



# Artificial Intelligence and User Experience in Online Education

Maria Cristina Enache<sup>★</sup>

## ARTICLE INFO

### Article history:

Received June 15, 2026

Accepted June 30, 2026

Available online September 1, 2026

### JEL Classification

D12, L86, D83

### Keywords:

e-learning, LLM, artificial intelligence

## ABSTRACT

The driving factors that can affect digital learning systems through transformative change include Artificial Intelligence (AI). In this case, the development of large language models, adaptive learning, and learning analytics gives us a wider picture of personalized teaching, automated feedback delivery, and intelligent tutoring systems. At the same time, the increasing usage of AI in education creates a number of issues that concern trustworthiness, transparency, explainability, cognitive dependency, and potential long-term implications for learning outcomes. This paper reviews the existing state of AI technology application in online education, identifies the gaps and challenges in current solutions, and discusses possible avenues for further innovation. The focus will be on explainable RAG tutors, adaptive scaffolding technologies, UX observatories, multimodal learning approaches, and contestable feedback solutions. Exploiting the discussed opportunities, the paper offers a concept architecture of a Socratic Adaptive Tutor, which integrates large language models, learning analytics tools, cognitive learner profiles, pedagogical policies, and retrieval-based knowledge systems to facilitate cognitive engagement and metacognition.

The Authors © 2026 is licensed under [CC BY 4.0](https://creativecommons.org/licenses/by/4.0/).

## 1. Introduction

Nowadays, Artificial Intelligence (AI) appears to be one of the most powerful factors driving the future of e-learning. The fast development of various models of AI such as generative models, adaptive learning techniques, and learning analytics software tools has changed the way in which learners access knowledge and communicate within digital learning environments. In contrast to initial investigations aimed at verifying the applicability of different AI applications in educational contexts, today's studies raise another important issue: under what conditions can AI help to improve user experience and ensure productive learning outcomes? The systematic reviews conducted recently indicate that the best educational applications of AI tend to occur in cases where technology is used as contextualized pedagogical assistance and not as a replacement for teachers. The most commonly used AI technologies for education include personalized learning paths, recommendations, automatic feedback systems, and conversational tutors. Despite the many advantages of introducing artificial intelligence into the education process, there are some issues that still need to be addressed. The challenges in question involve user experience evaluation, lack of user participation in the design and development of AI-enabled educational ecosystems, transparency and explainability problems, and increased cognitive reliance on artificial intelligence. Moreover, the wide-scale introduction of such technologies among students has brought about various educational and ethical dilemmas. Even though these innovations are widely utilized for educational purposes, they have also caused debates about the potential effects on academic integrity, critical thinking, learner autonomy, and high-level cognitive skills. This is the issue addressed in this study. The main problems regarding the currently available AI-powered systems are to be discussed, and the innovative ways to make education more efficient will be proposed, namely the development of Socratic tutoring systems will be discussed. Thirdly, there is another type of AI that should be mentioned; it is conversational assistants and chatbots using large language models. These assistants may help students get answers to their questions, generate examples, and even give feedback. With regard to generative AI, communication with artificial intelligence becomes much easier. The fourth category includes automated evaluation instruments and intelligent tutoring systems employing learners' models, knowledge databases on particular subjects, and algorithms making decisions on the basis of educational knowledge. Their goal is to replicate what humans do when they act as tutors, namely detecting misconceptions, adapting feedback, and tutoring as such.

<sup>★</sup>Dunarea de Jos University of Galati, Romania. E-mail address: [mpodoleanu@ugal.ro](mailto:mpodoleanu@ugal.ro) (M.C. Enache)

Regarding the user experience in the contemporary scientific discourse, the successful development of this concept cannot only be related to usability. The most recent developments indicate that there are many other criteria that should be taken into consideration in addition, such as cognitive, affective, and behavioral engagement, motivation, self-efficacy, trust in artificial intelligence, retention rate, and learning outcomes. In this regard, it is necessary to mention a significant distinction between the two concepts, as a user's experience can be positive without leading to any learning. [5]

## **2. The Current AI Ecosystem in Online Education**

According to recent literature, online learning using AI involves a convergence of educational technology, infrastructure of data, and user experience design. In this ecosystem, it is possible to outline certain types of learning systems powered by AI. The following can be listed among the most common types of these systems: first, there are recommendation systems that use artificial intelligence to tailor the learning process depending on the learners' previous knowledge, abilities, preferences, and needs. Secondly, there are platforms for learning analytics involving educational data for making instructional decisions. This means that the content of the course will be adjusted and appropriate recommendations will be given. The role of learning analytics in contemporary education cannot be underestimated since it helps achieve personalized learning outcomes. [6]

Today's market provides many AI-based educational solutions. Examples of such platforms as Coursera Coach, Khanmigo, and Duolingo Max are learner-oriented and are aimed at providing assistance in form of conversations, context-dependent explanation, and instant feedback. Such solutions employ large language models to provide individualized interactive experience for learners. On the contrary, solutions such as Blackboard AI Design Assistant and D2L Lumi are oriented toward teachers. For such ecosystems, the primary objectives may comprise content creation, instructional design support, and teaching process automation. The purpose here is to assist educators in their work to improve efficiency and decrease the number of hours needed for course development. Institutional ecosystems are those where artificial intelligence is applied in a learning management system environment. Such systems have capabilities like learning analytics, administration, educational management and governance, and personalized learning platforms. Even though these types of systems differ greatly from each other in terms of technological features and end-users, they do have one thing in common – the fact that all these ecosystems are rather designed. To put it simply, this implies that in future, innovations related to artificial intelligence in education will focus not on making algorithms better performing but on stimulating cognition. Nevertheless, although the progress made is remarkable, there are certain structural gaps present in the current situation with artificial intelligence-based education as per the literature review. [5]

Firstly, one of them is connected with the absence of strong empirical evidence about learning outcomes. While there are many studies suggesting positive results, much of them have quasi-experimental designs and use short-term interventions, therefore, cautioning about generalizing the findings. Secondly, there seems to be insufficient involvement of users in the process of system design. Despite the frequent emphasis on human-centered AI, students and educators are rarely engaged in the design process as co-designers but more like research subjects. Thirdly, trust is also considered to be crucial to the successful deployment of any educational technology based on AI. Recent research suggests that merely providing automatic explanations will not lead to greater user trust but that the perception of fairness and verification of the outputs produced by AI is more important. One of the biggest learning-related issues associated with AI would be that of cognitive dependency. If AI systems are mostly relied upon for giving students the answers and solutions to problems, then learners might eventually start reducing their cognitive exertion and end up becoming dependent on these kinds of tools. Such an issue has been discussed in several academic papers lately because of its direct impact on learners' autonomy and knowledge development.

Other problems to be considered include those of accessibility, bias within algorithms, privacy risks, data management, and even compliance with new regulations like the one from the European Union AI Act.

## **3. Innovation Opportunities for the Next Generation of AI Educational Systems**

The gaps found in the contemporary artificial intelligence-assisted learning spaces point to some of the most promising areas for future development. Instead of concentrating efforts on designing bigger models or more advanced algorithms, the future must focus on the basic problems with the pedagogical approaches and user experiences. The recent academic literature hints at some of the most important areas including explainability, cognitive assistance, accessibility, user-centered evaluations, and trust building.

### **3.1 Explainable and Uncertainty-Aware AI Tutors**

The most innovative solution in this regard would be building AI tutors that are able to give not just the answer, but also the rationale and confidence behind the answer. Correctness will not suffice in an educational setting since the learner needs to know not only that the answer is correct but also how correct. Retrieval Augmented Generation (RAG) systems provide us with a very good starting point for meeting this goal. While standard language models rely on their own internal parameters to generate the answer, RAG

systems first gather data from outside knowledge stores and then generate the answer based on them. Explainability pertains to the ability of the system to make its reasoning process comprehensible to the user. Explainable tutoring systems would be able to identify the documents that were used, provide justification for selecting the particular sources, as well as articulate how reasoning led to the conclusion. Explainability is especially desirable in education as it prompts users to think critically about what is presented and to verify the information.

Another equally significant concept is communicating uncertainty. As mentioned above, large language models have no trouble producing fluent and convincing responses despite lack of evidence or information inconsistencies. Therefore, it is important that future education systems will be able to demonstrate their confidence and warn when any further involvement of humans is required. The level of confidence may be assessed using such parameters as relevance of sources, agreement between the selected texts, and consistency of several pieces of created content. In case there are plenty of sources and they have similar content; the tutor should demonstrate its confidence. In other cases, the tutor should demonstrate lack of confidence. Explanation of results and indication of uncertainty may help combat hallucinations and develop trusting relationships. Taking all of that into account, many researchers consider explainability and uncertainty awareness in AI tutors a promising method of developing artificial intelligence in education.

### **3.2 Combating Cognitive Dependency Through Adaptive Scaffolding**

One potential avenue for innovation would be developing technologies that minimize cognitive reliance on AI tools. At present, many learning bots are developed so as to return answers as fast as possible. While efficient, this approach may impede the development of independent critical thinking among learners. One potential innovation for the future in the realm of education would be systems implementing adaptive scaffolding to assist in guiding the learners while completing tasks, rather than just offering immediate solutions. According to the theories of scaffolded learning and self-regulated learning, these systems provide assistance through gradual guidance via hints, questions, examples, and so forth.

Adaptive scaffolding does not intend to lower the cognitive efforts of the learner but aims to maximize productivity of efforts made by the learner. When problems arise, prompting starts with questions, then moves to hints, and lastly to explanations. Adaptive scaffolding provides for an active construction of knowledge on the part of the learners.

Adaptive scaffolding systems have an important place in fields where the process is valued over the outcome – mathematics, programming, science, and academic writing among others.

### **3.3 UX Observatories for Learning Platforms**

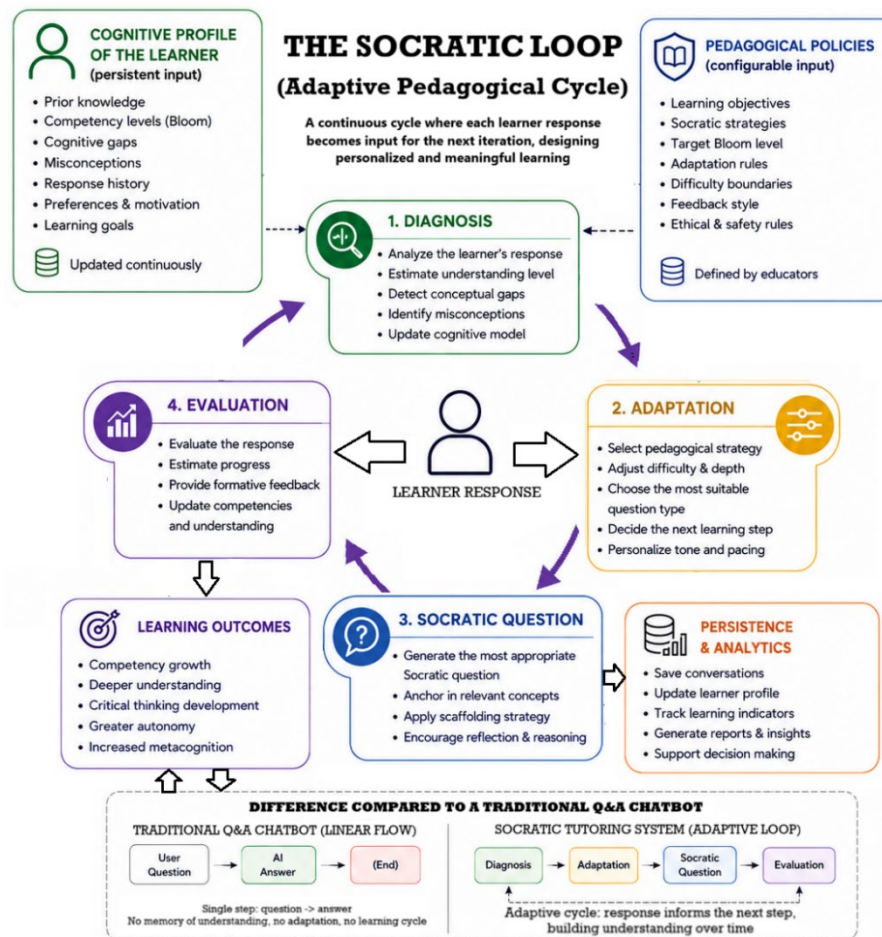
Finally, there is room for innovation connected to the creation of UX observatories within educational platforms. Traditional analytics in learning environments tend to focus on quantitative metrics, such as login activity, task completion rate, and test scores. No doubt, it gives important information about the learners' progress but cannot give the full picture of their experience. As it was noted above, UX observatories are broader tools which include learning analytics, behavioral data, feedback, accessibility indicators, and fairness metrics to have a full picture of the learning process. Given this kind of information, it would be easy to recognize some issues concerning the usability of a product or technology, determine what motivates people and what is needed to learn and achieve the intended goals. From observing how users interact with learning technologies, it is possible to identify various challenges regarding usage of such technology or product and their solutions. There may be found out some navigation problems or that technology contributes to the attrition rate among students or even causes discrimination. Machine learning technologies can help to find some behavioral patterns too. As mechanisms for institutions, user experience observatories may become essential instruments in making decisions based on facts. The institution does not need to consider only the technological side of an educational tool; it needs to pay attention to the effect the technology produces. This is becoming more important in the age of AI implementation in e-learning.

Speaking about institutions, UX observatories could turn out to be decision-making tools that would allow basing decisions on facts. Educational technologies must not be assessed in terms of their technological qualities; they should rather be assessed from the point of view of their effects on users' learning experience. Observatories of User Experience will become necessary in the light of growing use of artificial intelligence in e-learning.

## **4. Socratic Adaptive Tutors: A Conceptual Architecture for AI-Supported Learning**

A traditional educational chatbot operates predominantly on the question-answer model. The user formulates a question, and the system generates an answer based on the information available in the model or knowledge base. The main goal is to provide the requested information quickly and correctly, and this approach makes each interaction relatively independent, and the success of the system is measured by the accuracy of the response provided, so the bot does not explicitly track the mental development of the learner, does not detect gaps in his knowledge, and does not modify the pedagogical strategy for long-term purposes. Unlike a conventional chatbot, a system acts as an adaptive tutor oriented towards learning, not as a simple provider of

answers. Instead of answering the question directly, the system analyzes the student's answers, identifies the level of understanding, detects possible misconceptions, and adapts the pedagogical strategy before generating the next intervention. Thus, each student's answer becomes information for the next learning cycle. The process is organized in a continuous pedagogical loop: diagnosis → adaptation → Socratic question → evaluation → updating the student's profile. This loop allows for the progressive development of knowledge and critical thinking, since the objective of the system is not to immediately provide the solution, but to guide the student towards its discovery. The essential difference is that a regular chatbot optimizes the quality of the answer, and the Socratic tutoring system optimizes the learning process.



**Figure 1. Adaptive Socratic Loop for Artificial Intelligence-Based Tutoring**

Out of the mentioned opportunities associated with educational technology advancements, one might point out that the need to determine how to find the correct equilibrium between reducing cognitive dependency and enhancing cognitive involvement still requires extensive research. Application of Socratic adaptive tutors, in its turn, can be seen as a means to merge various innovative domains into one coherent concept. First of all, it must be noted that effectiveness of artificial intelligence systems within the context of education cannot be measured solely by means of accuracy of responses. It is also vital for such a system to motivate students to think critically about information and gain metacognitive skills. Although a considerable amount of evidence for reliability and effectiveness was demonstrated concerning the speed of AI applications, the impact of artificial intelligence on the development of critical thinking skills remains to be proved. At the moment, there already exists several chatbots for educational purposes that operate using a fairly simple communication model: the user asks a question and receives the answer. Even if the response will be correct and will reflect the context well, such mode of operation can still be regarded as a transmissive approach in learning, which involves only the transfer of knowledge without any hypothesis's generation, evaluation of evidence, etc.

The Socratic learning model differs from it significantly. Based on the idea of the ancient philosopher Socrates who believed that people should develop their knowledge through questioning, it suggests that learning becomes highly effective when the process of acquiring knowledge consists of posing, analyzing, and answering various questions aimed at helping people see how they can get an answer.

In the realm of AI-based education, the above-mentioned strategy can be implemented in an interactive way through developing AI-powered dialogue agents capable of assessing the learner's

performance and providing corresponding pedagogical interventions. In such a light, the efficiency of a tutoring program cannot be defined in terms of how fast it delivers solutions; instead, the measure of its effectiveness lies in its capability to facilitate reasoning, metacognition, self-regulation, and knowledge transfer.

### Conceptual Architecture of a Socratic Adaptive Tutor

This type of interaction calls for a different architectural approach. Figure 2 shows a conceptual architecture divided into multiple layers that include: User Interface Layer, Conversational Orchestrator, Student Cognitive Profile, Pedagogical Policies, AI Engines, Knowledge Layer, Data Persistence Infrastructure. In contrast to regular chatbot structures, the architecture under consideration utilizes two extra layers which function as mediators in the sphere of education, connecting language generation and instructional processes: the student cognitive profile and the pedagogical policy layer. The user interface layer represents the layer through which learners interact with the system. The elements of this layer include conversational interfaces, the history of sessions, learner dashboards, and methods for customizing the degree of instructional assistance. In terms of user experience, the user interface layer guarantees learners' awareness and agency, providing them with opportunities to control the process of studying on their own. The core of the discussed architecture represents the conversational orchestrator which is commonly realized with the help of a large language model. In contrast to traditional conversational bots, the orchestrator does not generate responses. The main aim of its work is dialogue state management, coordination of other specialized components of education, and choosing the most suitable educational action in each case. The conversational orchestrator constantly exchanges information with the student cognitive profile which is an ever-changing representation of learners' knowledge states.

These may range from measures such as understanding, conceptual errors, engagement behaviors, learning styles, previous success, and developmental paths. As the system keeps track of the learner model up-to-date, it will be more adaptable in intervention strategies compared to systems that are dependent only on conversational context.

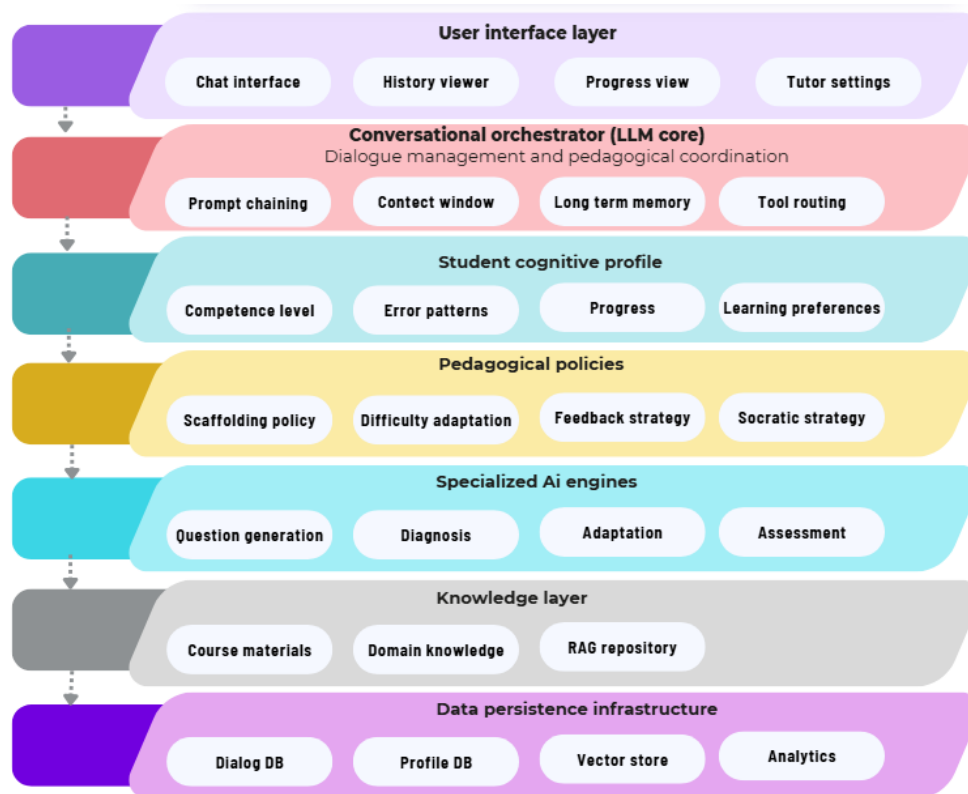


Figure 2. Conceptual architecture of an adaptive Socratic tutor

**Pedagogical Policies and Educational Decision-Making** - A unique element of this approach to design lies in the layer of educational policies. While other intelligent agents primarily concentrate on formulating the answer, educational agents should also be aware of how to deliver this response. Educational policies are composed of educational strategies that include scaffolding, adjusting difficulty, delivering feedback, and implementing Socratic questions. Unlike other approaches in which educational interventions are created by the language agent itself, these pedagogical policies will govern this process and set certain goals for these interactions. For instance, when the learner understands something partially, the tutoring system may be designed such that it asks a leading question instead of providing a solution or explanation. When there

have been several misunderstandings about one topic, the tutoring system may provide analogies, examples, and simplification of the concept.

**Specialized AI Engines** - The Adaptive Socratic Tutoring requires the use of different kinds of AI Engines that have specific roles to play in education. The Diagnostic Engine looks at the answers that the students give and identifies any misconception, any gaps in knowledge, uncertainty patterns, and even any errors. The engine does not simply concentrate on analyzing how accurate the answers are; it is more interested in understanding the thought process behind the answers. The Adaptation Engine will take advantage of the information given by the Diagnostic Engine and will decide what type of instruction is necessary. The adaptation engine will change the pace, degree of support, and rate of learning depending on the learner's condition. The engine for generating Socratic Questions serves as the heart of the entire system. Rather than giving an answer to something, the Socratic Question Engine provides a question that compels learners to think in terms of ideas. The type of questions that it generates is going to be determined by various contexts. For example, questions may demand justification, comparison, analysis of assumptions, and relationships among concepts. The engine for assessment is responsible for monitoring the progress of conceptual thinking of students. Unlike academic performance assessment that is common, this particular engine evaluates learners' abilities to argue, persist, regulate, and generalize. As a result, both of these engines make the tutoring system move from its reactive character to proactive participation in teaching.

**Knowledge Layer and Retrieval-Augmented Learning** - Effective tutoring requires access to reliable and contextualized knowledge. To accomplish this, the proposed architecture would include a specific knowledge layer consisting of course material, databases associated with different domains, and RAG-based knowledge base. This knowledge can be used by the tutor while formulating interventions and including them in the conversation process. There are several advantages of using such a strategy instead of working with the built-in knowledge of the language model only. For one thing, there is a guarantee of increased factual accuracy since answers are generated based on credible sources. Additionally, it provides an opportunity to enhance transparency by including source references within responses. Finally, it gives an opportunity to align interventions with curriculums as explanations become aligned with learning material.

Also, the application of RAG-based technologies opens the path to the development of explainable and uncertainty-aware systems, which were stated as crucial in educational AI products.

**Educational Benefits and Implications** - There are a number of advantages of the suggested architecture over the current architecture designs of conversational tutoring. First, this kind of architecture is helpful for promoting cognitive involvement since the person gets a chance to build their own knowledge through interaction. Instead of immediately receiving answers, learners are encouraged to engage in reflective inquiry, analysis, thinking, and reasoning. Second, this type of architecture can help address growing concerns of cognitive dependency as well. Limiting the usage of the answer generation feature will help the learner be in control of learning and build critical skills of solving problems. Finally, the developed architecture would also encourage metacognition by enabling the learner to have more knowledge about his/her cognitive skills and strategies.

## 5. Conclusions

Taking into account how rapidly artificial intelligence applications become used in various educational environments, one can conclude that there is a great chance to innovate. Apart from problems that were already identified, new ones have appeared. They include such problems like problems of trust, transparency, dependence and quality of education because of the use of AI in education. As can be seen from the content of this article, future developments should no longer be limited merely by attempts to improve models but above all, to create explainable, evidence-based and pedagogically relevant AI educational environments. All those mentioned problems make Socratic adaptive tutoring a great example of applying artificial intelligence in education.

## References

- Russell, S., Norvig, P. (2020). *Artificial Intelligence: A Modern Approach*. Pearson
- Ana Katalinic; Vanja Slavuj; Danijela Jaksic — Artificial Intelligence in Online Education: A Systematic Review of Its Impact on Learner Engagement and Satisfaction. *Education Sciences*. <https://doi.org/10.3390/educsci16030389>.
- Radek Pelánek; Tomáš Effenberger; Petr Jarušek — Personalized recommendations for learning activities in online environments: a modular rule-based approach. *User Modeling and User-Adapted Interaction*. <https://doi.org/10.1007/s11257-024-09396-z>
- Haoran Bai; Wing Cheung Lui; Paul Vinod Khatani — Promoting student engagement with GPTutor: An intelligent tutoring system powered by generative AI. *International Journal of Educational Technology in Higher Education*. <https://doi.org/10.1186/s41239-025-00571-9>
- Riordan Alfredo; Vanessa Echeverria; Yueqiao Jin; Lixiang Yan; Zachari Swiecki; Dragan Gašević; Roberto Martinez-Maldonado — Human-centred learning analytics and AI in education: A systematic literature review. *Computers and Education: Artificial Intelligence*. <https://doi.org/10.1016/j.caeai.2024.100215>
- Min Lan; Xiaofeng Zhou — A qualitative systematic review on AI empowered self-regulated learning in higher education. *npj Science of Learning*. <https://doi.org/10.1038/s41539-025-00319-0>