

# Research on the Design of Multi-agent Education Architecture for Innovative Thinking

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**Abstract:** *This study focuses on the design of a multi-agent educational framework aimed at fostering innovative thinking. With the advancement of educational digital transformation, multi-agent systems, leveraging their role diversity and dynamic interaction capabilities, offer new perspectives for innovative education. The research proposes a multi-agent architecture model that includes a creativity conflict engine, cross-domain knowledge integration module, and innovation path visualization tools, and suggests corresponding multi-agent-driven educational practice pathways. This framework stimulates students' dialectical thinking through role opposition and collaboration, integrates interdisciplinary knowledge to aid in idea optimization, and uses visualization tools to systematically present and evaluate innovative outcomes. The study not only promotes educational model innovation but also provides theoretical and practical guidance for the application of multi-agent technology in the field of education, holding significant theoretical and practical importance.*

**Keywords:** Multi-agent Systems; Innovative Thinking; Educational Framework; Practice Pathway

## 1. Introduction

In the context of the rapidly advancing technology, innovative capability has become the core driving force for social progress and economic development. Education, as a key field for nurturing future talents, is undergoing a paradigm shift from traditional knowledge dissemination to the cultivation of innovative capabilities. However, traditional educational models often focus on knowledge implantation and memorization, struggling to meet the demands of complex thinking training. Therefore, exploring an educational model that can effectively cultivate innovative thinking has become a significant challenge that the field of education urgently needs to address. Digital education, as a new educational paradigm, can provide students with a more personalized, convenient, and efficient learning experience (Wu et al., 2024). Online platforms can foster environments that support independent learning and enhance engagement behaviors, and may even stimulate creativity (Jin et al., 2022), thereby better stimulating students' innovative thinking. The Ministry of Education has clearly mentioned in its 2022 Work Priorities the need to implement strategic actions for educational digitalization, promoting the digital transformation and intelligent upgrading of education. In recent years, multi-agent architectures, with their role diversity, dynamic interaction capabilities, and strong tool invocation capabilities, have provided new ideas and methods for innovative thinking education. In recent years, multi-agent architectures, with their role diversity, dynamic interaction capabilities, and powerful tool invocation capabilities, have provided new approaches and methods for innovative thinking education. Multi-agent systems (MAS) consist of multiple autonomous agents that can interact and collaborate to accomplish complex tasks (Janbi et al., 2023). Multi-agent systems have strong dynamic interaction mechanisms, and learning environments with vitality that can encourage learners to engage in intellectual collisions with agents (Zhai et al., 2024), thereby promoting the development of students' innovative thinking. Furthermore, the integration of generative artificial intelligence (AIGC) technology with multi-agent technology (such as MetaGPT, AgentVerse) has further propelled the shift in educational agency from "teacher-led"

to "human-machine co-evolution," providing a richer set of tools and environments for the cultivation of innovative thinking.

However, in this educational transformation process, there are also many challenges and pressing issues that need to be addressed. First, multi-agent architectures can stimulate students' innovative thinking through role conflict and collaboration, and the rational design of the opposition and collaboration between roles is key to achieving this goal. Second, designing dynamic interaction mechanisms and tool invocation strategies is the core of supporting the innovation process. The cultivation of innovative thinking requires a flexible and dynamic environment, making the design of interaction mechanisms and tool invocation strategies among agents crucial. Furthermore, evaluating the long-term impact of multi-agent systems on students' innovative abilities is an important step in ensuring educational effectiveness. The development of innovative thinking is a long-term process, and how to measure the impact of multi-agent systems on students' innovative abilities through scientific assessment methods is also an issue that cannot be overlooked in current research.

This study aims to explore the design of a multi-agent educational framework oriented towards fostering innovative thinking, analyze its application advantages in education, and propose a multi-agent architecture model that can effectively stimulate students' innovative thinking. By conducting an in-depth study of the types of applications of multi-agent systems in education, a comprehensive multi-agent educational framework design scheme and specific multi-agent-driven teaching practice strategies are proposed. The research not only contributes to the innovation of educational models but also provides theoretical support and practical guidance for the application of multi-agent technology in the field of education, holding significant theoretical and practical importance.

## **2. Literature Review**

### ***2.1. Innovative Thinking***

Innovative thinking, also known as creative thinking, refers to the cognitive ability to identify problems, find solutions, generate novel ideas, and ultimately communicate outcomes (Dong & Chen, 2024). The evaluation dimensions of innovative thinking encompass critical thinking skills, interdisciplinary knowledge integration capabilities, social interaction and collaboration abilities, practical application skills, as well as self-reflection and self-regulation abilities, all aimed at comprehensively promoting the cultivation and development of students' innovative potential (Wang et al., 2024). The cultivation of innovative thinking focuses on encouraging students to diligently learn scientific foundational knowledge to establish a solid foundation, integrating innovative thinking with curriculum teaching to achieve a complementarity of thinking and capabilities, strengthening hands-on ability cultivation to exercise practical skills, reforming teaching methods to reflect creative instruction, creating an innovative atmosphere to stimulate creative potential, and enhancing innovative thinking capabilities through strengthened thinking training activities (Yan et al., 2012). Current issues in the cultivation of innovative thinking lie in the traditional educational model's difficulty in adapting to students' personalized learning needs, a lack of effective mechanisms to promote interdisciplinary knowledge integration, and insufficient opportunities for practice and application to exercise and test students' innovative abilities, leading to students' difficulty in forming interdisciplinary thinking and a lack of ability to solve complex problems (Zhou & Zhao, 2024). The application of multi-agent systems in education precisely meets the needs for personalized learning path customization, interdisciplinary knowledge integration, and practical skill training.

### ***2.2. Definition and Characteristics of Multi-Agent Systems***

An agent refers to a computer system capable of perceiving its environment and taking actions to achieve specific goals, possessing perceptual capabilities, action capabilities, goal orientation, autonomy, and environmental interaction capabilities (Stuart J. et al., 2011). A multi-agent system is a collection of several autonomous agents that can interact and collaborate with each other to accomplish complex tasks. In a multi-agent system, each agent is an independent computational entity with the ability to perceive the environment, make inferences, decide, and take actions (Yuan et al., 2025).

Multi-agent systems demonstrate strong problem-solving capabilities and adaptability through collaboration and interaction among agents. These agents can work together through role division, information sharing, and dynamic adjustment to complete complex tasks, providing new solutions for the field of education. The collaborative mechanism of multi-agent systems is mainly reflected in the role distribution and task collaboration between agents. In educational scenarios, agents can undertake different roles according to task requirements, such as teachers, learners, experts, etc., and provide multidimensional solutions through collaborative work (Yu et al., 2024). The interaction patterns of multi-agent systems mainly include static and dynamic types. In the static interaction pattern, the connections and interaction relationships between agents are fixed and unchanging, suitable for scenarios with relatively clear task structures. The dynamic interaction pattern allows agents to dynamically adjust interaction strategies based on real-time feedback, more suitable for complex and variable learning environments (Zhai et al., 2024). Additionally, multi-agent systems can further enhance their interaction capabilities and knowledge update speed through tool invocation and integration with external data sources, ensuring the timeliness and accuracy of knowledge, and further improving students' innovative abilities. For example, development frameworks like LangChain use knowledge distillation techniques to integrate knowledge from various sources into large language models, thereby providing agents with more accurate and rich information (Wu et al., 2024).

### ***2.3. The types of applications of multi-agent systems in education***

The applications of multi-agent systems in education are primarily divided into three types: instructional support, collaborative learning, and assessment feedback. Instructional support multi-agent systems demonstrate significant potential in teaching assistance, mainly reflected in course design and development, educational software development, and teaching scenario construction (Liu et al., 2025). These multi-agent systems may include multiple roles such as teachers, assistants, and administrators, providing comprehensive support across teaching, order maintenance, and learning analysis through collaborative coordination. Collaborative learning multi-agent systems can simulate real learning scenarios to provide personalized learning resources, promote collaboration among students, stimulate their sense of cooperation and team spirit, thereby helping students complete learning tasks and projects more efficiently, enhancing learning efficiency (Wu et al., 2024). Assessment feedback type multi-agent systems are mainly applied in the fields of test question generation, homework grading, and learning diagnosis, leveraging the collaboration of multiple agents to achieve more objective, comprehensive, and personalized educational assessments (Liu et al., 2025).

## **3. Multi-intelligence architecture design that supports innovative thinking**

The multi-intelligence architecture design proposed in this study aims to comprehensively support the cultivation of innovative thinking through a layered mechanism, specifically including three layers: creative stimulation, iterative optimization, and achievement transformation. The architecture stimulates students' innovative thinking, optimizes the creative process, and realizes the systematic presentation and evaluation of innovative outcomes through

role opposition and collaboration, cross-disciplinary knowledge integration, and the application of visualization tools, as shown in Figure 1.

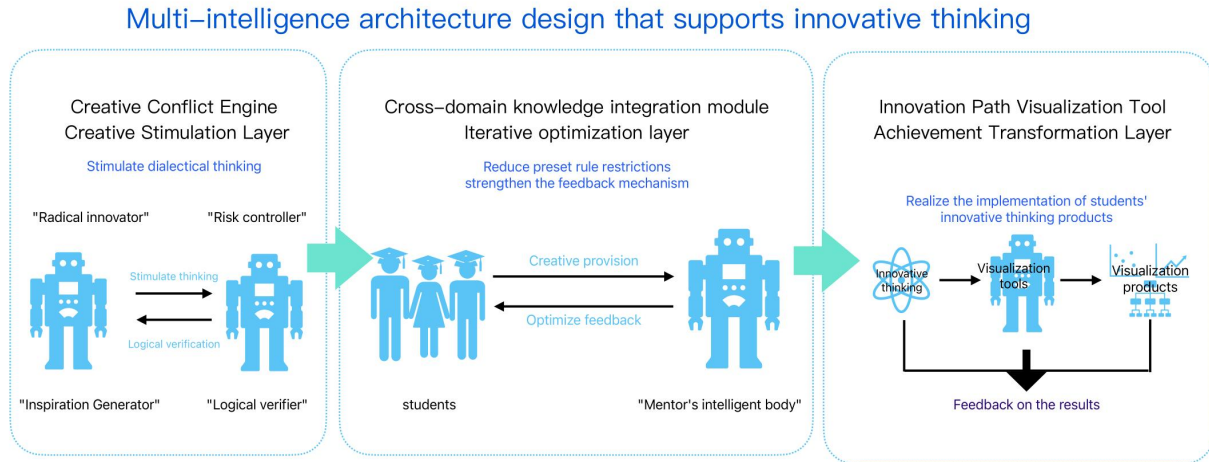


Fig. 1 Multi-intelligence Architecture Design Diagram

### 3.1. Creative Conflict Engine (Creative Stimulation Layer)

In the process of fostering innovative thinking, it is necessary to stimulate students' dialectical thinking abilities. To this end, the architecture includes a Creative Conflict Engine designed to create intellectual friction through opposing role agents, such as the "Radical Innovator" and the "Risk Controller." During the students' learning process, these agents generate cognitive collisions that encourage students to think dialectically about current issues, thereby promoting the emergence and development of innovative thinking. Additionally, within the horizontal architecture, a variety of role agents are deployed, such as the "Inspiration Generator" and the "Logical Verifier." By simulating free discussions akin to team collaboration, initial ideas are generated. The "Inspiration Generator" agent can offer novel creative solutions, while the "Logical Verifier" agent is responsible for logically analyzing and verifying the feasibility of these proposals. Together, they assist students in expanding their thought space, breaking away from established thinking patterns, and stimulating their innovative potential. This balance of conflict and collaboration can effectively ignite students' innovative thinking.

In specific educational scenarios, the Creative Conflict Engine is primarily applied to positively stimulate students' innovative ideas. For instance, in a classroom activity based on group collaboration and division of labor, the Creative Conflict Engine can equip each group with a system of agents, including the "Radical Innovator," "Risk Controller," "Inspiration Generator," and "Logical Verifier." The "Radical Innovator" and "Inspiration Generator" generate initial creative solutions based on the teacher's requirements and students' ideas. Students then diverge their thinking based on the initial solutions provided by the agents, and each group engages in human-machine collaborative dialogues. As the interaction with the agents deepens, multi-perspective arguments on the same topic inspire students to engage in independent thinking based on the initial schema. There are varying degrees of improvement in dimensions such as viewpoint expression and argument analysis (Jin et al., 2023). In this process of continuous in-depth thinking, each group produces personalized innovative solutions. These solutions are then submitted to the "Risk Controller" and "Logical Verifier" agent systems for feasibility analysis to validate the practical significance of the solutions generated by each group, thereby continuously improving the group's solutions. The application of the Creative Conflict

Engine can enhance the efficiency of the entire classroom by initiating different dialogues based on the ideas of each group and providing more personalized learning guidance, helping students better diverge their thinking and exercise their innovative thinking abilities.

### **3.2. Cross-domain Knowledge Integration Module (Iterative Optimization Layer)**

In the process of fostering innovative thinking, the integration and iterative optimization of interdisciplinary knowledge are essential components. To this end, our architecture has designed a dedicated cross-domain knowledge integration module aimed at breaking down traditional barriers between disciplines to promote the comprehensive application of knowledge and the development of innovative thinking. This module reduces reliance on preset rules and enhances real-time feedback mechanisms, such as incorporating Reflexion's self-assessment loop, to improve the performance of agents when executing complex tasks like decision-making, reasoning, and programming. Agents are capable of dynamically adjusting their behavioral strategies based on real-time feedback and can also continuously optimize their approach to problem-solving through self-assessment and reflection, which is beneficial when facing novel or unconventional problems. This allows agents to flexibly adjust their methods to adapt to the ever-changing demands. Within the vertical architecture, the mentor agent plays a crucial role, responsible for integrating ideas from various fields and calling upon appropriate tools, such as prototyping software, for rapid concept validation. The mentor agent can generate preliminary prototype designs based on students' ideas and use real-time feedback mechanisms to help students iterate and optimize their ideas, thereby transforming ideas into practical and feasible solutions. Moreover, the cross-domain knowledge integration module also encourages students to examine problems from multiple perspectives and seek innovative solutions through an interdisciplinary viewpoint. This interdisciplinary way of thinking helps students to propose more innovative and practical strategies when facing complex real-world problems.

For example, in an interdisciplinary innovation practice course involving multiple subject areas, a student team proposed a creative solution at the beginning of the project but was puzzled about how to integrate knowledge from different disciplines. At this point, leveraging the deep integration of artificial intelligence and education, which changes the established knowledge increment system and its generation mode (Jin et al., 2025), the “**Mentor Agent**” can intervene. Based on the students' ideas, the “**Mentor Agent**” can call upon a multi-party information knowledge base to generate a preliminary system architecture diagram. Subsequently, the agent utilizes Reflexion's self-assessment loop mechanism to evaluate the preliminary design, identifying potential problems and areas for optimization in the initial solution. Based on these evaluation results, the agent provides students with suggestions for improvement, guiding the student team to optimize the solution design from different disciplinary perspectives. The student team can then adjust their initial solution according to the agent's feedback to enhance the feasibility of the solution. Through this process of cross-disciplinary knowledge integration and iterative optimization, students can effectively improve their interdisciplinary collaboration and problem-solving abilities.

### **3.3. Cross-domain Knowledge Integration Module (Iterative Optimization Layer)**

To implement students' innovative thinking products, this architecture has set up an Achievement Transformation Layer. In the Achievement Transformation Layer, innovative thinking products can be realized through the Innovation Path Visualization Tool, which can transform students' thinking processes into dynamic graphs, similar to the graph structure of PLAG, clearly presenting the process from the germination of ideas to the formation of solutions. This visualization method not only provides students with an intuitive basis for reflection and

adjustment but also facilitates targeted guidance from teachers. At the same time, the dynamic team collaboration model refers to the DyLAN contribution assessment mechanism, dynamically adjusting roles and tasks according to members' contributions to ensure efficient team collaboration and the joint completion of the final solution. In addition, through structured output formats, such as documents and charts generated by MetaGPT, innovative achievements are systematically presented, which is not only convenient for students to review and summarize but also provides a strong handle for teachers to assess and guide, achieving closed-loop management in the cultivation of innovative thinking.

In the teaching scenario of an innovative design course, the application of the Achievement Transformation Layer provides students with a systematic path for the cultivation of innovative thinking. Through the Innovation Path Visualization Tool, students' thinking processes are transformed into dynamic graph structures, similar to the graph structure of PLaG, clearly presenting the entire process from the germination of ideas to the formation of solutions. This visualization method not only provides students with an intuitive basis for reflection and adjustment but also facilitates targeted guidance from teachers. Meanwhile, the dynamic team collaboration model, which refers to the DyLAN contribution assessment mechanism, dynamically adjusts roles and tasks according to members' contributions to ensure efficient team collaboration and the joint completion of the final solution. Research has shown that learning activities are generally accompanied by engagement, and students who actively participate in online peer feedback can provide specific and detailed feedback that provokes multiple perspectives and in-depth reflection on the creative content and process, potentially enhancing their innovative thinking abilities (Jin et al., 2024). In addition, structured output formats, such as documents and charts generated by MetaGPT, systematically present innovative achievements. This not only facilitates students' review and summary but also provides a strong handle for teachers to assess and guide, achieving closed-loop management in the cultivation of innovative thinking.

#### **4. Practice Pathway**

To achieve effective practice of the multi-intelligence educational architecture, this study proposes the following multi-agent-driven teaching practice strategies, including five stages: role division substitution, adaptive transformation, reorganization symbiosis, collaborative innovation, and iterative optimization, see Figure 2. This strategy not only optimizes the task execution process but also ensures the high-quality completion of tasks through dynamic collaboration among agents. The following are the specific application paths of the multi-agent-driven teaching practice strategy in this study:

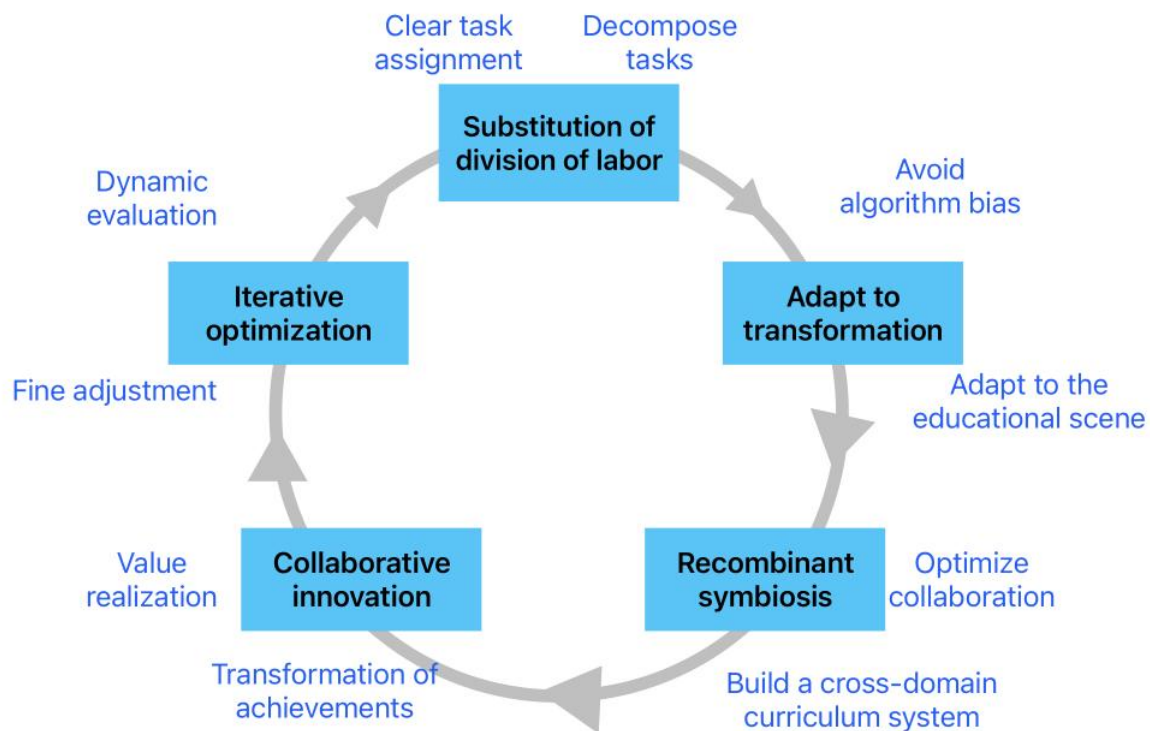


Fig.2 Multi-agent-driven Teaching Practice Strategies

#### 4.1. Substitution of division of labor

Due to the fine-grained subject expertise contained within educational large model agents, which possess the capabilities for subject knowledge retrieval and integration (Liu et al., 2024), they can undertake fundamental tasks such as data mining and process monitoring. Multi-agent systems, through explicit task allocation, break down complex tasks into multiple sub-tasks and assign them to different agents, thereby freeing up teachers' time and energy to focus on higher-level decision-making and creative tasks, such as ethical reviews and curriculum design, enhancing teaching efficiency. For instance, multi-agent systems can automatically generate interdisciplinary project resources through knowledge retrieval and resource integration, while teachers can customize personalized learning paths based on these resources to ensure the relevance and adaptability of the teaching content.

#### 4.2. Adapt to transformation

The Adapt to Transformation phase emphasizes the deep integration of agents with educational scenarios. Agents significantly enhance learners' grasp of knowledge through precise analysis of knowledge points, personalized recommendations of learning content, and efficient knowledge teaching. However, thinking is not an innate, naturally formed behavioral pattern, but is closely linked to the development of society, history, and culture, and is profoundly influenced and shaped by these factors (Li & Wang, 2020). Therefore, teachers need to "transform technology into education," training agents to understand educational scenarios, avoid algorithmic bias, and ensure that the agents' outputs align with educational goals and ethical requirements. At the same time, students also need to "transform application into creation," using agent tools (such as AR

laboratories) to explore multidimensional solutions and cultivate innovative thinking and practical skills.

#### ***4.3. Recombinant symbiosis***

In the Recombinant Symbiosis phase, the collaboration between agents and humans is optimized through dynamic team building and knowledge network integration. Agents can be dynamically recruited or eliminated according to task requirements, ensuring the flexibility and adaptability of the team structure. For instance, referring to the AgentVerse four-stage model, agents adjust the composition and collaboration methods of the agent team dynamically through four stages: expert recruitment, collaborative decision-making, action execution, and evaluation, to efficiently solve complex tasks, fostering the development of innovative thinking and teamwork skills. Additionally, the integration of subject knowledge with AI-generated content is also key in this phase; by building a cross-domain curriculum system, disciplinary boundaries are broken down to provide students with a more comprehensive learning experience.

#### ***4.4. Collaborative innovation***

In the Collaborative Innovation phase, the multi-agent system facilitates the transformation of educational value through debate protocols and collaborative creation of outcomes. Agents engage with each other through structured outputs, such as mind maps, to reach a consensus and collectively design innovative works, including solutions to social issues. This phase not only enhances students' innovative capabilities and teamwork skills but also drives innovation and transformation in educational practices through human-machine collaboration. During this phase, the multi-agent system operates as a platform where students and teachers can deeply engage with the content. The structured outputs serve as a medium for communication and idea exchange, allowing for a more comprehensive exploration of problems and the generation of creative solutions. The collaborative innovation phase encourages active participation from all parties, leveraging the strengths of both human and artificial intelligence to address complex educational challenges.

#### ***4.5. Iterative optimization***

The Iterative Optimization phase, as a key step in enhancing teaching quality, focuses on strengthening the effectiveness of the multi-agent collaboration framework through continuous evaluation and dynamic adjustment. This phase emphasizes close monitoring of multi-agent interactions during the teaching process, collecting and analyzing key performance data, such as student interaction frequency, collaborative outcomes, improvements in interdisciplinary capabilities, and the timeliness of agent feedback. Based on this data, educators can effectively evaluate the dynamic changes in students' innovative thinking and then make fine adjustments to the behavior parameters, interaction strategies, refining the creation of a positive online learning environment and stimulating students' enthusiasm to actively engage in the learning process (Wang et al., 2025), and algorithms of the agents to improve the targeting and adaptability of teaching support.

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