Research and Innovative Application of Multi-Agent Collaborative Architecture in Education

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Abstract. To address issues such as lack of dynamic adaptability and weak teaching standardization in generative AI education applications, this paper proposes an educational multi-agent collaborative system architecture. The system achieves closed-loop management of the entire teaching process through the collaborative operation of four specialized intelligent agents: "teaching, learning, administering, and evaluating". Key technological breakthroughs include knowledge graph using Neo4j-based cognitive graph, RAG-enhanced retrieval to boost semantic-level knowledge matchmaking accuracy and intelligent workflow engine to automate concatenation of teaching quests. It promotes the transformation of the education paradigm from static knowledge delivery to dynamic cognitive construction, and evolves from educator-centered to student-centered. In the future, this system will optimize the scheduling algorithm and retrieval performance of the agents and deepen the fusion path with traditional education models.

Keywords: Multi-agent collaboration; knowledge graph; retrieval-augmented generation; prompt engineering; workflow engine.

1. Introduction

Traditional large language models lack a refined functional positioning for teaching, making it difficult to balance costs and personalized demands. On the one hand, due to the lack of long running memory of individual learning trajectories, large language model answers cannot accurately recognize learners' intent requirements and dynamically adapt to individual variations. On the other hand, the mechanisms and algorithms within large models are difficult to explain, which easily induces problems such as knowledge hallucination and knowledge traceability blur [1].

To solve the limitations of the single large language model in the education scene, this paper proposes an education system based on multi-agent collaboration as shown in Fig. 1. In this system, multi-agents simulate the teacher-student interaction in the real classroom through educational role playing [2].Its innovation points focus on the diversified role anchoring of the intelligent agent and the collective decision-making procedure, so that the generative AI technology deeply fits the core demands of the education scene [3].

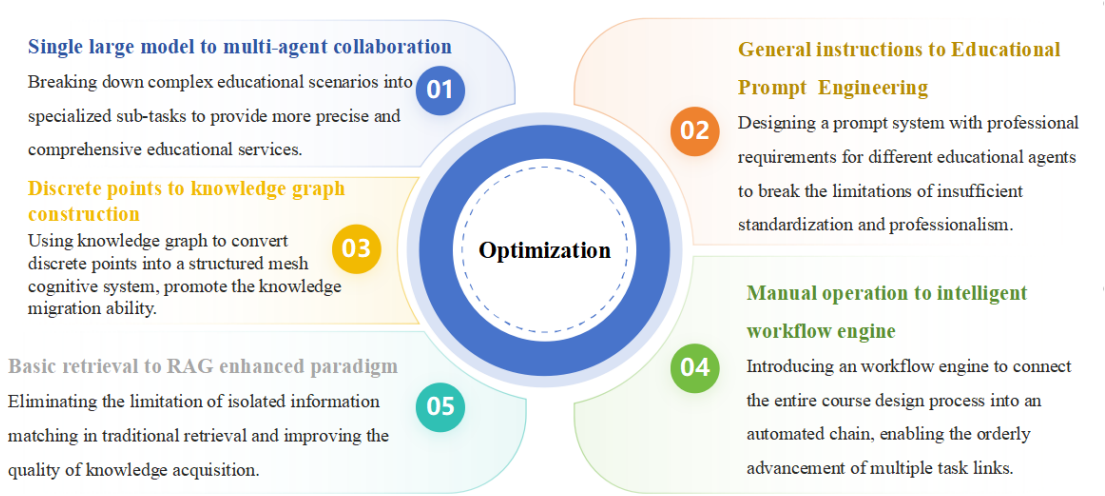


Fig 1. Optimization configuration diagram of multi-agent education system.

2. The main innovation points of the system

2.1. From single large model to multi-agent collaboration

Traditional large language models have various deficiencies in the multi-role collaboration scenarios of education [4].The insufficient flexibility of a single large model makes its thinking prone to limitations. Its learning process lacks a real-time monitoring mechanism, leading to deviation from the learning topic [5].The reason is that the generalization design of a single large model makes it not easy to continuously maintain high-quality answers.

The educational multi-agent cooperative system designed in this paper is anchored in the collaborative orientation to achieve functionalities such as task division among agents [6]. Its core destination is to turn complex educational scenes into specialized sub-task groups, allowing different agents to focus on their vertical realms. In this operational mode, the educational multi-agent system possesses comprehensive competencies including communications, perception, learning, and execution. Relying on this division of collaboration schema, this system will effectively promote educational intelligent agents to enter the evolutionary phase of autonomous intelligence, endowing them with competencies such as autonomous planning and decision-making of educational quests, etc, driving the innovation of teaching operational mode through a higher-impact collaboration mechanism.

2.2. From general instructions to prompt word engineering

General model architecture often suffers from structural defects, with their core logic relying on fixed templates summarized from human experience, leading to insufficient generalization competency [7]. This limitation manifests particularly when user input contains vague hints, causing model outputs to frequently deviate from expectation. Simultaneously, outputs from traditional large language models struggle to maintain consistent paradigms, commonly exhibiting issues such as disorganized output formats or redundancy.

In the intelligent classroom environment, prompt engineering technology possesses dual core advantages, focusing on content professionalism and dynamic optimization capability respectively. In terms of content professionalism, the outputs of various intelligent agents naturally incorporate the unique logic of disciplinary teaching, avoiding the cross-domain logical confusion common in general-purpose models. Regarding dynamic optimization capability, when new requirements arise in educational scenarios, rapid adaptation can be achieved by adjusting the prompt modules corresponding to specific functions. This educational function-based prompt engineering will make multi-agent systems truly become specialized tools that align with teaching principles, rather than merely being general-purpose content generators that complete format output.

2.3. From discrete knowledge points to cognitive graph construction

The knowledge organization schema of traditional courses exhibits a marked trait of discretion, with theoretical points scattered across textbook chapters, leading students into the predicament of knowledge point accumulation and fragmentation [8]. This static architecture has limited competency in integrating cross-realm knowledge, relying on textual descriptions to render correlations between knowledge points.

This study leverages knowledge graph technology to construct a course mind-guiding chain system, aiming to harden learners' ability to recognize the logical connections of prerequisites between concepts. Following the practical approach of syllabus deconstruction, knowledge layer extraction, graph construction, and visualization, the system interconnects discrete knowledge nodes into an organic networking fabric, affording an innovative implementation pathway for teaching supply-side reform [9].

2.4. From basic retrieval to RAG enhanced paradigm

Retrieval competency connects the database with model generation tasks, directly impacting the system's level of intelligence. Traditional basic retrieval relies on keyword-matching queries, struggling to understand semantics-tier correlations. For example, when users query "neural network and deep learning", basic retrieval can only recognize content containing exact literal matches like "neural network" or "deep learning" rather synonymous yet differently expressed terms such as "DL".

The introduction of enhanced retrieval mechanisms can elevate the system's knowledge acquisition competency and content generation quality. In the realm of knowledge management, the system can build a vector-query-based management system, significantly improving information storage density and update rates [10-11].

2.5. From manual operation to intelligent workflow engine

The traditional operation patterns suffer from fragmented processes in multi-step collaborative scenarios. In education system, executing a series of tasks, from course outline generation to final visualization, requires manual triggering, which not only increases operational complexity but also easily introduces operational errors.

The workflow engine possesses robust capabilities, allowing agents to adjust execution paths based on user experience feedback. By intelligently parsing user directives, the engine automatically matches the optimal workflow template, making the process more aligned with actual demand. Each agent strictly follows the preset logic scheduled by the engine for collaborative operation, ensuring seamless flow of task state among agents.

3. An overall overview of multi-agent collaborative architecture

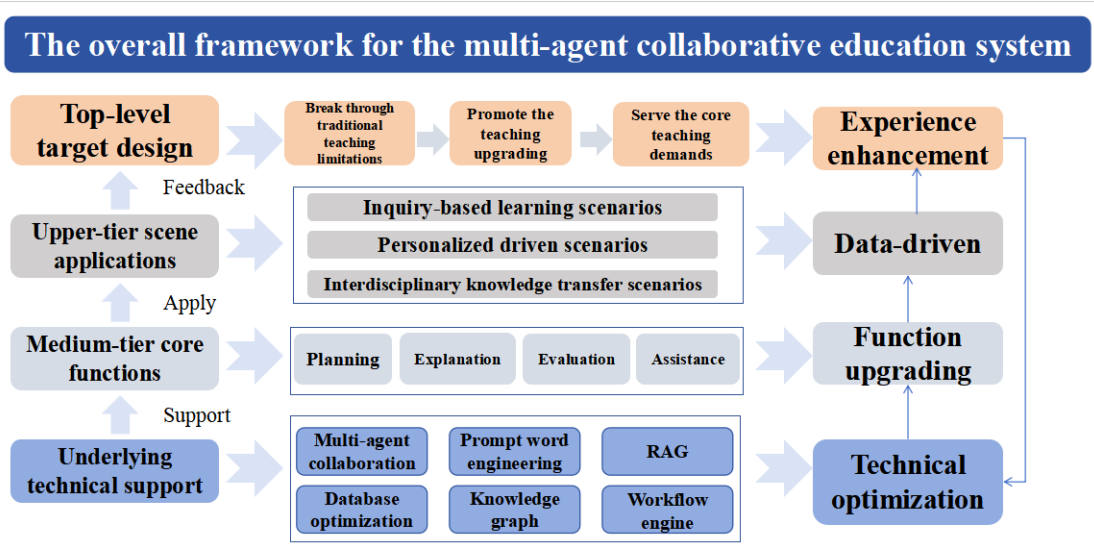


Fig 2. Overall framework diagram of the multi-agent collaborative education system.

3.1. Top-level target design

This education system aims to achieve the upgrade from basic tool innovation to systematic construction, which can be seen in Fig. 2. Its target is not only the realization of technical features but also the improvement of educational paradigm [12].

Breaking through the limitations of traditional instructional tools is the logical foundation. The system enables cross-disciplinary correlation of lesson content by integrating multi-dimensional education resources. This mechanism helps teachers focus on key sections like teaching innovation. For students, the measure of deeply embedding intelligent teaching technology into classrooms promotes learning tools in the classroom environment from passive response to active empowerment.

After achieving breakthroughs in tools and paradigms, spotlighting the closed loop of core teaching requirements is the ultimate guarantee for the system's implementation. The system provides teachers and students with closed-loop evaluation feedback, continuously optimizing teaching process design, resource allocation efficiency, and the precision of interaction between teachers and students.

3.2. upper-tier scene applications

The upper-tier scene application, as a practical carrier for the implementation of technological landing, mainly focuses on three types of scenes: Inquiry-based learning, personalized learning and interdisciplinary knowledge migration.

In traditional teaching classrooms, the diversity of learners' cognitive levels makes static problem chains difficult to cover the dynamic exploration requirements of complex knowledge. To address this problem, the system constructs a problem chain based on real-time conversation history, continuously guiding learners to explore and solve problems.

Personalized learning scenes rely on the synergy of intent recognition and retrieval optimization. The system conducts in-depth resolution of user requirements through regular pattern recognition technology and then performs the learning optimizer to locate relevant samples and resources for learners.

The core of the system's implementation of interdisciplinary knowledge migration scenes lies in taking advantage of the knowledge graph. This action conducts structural decomposition of discrete subject course outlines, building bridges for interdisciplinary concepts.

3.3. medium-tier core functions

The functionality of this multi-agent education system is closely spotlighted on the core requirements of "teaching, learning, administration and rating" in Fig. 3, fully promoting precise teaching, personalized learning, digital administration and diversified rating [13].

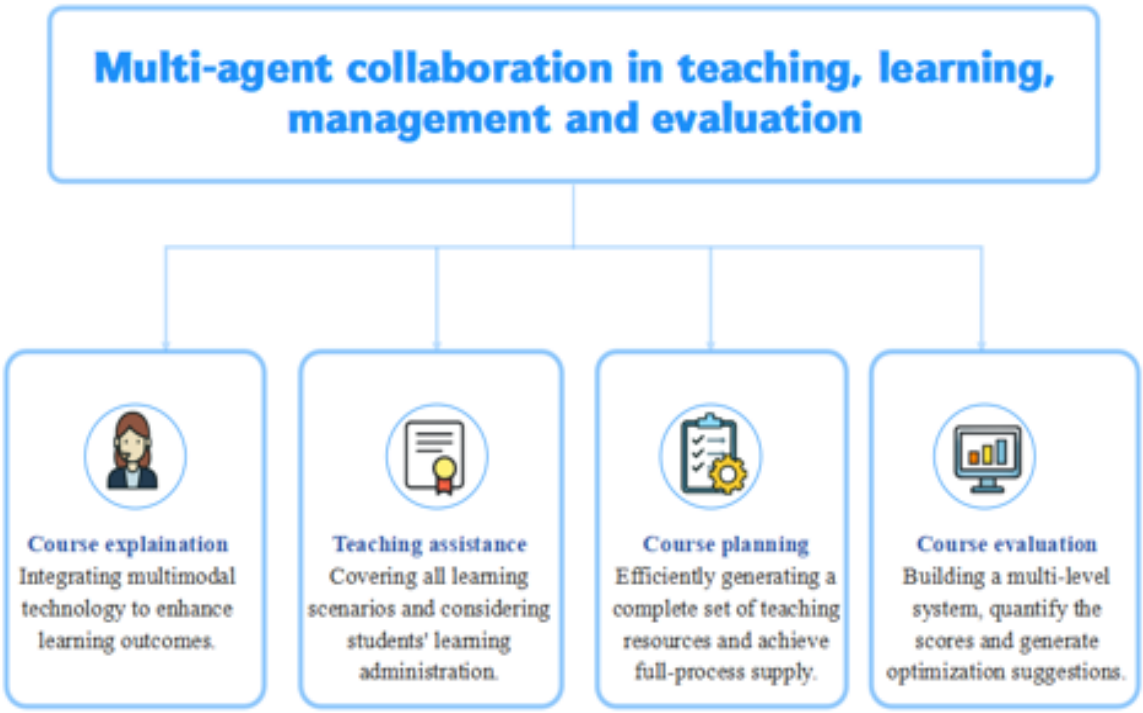


Fig 3. Framework diagram of a multi-agent collaborative system.

The course planning agent acts as the core generator of course content, producing a range of resources like syllabus, knowledge graphs, and tests, covering the entire teaching cycle [14]. A complete instructional closed loop is established from course design to teaching evaluation, which forms a cohesive teaching ecosystem.

The course explanation agent combines text-to-speech and virtual digital human technology to establish a multi-modal teaching system. Abstract knowledge points are converted into tangible dynamic teaching representation, facilitating a multidimensional enhancement of learners' comprehension.

The function centered around "student feedback-teacher correction-model evaluation" is established by the course evaluation agent. This system evaluates course quality along several dimensions, including content accuracy and logical coherence, facilitating ongoing enhancement of course content.

The teaching assistance agent covers the full class scenario. It supports learners in developing a systematic learning sequence to strengthen their foundational knowledge. In the domain of educational administration management, this intelligent agent supports educators by enabling functions including automatic course scheduling and resource scheduling, helping alleviate the administrative burden.

3.4. Underlying technical support

3.4.1. Multi-agent collaboration mechanism

A multi-agent collaborative framework is a distributed cognitive architecture designed for complex education scenes. This deep division of labor mechanism deconstructs the entire education process into vertical dimensions, conducting deep feature tuning to achieve discipline accuracy.

Current mainstream multi-agent frameworks include AutoGen, Coze and LangChain. The SWARM framework utilized by this system emphasizes flexible interaction and efficient collaboration among agents, reducing complexity via lightweight design. Compared to mainstream frameworks in Table 1, SWARM places greater emphasis on the self-organization competency of agent collectives, enabling individual agents to maintain their own professional cognitive accuracy.

Table 1. Comparison table of multi-agent frameworks.

Framework	Architecture	Coordination mechanism	Dynamic adaptability	Adaptability to educational scenarios	Learning curve
AutoGen	Multi-Agent Dialogue	Static task allocation	medium	medium	high
LangGraph	Directed cyclic graph	Loop control	high	medium	very high
Coze	Low-code platform	Visual workflow	low	low	Very low
SWARM	Lightweight Agent	Dynamic task allocation	high	high	low

3.4.2. Prompt word engineering

Prompt engineering techniques encompass the design, tweaking, and tuning of text prompts for large deep learning models to guide them in generating output results that meet expectations. Its core targeting aims to address potential blur in the model's output. Common types in this technology include directive-based structure, few-shot swatch prompting structure, chain-of-thought structure, persona-setting structure and constraint-based structure that shown in Fig. 4. The core variation among different prompt structures lie in the mechanism of guiding the model's output and the path of reliance on the model's competency. The constraint-based structure used in this paper clearly defines the format conditions to ensure that the core content complies with the requirements of the preset framework.

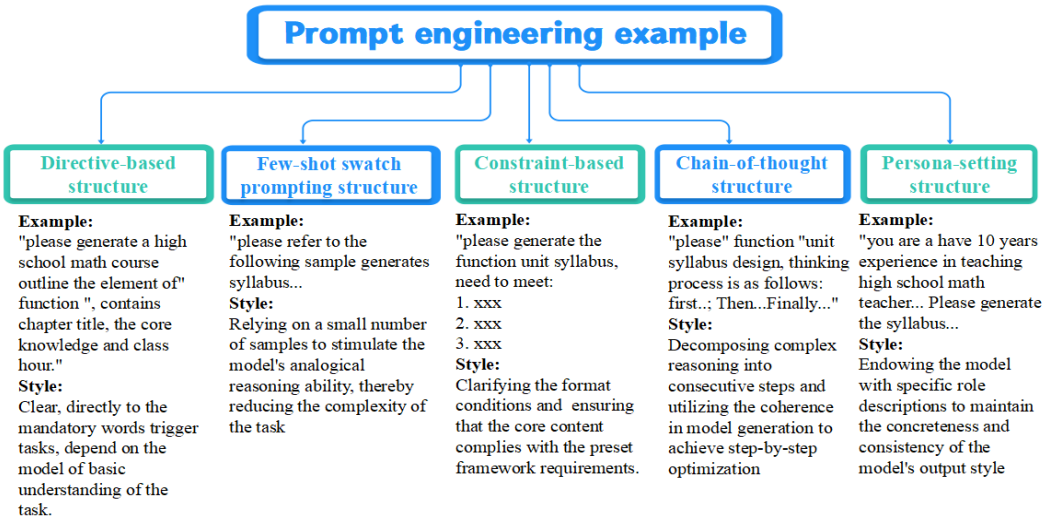


Fig 4. Prompt word engineering example architecture diagram.

3.4.3. Retrieval augmented generate

Enhanced retrieval serves as a key paradigm for augmenting the generative competency of large models, combining parameterized memory formed by the implicit knowledge of pre-trained models with non-parameterized memory constructed from explicit knowledge in external knowledge bases, thereby establishing the basic schema for enhanced retrieval. This structure is demonstrated in Fig. 5. Its goal is to optimize large model output through three stages, which involve knowledge base construction, hybrid retrieval and generative enhancement [15].

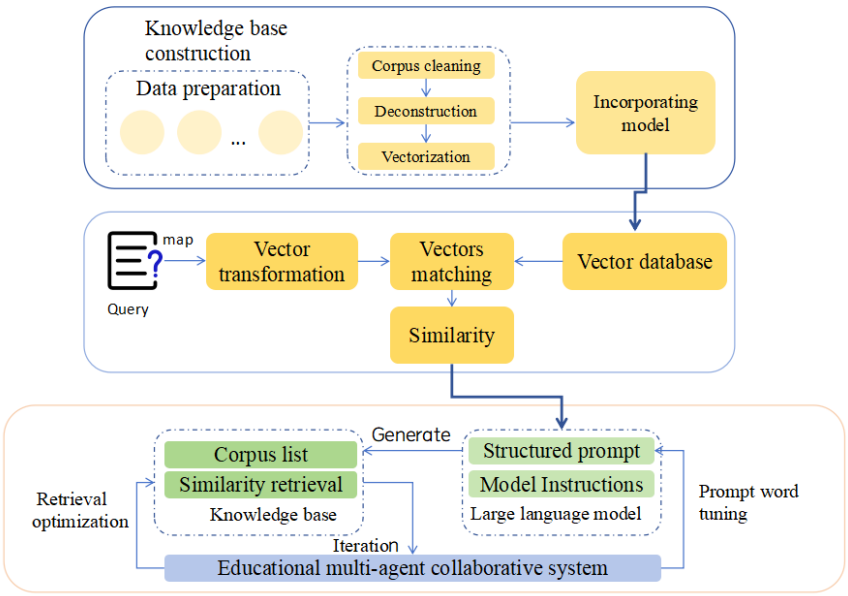


Fig 5. Enhanced retrieval architecture diagram.

At the technical framework level, the vector database Milvus is a distributed system specifically designed for managing large-scale and high-dimensional vector data. Unlike traditional keyword-based matching retrieval methods, this technology maps query external knowledge into a high-dimensional semantic space, conducting query operations by computing vector inner products to measure semantic similarity (Formula 3). Cosine similarity (Formula 1) focuses on the dimension of orientation consistency by eliminating the influence of vector magnitudes. Finally, Euclidean distance (Formula 2) is introduced to quantify the actual distance variation in vector space. Its technical advantage lies in the ability to rapidly compute vector distances in high-dimensional vector scenarios, retrieving results that are semantically similar to the target vector.

$$\cos(\vec{a}, \vec{b}) = \frac{\sum_{i=1}^{d} a_i \cdot b_i}{\sqrt{\sum_{i=1}^{d} a_i^2} \cdot \sqrt{\sum_{i=1}^{d} b_i^2}} \quad (1)$$

$$\text{Euclidean Distance}(a, b) = \sqrt{\sum_{i=1}^{d} (a_i - b_i)^2} \quad (2)$$

$$a \cdot b = \sum_{i=1}^{d} a_i \cdot b_i \quad (3)$$

3.4.4. Knowledge base optimization technology

This technology constructs a dynamically updated educational knowledge Base, which is shown in Fig. 6, by integrating subject materials, high-quality lesson plans, and past exam questions resources. At the semantic representation tier, the system adopts a dense vector embed model to achieve deep-level semantic trait capture. This feature module parses relevant content, converting literal content into vector representations based on the SentenceTransformer model, supporting natural language processing tasks such as semantic similarity computation, text clustering and information Research.

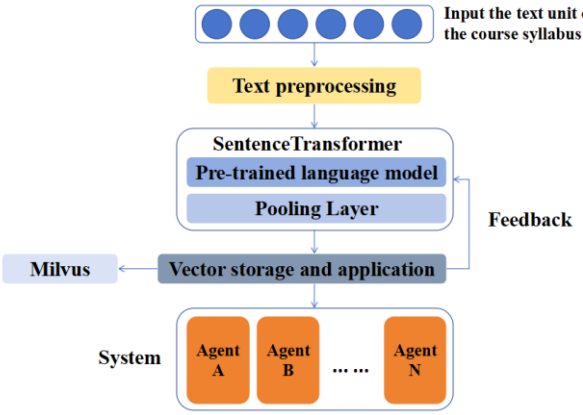


Fig 6. Architecture diagram of dense vector embedding model.

Reinforcement learning technology is applied to optimize the semantic retrieval procedure, utilizing the RLSearchOptimizer, which is illustrated in Fig. 7, to implement a self-adapting parameter mechanism based on users' feedback. This mechanism models treat user behaviors such as point-and-click on search results and dwell time as incentive signals. It dynamically adjust similarity threshold values and retrieval scope arguments to achieve an optimal balance between retrieval accuracy and response velocity.

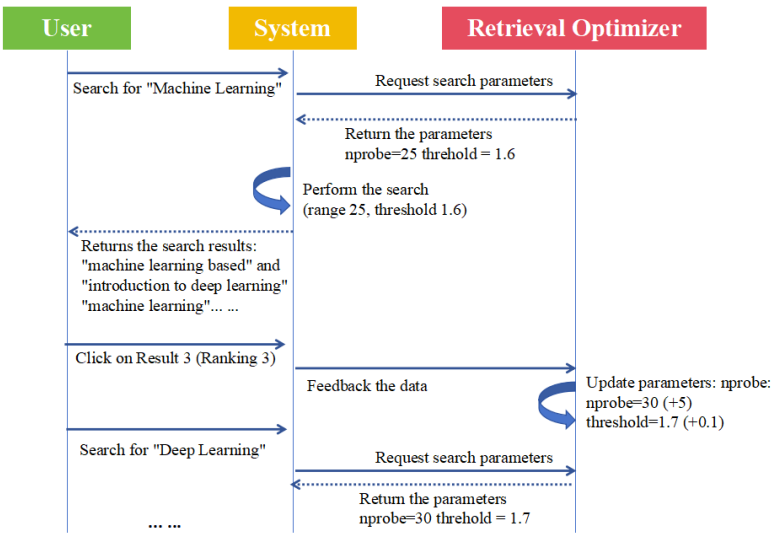


Fig 7. Retrieve the architecture diagram of the optimizer.

3.4.5. Knowledge graph

Knowledge graph technology shown in Fig. 8 is a crucial memeansor course content visualization, converting literal content into structured knowledge networks. This system employs the Neo4j graph database to construct symbolic knowledge graphs, enabling efficient operations through Cypher queries and rule engines [16]. The graph forms a structured topological network with entities as nodes and relationships as edges, intuitively rendering semantic correlations and excelling in processing large-scale nodes as well as complex data correlations.

The construction process firstly conducts hierarchical parsing of the course outline, identifying core elements such as courses, chapters, modules, etc. Subsequently, the system maps each element into different types of nodes and assigns specific attributes to them. The agent analyses the correlations between different nodes, including the composition relationship between courses and chapters, the hierarchical containment relationship among modules, etc. These relationships are transformed into directed edges in the knowledge graph.

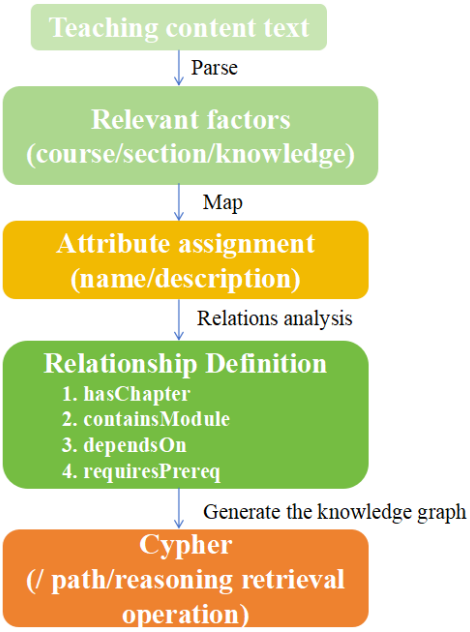


Fig 8. Technical architecture diagram of the graph.

3.4.6. Workflow engine

As a technical framework supporting the automation of business processes, the workflow engine enables automated scheduling based on predefined business logic. This technology clarifies task execution principles and continuously tracks the life-cycle state of the entire process, thereby constructing a structured path for managing automated tasks [17].

The workflow engine consists of several collaboratively operating components. The process definition module uses formal language to precisely describe the attributes, rule lines and business logic of each item in the process. The scheduling module drives the orderly execution of tasks. The status management module monitors and records the complete state transition trajectory of task instances in real-time. The exception processing module focuses on providing predefined recovery, retry, alerting or manual intervention mechanisms when process execution deviates from expectations, ensuring the robustness of the process.

4. Course planning agent

Course planning agent serves as the core component for achieving systematic construction and intelligent management of teaching resources. It forms a closed-loop system covering the entire process of teaching task, which centered around the generation and refinement of teaching syllabus. This agent aims to provide users with a full life-cycle solution for teaching resources.

4.1. Teaching syllabus

In the syllabus generation and management process, the system implements the transition from content output to subsequent management and retrieval features. After receiving the user input of course requirements, the course planning agent invokes the large language model following a predefined structured prompt engineering procedure to generate a complete syllabus containing elements such as course name, chapters, etc. It strictly adheres to the output requirement, ensuring the conciseness of the content and clarity of its structure.

Constraint-based structure demonstrates significant adaptability in teaching-related content. By presetting a unified format framework, its standardized response content normalization can effectively resolve content integration bias in multi-agent collaboration. This technique reduces errors or redundant information caused by format violations, thereby conserving computational resources while improving content generation accuracy. Compared to other prompt frameworks in Table 2, constraint-based structure ensure highly consistent output, which is difficult to guarantee with other structures.

Table 2. Comparison of prompt word frameworks.

Comparison indicators	Directive-based	Few-shot swatch prompting	Chain-of-thought	Persona-setting	Constraint-based
Integrity	Low	Medium	Low	Medium	High
Accuracy	Low	Medium	Low	Low	High
Preciseness	Low	Medium	Low	Medium	High
Normalization	Medium	Medium	High	Medium	High
Complexity	High	Medium	High	Medium	Low

When the user requirement is to design a course outline for neural networks and deep learning, the agent can generate a detailed outline in Fig. 9, covering the course name, multiple chapters and corresponding cases for each chapter.

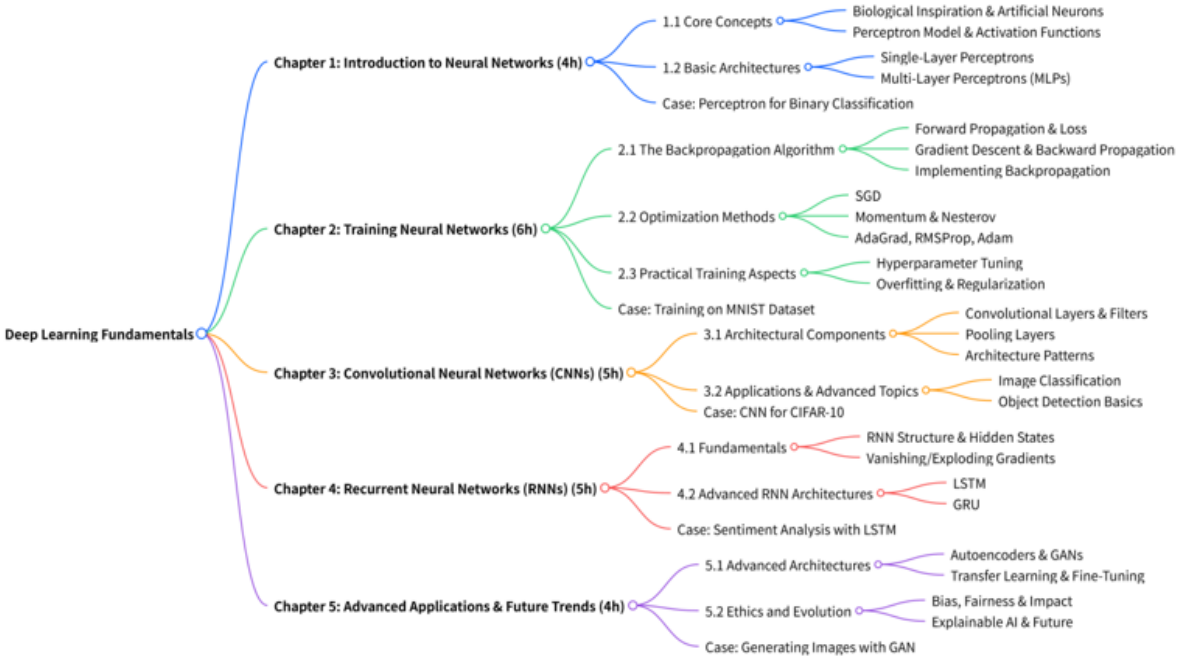


Fig 9. Course outlines mind map.

To support the full-life cycle management of course syllabus, the course planning agent has built an integrated process covering processing, storage, retrieval and maintenance. In the processing stage, the system relies on regular expressions to match course name. Meanwhile, the system assigns a unique identification number to each chapter and generates content overview entry to optimize the query efficiency.

In the storage step, the agent stores information such as course name and chapter data into the specific collection of the vector database. This collection creates predefined data models like primary key during the initialization stage, and adopts an index type suitable for high-dimensional retrieval.The intelligent retrieval function relies on approximate nearest neighbor search mechanism, which applies the retrieval optimization mechanism to enhances the dependence of search results.

In terms of data maintenance, the system supports precise deletion and query operation. The agent executes batch deletion operation and refreshes synchronously with the database status based on its unique identification of course name.

4.2. Teaching content

In the course planning framework, generating refined teaching content and knowledge graph based on course syllabus is a key to realize the systematic transformation of teaching resources. This procedure converts the structured syllabus into course content and knowledge graph conforming to teaching specifications.

This agent expands syllabus chapters into content containing multi-level teaching elements, which is demonstrated in Fig. 10. This part applies constraint-based structure to extend four core modules: detailed concept explanation, multi-type teaching samples, industry case studies and summaries of learning points, which forms a multi-dimensional teaching system covering knowledge delivery, consolidation training, and application expansion.

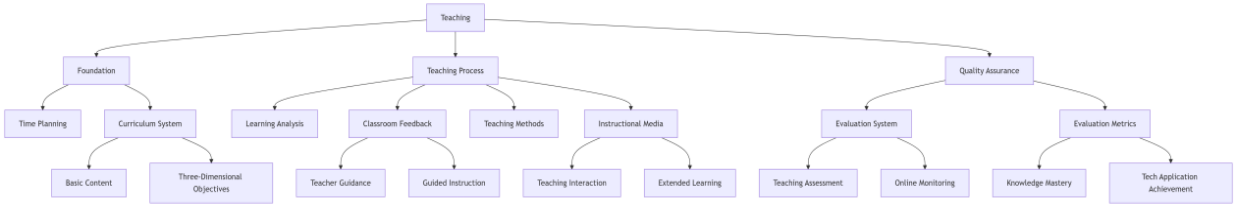


Fig 10. The standard tree diagram of the teaching plan framework.

This agent instantiates structured knowledge in the graph database and generates interactive visualization pages by executing Cypher scripts. This process strictly defines node attributes and relationship types. The Fig. 11 below show the classic diagram of knowledge graph.

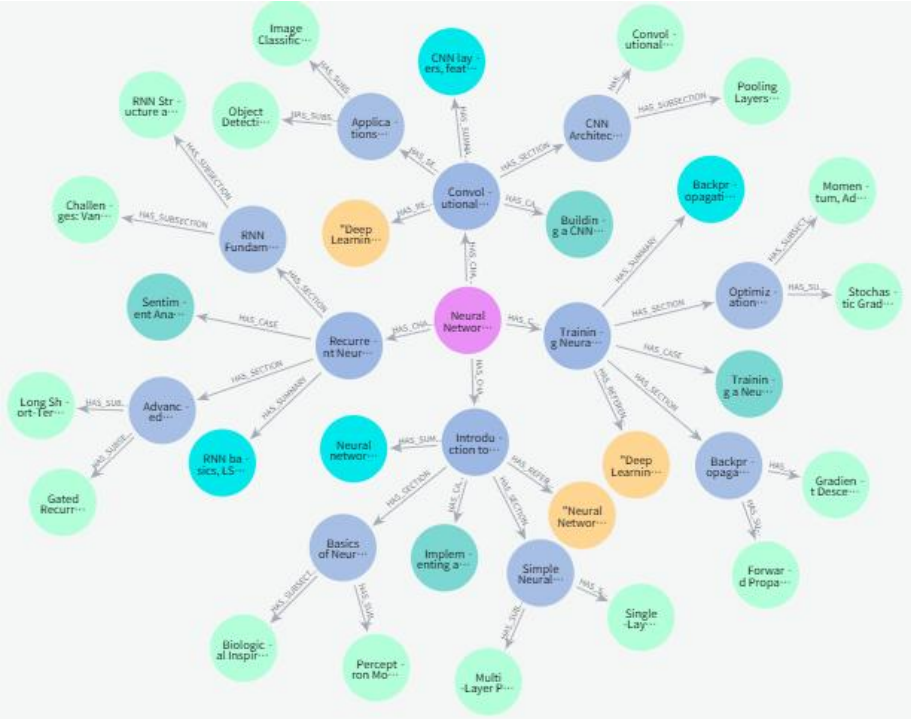


Fig 11. Course knowledge graph architecture diagram.

Based on the Bolt protocol, a real-time channel with the Neo4j database is established. Within the Neo4j environment, different types of nodes such as courses, chapters and knowledge points are distinguished by variation in colors and sizes, while the vertical subordinate relationships and horizontal correlations between concepts are topologically presented through weighted directed edges [18].

4.3. Teaching material

Courseware generation function is based on the overall structure of course syllabus, including elements such as teaching contents, chapters, case analysis, point summary, etc, which not only warrants that teaching information is concise, but also adapts to the requirement of classroom teaching.

In terms of visualizer integration, the system support converting structured content into editable PowerPoint files. By invoking the API of professional tools like Beautiful.ai, the system directly converts the generated JSON document into PPTX courseware like Fig. 12. Users can select to only save the content structure in JSON format, or directly obtain editable PPTX files to meet the instant application needs. This reduces the repetitive time cost for educators in manual collation, and also provides convenience for learners' needs of reusing and modifying courseware.

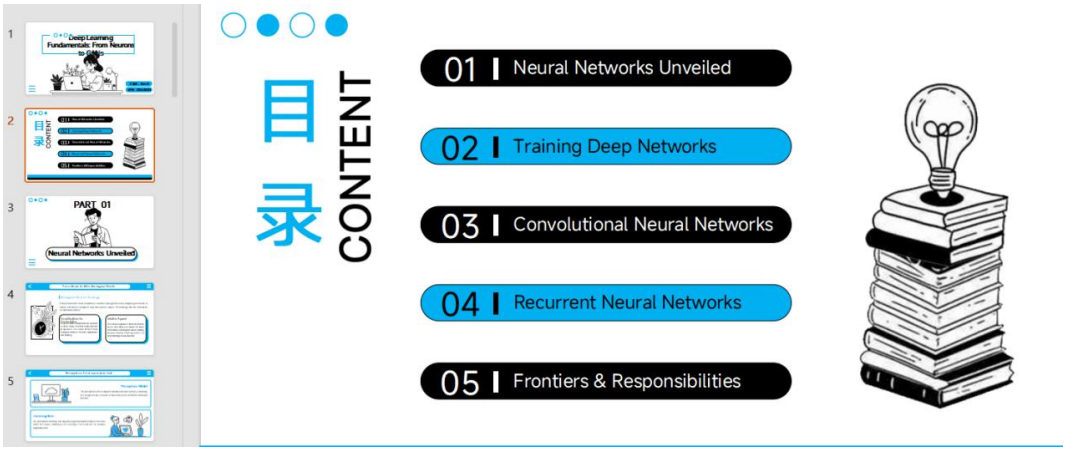


Fig 12. Schematic diagram of visual courseware.

5. Course explanation agent

Course explanation agent mainly focuses on implementing the multi-modal interaction in educational multi-agent systems. This section takes voice and virtual interaction as core pillars. The former relies on text-to-speech technology to create flexible interaction in the auditory dimension, while the latter leverages virtual digital human technology to build a scene-based participation mechanism. The two work together to promote the transformation of knowledge delivery patterns.

5.1. Multi-scenario voice interaction

In the intelligent classroom scene, voice interaction is an important part of providing personalized immersive learning experience. The agent supports customization of commentary style according to users' requirements. Learners can independently take advantage of voice interaction to deepen the understanding of knowledge points. This mechanism not only keeps the coherence of the teaching procedure, but also meets diversified learning habits.

The agent integrates text-to-speech technology that is shown in Fig. 13 to convert teaching content into natural voice fragments in real time. In this system, the in-depth fusion of TTS technology and large language model module is applied to break through the drawbacks of plain-text interaction patterns. It integrates tools such as speech engine initialization, multi-threading speech processing and text semantic segmentation. To avoid the response lag of the agent caused by the blocking of speech synthesis, the asynchronous processing mechanism will split the content text into semantic apartments and send them to the speech queue. Meanwhile, background threads continuously monitor

the queue and invoke the engine to conduct live synthesis, realizing the synchronized operation of generation and broadcasting.

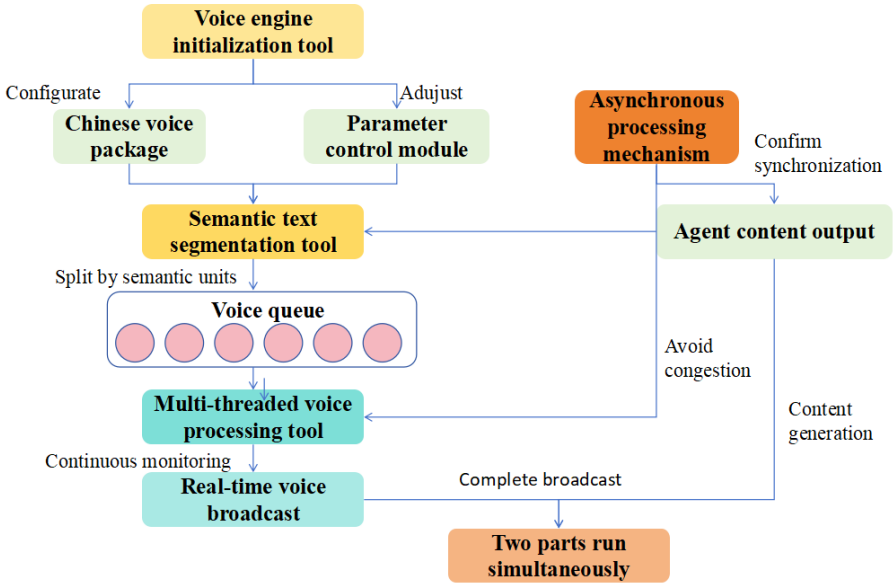


Fig 13. Voice interaction technology architecture diagram.

5.2. Concrete teaching interaction

Relying the virtual digital human technology, the virtual teacher's image, expressions and body movements impersonate the real teaching environment. In this scene, the system gives explanations through natural conversation interaction, promoting the transformation of the teaching procedure from one-way delivery to bidirectional interaction.

This technology refers to a virtual entity with anthropomorphic appearances and interaction capabilities. It uses 3D modeling or real-time rendering to simulate the facial traits of real humans and combines speech synthesis with motion capture to realize oral interaction [19]. As a phantom assistant to teachers, digital humans can facilitate students in building intuitive cognition when involved in complex practical operation Process or knowledge correlation tasks [20].

6. Course evaluation agent

The course evaluation agent is used to combine student feedback with teaching practice to construct a dynamic optimization mechanism for course content. This module integrates feedback from learners, educators, and large language model, continuously driving the update and iteration of subject knowledge content [21].

6.1. Suggestions on teaching content

In the dimension of content evaluation, learner's feedback is the core element, covering aspects such as content understanding, practical experience, and resources adaptation. The system deeply analyzes course evaluation data to identify conceptual gaps, which arise in theory-intensive teaching chapters [22]. Based on this interactive feedback mechanism, the system generates targeted optimization solutions, supplementing the chapter with detailed teaching materials.

To address the pain point of missing instant feedback in traditional classrooms, this agent constructs a multi-dimensional evaluation channel, collecting students' evaluation information on course sharpness, completeness and organization. The built-in machine learning algorithm can accurately profile the learning state. When it detects that the scoring feedback for a specific knowledge point is too low, the system triggers the intelligent tutoring process, offering data support and achieving a student-centered learning loop. By adding comprehensive application cases in course content, the system helps learners consolidate knowledge across different modules.

6.2. Optimization of teaching content

The teacher feedback mechanism centers on systematic professional evaluation, prioritizing alignment with cutting-edge disciplinary developments. In interdisciplinary contexts, the emphasis is placed on terminological consistency across chapters, clarifying correspondences between terms from different academic systems. The enhanced retrieval mechanism is employed to establish a dynamic updating process, ensuring teaching examples remain synchronized with technological progress [23].

Upon receiving instructor feedback, key optimization items, such as conceptual inaccuracies, logical discontinuities or outdated examples, are identified. While preserving the overall structural stability, the system adjusts chapter weighting, supplements knowledge points and refines expressions. To address issues like insufficient foundational knowledge or conceptual inconsistencies, global optimization is performed using the knowledge graph, ensuring coherence throughout the content system. By comparing evaluation metrics from before and after iteration, the agent quantifies improvements in content quality, thereby continuously advancing the teaching content.

6.3. Large model-assisted evaluation

Large language model undertakes the task of integrating multi-dimensional data and professional assessment conclusions. This part deeply analyses course content, student feedback and teacher suggestions, ensuring the objectivity and professionalism of the evaluation procedure. The system leverages the natural language understanding capability to fuse students' quantitative scoring on content difficulty and teachers' professional judgments on knowledge accuracy, forming a traceable evaluation analysis framework.

In the stage of sparse evaluation data, these referential recommendations serve as supplementary decision-making basis. As teaching practice data accumulates, the system adopts an attenuation mechanism to gradually reduce the weight of model recommendations, guaranteeing that course optimization decisions are always centered on empirical teaching feedback as the core benchmark, thereby avoiding the predicament of course optimization stagnation.

7. Teaching assistant agent

This module provides personalized learning preparation support for both teachers and students. Leveraging a multi-Intelligent agent collaborative workflows engine, the system integrates the rigorous course review and teaching tracing mechanism, significantly enhancing content quality and logical coherence.

7.1. Course plan formulation

In the pre-class phase, the teaching assistant agent supports learners in establishing a course plan. By interpreting user instructions, the mechanism identifies the course syllabus with the highest semantic similarity within the vector space. To accommodate individual cognitive differences among students, a personalized preview pathway is offered, which includes fundamental concepts, recommended reading sequences and configurations for learning tools. To support teachers in lesson preparation, the assistant automatically generates a structured resource topology comprising the courseware framework, sample materials and in-class exercises. This assists instructors in organizing the preparation workflow and alleviates the burden associated with teaching readiness.

7.2. Course review

The course review part employs the Prefect workflow engine that have a detailed introduction in Fig. 14 to integrate a collaborative multi-Intelligent agent mechanism, which build a well-structured workflow to improve the standardization and logical coherence of content.

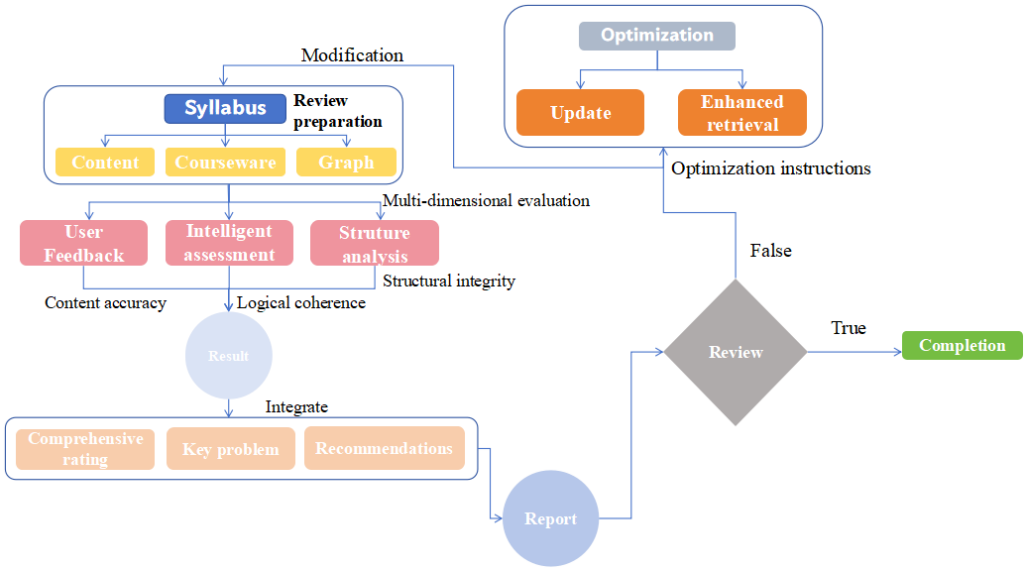


Fig. 14. Course review workflow architecture diagram.

Within this architecture, the @flow decorator is used to define the topological relationships among agents, while the @task decorator marks specific functional units, such as generating outlines or evaluating content. The task runner executes workflow instructions by invoking agents either sequentially or in parallel, following a systematic pathway that includes audit preparation, multi-dimensional evaluation, structured feedback, and closed-loop optimization.

The workflow engine dynamically utilizes the system's built-in three-dimensional evaluation entities—student groups, teacher teams, and artificial experts—to perform quantitative scoring. Student feedback focuses on content difficulty and practical utility, while teacher assessments emphasize accuracy and structural organization. AI-based subject experts provide automated evaluations from a specialized perspective. The review criteria encompass both explicit indicators and implicit aspects, mitigating issues related to fragmented standards in conventional methods.

7.3. Course Monitoring

In this systems, the instructional tracking module utilizes a multi-source data fusion mechanism to monitor learning progress through synthesizing data streams, including learners' dialogue history, course evaluations and assessment results.

Search preferences exhibited in learners' conversation history serve as external indicators of their underlying needs during instruction. Repeated searches for a specific topic may suggest difficulties in comprehension. These behavioral patterns collectively outline students' learning trajectories, cognitive obstacles and preference. From a technical implementation perspective, this module utilizes the retrieval optimizer referred to as RLSearchOptimizer. This technology constitutes an adaptive mechanism based on reinforcement learning for tuning search parameters. Its operation involves adjusting key parameters to improve the alignment between search outcomes and user intent. Additionally, the system supports threshold adjustments based on query length, establishing distinct thresholds for short and long queries.

8. Summary

This educational system has been successfully adapted to multiple functional modules. By constructing the four core educational tasks, including teaching, learning, management, and evaluation, the system employs a multi-agent coordination mechanism to achieve specialized division of labor among agents. The core value of this system lies in its multi-dimensional enhancement of educational models. The multi-Intelligent agent cooperative system fundamentally restructures the single-point education service mode. This transformation not only facilitates a shift in teaching

methodology from static knowledge transfer to dynamic cognitive construction, but also build an instructional system capable of self-regulation and continuous learning.

In addressing the challenges of applying generative models in education, the system employs a prompt engineering framework tailored to educational contexts along with cross-modal interaction technologies. These improvements enhance the agent's subject expertise and immersive teaching quality. Meanwhile, technology is deeply embedded into key teaching activities such as personalized tutoring and scenario-based practice, fostering a symbiotic ecosystem that aligns with educational principles. Furthermore, the system utilizes the knowledge graph and an adaptive workflow engine to enable dynamic evolution of learning paths, which allows the system to monitor learners' needs in real time. As a result, it offers a robust technological foundation and practical support for building a future educational paradigm centered around the learners.

In the future, this multi-Intelligent agent collaborative education system will focus on enhancing the smart level of task scheduling and resource allocation. The system will deepen its integration with traditional teaching patterns, achieving a natural connection between intelligent teaching and human instruction. In terms of data security, the system would emphasize strengthening information encryption to ensure data security and compliant use, which can help mitigate the conflict between standardized output and personalized requirements. In brief, the research can promote the implementation of multi-intelligent agent technology in broader educational scenes and advance the comprehensive popularization of educational intelligence.

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