

# Integration of multi-agent systems and large language models for the creation of personalized and collaborative digital educational environments<sup>1\*</sup>

Alberto Matilla-Molina<sup>1,\*†</sup>, Juan Manuel Dodero<sup>1,†</sup> and Andrés Muñoz<sup>1,†</sup>

<sup>1</sup> Universidad de Cádiz, Escuela Superior de Ingeniería, Av. Universidad de Cádiz, 10, 11519 Puerto Real, Cádiz, Spain

## Abstract

This research explores the integration of multi-agent systems and Large Language Models (LLMs) to design personalized, interactive, and collaborative digital learning environments. The main objective is to develop generative intelligent agents capable of dynamically adapting to user profiles and learning contexts within a multi-agent architecture. These agents will assume specific educational roles such as students, instructors, and learning resources. Preliminary pilot studies will validate the system's technical functionality, adaptability, and potential to enhance the effectiveness and personalization of the educational experience.

## Keywords

Multi-agent systems, Large Language Models (LLMs), Artificial Intelligence in Education, Generative Agents, Personalized Learning

## 1. Introduction and identification of the significant problem

In recent decades, the field of artificial intelligence (AI) in education has evolved from basic rule-based tutoring systems to highly adaptive digital learning environments [1][2]. However, current educational platforms lack holistic approaches integrating advanced language models and dynamic multi-agent architectures. Typically, Large Language Models (LLMs), such as GPT, are utilized as standalone tools, providing isolated responses or materials on demand without interactive coordination among educational components. Similarly, multi-agent systems have frequently relied on simple, limited-capacity agents, insufficiently leveraging recent advances in generative AI. Consequently, digital education environments still struggle to deliver genuinely personalized, interactive, and collaborative experiences. This research addresses this gap by proposing an integrated approach combining generative agents powered by LLMs within a robust multi-agent framework, enhancing both user engagement and educational effectiveness.

While the integration of LLMs and multi-agent systems represents a promising technological advance, it is essential to ground this research in specific educational challenges that persist in current digital learning environments. Notably, two interconnected problems have been consistently highlighted in the literature: (1) the lack of real-time, context-aware personalized feedback, and (2)

---

<sup>1</sup>SNOLA LASI SPAIN 2025 DC: Doctoral Consortium of the Learning Analytics Summer Institute Spain, May 29-31 2025, Vitoria, Spain

\* Corresponding author.

† These authors contributed equally.

 [alberto.matillamolina@alum.uca.es](mailto:alberto.matillamolina@alum.uca.es) (A. Matilla); [juanma.dodero@uca.es](mailto:juanma.dodero@uca.es) (J.M Dodero); [andres.munoz@uca.es](mailto:andres.munoz@uca.es) (A. Muñoz)

 [0009-0002-8968-8130](https://orcid.org/0009-0002-8968-8130) (A. Matilla); [0000-0002-4105-5679](https://orcid.org/0000-0002-4105-5679) (J.M.Dodero); [0000-0002-8491-4592](https://orcid.org/0000-0002-8491-4592) (A. Muñoz)

the limited support for meaningful asynchronous collaboration among learners and between learners and resources [30][31]. These issues are especially prevalent in online higher education and adult learning programs, where students must often navigate complex tasks with minimal guidance and limited interaction. Despite the availability of adaptive components in many platforms, these are frequently deployed in isolation and without semantic alignment. LLMs are typically used as standalone tools for content generation or summarization [32], while multi-agent systems tend to focus on task distribution without generative or adaptive capabilities [33]. As a result, learners experience fragmented interactions that fail to promote sustained engagement, self-regulation, or collaborative knowledge construction. By addressing these pedagogical gaps directly, the proposed research aims to demonstrate how the integration of generative agents—each assuming distinct educational roles within a multi-agent framework—can enhance personalization, interaction coherence, and collaborative learning. The emphasis shifts from a purely technological proposition to one that is pedagogically informed and context-sensitive, aligning with ongoing concerns in the Learning Analytics and AI in Education communities.

## 2. Research objectives and questions

The primary objective of this research is to design, implement, and evaluate an advanced digital learning environment integrating generative intelligent agents based on Large Language Models (LLMs) within a multi-agent architecture. Specifically, the research seeks to develop context-aware agents capable of dynamically assuming educational roles (students, teachers, learning resources), adapting to user profiles and diverse learning contexts through clear methods of translating agent roles, goals, and relationships into actionable instructions for LLMs. The effectiveness of the proposed system will be validated empirically in real educational settings, focusing on improved personalization, user satisfaction, and interaction coherence. To better address the complexity of the proposed research, the main research question is articulated in two complementary levels:

- Technological perspective: *How can generative agents based on Large Language Models (LLMs) be effectively integrated into a multi-agent system to support differentiated educational roles and dynamic interaction strategies?*
- Educational perspective: *What is the impact of this integrated multi-agent framework on personalization and collaborative learning in asynchronous digital educational environments?*

This dual formulation enables a clearer distinction between the system's architectural development and its pedagogical impact, allowing the research to align both technological design and educational evaluation more precisely.

## 3. Current state of knowledge

Over the past few decades, the field of artificial intelligence (AI) applied to education has evolved from relatively simple and rigid systems to interactive and adaptive environments, with the aim of improving the quality, accessibility, and personalization of learning [3,4]. This trajectory has been marked by the transformation from symbolic computing to increasingly complex machine learning techniques, culminating in the adoption of both small- and large-scale language models, as well as the implementation of multi-agent systems [5,6]. These two pillars—language models and intelligent agents—constitute the core of the current line of research in more advanced digital educational environments. In the early stages of AI in education, the focus was on Intelligent Tutoring Systems (ITS) based on rules and limited adaptations [7,8]. These tutors employed relatively simple algorithms, used static representations of knowledge, and offered a learning experience centered on text and static content. Later, thanks to the rise of machine learning, models capable of adapting

content and instructional sequencing based on student responses began to be integrated, gradually enhancing the personalization of the educational experience [9,10]. The arrival of large-scale language models, such as GPT or BERT, among others, has brought about a revolution in the educational domain [11,12]. These architectures, trained on massive amounts of text, demonstrate a remarkable capacity to understand and even produce coherent and contextually appropriate texts, enabling their use in various applications: automated tutoring, generation of study materials, assisted grading, recommendation of supplementary readings, and linguistic support for students facing difficulties [13,14]. At the current state of the art, consolidated experiences are already in place using LLMs to provide immediate feedback to students, improve accessibility (e.g., through text simplification or creation of adapted summaries), as well as to assist teachers in content management and exam grading [15]. Likewise, there are systems that employ these models to generate, on demand, exercises and didactic materials tailored to different levels of knowledge [16]. However, until recently, the integration of LLMs into educational environments was not usually conceived holistically: in many cases, they were treated as isolated tools that provided responses or content on demand, without dynamic interaction or coordination with other components of the educational environment [5]. This is where multi-agent systems come into play. The theory and practice of multi-agent systems in education date back decades, with research proposing autonomous pedagogical agents collaborating to present information, guide students, or facilitate communication among different actors [17,18]. Nevertheless, most of these approaches relied on agents with limited capabilities and simple communication languages [19]. The current state of research, driven by advances in AI and increased computational power, allows for the conception of an ecosystem of generative agents, each specialized in a specific role (for example, a “tutor” agent answering complex questions, an “administrative” agent managing time and resources, or a “learning object” agent acting as the semantic representation of a specific educational resource) [20,21]. These lines of research have been fueled by a growing interest in creating more social, collaborative, and realistic learning environments [22]. The notion of agents representing different types of users (students, teachers, administrators) and elements (learning objects, assessment tools, planning resources) is based on the hypothesis that the interaction between multiple intelligent entities, each with its own semantically defined “personality” and “goals,” can simulate the complexity of a real classroom or even surpass it in terms of adaptability and scope [23]. This multi-agent paradigm fosters fluid and personalized communication, collaboration on complex projects, ongoing formative assessment, and adaptive support throughout the entire learning process. At the level of research projects and groups, initiatives have emerged that have achieved some of these objectives in a fragmented manner [24,25]. On the one hand, there are groups that have delved into the use of LLMs and conversational tutors to support problem-solving or explain complex concepts [26]. On the other hand, teams specialized in multi-agent systems have developed platforms aimed at coordination and task distribution among various educational agents [27]. The specific contribution of the present project, compared to those previously mentioned, lies in the holistic integration of multi-role generative agents with advanced contextual capabilities through Fine-Tuning techniques [28] and Retrieval-Augmented Generation (RAG) [29], as well as in their systematic evaluation in real educational scenarios, something that has not been thoroughly addressed by previous research. The convergence of these developments marks the current state of research. The literature reflects a growing interest in integrated solutions that not only provide on-demand answers but also generate an organic learning space with multiple voices, roles, and perspectives. The emerging vision is that of enriched environments where intelligent agents are not mere conversational assistants but active components of a digital academic community. This community spans from the generation and reuse of high-quality educational content, through mediation in collaborative dynamics, to the safeguarding of user privacy, rights, and ethics.

## 4. Methodology

This thesis uses a structured methodology based on Design-Based Research (DBR), adapted from Reeves' model for Technology-Enhanced Learning (TEL), integrating multi-agent systems and Large Language Models (LLMs). Initially, a systematic literature review identifies gaps guiding the research design. A multi-agent architecture using Fine-Tuning and Retrieval-Augmented Generation (RAG) ensures contextual interaction. Educational datasets from Kaggle and Datahub.io, diverse in size and demographics, support the research. The initial hypothesis proposes that generative LLM-based agents enhance learning personalization compared to traditional methods, with future phases addressing academic performance, student motivation, and educational effectiveness. Experiments will test various LLMs, adjusting parameters like temperature and tailored prompts. Evaluation of the results will be carried out with statistical metrics (precision, mean absolute error, mean score difference, AUC) with qualitative feedback from users to validate the performance and adaptability of the system. The adoption of a Design-Based Research (DBR) methodology is particularly appropriate for this work, as it enables the iterative development and refinement of technological solutions grounded in authentic educational practice. Following the four-phase model proposed by Reeves, the research will proceed through: (1) analysis of practical problems in online higher education contexts; (2) design of a prototype integrating LLM-based agents within a multi-agent architecture; (3) iterative testing and refinement through classroom interventions; and (4) reflection to produce design principles and theoretical insights. These cycles will be implemented in a postgraduate blended course where students will access the deployed multi-agent system via a dedicated campus server. This environment allows for fine-grained control of experimental conditions while enabling realistic interactions with generative agents in both synchronous and asynchronous learning tasks. This approach ensures that technical feasibility and pedagogical relevance are addressed in parallel, generating knowledge that is both actionable and generalizable.

Although the proposed framework emerges from the tradition of Artificial Intelligence in Education, it also establishes a clear alignment with the Learning Analytics (LA) paradigm. In particular, the architecture includes a specialized "metrics agent" responsible for capturing structured interaction data during learning sessions. This agent logs key behavioral indicators such as response times, content navigation paths, dialogue coherence, frequency of agent-student exchanges, and indicators of collaborative engagement. These data points are not only stored for posterior analysis but also processed in real time to support adaptation of the system's responses and resources, forming a closed feedback loop that is central to LA. Where possible, data interoperability will be ensured by aligning the captured events with standard specifications such as Experience API (xAPI) or IMS Caliper, enabling future integration with external learning record stores and dashboards. Furthermore, aggregated metrics will inform post-hoc evaluations of learning effectiveness, usability, and collaboration, following standard LA practices. In this way, the framework supports both formative and summative analytics, contributing insights for learners, instructors, and system designers alike.

All interaction data will be collected and processed under strict ethical protocols, ensuring user privacy, informed consent, and compliance with relevant institutional and legal guidelines for educational research.

## 5. Expected contributions

This research contributes by integrating generative intelligent agents, powered by LLMs, within a comprehensive multi-agent educational framework. Unlike existing fragmented approaches, this system uniquely employs advanced Fine-Tuning and Retrieval-Augmented Generation (RAG) techniques, enabling adaptive, context-aware agent interactions. Empirical validations in real

educational environments will demonstrate enhanced personalization, learner engagement, and coherent collaboration, surpassing current isolated implementations.

## 6. Current state of the work and results achieved so far

The research has completed a systematic literature review identifying gaps in integrating multi-agent systems and LLMs for education. Initial prototypes of generative agents (students, tutors, learning resources) have been designed and preliminary tests confirm technical feasibility and contextual adaptability. Further work involves advanced Fine-Tuning, RAG integration, scalability testing, and comprehensive empirical validation in authentic educational scenarios.

## 7. Acknowledgments

This publication is part of the R&D&i Project PID2023-149674OB-I00, funded by MCIU/AEI/10.13039/501100011033 and ERDF, EU.

## Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

## 8. References

- [1] Servicio de Publicaciones de la Universidad de Murcia. (2023). Incidencia de la Inteligencia Artificial en la educación. *Educatio Siglo XXI*, 41(3), 235–264. <https://doi.org/10.6018/educatio.555681>
- [2] UNESCO. (2025). La inteligencia artificial en la educación. Recuperado de <https://www.unesco.org/es/digital-education/artificial-intelligence>
- [3] Luckin, R. (2017). Towards artificial intelligence-based assessment systems. *Nature Human Behaviour*, 1.
- [4] Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and learning. Center for Curriculum Redesign.
- [5] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where Are the Educators? *International Journal of Educational Technology in Higher Education*, 16(1), 1-27. <https://doi.org/10.1186/s41239-019-0171-0>
- [6] VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197–221. <https://doi.org/10.1080/00461520.2011.611369>
- [7] Nkambou, R., Mizoguchi, R., & Bourdeau, J. (2010). Advances in Intelligent Tutoring Systems. Springer.
- [8] Woolf, B. P. (2009). Building Intelligent Interactive Tutors: Student-centered Strategies for Revolutionizing E-learning. Morgan Kaufmann. <https://doi.org/10.1016/B978-0-12-373594-2.00019-8>
- [9] Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L.J., & Sohl-Dickstein, J.N. (2015). Deep Knowledge Tracing. ArXiv, abs/1506.05908.
- [10] A Review on Artificial Intelligence in Education. (2021). *Academic Journal of Interdisciplinary Studies*, 10(3), 206. <https://doi.org/10.36941/ajis-2021-0077>
- [11] Qiu, X., Sun, T., Xu, Y. et al. Pre-trained models for natural language processing: A survey. *Sci. China Technol. Sci.* 63, 1872–1897 (2020). <https://doi.org/10.1007/s11431-020-1647-3>
- [12] Peláez-Sánchez, I. C., Velarde-Camaqui, D., & Glasserman-Morales, L. D. (2024). The impact of large language models on higher education: Exploring the connection between AI and Education 4.0. *Frontiers in Education*, 9, Article 1392091. <https://doi.org/10.3389/feduc.2024.1392091>
- [13] Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, Article 102274. <https://doi.org/10.1016/j.lindif.2023.102274>

[14] Zhai, Xiaoming. (2023). ChatGPT and AI: The Game Changer for Education. [10.13140/RG.2.2.31107.37923](https://doi.org/10.13140/RG.2.2.31107.37923)

[15] Baidoo-anu, D., & Owusu Ansah, L. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. *Journal of AI*, 7(1), 52-62. <https://doi.org/10.61969/jai.1337500>

[16] Lohr, D., Berges, M., Chugh, A., Kohlhase, M. and Müller, D. (2025), Leveraging Large Language Models to Generate Course-Specific Semantically Annotated Learning Objects. *J Comput Assist Learn*, 41: e13101. <https://doi.org/10.1111/jcal.13101>

[17] Jiang, Y.-H. (2024). AI Agent for Education: von Neumann Multi-Agent System Framework. *arXiv preprint arXiv:2501.00083*. <https://arxiv.org/abs/2501.00083>

[18] Schroeder, N., & Adepo, A. (2014). An evaluation of the effectiveness of using pedagogical agents for learning. *AI and IE Book Chapter*. <https://maggisavinbaden.wordpress.com/wp-content/uploads/2018/09/ai-and-ie-book-chapter.pdf>

[19] Murciano A, Millán J del R. Learning Signaling Behaviors and Specialization in Cooperative Agents. *Adaptive Behavior*. 1996;5(1):5-28. doi:10.1177/105971239600500102.

[20] Castillo Herrera, M. E. (2023). Impacto de la inteligencia artificial en el proceso de enseñanza y aprendizaje en la educación secundaria. *LATAM Revista Latinoamericana de Ciencias Sociales y Humanidades*, 4(6), 515-519. <https://doi.org/10.56712/latam.v4i6.1459>

[21] González-González, C. S. (2023). El impacto de la inteligencia artificial en la educación: transformación de la forma de enseñar y de aprender. *Revista Qurriculum*, 36, 51-60. <https://doi.org/10.25145/j.curricul.2023.36.03>

[22] Dillenbourg, P. (2013). Design for classroom orchestration. *Computers & Education*, 69, 485-492. <https://doi.org/10.1016/j.compedu.2013.04.013>

[23] Park, J. S., Fong, C., Kleeman, H., Chadha, S., & Feinberg, J. (2023). Generative Agents: Interactive Simulacra of Human Behavior. *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, 1398–1413. <https://doi.org/10.1145/3586183.3606763>.

[24] Chung, H. J., Iorga, M., Voas, J., & Lee, S. I. (2023). Emerging AI-Based Models for Tutoring: A Preliminary Study. *arXiv preprint arXiv:2305.14595*. <https://arxiv.org/abs/2305.14595>

[25] Xue, S., Wu, Y., Hailu, S., Feng, F., & Wang, J. (2023). Enhancing Multi-Agent Coordination via Quasi-Recursive Policy Optimization. *arXiv preprint arXiv:2307.08241*. <https://arxiv.org/abs/2307.08241>

[26] University of Sydney. (2023). AI tutoring system to guide first-year university students. <https://www.sydney.edu.au/news-opinion/news/2023/05/22/ai-tutoring-system-to-guide-first-year-university-students.html>

[27] Xue, S., Wu, Y., Hailu, S., Feng, F., & Wang, J. (2023). Enhancing Multi-Agent Coordination via Quasi-Recursive Policy Optimization. *arXiv preprint arXiv:2307.08241*. <https://arxiv.org/abs/2307.08241>

[28] Fine-Tuning: Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). *Language models are unsupervised multitask learners*. OpenAI. [https://cdn.openai.com/better-language-models/language\\_models\\_are\\_unsupervised\\_multitask\\_learners.pdf](https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf)

[29] Retrieval-Augmented Generation (RAG): Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Kütter, H., Lewis, M., Yih, W.-t., Rocktäschel, T., Riedel, S., & Kiela, D. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. In *Advances in Neural Information Processing Systems (NeurIPS 2020)* (pp. 9459-9474). <https://proceedings.neurips.cc/paper/2020/file/6b493230205f780e1bc26945df7481e5-Paper.pdf>

[30] Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Center for Curriculum Redesign.

[31] Dillenbourg, P. (2013). Design for classroom orchestration. *Computers & Education*, 69, 485–492. <https://doi.org/10.1016/j.compedu.2013.04.013>

[32] Kasneci, E., Sessler, K., Küchemann, S., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>

[33] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16(1), 1–27. <https://doi.org/10.1186/s41239-019-0171-0>