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Chapter · October 2024

DOI: 10.52305/RUIG5131#Chapter3

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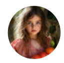

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Enhancing Educational Practices with Multi-Agent Systems: A Review

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Abstract

Large Language Models (LLMs), as a kind of robust technology in natural language processing, exhibit sophisticated language comprehension and generation capabilities. Recent advancements in LLMs have spurred the rapid development of Multi-Agent Systems (MAS), which have found extensive applications in education, ushering in novel opportunities for the field. This Chapter delves into the utilization and impact of LLM-based methodologies in education. LLM-based MAS fosters more seamless and intelligent interactions with students by offering tailored teaching materials and learning assistance, thereby expanding the horizons for improving educational practices. Moreover, we examine the paradigmatic shift in MAS's role in advancing artificial intelligence (AI) for education, encompassing the transition from singular Agents to MASs from predetermined modes to LLM-driven methodologies, and from general domains to subject-specific pedagogy. These transitions respectively facilitate the emergence of swarm intelligence, the evolution of Agents' cognitive capacities, and the acquisition of knowledge. Through a systematic review of existing literature and case studies on MAS applications in educational settings, this Chapter aims to provide comprehensive insights and inspiration for both research and practical implementations in the field of education. Additionally, it explores the potential benefits of MAS and diversified application scenarios in education, while addressing Human-Computer Interaction in MAS-driven teaching and learning environments and elucidating current challenges and future prospects. By undertaking this review, we aspire to furnish valuable references for scholars and practitioners in the educational technology domain, envisioning forthcoming technological advancements in education propelled by MAS.

Keywords: human-computer interaction, large language model, AI Agent, AI for education, multi-Agent system

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Jiang, Y.-H., Liu, T.-Y., Zhuang, X., Hu, H., Li, R., & Jia, R. (2024). Enhancing Educational Practices with Multi-Agent Systems: A Review. In Y. Wei, C. Qi, Y.-H. Jiang, & L. Dai (Eds.), *Enhancing Educational Practices: Strategies for Assessing and Improving Learning Outcomes* (pp. 47–65). Nova Science Publishers. https://doi.org/10.52305/RUIG5131

Note: This is an earlier version of the chapter provided by the authors in accordance with Nova Science Publishers' policies. The content may differ from the final version published by Nova Science Publishers.

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Introduction

The concept of Agent originated in the field of philosophy, where "Agent" is typically used to refer to a conscious or willing entity that is capable of taking action and making decisions[1]. The forms of Agent include humans, animals, intelligent hardware or software, etc. After the concept of Agent was transferred to the field of software applications, it was regarded as a professional term in the field of distributed artificial intelligence, representing an artificial entity that can use sensors to perceive the environment, make decisions, and take action through actuators[2].

In the early years, Agents relied on symbolic artificial intelligence for logical reasoning to simulate modes of human thinking. With the development of technology, reinforcement learning[4][5], Meta-learning[6], and transfer learning[7][8]methods are increasingly introduced into Agent training and application. These methods enabled Agents to learn by themselves and deal with complex scenarios. Since 2022, large language models have demonstrated impressive new capabilities and gained a lot of attention. Large language models have been pre-trained on large-scale corpora and exhibit few-shot and zero-shot generalization capabilities[9]. Researchers have begun to utilize large language models to build artificial intelligence Agents. When large language models are used to build Agents, they often act as brains or controllers, acting as "decision centers"[3]. Complete Agent development also needs multimodal sensors to endow perception capabilities and external tools to enable the execution of specific tasks. Large language models make decisions about when to use tools, what tools to use, and how to use them, based on environmental information collected by sensors.

With the continuous maturation and development of Large Language Model (LLM) technology, its significance in the field of education is becoming increasingly prominent. Firstly, LLM will emerge as an indispensable tool for personalized learning. By employing natural language processing techniques, LLM can discern the personalized learning needs of individual students and offer tailored assistance for comprehension exercises, providing customized solutions based on their unique learning preferences. Secondly, LLM has the potential to catalyze innovations in educational paradigms. It can furnish students with more dynamic learning experiences through intelligent question-answering or virtual laboratories, thereby enhancing student engagement and enthusiasm.

In addition to the evolution of the technologies used by Agents, their design patterns are also evolving. To make Agents have the ability to migrate, generalization, and cope with complex tasks, several studies proposed that Agents should own the following three main features: (a) Sociability (b)Autonomy, and (c)Proactivity[10][11]. Autonomy refers to that Agents should be able to make decisions and perform tasks independently. Proactivity indicates that Agents should be able to use historical data to improve decision-making. Sociability puts forward a higher standard, which requires that Agents should have the ability to share and obtain information from other Agents. That is, they can decompose complex tasks into several sub-tasks and assign them to multiple Agents to solve them collaboratively to achieve better results. This design pattern is summarized as the Multi-Agents System (MAS) design paradigm and has been widely used in different scenarios.

Multi-Agent Systems (MAS) based on LLM demonstrate extensive intelligence and practicality, ushering in numerous changes and innovations in various traditional application scenarios. LLM equips MAS with language understanding, generation, and reasoning capabilities, enabling them to engage in more intricate and human-like interactions and decision-making processes. This capacity empowers LLM-based MAS to assume pivotal roles in multiple fields: MAS can harness LLM's semantic understanding and conversational interaction capabilities to extract information and context from natural language and engage in intelligent dialogue. Consequently, MAS can respond to inquiries, elucidate concepts, and even participate in debates and explanations, thereby enhancing the quality and efficiency of human-computer interaction. LLM furnishes MAS with an extensive knowledge base, enabling them to acquire knowledge and information from various domains through interaction with LLM to aid in decision-making and problem-solving. Additionally, the reasoning capability of LLM can assist MAS in deducing new conclusions and insights from acquired knowledge, thereby further enhancing their decision-making ability.

In the educational scene, the design of the Intelligent Tutoring System (ITS) is also increasingly integrated into the design pattern of MAS and has entered the stage of a virtual role. Different from the early hypermedia-based ITS and modeling-simulation-based ITS, the Agent-based ITS lets the robot play a virtual role to interact with the learner through text, speech, image, and other multi-channel and multi-way. MetaTutor uses four Agents as the core part of the inner loop of the ITS system (providing support guidance for students' problem-solving process) [12]. It monitors and tracks learners' learning data, provides learning support through prompts, questions, and suggestions, helps students set learning goals, and monitors cognitive and metacognitive processes. SimStudent explains the solving process of students' reasoning algebraic equations through two Agents and provides examples of explanation and problem solving[14]. DuoLingo created an interesting gamified story background, designed different personality and character relationship graphs for more than a dozen Agents, and gave corresponding feedback to users in different scenarios[15]. The integration of MAS and ITS can customize teaching activities according to the requirements and preferences of each learner while providing high interactivity and personalized learning support throughout the learning process[16].

Paradigm Shift: MAS Promoting AI for Education

Emergence of Swarm Intelligence: from Agent to Multi-Agent System

In nature, the macroscopic intelligent behavior of social organisms through cooperation is known as swarm intelligence [1], [2]. Through effective collaboration among multiple AI Agents, Multi-Agent Systems (MAS) demonstrate increased capability in accomplishing complex tasks such as software development [3]. By engaging in collaboration and simulation, Agents interact with their environment through various actions, thereby altering their states and enhancing the efficiency of mutual cooperation. Guided by the pursuit of greater benefits, Agents are incentivized to cooperate and complete tasks. The application of Agents in education can be categorized into multi-Agent and single-Agent systems based on the number of Agents involved.

Strug et al. [4] proposed a design approach for educational facilities centered around an Agent-based system. Martens et al. [5] suggested enhancing students' learning concentration and efficiency through a learning Agent conversation system. Bruner et al. [6] simulated the efficiency of collaborative learning in adult education classrooms by modeling cooperative learning groups using Agent networks. Babalola [7] introduced a framework for construction safety training, using simulation results to guide construction worker training. Yang et al. [8] addressed corporate education and training investment challenges by analyzing them as spatial problems to determine long-term profitability. Ramadhevi et al. [9] employed intelligent systems to support cooperative learning among students in real classrooms. Lee [10] proposed employing language models combined with Agents to analyze trends in English learning platforms. Guo et al. [11] constructed an educational model using an Agent connection model combining linear tables and hierarchies. Zaytsev et al. [12] utilized a distance education (DE) model to provide students with personalized courses. Uchiya et al. [13] designed educational tools to train developers of learning Agent systems, thereby improving educational efficiency. Stummer et al. [14] used an Agent-based model to deepen students' understanding of key concepts in innovation management. Li et al. [15] employed Agent technology and web services to construct educational models and enhance learners' efficiency. Drzewiecki et al. [16] simulated the feasibility of using Agent-Based Modeling (ABM) to address educational research questions in real classroom settings. Winkler et al. [17] employed voice and scaffold-based Conversational Agents (CAs) to foster meaningful interactions in online video lectures. Perrie et al. [18] constructed a simulation model to assess the impact of learners' health, parental education, and family type on academic progress. Yin et al. [19] proposed an approach to intelligent web data mining using semantic processing and data mining. Walters et al. [20] utilized a conversational Agent (CA) as a teaching aid to provide students with instructional information. Musaeus et al. [21] examined whether computational thinking could facilitate students' understanding of biotechnology concepts. Masayuki [22] created virtual players based on game records and trained them using player data. García-Magariño et al. [23] developed an Agent-based social simulation tool to explore the effects of higher education teaching strategies on student social networks.

Aguayo et al. [24] explored how Agent-Based Modeling (ABM) could enhance understanding of the human experience using custom educational technologies. Chandra Reka et al. [25] employed virtual display technology to simulate teaching environments and study student emotions. Talib et al. [26] developed a MAS system to facilitate coordination and communication between teachers and students during examination scheduling and assignment. Sowmiya et al. [27] utilized a novel ant colony optimization model to predict and recommend teachers' teaching styles.

As the scope of AI applications expands, many tasks become increasingly complex. A single Agent may not effectively manage these complexities. With a multi-Agent system, tasks can be decomposed into smaller, more manageable segments, each handled by a different Agent. This division of labor enhances overall system efficiency and performance. Multi-Agent systems are also more resilient and fault-tolerant. If one Agent fails, the rest of the system can continue to function. This redundant and distributed design enhances system stability and reliability.

Khaing et al. [28] proposed a project-based collaborative filtering method for recommending related topics to users and a multi-dimensional association rule approach for providing insights into the relationship between users and degree programs. Xie [29] introduced a multi-Agent teaching management system to improve teaching efficiency. Nazir [30] leveraged multi-Agent systems and comparative machine learning to enhance university efficiency and mitigate failure risks. Molnar et al. [31] employed multiple Agents to allocate educational video resources. Boudabous et al. [32] introduced a multi-Agent system for ubiquitous learning (MASUL) catering to both patients and clinicians. Singh et al. [33] implemented a multi-Agent-based model using JADE to enhance the security, quality, trust, and accessibility of distance education through intelligent Agents. Miura [34] suggested that junior students without programming knowledge could utilize the MAS platform "artisoc" to develop multi-Agent simulations. Ma et al. [35] proposed applying multi-Agent cooperative information technology in the control engineering education model to efficiently handle tasks in an open network environment. Yan [36] found that establishing a computer-aided teaching platform is conducive to comprehensive quality education, improving teaching quality, and instilling students with a lifelong passion for sports. Wei et al. [37] utilized neural networks to construct an English teaching platform with multiple Agents.

Evolution of Agent's Mind: from Preset Mode to LLM Driven

An Agent system operates by sensing its environment and making decisions to maximize certain performance metrics. Typically, such systems encompass functions like perception, reasoning, decision-making, and action. Large Language Models (LLMs) serve as a component within an Agent system, primarily tasked with language understanding and generation. In this context, LLMs play a crucial role in perception and inference, processing natural language input and generating corresponding responses.

Bruner [6] conducted simulations and analyses to assess the efficacy of collaborative learning in adult education, leveraging local information through Agent networks. Khasianov [38] explored the role of a three-subject education platform in fostering self-motivated learning and mitigating student frustration. Khasianov et al. [39] suggested that increasing the price of Sugar-Sweetened Beverages (SSB) in schools could curb children's preference for them, potentially reducing their consumption after physical education. Yan et al. [36] developed a computer network-aided teaching platform to enhance teaching quality and foster lifelong sportsmanship among students. Simon [40] employed simulation models to evaluate the functioning of the higher education system and formulate long-term development strategies. Samra et al. [41] proposed a conceptual model for an intelligent simulation-based learning system, integrating data mining Agents to optimize clinical skills education. Hantono et al. [42] explored the role of augmented reality Agents in enhancing learning outcomes, finding positive effects on motivation, performance, engagement, and collaboration.

In the absence of LLM support, Agent systems rely solely on basic syntax rules and fixed rule bases to process natural language input, limiting their comprehension of complex semantics and polysemy. Such systems may only execute predefined interaction patterns or commands, lacking adaptability to diverse contexts and user inputs. Integrating LLMs significantly enhances language processing and interaction flexibility, enabling comprehension of complex, natural language input and dynamic adjustment of responses based on context and user input. This enhanced capability allows Agent systems to provide more personalized and intelligent services, enabling efficient and accurate interaction experiences.

Ocha et al. [43] utilized LLMs to develop adaptive educational assistants. Walton [44] employed chatGPT to analyze genetic disease-related issues. Lee et al. [10] utilized language models to analyze trends in English learning platforms. Zheng et al. [45] employed Embodied Agents for conversations, leveraging LLMs for language understanding and sub-goal planning, integrating visual observations to construct semantic graphs for symbolic representations, enabling inference of sub-goal planning and action generation based on common sense at the task and action level.

Acquisition of Knowledge: from General Area to Subject Teaching

The application of Agents spans various fields and industries, offering solutions that are intelligent, personalized, and efficient. Agents find utility in natural language processing and dialogue systems, enabling the creation of intelligent conversation assistants, customer service systems, and Q&A platforms. In image recognition and computer vision, Agents facilitate tasks like object and face recognition, as well as autonomous driving. Furthermore, Agents contribute to intelligent recommendation systems, personalizing content such as products, music, and movies. In the realm of medicine and health, Agents aid in medical diagnosis and personalized treatment plans, while in finance, they perform tasks like risk assessment, transaction forecasting, and customer service. Various other domains, including education, automation and control, data analysis, and decision support, can also leverage Agent technology, thereby advancing technology and society.

Biloria [45] advocates for a circular process of iterative information exchange, fostering the evolution of performance-driven architectural forms through real-time interactive behavior. Coneglian et al. [46] extract pertinent information via semantic analysis and search processes, enriching meaning and value. Ma [35] utilizes multi-Agent cooperative information technology in control engineering education, enhancing task handling in open network environments. Yang et al. [47] leverage intelligent Agent technology to develop an innovative education network platform for college students, enhancing system intelligence and operability while reducing development costs. Yonah [48] employs external Agents to interact with learners through system-embedded Agents, providing real-time feedback to minimize wasted time and additional costs. Alexandru et al. [49] offer personalized support to end-users, tutors, and students by assimilating information generated by other Agents and considering their attitudes toward the learning environment. Gu [50] systematically reviews the application of Agent-based modeling and simulation (ABMS) in higher education (HE), while Jawahar et al. [51] facilitate and guide learning processes, fostering educational interaction among students through instructional Agent models.

In education, Agents play pivotal roles in personalized learning support, intelligent tutoring and Q&A, virtual labs and simulation environments, personalized content generation, learning process monitoring and analysis, as well as educational games and entertainment-based learning. These applications leverage Agent technology to deliver a more flexible, personalized, and enjoyable learning experience, enhancing teaching effectiveness and learning efficiency. While Agents drive innovation in education methods and expand educational boundaries, attention to privacy protection and data security is imperative to ensure the rational and sustainable development of educational technology.

Lee et al. [10] employ language models to analyze trends in English learning platforms. Xie et al. [29] utilize a multi-Agent teaching management system to enhance physical education teaching efficiency. Yan [38] observes that establishing a computer network-aided teaching platform fosters comprehensive quality education, improving teaching quality and cultivating students' lifelong appreciation for sports. Samra et al. [40] develop a conceptual model for an intelligent simulation-based learning system, employing data mining Agents in clinical skills education to better understand student performance and provide an improved educational environment. Dubovi et al. [52] highlight the advantage of explanatory ABM simulations in learning biological disciplines, making underlying microscopic mechanisms behind phenomena visible. Chen [39] suggests that increasing the price of Sugar-Sweetened Beverages (SSB) in schools and reducing children's preference for SSB may mitigate adverse effects associated with vending machine usage after physical education.

Educational Applications: MAS Expands Diversified Application Scenarios

When applied in the field of education, Agent systems demonstrate adaptability across various usage scenarios. In the classroom setting, Khasianov [36] integrates students into self-motivated learners, expediting the acquisition of new knowledge, influencing memory, and mitigating student frustration through a comprehensive education platform spanning three subjects. Sowmiya et al. [27] employed a novel ant colony optimization model to forecast and propose teaching styles for educators.

In virtual simulation environments, Masayuki [22] generates virtual players based on players' gaming records and refines them through player interactions. García-Magariño [23] developed an Agent-based social simulation tool to assess the impact of higher education teaching strategies on the social dynamics within a specific student cohort. Dubovi et al. [53] highlight the pedagogical advantage of explanatory Agent-Based Model (ABM) simulations, elucidating underlying microscopic mechanisms behind observed phenomena. Drzewiecki [16] investigates the feasibility of employing ABM to address educational research queries within authentic classroom settings.

In e-learning contexts, Khaing [28] employs collaborative filtering techniques to recommend relevant topics of interest to users and utilizes multi-dimensional association rule methods to provide insights into the relationship between users and degree programs. Molnar et al. [31] employ multiple Agents to manage the allocation of educational video resources effectively. Atiquzzaman et al. [11] construct an educational model using an Agent connection model that combines linear tables and hierarchies.

In teaching management applications, Sebnem et al. [53] simulate the impact of science education on students' behavioral tendencies within a simulated school environment. Alexandru et al. [49] leverage information aggregated by other Agents to deliver personalized support to end-users, tutors, and students based on their attitudes toward the learning environment. Coneglian [46] utilizes semantic analysis to extract salient information through processes of meaning and value.

In data analysis scenarios, Nazir et al. [30] utilize multi-Agent systems and comparative machine learning to enhance university efficiency and mitigate failure risks. Schnitman [54] scrutinizes whether mobile device use for learning correlates with increased interest in learning. Jezic [55] facilitates the learning process through interactions with students, educators, and other participants, fostering collaboration among similar Agents.

In distance education settings, Živojinović [50] enhances learning efficiency through subject-based simulations. Yonah [48] employs external Agents to engage with system-embedded Agents, providing learners with real-time feedback to minimize time wastage and additional costs. Yang et al. [47] leverage intelligent Agent technology to construct an innovative education network platform for college students, enhancing system intelligence and reducing developmental costs.

Human-Computer Co-Evolution: Human-Computer Interaction in MAS-Driven Teaching and Learning Scenarios

The chapter categorizes Agent systems into AI assistant type, human-machine collaboration type, instruction executor, and general type based on their interaction modes with users. Diverse interaction methods offer several advantages. Firstly, they enhance user choice flexibility, allowing users to select the most suitable communication mode according to their preferences and needs, thereby enhancing convenience and personalization. Secondly, diverse interaction methods improve accessibility, enabling easier communication with Agents, especially for visually impaired individuals or those with limited mobility. Additionally, varied interaction methods enhance user engagement and provide a more natural and enjoyable interactive experience. Moreover, selecting appropriate interaction methods based on task characteristics and user needs improves efficiency, and accuracy, and widens application scenarios, offering users comprehensive services. Overall, diverse interaction methods optimize user experience, expand Agent application fields, and provide users with convenient and personalized intelligent experiences.

General-purpose Agent systems offer high universality and broad application potential. Biloria et al. [45] propose an iterative information exchange process to evolve performance-driven architectural forms. Coneglian et al. [46] suggest semantic analysis to extract relevant information, enhancing meaning and value comprehension. Schnitman [55] examines the impact of mobile device usage on learning interests. Simon et al. [40] employ simulation models to analyze higher education system functionality and long-term development strategies.

AI assistant-type Agent systems autonomously make decisions and provide users with convenient options. Rocha et al. [42] offer educational support through intelligent educational Agents utilizing long language models. Molnar et al. [31] employ multiple Agents for the autonomous allocation of educational video resources. Wei [56] utilizes neural networks to construct an English teaching platform with multiple Agents.

Human-computer collaborative Agents achieve system functions through Agent-user interaction. Simon [57] applies automatic guided vehicle systems combined with Multi-Agent technology to higher education. Walters [20] uses Conversational Agents (CAs) to provide instructional information to students. García-Magariño et al. [23] developed an Agent-based social simulation tool to assess teaching strategy impacts on student social networks. Talib et al. [26] establish MAS systems facilitating coordination and communication between teachers and students during exam scheduling. Jawahar [51] utilizes instructional Agents to facilitate learning processes and increase educational interaction between students. Ma et al. [35] employ multi-Agent cooperative information technology in control engineering education for efficient task handling in open network environments.

The Instruction Executor Agent system achieves the purpose of implementing system functionality by executing user commands. Walton et al. [43] analyze genetic disease-related problems using chatGPT. Zheng [44] leverages Embodied Agents for conversations, facilitating large language model (LLM) utilization for language understanding and sub-goal planning, constructing semantic graphs for symbolic representation, and inferring sub-goal planning and action generation based on common sense at task and action levels.

Conclusion

In the preceding Chapter, we delved into the concept of Agent for education. In this Chapter, we extend our exploration to the concept of MAS for education. Serving as an extension of LLM-based Agents, LLM-based MAS harnesses its language understanding and reasoning capabilities to offer decision support for intricate problems. MAS can query LLM for pertinent information and guidance, facilitating optimal decision-making in uncertain or complex scenarios. Drawing from user language input and context, MAS can employ LLM to furnish personalized services and interactions, thereby tailoring responses and suggestions to individual needs and preferences. This adaptability enhances user experience and caters to personalized requirements. The integration of LLM into MAS presents novel prospects for educational practices. LLM-based MAS can function as an educational tool, engaging with learners, addressing inquiries, elucidating concepts, and even generating educational content to facilitate improved understanding and comprehension. The incorporation of LLM into MAS aligns with the objectives of automation and efficiency, enabling MAS to autonomously process vast amounts of natural language input and execute diverse tasks. Consequently, this integration contributes to time and resource savings while augmenting work efficiency and quality.

This Chapter seeks to elucidate the potential benefits and applications of employing MAS to augment educational practices through a comprehensive review of existing literature. Presently, LLM-based MAS has showcased extensive potential across various domains, including language comprehension, reasoning, and interaction, thereby furnishing intelligent solutions tailored to diverse scenarios to bolster efficiency and user satisfaction. These solutions encompass intelligent dialogue exchange, personalized learning experiences, knowledge acquisition, and inference. Furthermore, LLM can serve as a repository of knowledge, equipping educators and learners with extensive background information to enhance the quality of teaching and learning outcomes. We posit that the advancement of MAS technology will further propel the adoption and integration of artificial intelligence across diverse domains, fostering the diversified evolution of educational application scenarios. Moreover, it will continually innovate human-computer interaction paradigms in educational settings, thereby fostering greater convenience and innovation in educational development, ultimately leading us toward a future of enhanced education.

Acknowledgments

This work was partially supported by the Doctoral Research and Innovation Foundation of the School of Computer Science and Technology, East China Normal University, under the title of “Intrinsic Mechanisms of Collaborative Learning Achievements Formation and Their Interpretability Analysis: from Game Theory Simulation, AI Agent Simulation to Empirical Analysis”, and the Postgraduate Research & Practice Innovation Program of Jiangsu Province, China, under the title of “Research on Evolutionary Computation with Educational Applications Driven by Co-Evolution of Multiple Sub-Populations ”.

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