Learning with Conversational AI and Personas: A Systematic Literature Review

Antun DROBNJAK[a], Ivica BOTICKI[a*], Peter SEOW[b], Ken KAHN[c]
[a]*Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia*
[b]*National Institute of Education, Nanyang Technological University, Singapore*
[c]*University of Oxford, United Kingdom*
*ivica.boticki@fer.hr

Abstract: This paper describes the results of a systematic review dealing with the use of personas, avatars, and characters in conjunction with AI-supported tools such as chatbots or generative AI in education. Although the use generative AI in education is gaining traction, this study seeks to systematically review the body of knowledge dealing with personified and conversational approaches to education with both pre-generative and generative AI. The results of the study emphasize the importance of the three key elements of such systems: the use of pedagogical agents, interaction, and personalization. These key elements can be relevant when considering the adoption of the new generation of generative AI in education. Such systems should scaffold learners' understanding providing guidance and support, promote self-directedness and ensure effectiveness in learning, provide customized learning paths, and promote ethical use.

Keywords: Conversational AI, Generative AI, learning, education, pedagogical agents, personas

1. Introduction

This paper deals with the domain of AI use in education to achieve greater interaction and hence a more immersive educational environment for the students. With the rise of AI in all facets of society, researchers and practitioners have been keen on using it as a tool to supplement pedagogies, which could possibly lead to improved educational outcomes (Huang et al., 2021). The development of AI has had a profound impact on the field of pedagogy by providing new opportunities and opening new challenges. Traditional educational approaches often rely on human teachers delivering instruction, but AI opens up possibilities for automated teaching and content delivery.

With the appearance of generative AI, the potential of AI in education is even more obvious and has gained traction across the globe. In terms of interaction, generative AI has led to the creation of various interactive tools and systems. Additionally, large language models (LLMs), such as the GPT-based models, enable learners to interact with AI systems through natural language, facilitating more nuanced and contextualized conversations.

With generative AI there is a potential to contribute to the improved interaction in the educational process potentially leading to educational benefits (Xu et al., 2022), but pedagogical approaches to achieve so are still work in progress. The challenges become increasingly evident when we delve into the technological peculiarities of generative AI. In this domain, one must closely examine these tools within the context of the machine learning language models they produce, which inherently operate on a probabilistic basis (Lim et al., 2023).

The study is a systematic review study conducted according to the PRISMA methodology yielding a specific set of relevant research papers in the field. The study results indicate that the most relevant studies using virtual agents, avatars, personas, chatbots and other AI-empowered tools in education emphasize pedagogical agents, interaction and personalization as key elements contributing the improved educational results and processes. These are further discussed in the paper.

2. Background

Pedagogy for AI in education refers to the principles and practices that should guide the development and implementation of AI technologies in educational settings. The goal of pedagogy for AI in education is to ensure that these technologies support effective teaching and learning practices and align with the educational objectives (Huang et al., 2021). AI technologies have the potential to revolutionize education, providing students with customized learning experiences and educators with valuable insights into learning processes and outcomes.

According to Järvelä (2006), personalized learning has the potential to enhance student interest and motivation, particularly when students are provided with opportunities to stimulate their creativity and curiosity. Personalized learning can take many different forms, from adaptive learning systems that adjust the difficulty of content based on learner performance to project-based learning that allows learners to explore topics that interest them. For example, according to the findings of Brown et al. (2006), university students expressed a preference for utilizing a personalized virtual learning environment (VLE) for exam revision as compared to non-personalized methods.

Ouyang & Jiao (2021) proposed three paradigms - intelligent tutoring systems, learning analytics, and educational data mining, that can support personalized learning experiences, improve educational outcomes, and inform decision-making in educational settings. These paradigms align with the goals of pedagogy for AI in education, which prioritize the ethical and responsible use of AI technologies while also promoting effective teaching and learning practices.

In their paper Van Brummelen et al. (2021) presented four design recommendations for Human Computer Interaction (HCI), including considering personification, transparency, playfulness, and utility that could improve design of AI-based systems. When designing AI-based learning systems, it is crucial to consider how users interact with the system, what information they need to provide, and how the system provides feedback and guidance. Xu et al. (2022) proposed scaffolding as a solution to improve feedback and guidance. In their paper Crearie (2013) emphasizes the need for HCI to be integrated into the development of such systems and notes that AI-based learning systems have the potential to revolutionize education by providing personalized learning experiences. Main challenge in designing HCI for AI-based learning systems is to balance the need for personalization and standardization.

3. Methodology

The PRISMA method is a systematic approach to conducting reviews that involves three main stages: identification, screening, and eligibility assessment. (Liberati et al., 2009).

The search query was designed to cover the three main areas and to explore the studies at their intersection: personas, characters and avatars; AI-powered tools including chatbots and generative AI tools; and education (Table 1).

Table 1. *Search query*

Search query (Web of Science)

ALL=((persona or personas* or character or characters* or avatar or avatars*) and (chat-bot or "chat bot" or chatbot or chatgpt or "gpt*" or ai or "open ai") and (education* or school*))

The query was applied (in April 2023) to the Web of Science database yielding 576 results (both journal and conference papers). Papers had to focus on the use of AI, chatbots and virtual environments in education and had to be oriented towards the interaction between AI and students. Additionally, the papers should be based on a conducted study rather than being purely theoretical (Table 2).

Table 2. *The first set (A) of the study inclusion and exclusion criteria*

	Criteria
A1	The paper should focus on the use of AI-empowered chatbots, avatars, personas and virtual environments in education
A2	The paper should include studying interaction between the tools and students
A3	The paper should be based on a conducted study rather than being purely theoretical

These initially agreed-upon criteria were applied to 80 papers by examining the papers' titles and abstracts by both coders. The degree of mutual agreement was measured in the form of Cohen's kappa coefficient (Altman, 1990; Landis & Koch, 1977). Coding resulted in excellent agreement with the interrater reliability for the raters found to be Kappa = 0.91. The selection of the remaining papers was performed by one coder by applying the approach agreed upon by the two coders.

The application of inclusion and exclusion criteria resulted in a set of 56 studies. To extract the most relevant and the most rigorous studies, the second set of inclusion and exclusion criteria was applied to further narrow the results (Table 3).

Table 3. *The second set (B) of the study inclusion and exclusion criteria*

	Criteria
B1	Study needs to explore the concept of interactive or personalized learning
B2	Study needs to measure the impact on learning and wellbeing

This finally resulted in 35 studies for which full-text screening was conducted. The full-text screening was more thorough compared to the title and abstract screening and especially focused on selecting the studies that used techniques based on interaction and personalized learning in improving the educational processes. Following that, 25 papers were excluded, leaving 10 papers in the final list.

The whole PRISMA process is depicted in the diagram in Figure 1.

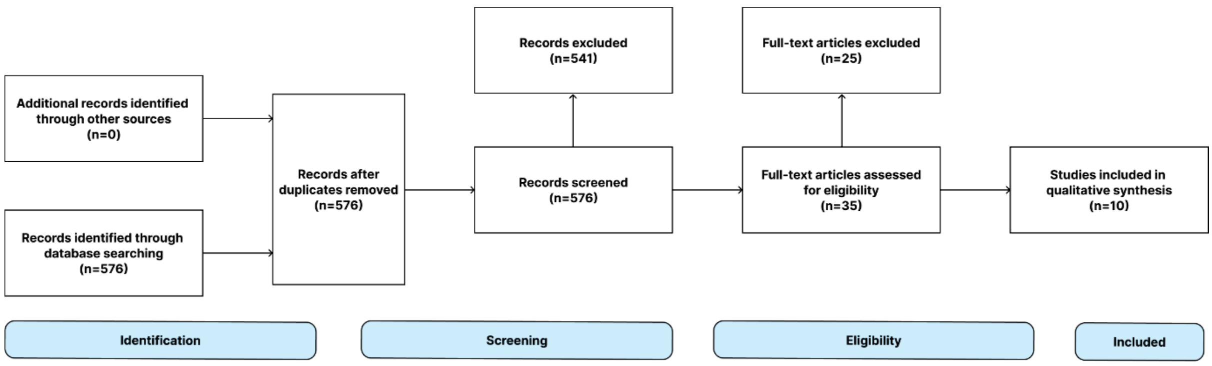

Figure 1. Prisma diagram flow for the study.

4. Results

A total of 10 studies were selected for close examination as part of this review. All of them focus on education or propose an approach that could be applied in educational scenarios. They are oriented towards all ages of participants including students and children, with sample sizes ranging from 20 to 47. (Table 3).

Table 3. The final set of selected studies (N=10) after the application of the literature review steps

Author and year	Topic	Targeted age groups	User study participants
Terzidou et al., 2016	Pedagogical agents	Students	41
Pataranutaporn et al., 2021	AI generated characters	All ages	-
Van Brummelen et al., 2021	Conversational agents	Students	47
Haller & Rebedea, 2013	Chatbots	All ages	-
Chien & Yao, 2020	Chatbots	Students	12
Xu et al., 2022	Interactive video	Children	20
Park et al., 2022	Humanoid robot	All ages	-
Almahri et al., 2019	Persona design	All ages	-
Fu et al., 2022	Knowledge-grounded conversation	All ages	-
Almahri et al., 2021	Persona design	All ages	-

Overall, the studies problematize interaction between humans and technology as a key to students' better performance and. Xu et al. (2022) suggest that enabling the kind of contingent interaction between child viewers and media characters can bring additional educational benefits not available through standard video programming.

There is an overarching focus on pedagogical agents which are intelligent computer programs that can interact with students to provide guidance and feedback. They are designed to be conversational and engage students in a personalized and interactive learning experience. Terzidou et al. (2016) problematized the effectiveness of pedagogical agents in supporting student learning in online courses and found that the use of pedagogical agents can have a positive impact on students' learning.

Pataranutaporn et al. (2021), Fu et al. (2022), Almahri et al. (2019), Almahri et al. (2021), Park et al. (2022) and Chien & Yao (2020) found that personalization can positively affect students' motivation, engagement, and outcomes while similarly Van Brummelen et al. (2021) found that collaborative virtual environments can enhance student learning outcomes.

Haller & Rebedea (2013) presented a method for building a conversational agent with personality and knowledge about historical figures, which can be used in educational contexts. Similarly, Fu et al. (2022) highlighted importance of agents' personal memory in conversation that can significantly improve their responses. Xu et al. (2022) proposed a more advanced framework for designing pedagogical agents that ask questions, give feedback, use scaffolding, and can adapt to students' learning needs in real-time. The study showed that this kind of framework can improve the effectiveness of pedagogical agents in supporting student learning.

5. Discussion

By integrating pedagogical approaches into generative AI, educators can leverage these systems as valuable teaching tools that support and enhance student learning outcomes. For example, in their study Xu et al. (2022) show that scaffolding, a concept rooted in pedagogy that refers to providing learners with support and guidance as they progress in their learning journey, can enhance learning experience. In the context of generative AI, the AI models can be designed to scaffold learners' understanding by providing step-by-step explanations, hints, or examples tailored to their individual needs and can act as virtual tutors offering personalized guidance and support.

Interaction is a key element in the integration of generative AI into educational settings, enabling learners to actively engage with AI systems in meaningful and dynamic ways. One form of interactive AI is chatbots, which have gained popularity in education. Chatbots can serve as virtual tutors or assistants, providing instant feedback, answering questions, and guiding learners through various educational tasks. Another form of interactive AI is humanoid robots, which offer a physical presence and mimic human-like interactions. These robots can engage in conversations, demonstrate concepts, or facilitate hands-on activities. Language models, such as large language models (LLMs), are another powerful tool for interactive AI in education. These models have been trained on vast amounts of data and can process and generate human-like responses to text inputs. LLMs can engage in natural language conversations with learners, providing information, explanations, and insights.

Through dialogue and interaction, AI systems can adapt to learners' responses, tailor content and activities to their specific needs, and offer customized feedback. The interactive nature of AI systems fosters active learning, promotes self-directed exploration, and empowers learners to take an active role in their educational journey. However, the integration of interactive AI in education should be carefully designed and accompanied by human guidance to ensure its effectiveness and ethical use.

Personalization is a key objective in education, and generative AI has the potential to adapt to individual learners, enhancing personalized learning experiences. By leveraging data and advanced algorithms, generative AI models can analyze student performance, preferences, and learning patterns. This information can then be used to tailor the content and delivery of educational materials to meet each student's specific needs. The configuration and adaptability of generative AI models allow for dynamic adjustments, providing customized learning paths, adaptive assessments, and individualized support. This personalized approach empowers students to learn at their own pace, explore their interests, and maximize their learning potential.

6. Conclusions

The development of generative AI has brought the potential for significant advancements in the fields of pedagogy, interaction, and personalization in education. By integrating pedagogical principles into AI systems, educators can leverage generative AI as powerful teaching tools, supporting and enhancing student learning outcomes. The interactive nature of AI systems, such as chatbots, humanoid robots, and LLMs, promotes engagement and facilitates dynamic learning experiences. These systems allow learners to actively interact with educational content and receive immediate feedback fostering active participation and deeper understanding. The combination of pedagogy, interaction, and personalization in generative AI holds great potential to revolutionize education, providing learners with more effective, engaging, and personalized learning experiences. However, it is important to ensure that the integration of AI in education is accompanied by ethical considerations and human guidance to maximize its benefits and mitigate any potential challenges. With further research, development, and collaboration between AI technologies and human educators, the future of generative AI in education looks promising, with a transformative impact on teaching and learning.

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