efficiency, among others. The experimental results indicated that students in the experimental group significantly outperformed those in the control group in terms of academic performance and learning satisfaction. Additionally, the students in the experimental group also demonstrated a clear advantage in terms of learning efficiency. This suggests that the adaptive learning system based on enhanced knowledge graphs using LLMs can significantly improve the learning outcomes and experiences of college students.

5. Discussion and Outlook

5.1 Discussion

The adaptive learning system based on enhancing knowledge graphs with LLMs proposed in this paper has significant advantages. Firstly, the system is capable of fully mining and integrating learning resources, providing structured knowledge queries and reasoning functions; secondly, the system can generate the most suitable learning paths and recommendation strategies based on students' individual characteristics and learning behaviors; finally, the system can collect students' learning feedback in real-time and dynamically adjust learning paths and recommendation strategies, ensuring the relevance and effectiveness of the learning content. However, the system still faces some challenges and difficulties in practical application, such as data quality issues, algorithm complexity issues, etc.

5.2 Outlook

The adaptive learning system based on LLMs to enhance knowledge graphs proposed in this article has significant advantages. Firstly, the system is capable of fully mining and integrating learning resources, providing structured knowledge queries and reasoning functions; secondly, the system can generate the most suitable learning paths and recommendation strategies based on students' individual characteristics and learning behaviors; finally, the system can collect students' learning feedback in real-time and dynamically adjust learning paths and recommendation strategies, ensuring the relevance and effectiveness of the learning content. However, the system still faces some challenges and difficulties in practical application, such as data quality issues, algorithm complexity issues, etc.

6. Conclusion

In summary, the integration of large language models (LLMs) with knowledge graphs (KGs) represents a promising approach to enhancing college students' adaptive learning abilities. By leveraging the strengths of both technologies, the proposed system not only facilitates deep mining and organization of educational resources but also tailors learning experiences to individual students' needs and behaviors. The system's capacity for real-time feedback and dynamic adjustment further ensures the relevance and effectiveness of the learning content, fostering an environment conducive to autonomous and lifelong learning. Despite the challenges posed by data quality and algorithm complexity, the potential benefits of this innovative system in revolutionizing education are substantial. Future research should focus on addressing these challenges through refined algorithms, improved data processing techniques, and user-centered design approaches, ultimately paving the way for wider adoption and impact in educational settings.

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