Generative AI as Peer Learning Companions: A Literature Review

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Abstract

The emergence of generative artificial intelligence (AI) has gained significant attention from researchers in the field of Artificial Intelligence in Education (AIED), particularly concerning its potential applications in next-generation e-learning systems. However, much of the existing literature—including studies on earlier AI techniques—tends to emphasise the role of AI primarily as tutors or analytic tools. This focus often overlooks the possibilities of AI functioning as peer learning companions or in other terms - co-learners. This literature review examines the current state of research in this domain, outlining the theoretical foundations and highlighting representative previous experiments. In addition, it summarises the roles and interaction models of AI as learning companions while addressing the limitations and challenges associated with future development of similar peer learning systems that incorporate generative AI agents as participants.

Keywords *AIED, Learning companions, Artificial Intelligence, Generative AI*

1 Introduction

Artificial Intelligences (AI) have revolutionised modern education by assisting teachers or students or even taking their roles and becoming parts of the digital learning environment. The recent boom of Generative AI technologies, which is a distinct class of AI, has particularly made a significant global impact, sparkling considerable debate and tension, especially within the education sector - the AIEd (Artificial Intelligence in Education) (Lim et al, 2023). The concept of Generative AI is popularised by ChatGPT, which amazed the world with its capability to comprehend diverse and complex human language and generate rich and structured human-like responses. Bringing radical reform to human-computer interactions, both academic institutes and commercial companies are exploring its applications in education.

Before artificial intelligence (AI) achieved its current remarkable capabilities in communication and interaction, it was predominantly employed in computer-supported learning environment as an analytical tool. These AI tools manipulate study materials, track student performance, and deliver timely feedback. A more interventionist application of AI involves it substitutes the role for tutors or peers, actively participating in the learning process rather than merely serving as recorders or observers when being tools. This approach is known as a learning companion system (LCS), a variant of intelligent tutoring systems (ITS). In such systems, AI learning companions can play various roles; they may collaborate with human learners, create challenges or troubles, or even compete against them. The ultimate objective of these interactions is to enhance student motivation, deepen their understanding of knowledge, and cultivate essential soft skills, such as collaboration and critical thinking. In the following sections, we will delve into relevant previous studies that explore these concepts further.

Despite the well-development of AIEd literature reviews, there aren't many directly focusing on AI as human-like peer learning companions, most of them are about AIs as analytic tools or as tutors. The main reason might be that before this recent attention on Generative AI, there weren't many such implementations due to lack of advanced technologies, which not only entail the possibility for AI to build real-time and spontaneous communications with human users, but also open the potential for AI to have personalities. So **this paper aims** to serve as a practical guidance on the future development of such a learning system, providing support on theoretical framework on the system design. In sum, this term paper is a literature review on the implementation of and support from artificial intelligent agents as learning companions in the collaborative learning environment, with a special focus on their roles as human-like peer classmates. More specifically, this review paper seeks insights into the following key questions: (1) What could be the roles of AI agents as learning companions? (2) How can their contributions or performance be evaluated?

2 The Field: ITS and Learning Companions

One form of AIEd's disruptive and transformative application is Intelligent Tutoring Systems (ITSs). Originally proposed by Carbonell (1970), it refers to computer programs "designed to incorporate techniques from the AI community in order to provide intelligent tutors which know what they teach, who they teach, and how to teach it" (Nwana, 1990). In short, they are AI-driven educational tools designed to provide personalised and adaptive instruction (Lin et al., 2023). These systems can assess students' psychological states alongside the knowledge and skills, track progress, and offer in-time and adaptive feedback to individual needs.

The four key components of such a system are: (1) Domain expert module for subject knowledge which is used to evaluate the students' performance and to represent the goal of teaching. (2) A student diagnosis module to "model" the student, track their progress and provide adaptive, (3) a pedagogical module for delivering personalised content and determining when and how to instruct the student. And (4) a user interface for communication and interaction between users and systems, and it often processes natural language. (Burns and Capps, 1988; Carter, 2014; Ma et al., 2014) However, it's not required to have all four of them, what matters most are the learning companions and the students. For example, the "People Power" system designed by Dillenbourg and Self (1992) has no domain model, but tries to acquire it by interacting with the student; it has no tutoring component, the co-learner having no hidden didactic plans.

Since the origin in 1970 and the growth from 1980s, it has increasingly incorporated **artificial intelligence techniques**. For instance, natural language processing (NLP) is used in chatbots for student interaction and feedback (Lin and Mubarok, 2021), while machine learning aids in performance prediction and learning analytics (Ouyang et al., 2023). Additionally, image recognition technology can analyse students' emotions or gestures to help educators adjust their teaching strategies (Singh et al., 2022). Generative AI as a relatively new technique, its potential is yet to be discovered.

AI integration in tutoring systems can be categorised into two main approaches. The first approach analyses log data without interfering with the tutoring process, using data mining and unsupervised learning to understand learning behaviours (Ouyang et al., 2023). The second, more complex approach involves embedding AI for performance prediction and personalised learning (Singh et al., 2022), allowing real-time adaptations and interventions to enhance student support. This integration necessitates careful system architecture to accommodate the tightly coupled AI algorithms and their adaptive learning capabilities.

Generative AI agents as learning companions would belong to this second category as it actively intervenes in the learning process, but the system would be slightly different.

As a matter of fact, the paradigm of this field has shifted to de-emphasizing the role of computers as authorised teachers for transmitting certified knowledge and the development of **learning companion systems** is one of them (Chou et al., 2003). ITS has been criticised for being inherently based on one-to-one interactions between a student and a tutor and cannot encompass the richer learning possibilities opened up by involving more than one learner. To improve this, an additional role besides students and tutors are added, which gives us the Learning Companion System (LCS). LCS is a variation of an Intelligent Tutoring System (ITS), yet on the contrary to ITS, it involves at least three characters - the human students, the computer-simulated teacher, and most importantly, the additional computer-simulated learning companions, or simply companions (Chan and Baskin, 1988, 1990). A learning companion, according to Chou et al. (2003), is "a computer-simulated character which has human-like characteristics and plays a non-authoritative role in a social learning environment".

It is important that we **distinguish two terms**: Computer-Supported Collaborative Learning (CSCL) and ITS. CSCL is defined as a means of learning and instruction that can foster the social nature of learning by using a variety of technological and pedagogical strategies (Stahl et al., 2006). CSCL shifted attention from individual learning processes to the ways groups learn together through interaction. Instead of relying on computers to replicate human teaching (as ITS did), CSCL focused on using technology to support group discussions and collaboration, where learning happens through shared activities among students. Instead of replacing the tutors or peers as in ITS, the primary role of CSCL systems is to facilitate communication, often integrating multiple media like chat, email, discussion forums, and video conferencing. These platforms are designed to enhance group collaboration, sometimes using AI to provide scaffolding through feedback or alternative views on student discussions. In short, while AI in CSCL serves primarily as a tool for facilitating communication and enhancing collaboration, positioning the teacher as more of an observer, AI in ITS plays a more central role, acting as an active agent that emulates the instructional functions of human tutors or human peers.

LCT emphasises that knowledge is co-constructed through social interaction. It is a learning situation where two or more students learn together to achieve a common goal or solve the task at hand, mostly through peer-directed interactions (Dillenbourg, 1999). This peer learning, particularly in the form of a learning companion system, is rooted in several **theoretical foundations**.

First, Piaget's (1965) concept of cognitive conflict has highlighted that peer interactions help reduce ego-centrism and promote cognitive development, especially those interactions that bring differing viewpoints to the fore. When peers challenge each other's ideas, cognitive disequilibrium which fosters deeper learning is created. Vygotsky (1978) complements this view by emphasising that social interactions fundamentally shape cognitive structures with his theory of the Zone of Proximal Development (ZPD), which suggests that peers can provide cognitive scaffolding and assist each other in reaching higher levels of understanding through cooperative problem-solving.

Additionally, peers can serve as motivators in learning. Comparative performance among students can enhance motivation and drive, but excessive competition may result in negative effects. Therefore, it is important to balance student-companions interaction and maintain human students' motivation and foster positive learning outcomes when designing learning companion systems. In LCS environments, students engage in collaborative learning where they must articulate, justify, and defend their ideas in response to peer feedback. This dynamic interaction promotes a deeper understanding as both students are actively teaching and learning from one another. The process of mutual justification (refers to the situation when students critically evaluate each other's ideas) is less likely in traditional one-to-one teacher-student settings due to the difference in social status and knowledge levels. But it is feasible when learning companions are involved, thus peer learning encourages a much fairer exchange of knowledge (Chan, 1991).

3 The Design: the roles and interactions with AI

According to the definition, a learning companion is not an expert in the subject but rather a peer, such as a classmate, that supports the student during learning activities. The companion learns from the teacher and either collaborates with or competes against the student during the process. Chan and Baskin (1990) proposed **three types of interaction models** within a learning companion system: (1) collaboration, where both the student and companion work together, sharing responsibility for tasks; (2) competition, where both work independently and then compare their results; and (3) suggestion, where one works while the other observes and provides input.

Based on these three models, AI agents could have the following **roles**: peer tutor and tutee, which are more towards the tutoring role and thus not the focus of this review, and teachable student, collaborator, competitor, troublemaker. We will look into the later ones and further describe them as: (1) the companion could be a student of the human student (teachable student and troublemaker), the theoretical foundation is the learning by teaching (LBT) (2) all students and companions could collaborate or compete as equals (collaborator and competitor) (Uresti, 01)

In order to teach others, students are required to revise, clarify, organise, and reflect on their own knowledge, which leads to a deeper understanding and mastery of the learning material. This idea forms the basis of the **teachable students** model, which suggests that having a less capable learning companion helps students learn more effectively by encouraging them to teach it - a concept known as learning by teaching (Berliner, 1989; Nicholas, 1994). In a human-computer collaborative learning system (HCCL) called "People Power" developed by Dillenburg and Self (1992), if the learning companions are the ones to solve the problem, they would ask the student for agreement and to express its lack of knowledge of a concept to encourage the students to teach them. If the students refuse to help, the AI learning companions could still solve it by themselves.

Another recent work is conducted by Biswas et al (2001). Their system operates as a computer-based teachable agent environment where students teach a virtual agent called Billy by providing explicit instructions. The teachable agent exhibits two key traits: it lacks prior domain knowledge and requires guidance from the student to perform tasks. Students teach Billy by creating concept maps or answering questions, and then the system responds by simulating the agent's learning process and prompting students to refine their instructions. This interactive process helps students deepen their understanding of the subject, promotes self-assessment, and also improves problem-solving skills as they would observe and correct Billy's behaviours.

A most recent study which actually applied large language models is project by Jin et al (2024), it investigates large language models (LLMs) as teachable agents for learning by teaching (LBT) framework to help learners identify knowledge gaps. To address the challenge of LLMs' extensive knowledge discouraging teaching, the authors developed a prompting pipeline that limits LLMs' knowledge and encourages them to ask "why" and "how" questions. The approach was implemented in TeachYou, an LBT environment, and AlgoBo, an LLM-based chatbot. Evaluation showed that this method improved problem-solving and facilitated knowledge-rich discussions among learners. However, some paradoxes of generative AIs also appear along the application, which will be discussed in the later section.

There are much rarer studies on AI learning companions being **troublemakers**. Aimeur and Frasson (1996) is one of the few. The strategy behind this role is the "learning by disturbing", which is the inverted version of learning by teaching. The system in this study is an intelligent tutoring system (ITS) that enhances learning through a cooperative approach - learners interact with the system to build knowledge. The key feature of the system is the "troublemaker" companion, which is a virtual peer that occasionally provides incorrect advice or suggestions alongside correct ones. This strategy is an inverted one from learning by teaching. It is called "learning by disturbing" and is designed to provoke the learner into actively engaging with the material, prompting them to critically evaluate the companion's suggestions and refine their understanding. By challenging the learner, the troublemaker encourages deeper cognitive processing, improving overall learning performance and promoting self-assessment.

When acting as **collaborators** or competitors, the capability level of AIs could be higher than the previous situation. Dillenbour and Self (1992) developed a system in human-computer collaborative learning (HCCL) environment. A human and a computational co-learner collaborate to explore relationships within this system. The computer co-learner acts as a collaborator by engaging in dialogue with the human learner, simulating "socially distributed cognition" (SDC) where both learners together form a single cognitive agent. The co-learner learns through dialogue, creating and refining links between rules. It uses "continue-links" to follow reasoning paths and "refute-links" to challenge and revise rules. Reinforced by feedback from election simulations, this process helps both learners enhance reasoning and problem-solving abilities.

A later project conducted by Goodman et al (1998) also used computer-simulated learning companions as collaborators. This research focused on an intelligent tutoring system (ITS) that integrates a simulated learning companion which serves as a peer collaborator. The purpose of this companion is to encourage student reflection and articulation. The computer co-learner (named LuCy) promotes collaboration by encouraging the human learners to explain, reflect on, and justify their actions and reasoning. Through building up dialogues, LuCy reinforces learning by asking relevant questions, reminding the human learners of key information, and encouraging them to reconsider their decisions. These interactions foster deeper understanding and critical thinking. Additionally, LuCy simulates the benefits of peer learning which mentioned before. It improves the learning process through continuous guidance, reflective thinking, and engagement, while also providing personalized coaching in a collaborative learning context.

It is quite difficult to find recent projects (at least in the 2020s) on AI learning companions as collaborators, but there are some similar ones with AI being reading companions and they might also be inspiring. In the study conducted by Liu et al (2022), the system is a chatbot designed to act as a book talk companion and enhance students' engagement in reading. Using natural language processing techniques like co-reference resolution and dependency parsing, the chatbot understands the key elements of 157 books and engages students in dialogue about the storylines. It mimics human interactions by responding with deliberate delays and recalling prior conversations, creating a more natural and social atmosphere. By prompting questions, offering social-affective cues, and reciting past interactions, the chatbot sustains students' interest and engagement, making the reading experience more interactive and personalised. This interaction fosters a sense of social connection and helps to maintain students' interest in reading over time.

Similar to the pattern in collaboration, in competition the learning companions stimulate motivation by introducing moderate challenges. Competition promotes social comparison, encouraging human students to evaluate their competence comparing to others, which in turn drives a sense of achievement and deepens their engagement. But for competitors too, the relevant projects are rare, the only one found is Chan et al (1992). In this study, the system is a distributed learning environment designed to teach binary numbers through competitive gameplay between two groups. Each group plays on a connected PC to compete on solving binary number problems. The system has a computer tutor (or a "couch", a more accurate name in this study) called an "evaluator" to assist students in some models, while in some they offer no assistance and the competition is purely between students or between students and learning companions. By fostering an environment where students must actively engage in problem-solving to outperform their peers, the system taps into the social comparison process. Students reported the learning becomes "more exciting" with competitor involved and also stimulated them to "think more deeply". Most students felt that competition motivated them to improve, with many appreciating the fairness and autonomy in models without the evaluator. However, some students found competition stressful, particularly if they struggled to keep up with their peers or lacked the means to identify their mistakes without the evaluator's guidance. Overall, the competitive model was favoured for its ability to engage students and sustain their interest in learning the binary numbers.

The **evaluation** of a learning companion system encompasses multiple perspectives. As the techniques used vary from experiments to experiments: software development, machine learning, NLPs, Chatbots, and LLMs etc, the methods for conducting evaluations could be different. But typically, as suggested in those previous studies listed, the dimensions these evaluations focus on are pretty similar, and the most frequent ones are: (1) pre-experimental assessment of the AI learning companions' capabilities, to make sure that they could play the role intended. (2) pre-experimental assessment of the students' levels and their relationships. Levels and relationships of students may also affect students' learning. Some students prefer learning with more advanced students for more challenges and being able to learn from better performance, and some do not prefer doing so for avoiding pressure and being nervous (Chan et al., 1992). Likewise, some students would like to place themselves out of sight of their learning companions or do not want their companions to know who they are, because they may feel humiliated for their faults or slow response. (2) the academic performance of human students, usually using post-study exams to test; (3) the effectiveness and utility of the AI learning companions, usually done by asking participants to finish relevant questionnaires either qualitative or quantitative; and (4) technical assessments or validation of the system architecture or the operational pipeline.

4 The Challenges and Limitations

The application of generative AI as peer learning companions could have several challenges from different perspectives. Here we discuss the following: the balance on optimal expertise level of learning companions, the limited interaction format, the monotony of singularity of discipline, the paradox of generative AI itself, and a research gap.

The challenge of determining the optimal **expertise level** of a learning companion is central to its effectiveness in education setting. Research by Hietala and Niemirepo (1998) distinguished between “weak” and ”strong” learning companions. The difference lies in the level of expertise: the weak companions have minimal expertise while the strong ones are nearly experts. Their findings show that students generally preferred strong companions, especially for difficult tasks as these companions could provide clearer guidance and thus easier to complete these tasks. However, replying too much on these strong companions could hinder active learning and cause students to study more passively. In contrast, the weak companions, though less helpful when completing the tasks, could encourage students to explain concepts and foster deeper understanding and engagement by teaching them (the LCs). This creates a trade-off between short-term task success with strong learning companions and long-term learning benefits with weak learning companions. Therefore, balancing the expertise level of learning companions remains a critical challenge in designing effective learning environments.

Most experiments mentioned are based on **dialogue**s between students and the learning companions. But the format itself has restricted nature. Simpler dialogues could be confined to statements to either agreement or disagreement as in Dillenbourg and Self (1992). Yet authentic conversations involve a more intricate process of elaboration and shared understanding, characterised by various conversational operators, such as specification, elaboration, reformulation, restrictions, and reasons (Baker, 1992). The absence of these operators restricts the development of "social grounding," which is essential for ensuring that participants believe their interlocutor has comprehended their utterance to an acceptable degree (Clark, 1991). Other studies mostly use menu-based comments and responses. Though these are useful for collecting information and assessing students' knowledge, it often results in interaction that feels mechanical and unnatural, or in other words, too "artificial". This limitation not only hindered the flow of conversion, but also diminished the potential for deeper and more meaningful engagement between human students and the computer learning companions. Yet this engagement is vital for the promotion of critical thinking and personalised learning (Goodman et al., 1998). The introduction of generative AI which has the capability to facilitate more natural and contextual communication may improve this issue to some extent, but empirical verification is still needed. Future implementations must be approached with caution.

Most experiments focus on **single discipline**, for example, programming, algorithm learning, mathematics, language learning etc. While the findings could be significant in that subject, it does not demonstrate generalisation across various topics, and it remains to be validated if the system can be applied effectively to other disciplines, especially for generative AIs where the prompts are specifically tailored and the model especially trained. For example, in Jin et al (2024), when considering the distinct cognitive processing and effective learning strategies associated with procedural versus declarative knowledge, the system *TeachYou* might not be optimal for facilitating the acquisition of declarative knowledge and it needs future research to explore broader topics beyond just algorithm learning.

Generative AI in education, particularly as learning companions, presents some paradoxes. (1) Given the powerful capability and strong knowledge foundation of generative AIs, when having them as collaborators, students might be overly reliant on them and have less opportunities for critical thinking and deep learning, which in the end leads to passive learning. (2) AI-generated content could contain outdated or inaccurate information due to limitations like reliance on old data. This raises concerns about the reliability of information provided to students. And unfortunately so far there isn't a perfect solution for generative AIs to offer information 100% accurately. Later validations are required, which could be time and resource consuming. Ethical concerns also arise when AI-generated content spreads misinformation or biased information (Zhai, 2022). (3) Generative AI could be over-confident in its answer despite a lack of deep understanding. This is called the Dunning-Kruger effect (Kruger and Dunning, 1999). AI's success depends heavily on the quality of the input it receives, while AI can produce detailed responses, it often struggles with ambiguity and limitations in citing sources correctly. (4) To date, most studies have involved only one or two agents with a maximum of four, few have attempted to realistically mimic a classroom setting that would typically include at least ten participants (at least I haven't found it). This raises questions regarding the feasibility of such approaches. Training generative AI can be expensive and resource-intensive, potentially imposing a significant burden on students, educational institutions, and government. This may lead to limited access and implementation of such technologies. In simpler terms, even if a learning companion system based on generative AI has been developed, it is likely that only a few elite schools will be able to utilize it effectively.

It is somewhat surprising that there rarely are projects, research studies, or experiments related to AI learning companions since the 2000s. In contrast, related terms such as Intelligent Tutoring Systems (ITS) and Computer-Supported Collaborative Learning (CSCL), which have been mentioned in this review previously, continue to evolve and develop within the field and with the development of AI techniques. This observation raises the possibility of a shift in focus or a transition in terminology from Learning Companion Systems (LCS) to other distinct concepts. However, I have not identified a confirmed reason for this trend. This **gap in the literature** indicates a need for further exploration to understand the underlying factors that may have contributed to the decline in research specifically addressing AI as learning companions. A comprehensive analysis could reveal insights into current educational priorities and how they may have influenced the implementation of AI technologies in computer-supported learning environments.

5 Reference

Baker, M. (1992). The collaborative construction of explanations. *Deuxièmes Journées Explication du PRC-GDR-IA du CNRS*, Sophia-Antipolis.

Biswas, G., Katzlberger, T., Bransford, J., & Schwartz, D. (2001). Extending intelligent learning environments with teachable agents to enhance learning. In

Artificial intelligence in education (pp. 389-397). IOS Press.

Burns, H. L., & Capps, C. G. (1988). Foundations of intelligent tutoring systems: An introduction. In M. C. Polson & J. J. Richardson (Eds.), *Foundations of intelligent tutoring systems* (pp. 1–19). Lawrence Erlbaum. https://www.taylorfrancis.com/chapters/mono/10.4324/9780203761557-6/foundations-intelligent-tutoring-systems-introduction-martha-polson-jeffrey-richardson

Carter, E. E. (2014). An intelligent debugging tutor for novice computer science students. [Doctoral dissertation, Lehigh University]. ProQuest Dissertations & Theses Global. Retrieved December 29th, 2022, from https://www.proquest.com/dissertations-theses/intelligent-debugging-tutor-novice-computer/docview/1540757322/se-2

Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. *IEEE Transactions on Man-Machine Systems*, 11(4), 190–202. https://doi.org/10.1109/TMMS.1970.299942

Chan, T. W., & Baskin, A. B. (1988). Studying with the prince: The computer as a learning companion. In *The Proceedings of International Conference of Intelligent Tutoring Systems, ITS'88* (pp. 194–200). Montreal, Canada.

Chan, T. W., & Baskin, A. B. (1990). Learning companion systems. In C. Frasson & G. Gauthier (Eds.), *Intelligent Tutoring Systems: At the Crossroads of Artificial Intelligence and Education* (Chapter 1). New Jersey: Ablex Publishing Corporation.

Chan, T. W., Chung, I. L., Ho, R. G., Hou, W. J., & Lin, G. L. (1992). Distributed learning companion system: WEST revisited. In *Intelligent Tutoring Systems: Second International Conference, ITS'92 Proceedings* (pp. 643-650). Springer Berlin Heidelberg.

Chou, C. Y., Chan, T. W., & Lin, C. J. (2003). Redefining the learning companion: The past, present, and future of educational agents. *Computers & Education*, 40(3), 255-269.

Clark, H. H. (1991). Grounding in communication. In *Perspectives on socially shared cognition.* American Psychological Association.

David Berliner. (1989). Being the teacher helps students learn. *Instructor*, 98(9), 12-13.

David Nichols. (1994). Issues in designing learning by teaching systems. In P. Brusilovsky, S. Dikareva, J. Greer, & V. Petrushin (Eds.), *Proceedings of the*

East-West International Conference on Computer Technologies in Education (EW-ED'94) (Vol. 1, pp. 176-181).

Dillenbourg, P. (1999). What do you mean by collaborative learning? In P. Dillenbourg (Ed.), *Collaborative-learning: Cognitive and computational approaches* (pp. 1-19). Oxford: Elsevier.

Dillenbourg, P., & Self, J. (1992). People power: A human–computer collaborative learning system. In C. Frasson, G. Gauthier, & G. McCalla (Eds.), *The 2nd International Conference of Intelligent Tutoring Systems, Lecture Notes in Computer Science* (Vol. 608, pp. 651–660). Springer-Verlag.

Goodman, B., Soller, A., Linton, F., & Gaimari, R. (1998). Encouraging student reflection and articulation using a learning companion. *International Journal of Artificial Intelligence in Education*, 9, 237–255.

Hietala, P., & Niemirepo, T. (1998). The competence of learning companion agents. *International Journal of Artificial Intelligence in Education*, 9, 178-192.

Jin, H., Lee, S., Shin, H., & Kim, J. (2024, May). Teach AI how to code: Using large language models as teachable agents for programming education. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (pp. 1-28).

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, 77(6), 1121–1134. https://doi.org/10.1037/0022-3514.77.6.1121

Lin, C. J., & Mubarok, H. (2021). Learning analytics for investigating the mind map-guided AI chatbot approach in an EFL flipped speaking classroom. *Educational Technology and Society*, 24(4), 16–35.

Lin, Chien-Chang, Huang, A. Y. Q., & Lu, O. H. T. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: A systematic review. *Smart Learning Environments*, 10(1), 41.

Liu, C. C., Liao, M. G., Chang, C. H., & Lin, H. M. (2022). An analysis of children's interaction with an AI chatbot and its impact on their interest in reading. *Computers & Education*, 189, 104576. https://doi.org/10.1016/j.compedu.2022.104576

Ma, W., Adesope, O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psy-*

chology, 106(4), 901–918. https://doi.org/10.1037/a0037123

Mascarenhas, S., Guimarães, M., Prada, R., Dias, J., Santos, P. A., Star, K., Hirsh, B., Spice, E., & Kommeren, R. (2018). A virtual agent toolkit for serious games developers. In *2018 IEEE Conference on Computational Intelligence and Games (CIG)* (pp. 1–7). IEEE. https://doi.org/10.1109/CIG.2018.8490399

Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, 20(1), Article 4. https://doi.org/10.1186/s41239-022-00372-4

Shan Wang, F., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications*, 252, 124167. https://doi.org/10.1016/j.eswa.2024.124167

Singh, N., Gunjan, V. K., Mishra, A. K., Mishra, R. K., & Nawaz, N. (2022). Seistutor: A custom-tailored intelligent tutoring system and sustainable education. *Sustainability (Switzerland)*, 14(7), Article 4167. https://doi.org/10.3390/su14074167

Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 409–426). Cambridge University Press.

Uresti, J. A. R. (2001). The LECOBA learning companion system: Expertise, motivation and teaching. *International Journal of Continuing Engineering Education and Life Long Learning*, 11(3), 216-228.

Zhai, X. (2022). ChatGPT user experience: Implications for education. Available at SSRN 4312418.