Design and Teaching Practice of an Intelligent Learning Path Planning System Based on Large Language Models and Multi-Agent Collaboration

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Abstract: To improve personalized teaching quality and autonomous learning outcomes, and to address the common problems in traditional online education, including uniform learning paths, fragmented knowledge systems, and rapid forgetting after learning, this paper takes the design and implementation of an intelligent learning path planning system as a case of teaching reform. The system integrates large language models, knowledge graphs, and multi-agent technologies, and builds core functional modules for intelligent path generation, multi-channel retrieval enhancement, adaptive replanning, and review scheduling. The system supports a shift in teaching practice from a course-centered model to a learner-centered model. The teaching practice results show that the proposed system, which is based on advanced artificial intelligence technologies, effectively reduces students' cognitive load, stimulates their interest in autonomous learning, and improves the teaching effectiveness and adaptive intervention capability of intelligent education systems.

Keywords: Learning Path Planning; Multi-Agent; Large Language Model; Knowledge Graph; Adaptive Learning; Teaching Reform

1. Introduction

With the rapid development of generative artificial intelligence and large language models, education is undergoing a profound shift from digitalization to intelligence-driven development [1,2]. In complex engineering courses such as modern digital electronics and computer science, providing students with accurate personalized learning paths remains a key and difficult issue in teaching reform [3]. Traditional learning management systems usually provide all learners with static and fixed course structures, and they can hardly adjust learning content in real time according to students' initial backgrounds, dynamic learning performance, and knowledge gaps [4]. At the same time, when students face a large number of online learning resources, they often lack systematic guidance on prerequisite relationships. This leads to fragmented knowledge structures. In addition, because scientific review scheduling is often absent, the phenomenon of forgetting soon after learning is common.

To address these teaching problems, this paper proposes a blended teaching reform method that combines cognitive science theory with AI-based intelligent decision-making, with the development of an intelligent learning path planning system as its core. The system moves beyond the traditional single recommendation algorithm and places the large language model at the center of decision-making. Around three key processes, namely multi-agent collaboration, semantic association through knowledge graphs, and formative evaluation feedback, the system constructs a complete teaching loop from knowledge acquisition and path organization to adaptive dynamic adjustment. The aim is to provide a practical engineering and teaching practice solution for large-scale personalized education. In addition, the difficulty of learning path planning lies not only in recommending isolated learning resources, but also in continuously judging whether a learner is ready to enter the next knowledge unit. For engineering courses, many concepts have strict prerequisite relationships. If students skip a hidden prerequisite, they may encounter repeated failure even when the recommended resource itself is accurate. Therefore, an effective intelligent learning system should be able to diagnose prerequisite gaps, explain the reason for each path arrangement, and adjust the learning sequence according to formative assessment results. Large language models provide strong semantic understanding and reasoning ability, while knowledge graphs provide explicit structural constraints among concepts. Multi-agent collaboration further makes it possible to divide complex educational tasks into planning, diagnosis, resource matching, assessment, and review scheduling. This combination provides a feasible technical route for transforming personalized learning from static recommendation to dynamic instructional decision-making.

2. Teaching Objectives and Core Ideas of the Intelligent Learning System

Guided by constructivist learning theory, the teaching design of this system uses artificial intelligence technologies to reshape students' autonomous learning process [5]. The first objective is to reconstruct the knowledge navigation system. The system changes the traditional chapter-based teaching mode and uses a knowledge graph to structure domain knowledge. It derives prerequisite concepts and core dependencies through algorithms, helping students build an overall understanding of the subject. The second objective is to achieve adaptive intervention. Based on large language models and an Agent architecture, the system dynamically generates local or global replanning paths according to learners' real-time test feedback and interaction data, thereby providing accurate differentiated teaching intervention [6]. The third objective is to operationalize cognitive science theory in the learning process. The system transforms psychological models such as the Ebbinghaus forgetting curve into an engineering mechanism, changing short-term intensive learning into scientific distributed review and strengthening the long-term internalization of knowledge. Through these objectives, the teaching concept shifts from the traditional teacher- and course-centered model to a learner- and competence-centered model.

3. Architecture Design and Core Modules of the Intelligent Learning System

The overall technical architecture of the system adopts a six-layer microservice design. The core business logic is jointly completed by a large language model API such as DeepSeek, a graph database such as Neo4j, a vector database such as Milvus, and local application services. The core modules of the system are designed as follows. Specifically, the six layers include the user interaction layer, the learner profile layer, the intelligent decision-making layer, the knowledge organization layer, the resource retrieval layer, and the assessment and feedback layer. The user interaction layer receives learners' goals, questions, test responses, and learning records. The learner profile layer maintains relatively stable information such as prior knowledge, learning preference, target difficulty, and historical performance. The intelligent decision-making layer is responsible for agent scheduling, path generation, and replanning decisions. The knowledge organization layer stores the prerequisite relationships, concept hierarchy, and semantic associations of the course knowledge graph. The resource retrieval layer integrates structured course materials, vectorized learning resources, and external search results. The assessment and feedback layer records formative test results, mastery changes, review performance, and intervention effects. Through this layered architecture, the system separates educational logic from technical implementation, which improves maintainability and makes it easier to migrate the system to different courses.

3.1 Teaching Business Process and Architecture Overview

In practical teaching scenarios, the core business loop of the system follows a spiral logic of intention analysis, path generation, learning feedback, and adaptive replanning. As shown in Figure 1, the figure presents the core business process of the intelligent learning path planning system and the interactions among its modules.

3.2 Agent-Based Decision-Making and Generation Module

Traditional recommendation systems usually use the LLM as a terminal generator, whereas this system adopts a multi-agent architecture and uses the large language model as the core engine for path planning. Through a multi-round cycle of Think, Act, and Observe, the system gradually deepens its understanding of students' learning needs.

After receiving a student's learning goal, the system first loads Redis-based semantic memory, which stores hot data from the student profile, and SQLite-based episodic memory, which stores historical learning behavior [7]. The Agent then autonomously decides whether to call pluggable tools, such as launching kg_query to query the knowledge graph or launching web_search to supplement online resources. In this process, the multi-step reasoning ability of the LLM enables the system to handle vague or complex interdisciplinary learning needs effectively. In the implementation process, the multi-agent collaboration mechanism can be divided into several functional roles. The planning agent is responsible for decomposing the learner's final goal into staged learning objectives. The diagnostic agent compares the learner's current mastery state with the prerequisite structure in the knowledge graph and identifies missing concepts. The resource agent selects appropriate learning materials according to difficulty level, media type, and semantic relevance. The assessment agent generates formative questions and evaluates whether the learner has reached the expected mastery threshold. The reflection agent summarizes the learner's errors and provides explanations for the next intervention decision. These agents do not work independently, but exchange intermediate results through a shared memory mechanism. As a result, the final learning path is not a one-time recommendation result, but a continuously updated plan generated through collaborative reasoning.

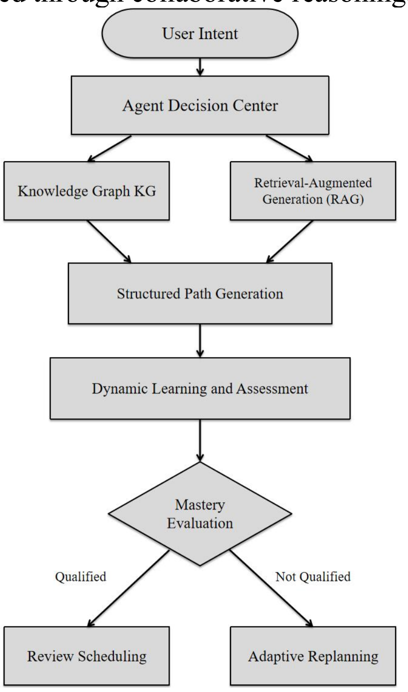

Figure 1. Core Business Process of the Intelligent Learning Path Planning System

3.3 Retrieval-Augmented Generation and Multi-Channel Fusion Module

To reduce the hallucination problem that may occur when a large language model generates professional educational content, the system designs a content retrieval mechanism based on retrieval-augmented generation [8]. When matching learning content for a specific knowledge point, the system adopts a multi-channel parallel recall mechanism, including reasoning-based recall from the knowledge graph, semantic vector recall based on Milvus, and keyword recall based on Elasticsearch. To integrate retrieval results from different dimensions and with different scales, the system adopts the Reciprocal Rank Fusion algorithm. The RRF algorithm does not depend on the normalization of absolute scores and therefore has strong robustness. Its mathematical expression is as follows:

$$RRF\_Score(d)=\sum_{r\in R}\frac{1}{k+r(d)} \quad (1)$$

In this formula, d denotes a candidate learning content item or document, R denotes the set of multiple recall channels, r(d) denotes the ranking of content d in a specific channel, and k denotes a smoothing constant. In this system, the empirical value of k is set to 60. Through RRF fusion and subsequent maximal marginal relevance reranking, the system can provide students with high-quality learning resources that are both highly relevant and diverse in media form, such as videos and text-image integrated materials.

3.4 Adaptive Replanning Module Driven by Cognitive Science

Adaptive intervention is the core of an intelligent education system. The system collects students' interaction data on each knowledge point in real time and calculates their comprehensive mastery level through an algorithm. The calculation model integrates completion progress, test feedback, and time decay:

$$Mastery=\lambda_1 C_r+\lambda_2 P_r+\lambda_3 B_t \quad (2)$$

In this model, C denotes the completion rate of conceptual learning content, Q denotes the pass rate of dynamically generated objective tests, and A denotes the reward or penalty term based on recent learning activity. The weights are set to 0.4, 0.4, and 0.2, respectively. When the mastery model outputs an abnormal signal, such as when a student scores below 60% twice in a row on a knowledge point, the system triggers local replanning [9]. The Agent analyzes the cause of failure and autonomously decides whether to replace the existing high-difficulty learning material or insert supplementary exercises for prerequisite knowledge. In addition, to support the long-term retention of learning outcomes, the system integrates the mathematical model of the Ebbinghaus forgetting curve. The decay pattern of memory retention rate R(t) is calculated as follows:

$$R(t)=e^{-\frac{t}{S}} \tag{3}$$

In this formula, t denotes the time elapsed since the last review, and S denotes memory stability. Each time a student successfully passes a review test, the value of S is updated and increased. The system calculates R(t) in real time. When R(t) falls below a preset threshold, such as 0.9, the system automatically adds the corresponding knowledge point to the review schedule of the day, thereby realizing fully data-driven scientific review.

4. Operation and Effect Analysis in Teaching Practice

The system is applied and verified through teaching practice and simulation in courses such as Circuit Analysis at a university [10]. The teaching practice mainly focuses on whether the system can improve learning efficiency, reduce repeated failure on prerequisite concepts, and enhance long-term retention. In the implementation process, students are divided into an experimental group and a control group according to comparable prior learning performance. The control group uses a conventional online course platform with a fixed chapter sequence, while the experimental group uses the intelligent learning path planning system. Both groups study the same knowledge units and complete the same formative tests and final comparative test. The evaluation indicators include effective learning time, number of repeated errors, completion rate of learning tasks, accuracy of delayed tests, and students' subjective learning experience. Teachers also observe whether the system can reduce repetitive tutoring work and provide more timely diagnosis of common learning difficulties. Although the current practice is still exploratory, the comparison provides useful evidence for judging whether the system can support personalized teaching in real course scenarios.

In a practical case from the study of linear network theorems in the Circuit Analysis course, Student A sets the learning goal as mastering Thevenin's theorem for analyzing complex DC circuits. After analyzing the prerequisite knowledge graph, the system Agent finds that Student A lacks mastery of the core concept of calculating the input resistance of a one-port network with dependent sources. The system automatically plans a structured adaptive learning path that includes Kirchhoff's current law and Kirchhoff's voltage law, the volt-ampere characteristics of dependent sources, equivalent resistance simplification for networks with dependent sources through the test-source method, and the application of Thevenin's theorem. During the learning process, Student A makes errors exceeding 50% in two consecutive formative tests related to calculating the equivalent resistance of circuits with dependent sources using the test-source method. The system detects a sharp drop in the Mastery value and immediately triggers the adaptive adjustment mechanism. The Agent performs local replanning. It removes the original academic reading material on matrix nodal equations, which contains a relatively complex theoretical derivation, and replaces it with a dynamic animation based on circuit simulation software that visualizes current paths and voltage drops. It also adds three basic logical multiple-choice questions on identifying control variables in dependent sources. Background trace data show that after this targeted replanning intervention, the student eliminates the knowledge gap within 20 minutes and successfully passes the adaptive test for this knowledge point.

Compared with the control group using a traditional fixed MOOC platform, the experimental group using this intelligent system shows three clear advantages. First, the learning path becomes more targeted. The system automatically skips redundant content that students have already mastered, increasing effective learning time by about 35%. Second, students' frustration decreases significantly. The local replanning mechanism prevents students from being stuck on a difficult point for a long time and reduces negative learning emotions, which improves the overall course completion rate. Third, long-term memory improves. The final comparative test shows that after review intervention scheduled by the forgetting curve, students' long-term memory accuracy for core concepts increases by 22% compared with the control group.

5. Conclusion

This paper focuses on the teaching design and practice of an intelligent learning path planning system. Taking artificial intelligence technology and cognitive science theory as the main line, it systematically discusses the design and implementation of core functions, including multi-agent decision-making, retrieval-augmented generation, the forgetting curve, and adaptive replanning. Compared with traditional fixed-path online teaching, this system realizes data-driven and scalable personalized instruction in a real sense. This teaching reform practice not only improves students' learning motivation and knowledge retention, but also greatly reduces teachers' workload in repetitive question answering and progress tracking. It provides a valuable engineering example for the deep application of generative artificial intelligence in the reform of higher education teaching models. However, the current system still has some limitations. First, the quality of path planning depends on the completeness and accuracy of the knowledge graph. If prerequisite relationships are incomplete, the generated path may still miss important hidden concepts. Second, the evaluation of learning effectiveness is mainly based on formative tests and process data, while long-term large-scale empirical validation is still needed. Third, although retrieval-augmented generation can reduce hallucination, the quality control of generated explanations and assessment questions still requires teacher review in important teaching scenarios. Future work will further improve the automatic construction of course knowledge graphs, optimize multi-agent collaboration strategies, and conduct larger-scale comparative experiments in different engineering courses.

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