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LLM AGENTS: ADVANCING TRULY PERSONALIZED ONLINE EDUCATION

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Abstract

Since the advent of ChatGPT, the development and release of Large Language Models (LLMs) have accelerated at an unprecedented pace. The most advanced LLMs, such as Deepseek R1 and ChatGPT-4o, exhibit sophisticated reasoning capabilities with significant potential for transforming education. These models can enable personalized learning by dynamically adapting to individual preferences and needs. However, despite their growing adoption, the real-world impact of LLMs in education remains limited, with few implementations demonstrating measurable effectiveness. In this paper, we investigate the potential of LLMs to transform education and propose a framework centered on LLM agents in online learning environments. First, we advocate for a new generation of online learning platforms where LLM agents are not merely add-ons but integral components, shifting from traditional Learning Management Systems (LMS) that function as static content repositories to dynamic, interactive ecosystems. In these environments, agents actively "intervene" to support and guide learners. Second, we emphasize the development of multi-agent systems that facilitate content delivery, foster interaction, promote critical thinking, enhance engagement, and provide personalized feedback. Finally, we highlight the necessity of rigorous evaluation methods to assess the actual impact of these technologies on learning outcomes. This paper presents the initial findings of our approach, which focuses on automating content generation in online learning environments while addressing predominant learning styles: Visual, Auditory, Read/Write, and Kinaesthetic. We aim to convert traditional text-based content into multimodal formats tailored to diverse learning preferences. While this transformation presents significant challenges, it is greatly facilitated by LLM agents leveraging advanced generative AI capabilities, including text-to-text, text-to-image, text-to-audio, and text-to-video generation.

Keywords: *Personalized education, LLM agents, generative AI, learning styles, online learning.*

1. Introduction

Personalized education has long represented a central aspiration within the Artificial Intelligence (AI) research community. Despite the proliferation of theoretical frameworks over the past several decades, their practical implementation has remained largely constrained, only becoming more feasible with recent technological advancements (Gao et al., 2024). This paper explores how the integration of intelligent agent architectures with Large Language Models (LLMs) presents transformative potential for the realization of viable personalized education systems. Intelligent agents, introduced in the 1990s as promising frameworks for managing complex tasks, contributed significantly to theoretical developments in areas such as agent planning and communication protocols. However, their practical deployment was hindered by a fundamental limitation: insufficient reasoning capabilities (Chu et al., 2025). Early reasoning mechanisms were largely rule-based and computationally intensive, rendering them unsuitable for dynamic, real-world educational environments. The emergence of advanced LLMs has revitalized interest in agent-based approaches by effectively addressing these reasoning limitations. These models offer robust simulations of cognitive processes, enabling intelligent agents to function with a level of flexibility and responsiveness previously unattainable. Furthermore, the ReAct paradigm enables LLMs to simultaneously "think" and "act" via external tools, facilitating agent applications across multiple domains. The robust natural language understanding capabilities inherent in LLMs, combined with the task automation functionalities of LLM-powered agents, render them particularly suitable for addressing persistent challenges in educational contexts (Wang et al., 2025).

The evolution of online education necessitates a critical examination of how recent technological advancements can be optimally integrated into pedagogical frameworks. While the global pandemic precipitated widespread adoption of virtual learning environments, significant deficiencies persist in current implementations. Specifically, contemporary online educational platforms demonstrate inadequate mechanisms for instructors to comprehensively assess collective student engagement and comprehension in real-time (Xu et al., 2024). This paper proposes a novel framework for online education in which the instructor maintains a central but augmented role through the strategic deployment of LLM agents. The underlying principle asserts that technological integration should enhance, rather than supplant, human creativity and pedagogical oversight. We argue that the integration of advanced technologies, particularly LLM-based agent systems, holds substantial potential to enhance the personalization of education and, in turn, produce measurable improvements in learning outcomes. Realizing this potential necessitates a fundamental re-evaluation of current content delivery paradigms employed by mainstream Learning Management Systems (LMS) such as Moodle and Canvas. Specifically, we advocate for a shift from static, content-centric repositories to dynamic, agent-mediated learning environments characterized by high levels of collaboration, interoperability, and adaptability. Our research focuses on the design and deployment of multi-agent systems composed of proactive computational entities capable of identifying knowledge gaps, optimizing instructional content delivery, facilitating meaningful learner interactions, promoting critical thinking, increasing student engagement, and delivering personalized assessment feedback.

The actualization of this advanced learning platform requires a sequenced implementation approach. Our initial research phase concentrates on automating content generation processes within online learning environments while accommodating the four predominant learning modalities: Visual, Auditory, Read/Write, and Kinaesthetic (Gao et al., 2024). This phase aims to transform conventional text-based instructional materials into multimodal formats optimized for diverse learning preferences: i) Visual modality: Implementation of conceptual maps, statistical visualizations, diagrammatic representations, and abbreviated video content ii) Auditory modality: interactive activities involving speech and listening. iii) Read/Write modality: Creation of textual assessment instruments, including examinations, assigned tasks, structured worksheets, and analytical compositions. iv) Kinaesthetic modality: Design of experiential learning activities including scenario-based role simulations, practical exercises, and immersive simulations. While this comprehensive modality transformation presents considerable technical challenges, the process is substantially facilitated through LLM agent architectures that leverage contemporary generative artificial intelligence capabilities, including sophisticated text-to-text, text-to-image, text-to-audio, and text-to-video conversion technologies. Preliminary experimental findings are presented in subsequent sections.

2. Related work

The application of artificial intelligence within educational frameworks has demonstrated significant expansion during recent decades. Kamalov et al. (2023) categorize these implementations into four principal domains: (1) Personalized Learning Systems, (2) Intelligent Tutoring Systems, (3) Assessment Automation Mechanisms, and (4) Teacher–Student Collaborative Interfaces. Within the scope of the current investigation, personalized learning approaches and intelligent tutoring systems demonstrate particular relevance. Personalized learning methodologies enable individualized educational progression, allowing students to advance according to their specific cognitive capabilities and temporal requirements. Luan & Tsai (2021) documented enhanced engagement parameters and improved learning outcomes associated with these approaches. Intelligent Tutoring Systems (ITS) provide immediate formative assessment, respond to learner inquiries, and facilitate comprehension of complex conceptual structures. Mousavinasab et al. (2021) observed that customization of instructional components according to individual student characteristics facilitates the development of engaging educational environments that enhance motivational factors and promote active learning behaviors. Our proposed framework incorporates elements of both personalized learning and intelligent tutoring systems, specifically implemented through LLM agents that leverage advanced reasoning capabilities and tool integration to deliver highly individualized educational experiences.

Despite their relatively recent emergence, LLM agents have demonstrated considerable potential for educational applications. A comprehensive taxonomic examination of LLM agents in educational settings by Chu et al. (2025) delineates two principal categories: (1) Pedagogical Agents and (2) Domain-Specific Educational Agents. Within this classification framework, our proposal is situated within the pedagogical agents category, which encompasses technologies designed to automate complex instructional functions, including classroom simulation and learning resource recommendation. Significant developments in this domain include EduAgent (Xu et al., 2024), which introduces a structured profiling methodology comprising distinct cognitive patterns to facilitate adaptive learning processes. Wang et al.

(2025) further advanced this field by providing mechanisms for personalized content delivery. Our proposal diverges from previous LLM agent approaches by specifically targeting online learning environments through the development of a novel platform architecture. The fundamental infrastructure of this platform consists of a multi-agent system that deploys specialized LLM agents to create highly personalized learning experiences.

3. LLM Agents

Computational agents are defined as autonomous software entities that execute planning and action sequences based on underlying reasoning architectures. LLMs demonstrate significant efficacy when implemented as agent systems capable of coordinating sequential actions to achieve predetermined objectives. These LLM-based agent architectures maintain essential functional components, including model input/output interfaces, processing chains, and memory structures, while integrating two critical additional elements (Alammar & Grootendorst, 2024): 1) External tools that transcend inherent model limitations. 2) Strategic planning systems that coordinate tool selection and execution processes.

Contemporary high-performance agent systems predominantly operate through the Reasoning and Acting (ReAct) framework as their foundational architecture (Yao et al., 2023). This framework establishes systematic integration between complementary cognitive and execution processes. To facilitate action capabilities, LLMs receive structured information regarding available tool sets and specific textual command protocols that activate these external functional modules. In contrast to isolated LLM agent implementations that function independently, LLM-based multi-agent systems deploy multiple coordinated LLM agents with differentiated functional profiles to collaboratively address complex task requirements (Guo et al., 2024).

4. A new generation of online learning platforms based on LLM agents

Conventional LMSs have predominantly functioned as static repositories for educational content, despite offering supplementary features such as asynchronous discussion forums, interactive exercises, and collaborative functionalities. These systems exhibit inherent limitations regarding adaptability and personalization. We propose a paradigm shift toward next-generation online learning platforms characterized by deep integration of multi-agent systems, leveraging LLMs as their cognitive architecture. Within this dynamic learning environment, computational agents proactively intervene to provide individualized support and guidance to learners. The proposed platform architecture comprises three principal components:

Content Repository and Delivery System: The platform maintains instructional materials in various modalities, including presentation slides, portable document format (PDF) files, video-based instructional content, interactive assessment instruments, and evaluation mechanisms. While traditional hierarchical navigation through instructor-designed content sections remains available, we have prioritized the implementation of a conversational interface (chat) to facilitate human-system interaction, thereby enabling learners to access the multifunctional capabilities provided by the LLM-based agent system.

Enhanced Information Retrieval Mechanism: The platform implements semantic search functionality based on vector embeddings and keywords, augmented through Retrieval-Augmented Generation (RAG) methodologies.

Multi-Agent System Architecture: This component constitutes the central architectural element of the proposed platform. We have designed and implemented multiple specialized LLM agents that perform complementary educational functions, including content delivery, interaction facilitation, critical thinking development, engagement enhancement, and personalized assessment feedback provision. Figure 1 illustrates the multi-agent system architecture comprising three primary LLM agents: content generation agents, proactive learning guidance agents, and learning process feedback agents, each fulfilling specific pedagogical functions within the integrated learning environment.

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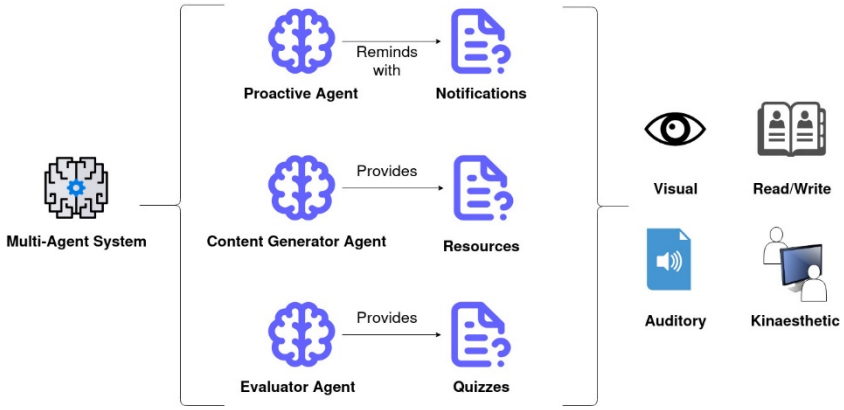
Figure 1. A new generation of online learning platforms based on LLM agents.



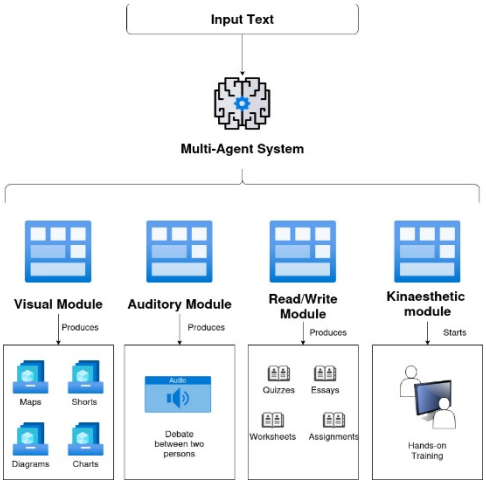
5. Preliminary results

The principal architectural component of this next-generation online learning platform is the multi-agent system. Despite inherent implementation complexities, the development of LLM agents is facilitated through established frameworks including Langchain, LlamaIndex, and Agent Development Kit (ADK). Our implementation utilizes LlamaIndex (accessible via https://docs.llamaindex.ai/en/stable/) as the primary development framework for LLM agent architecture. Additionally, we have employed Gemini 1.5 (accessible via https://gemini.google.com/) as the underlying LLM. It is worth noting that the architectural principles presented herein demonstrate framework-agnostic applicability and can be implemented across diverse agent frameworks and language models with tool execution or code execution capabilities.

To maximize student engagement parameters, we have developed mechanisms for dynamic, multimodal, and pedagogically valuable content generation. This functionality is implemented through LLM agents integrated within the online platform architecture described in the preceding sections. Acknowledging established learning modality preferences (Visual, Auditory, Read/Write, and Kinaesthetic), we have designed adaptive LLM agents capable of identifying and accommodating individual learning style preferences through iterative interaction analysis. Consequently, these agents demonstrate the capacity to transform conventional text-based instructional materials into multimodal formats optimized for diverse learning preferences: 1)Visual content generation: LLM agents equipped with visual generation tools process textual materials uploaded to the platform to create visual representations, including conceptual maps, statistical visualizations, diagrammatic illustrations, and abbreviated video content. 2)Auditory content synthesis: Utilizing text-to-speech conversion technologies, LLM agents can transform textual content into simulated dialectical exchanges between multiple speakers to facilitate comprehension of specific subject matter through auditory processing channels. 3) Read/Write content development: Through text-to-text transformation mechanisms, LLM agents generate assessment instruments, including examinations, assigned tasks, structured worksheets, and analytical compositions according to predetermined pedagogical criteria. 4) Kinaesthetic learning facilitation: LLM agents demonstrate behavioral adaptability based on learning outcome metrics and can simulate role-based scenarios through integrated visual, auditory, and textual modalities to provide experiential learning opportunities. This multimodal content generation architecture is illustrated in Figure 2.

To assess the viability of the proposed platform, we plan to conduct A/B testing within the online course offerings of the Department of Computer Science at UCSP. These courses currently utilize Moodle to provide access to learning materials and exercises, supplemented by real-time online instruction. Our evaluation will compare the learning outcomes of students using the traditional Moodle-based system with those engaging with the new platform, under equivalent instructional conditions and over the same period.

Figure 2. Content generation based on learning styles.



6. Conclusions

Most current LMSs function primarily as data repositories, which is useful for organizing content but limited in supporting active learning due to their static nature. To address this, we propose a new generation of online learning platforms centered around a multi-agent system powered by large language models (LLMs). These LLM agents deliver an engaging and highly personalized learning experience by answering specific questions, guiding learners through individualized learning paths, mediating discussions, and collaboratively supporting the achievement of targeted learning outcomes. While our findings are still preliminary, we plan to assess the impact of this approach through A/B testing.

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