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BOARD # 82: WIP: A scoping review of AI agent systems supporting students' navigation of open-ended problems: Towards a model to support design thinking

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WIP: A scoping review of AI agent systems supporting students' navigation of open-ended problems: Towards a model to support design thinking

Introduction

In this Work In Progress (WIP), we aim to explore the ways in which research has discussed the opportunities students have to be creative in an open-ended Learning Environment (OELE) that has the supportive structure of an AI agent. At present, technology interventions have spread in most domains, including education. While AI experts are involved in designing intelligent systems for education and knowledge, learning scientists are interested in learning in real-world environments [1] proposed a complex system at the intersection of Artificial Intelligence (AI) and Learning Sciences (LS) which sheds light on how to design software that can address the learner's needs to interact with that environment [2]. The complex system in [2] illustrates the advantage of simulation, but in real-world situations such a system faces challenges. In early literature, Intelligent Tutoring Systems (ITS) were used to create a learning environment, give support, provide feedback on requests, and evaluate students' progress by observing their actions. These studies reported that the best feedback messages were generated by the teachers [3]. Student interactions with teachers and peers have been shown to prompt social-cognitive conflicts during debate, in discussion, and when sharing knowledge, and to provide opportunities to re-think when their thinking does not align with that of others. This is an ideal situation from the perspective of social learning theory, which situates learning within interactions with others [4]. Further, the author has recommended a revision to the ITS architecture to support a greater degree of freedom for students, although it remains a grey area how and when the ITS should intervene with the learner during the process of learning; future research is needed [4]. AI agents have their roots in inner speech on the intra-psychological plane and social speech on the inter-psychological plane, based on the importance of tools and language mediation [5], and it is worthwhile to explore the scholarship on how interactions evolve between students and AI agents.

In the ideal AI-LS system, the learner interacts with the agent and forms new knowledge and information. On the other side, the System learns from the interaction with the user and adjusts its behaviour based on individual user interaction. In addition to studies in education, there is a long history of leveraging AI to support design practitioners [6], [7], [8], [9] and a newer but growing interest in using AI to support design education [10], [11], [12], [13]. A key student learning outcome for many studies is students' ability to engage in design thinking, a mode of thinking through problems that involves creativity, iteration and empathy to transform an open-ended problem to a design solution [14], [15].

Drawing these ideas together, we aim to explore how learner/AI interactions occur and can be facilitated in the context of an open-ended learning environment to support design thinking. This encourages us to consider the humanistic paradigm in education [16] as a significant aspect guiding our work. To employ this approach there are two essential requirements: providing interaction and providing a learning environment. Our research questions will use the tenets of humanistic education to achieve the ultimate goal according to this paradigm, to treat each student as a unique learner. This involves having the AI agent communicate customized feedback based on the student's need and learning level to demonstrate respect for the students [17], [18] and create a trustworthy learning environment. Another aspect of this exploration is how students experience open-ended problem-solution processes supported by the AI agent and whether students have the opportunity to be creative in the design thinking process. Thus, we also focus our attention on how learning materials are presented to students for open-ended problems in design thinking, creating an open-ended learning environment (OELE). Scholarship on "scaffolding" defines it as the support provided by an expert to learners, continuing their engagement in learning activities beyond their current abilities; for example, to help students solve a problem and justify an unfamiliar method [19], [20]. Here, scaffolding support will be provided by an AI agent. However, our goal is to explore how researchers have delineated students' problem space in a way that still allows creativity and agency. We want AI agents to respect the complexities of the problem while supporting it, motivating students to be interactive.

Previous systematic reviews of design thinking and AI have focused on other issues. For instance, [22] considered justice, bias and ethics embodying AI in the design process, with a focus on business design. Chen et al. [28] conducted a bibliometric analysis of AI robots for precision education, explored the various applications of AI robots in education, and suggested future studies on individual learner-centric Human Computer Artificial Intelligence that researches interactions between learners and AI robots. By contrast, we are interested in the roles and responsibilities shared by students and AI agents, what students do and what AI does, how they interact with each other and advance learning, and the researchers' perspectives on those factors.

In summary, the existing literature on the intersection of AI, design thinking, and open-ended problems is both limited and dispersed across different research areas but reveals a broad understanding of AI agent systems requirements to support students in monitoring and controlling the learning process. A need remains to explore the literature to identify interventions/interactions between learners and AI situated within open-ended environments designed to promote learning without overly constraining the creativity and agency of the students. This paper uses a scoping review to synthesize the current body of knowledge in these areas to contribute new insights into human-computer interactions. We focus on the following research questions.
RQ1: What kinds of interactions between learners and AI agents have been explored in the context of open-ended learning environments? How have these interactions occurred during the learning process?
RQ2: How do AI agent Systems facilitate learning without overly constraining creativity?
In the following section, we will discuss how we used our research questions to guide the selection of inclusion and exclusion criteria for this scoping review, with the objective of highlighting and synthesizing the significant literature study on AI agents, design thinking, and open-ended problems, and exploring the various aspects of the interaction of AI agents and learners.

Method

Scoping review

Scoping reviews have emerged as a means of synthesizing literature in engineering education. For instance, Klein, Zacharias and Ozkan [21] employ a scoping review to understand how engineering educators contextualize engineering in their courses and what motivates them to do so. While researchers using scoping reviews advocate following a similar process to systematic reviews in terms of documentation and search transparency [21], [22], the goals and output from a scoping review differ [22], [23]. They are intended to help identify what literature may be relevant for a given topic, exhibit somewhat broader research questions than a systematic review, and are frequently used to help define key concepts in an area across the breadth of literature analyzed. In terms of outcomes, scoping reviews focus less on the quality of particular papers since the scope is not known at the outset, and rather focus on summarizing key themes, concepts, or ways the topic is addressed across the spectrum of work identified [22], [23]. Given that our search uncovered literature across several areas that were difficult to delineate upfront, including design research, AI in education and education technology, and concepts like open-endedness and what did or did not count as AI varied across this work, we ultimately chose a scoping review approach. This search began during research and development for an AI agent for the project [24]. During our initial phase, we searched the Journal of Learning Science for discussions on how learning environments are created using AI. Against our expectations, very few articles were identified representing the common space of the learning environment with a complex structure of open-ended problems and AI. After an initial review of research articles, we decided to synthesize the scholarship on using Artificial Intelligence in design thinking for open-ended problems, following the scoping review process. Within the broad research topic of interactions between learners and AI agents, we focus on studies that had digital learning environments. By exploring key factors of those interactions, we can study how AI facilitates creativity, respecting the complexities and ambiguities of open-ended problems. Our project, Mobile Design Studio (MODS), facilitates students collaborating on front-end design to approach earth science design challenges [24], so we wish to use this search to identify the strategies that can be incorporated into AI agent systems to enhance design thinking for open-ended problem-solving processes.

PICOS Framework positioning research

Our main area of interest is to identify the evidence of the use of AI in a design-thinking learning environment that is student-centric, with a focus on exploring the learning interaction between students and AI. We have followed the PICOS (Population, Intervention, Comparison, Outcome, and Study Design) framework (see Appendix A) to prepare our broad research questions and inform our inclusion-exclusion criteria. The scoping review process is iterative [23], and the research team has revised inclusion-exclusion criteria with further investigation.

Search Strategy

After our initial search on Artificial Intelligence in The Journal of Learning Science, two of the authors discussed the search terms for terminology and criteria. A librarian helped identify all the relevant databases available in the university library. We did not apply any restrictions on publication year, ensuring that all available scholarship pertaining to our research questions was covered. We searched all the databases within EBSCOhost (e.g., ERIC, Academic Search Complete, Applied Science and Technology) by using all the parameters below. The Engineering Village database was searched by using a placeholder of subject, title and abstract. Table 1 shows the different search strings used to identify the research articles.

Table 1
Search criteria with outcomes

String 1	Operator	String 2	Operator	String 3
AI / Intelligent Systems / Computer supported Learning / Intelligent Tutoring System / AI agent / Teachable agent	AND	Design thinking	AND	Open ended problem / ill-structured problem

Inclusion Exclusion Criteria

Our initial data search outcomes revealed very few scholarly articles representing the intersections of AI, Design thinking and Open-ended problems, leading us to reconsider inclusion and exclusion criteria for the scoping review. Few or no articles discussed the interventions of AI Agent systems or adaptive learning, or they discussed AI agent systems that were not interactive and did not provide personalized feedback to students, missing the role of a virtual companion in learning. Because we are interested in AI/student interactions, we agreed to exclude articles that only discussed the improvement and architecture of an AI system or improvement of Machine learning algorithms. We also decided to include only evidence-based articles and excluded opinion-based articles, commentary, and editorials. Two of the authors prepared the initial document of inclusion/exclusion criteria, then all three authors discussed each exclusion criterion in detail and reached a consensus on the final document following Petticrew et al. [25], presented in Table 2.

Table 2
Inclusion and Exclusion Criteria

	Inclusion	Exclusion
Population	K-12, Undergraduate Students, English Language	--
Interventions	AI agent/AI systems/Computer supported learning for design thinking for open ended problem, discuss outcomes and challenges to support learning, includes interactions between computers and humans observing learning	AI agent/AI system that lack adaptive learning, not interactive, do not provide personalized feedback, and do not discuss learning and discrete interactions to support learning
Outcome	Provide future directions to improve AI to support learning	Only discussion on the improvement of the machine learning algorithm and architecture of the system
Study Characteristics	Theoretical and empirical peer reviewed journal and conference papers	Newsletter, company blogs, editorial, opinion-based articles

Data Extraction

We included all the papers (n=653) for the first screening, and uploaded them to Covidence, a systematic review management software, out of which 157 duplicates were removed by the system. During the abstract screening process, the first author identified 3 more duplications and removed them from the full review process. The first author reviewed all 493 abstracts and categorized them with "Yes", "No" or "Maybe". The second author reviewed all abstracts marked as "Maybe", and these two authors discussed the inclusion and exclusion criteria of the papers for final appraisal, adopting a collaborative process to ensure the reliability of the review [26]. The first screening process resulted in 59 papers for the full review process. All the papers were randomly distributed across the three authors, following the paper ID numbers. Each paper was assigned two reviewers. This work is in progress. We have read 21 articles and discussed them in weekly meetings. 11 of these were determined to meet the inclusion and exclusion criteria. Discrepancies were discussed and resolved by consensus. During our discussion, the primary point raised was whether or not what was described in a given paper could be considered an AI agent or an open-ended problem space. The following section presents our critique summary.

Critiques

During our initial screening of abstracts, we used three terms with the "AND" operator to search the articles, "AI", "Design Thinking", and "Open-ended Problem," which yielded very few papers. We decided to use various combinations of search terms related to AI, considering design thinking as the first condition and then adding open-ended problems as another criterion, as presented in Table 1. The result was many papers more inclined towards the discussion of various Large

Language Models (LLM) and how different computer-aided design software is enhanced with AI tools than they were toward AI/student interactions; these papers were excluded.

During our full-text review of the papers, we identified many utilizing game-based learning. Of these, we excluded several that did not have an AI system or interactions of students with AI. For instance, Cutumisu et al. [27] developed animal characters agents students could choose for confirmatory or critical feedback. However, their research was focused on choice-based assessment vs traditional assessment in the game environment, and students had limited autonomy to seek positive feedback or critique on their poster design. Other articles fell into computer-supported learning and project-based learning with no clear AI system and were excluded. We also agreed to exclude articles that appear to be a post hoc analysis of students' concepts or systems maps using data mining, as those did not have an agent or system responsive to students [28].

Result and Discussion

At this point in our scoping review process, 21 articles have been read in full by at least two of the authors. Of these, 11 articles satisfied the inclusion criteria and are discussed below. Our RQ1 focuses on interactions and how they occurred, what led to the ownership of the interactions, and the students' agency to initiate those interactions. Huang [29] investigated the use of Generative AI (GAI) to support co-regulative learning and foster the design thinking abilities of students. However, there was no specific AI agent. The students asked GAI questions to support their learning and were supposed to maintain a log of those responses with their question prompts. The AI system did not "learn" or know anything about the student and answered each prompt without any student context. This research did not include the role of GAI in monitoring and regulating the learning process. Hirashima [30] introduced the intelligent computer system "MONSAKUN", an environment for learning by having students pose arithmetic word problems. The system diagnoses the problem, judges whether the problem can be calculated, and provides the reasons if it cannot. Since the problems can include any of the four basic operations, the author reported there was much space to explore in this domain of moderately ill-structured problems. Language learning in collaboration with an AI agent companion is in many respects similar to an AI approach to support design thinking, in that it creates an open-ended learning environment. Computer-supported English language content learning needs interactive and adaptive agents to ensure learner motivation by providing personalized instructions based on the learner's ability level [31]. In their study, Lee and Lim [31] proposed an interactive AI agent. This chatbot assesses students' English speaking ability, relying on prior data from native speakers and performance analytics. In another such study in language learning, students questioned their chatbots about stories they were reading and provided answers if the chatbot did not answer correctly. Additionally, they could pose questions to challenge chatbots trained by their peers. However, the agent could only answer if student questions were strictly derived from direct sentences from the story [32]. Such chatbots are reported for the beginner level, with a limitation to providing individual feedback to learners at other levels. This study did not focus on AI/student interactions or creativity.

Learning by teaching may be a promising technique, and articles on Betty's Brain, a Teachable Agent (TA) [33], [34] discuss valuable insights into AI agent interactions and how an AI agent can facilitate learning. This study involved the use of two AI agents. The first agent, Betty, a TA, learns from the students and answers questions based on this learning by using links and relations from a causal map. If she is asked, she explains her reasoning in text, speech, and animation. The second agent, a mentor Agent, provides support for general questions whenever a student clicks the button. Once Betty takes a quiz, the Mentor agent provides grades, feedback and how to improve it. Occasionally, the mentor agent provides spontaneous self-regulated learning feedback to the student, promoting metacognitive skills [33]. Learners teach and query, and in this process, they begin to understand the concepts of the subject domain. Students largely control the interactions. However, the mentor Agent and teachable agent do initiate just-in-time feedback, creating an opportunity for the students to build and monitor the causal map and self-regulate their learning with Betty [33], [34]. Betty's Brain study uses the concept map as an interactive learning artifact, which poses limitations for an expandable learning environment. For constrained topics such as concept-related material or causal effects, Song [35] used different methods for communication, symbol manipulation between a human learner and TA systems for mathematics learning. However, if a student only provides specific examples, such an agent will only be able to solve problems of that specific type, raising our concern about creativity (RQ2).

Building on teaching by learning, pivoting with adaptive scaffolding, an Artificial Peer Learning environment Using SimStudents (APLUS) is designed with metacognitive scaffolding provided on request or proactively by a meta tutor, aka mentor agent, enhancing the teachable agents. Analysis of interactions between students and the system showed that students often taught algebra equations incorrectly to the TA without knowing they had made an error. In response, the authors developed a teacher agent that provides adaptive metacognitive scaffolding while students are teaching. Pre/post-test scores suggest that to create an effective learning environment, a teachable agent needs to ask more reflective and constructive questions [36].

A system that offers critical feedback can play a key role in motivation to continue learning. One study [37] on critical constructive feedback (CCF) with student control showed that for low-achieving students, the presence of a TA led them to choose CCF more often and neglect CCF results less. This was in a game-based AI agent-supported learning environment for history lessons that gave students ownership of the communication with the AI agent. Another game-based study discussed how the self-efficacy (SE) of a tutee agent has an impact on students' performance [38]. However, the conversation was scripted, the questions were multiple-choice, and feedback was communicated through a chat window. In view of their results, the authors recommended not only designing more SE into the system but also that the SE level of teachable agents should change over time as students progress. Referring to our research questions, we argue that the ownership of the interactions and how those interactions will occur (bi-directional) should modify the SE level of the AI agent. Weaver et al. [39] used intelligent sketch tutoring software to enhance the sketching ability and spatial visualization skills of students. The platform provided instant feedback on each sketch, summative feedback at the end of each lesson, and suggestions on ways to improve throughout the process by offering dynamic, personalized feedback on sketch accuracy, smoothness, and speed. This study, as with most of the others we found, did not address two-way interactions between AI and students or how the AI platform learned from students' activity.

To summarize, researchers have tapped into the use of AI agents as a peer and companion for learning in education, yet its application for design thinking and open-ended problems appears to be a largely untapped area. As we continue to synthesize articles in this space, we plan to generate detailed guidelines for supporting interactions between AI agents and learners for complex-space design thinking for open-ended problems.

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References

[1] R. K. Sawyer, “The New Science of Learning,” in Cambridge Handbook of the Learning Sciences, 2005, pp. 1–16.

[2] S. Doroudi, “What happened to the interdisciplinary study of learning in humans and machines?,” J. Learn. Sci., vol. 32, no. 4–5, pp. 663–681, Oct. 2023, doi: 10.1080/10508406.2023.2260159.

[3] S. Ritter and S. B. Blessing, “Authoring Tools for Component-Based Learning Environments,” J. Learn. Sci., vol. 7, no. 1, pp. 107–132, Jan. 1998, doi: 10.1207/s15327809jls0701_4.

[4] J. Siemer-Matravers, “Intelligent Tutoring Systems and Learning as a Social Activity,” *Educ. Technol. Publ. Inc*, vol. 39, no. 5, pp. 29–32, 1999.

[5] J. Wertch, “PSYCHOLOGY: L. S. Vygotsky’s ‘New’ Theory of Mind,” Am. Sch., vol. 57, no. 1, pp. 81–89, 1988.

[6] X. Li, Y. Sun, and Z. Sha, “LLM4CAD: Multimodal Large Language Models for Three-Dimensional Computer-Aided Design Generation,” J. Comput. Inf. Sci. Eng., vol. 25, no. 2, p. 021005, Feb. 2025, doi: 10.1115/1.4067085.

[7] J. T. Allison et al., Eds., “Special Issue: Artificial Intelligence and Engineering Design,” J. Mech. Des., vol. 144, no. 2, p. 020301, Feb. 2022, doi: 10.1115/1.4053111.

[8] L. Hanna and J. Cagan, “Evolutionary Multi-Agent Systems: An Adaptive and Dynamic Approach to Optimization,” J. Mech. Des., vol. 131, no. 1, p. 011010, Jan. 2009, doi: 10.1115/1.3013847.

[9] M. I. Campbell, J. Cagan, and K. Kotovsky, “A-Design: An Agent-Based Approach to Conceptual Design in a Dynamic Environment,” Res. Eng. Des., vol. 11, no. 3, pp. 172–192, Oct. 1999, doi: 10.1007/s001630050013.

[10] A. Brown, M. H. Goldstein, J. Clay, H. O. Demirel, X. Li, and Z. Sha, “A Study on Generative Design Reasoning and Students’ Divergent and Convergent Thinking,” J. Mech. Des., vol. 146, no. 3, p. 031405, Mar. 2024, doi: 10.1115/1.4064564.

[11] W. Zhu, R. Guo, Y. Wang, W. Xing, E. M. Kim, and C. Li, “Designing with AI: Integrating Image-Generative AI into Conceptual Design in a CAD Class,” in 2024 ASEE Annual Conference & Exposition Proceedings, Portland, Oregon: ASEE Conferences, Jun. 2024, p. 47146. doi: 10.18260/1-2--47146.

[12] C. T. Schimpf, X. Huang, C. Xie, Z. Sha, and J. E. Massicotte, “Developing Instructional Design Agents to Support Novice and K-12 Design Education,” presented at the 2019 ASEE Annual Conference & Exposition, Jun. 2019. Accessed: Jan. 04, 2025. [Online]. Available: https://peer.asee.org/developing-instructional-design-agents-to-support-novice-and-k-12-design-education

[13] Y. Hu and M. Taylor, “WORK IN PROGRESS: A Computer-Aided Design Intelligent Tutoring System Teaching Strategic Flexibility,” in 2016 ASEE Annual Conference & Exposition Proceedings, New Orleans, Louisiana: ASEE Conferences, Jun. 2016, p. 27208. doi: 10.18260/p.27208.

[14] Y. Li et al., “Design and Design Thinking in STEM Education,” J. STEM Educ. Res., vol. 2, no. 2, pp. 93–104, Dec. 2019, doi: 10.1007/s41979-019-00020-z.

[15] R. Razzouk and V. Shute, "What Is Design Thinking and Why Is It Important?," Rev. Educ. Res., vol. 82, no. 3, pp. 330–348, Sep. 2012, doi: 10.3102/0034654312457429.
[16] R. J. DeCarvalho, "The humanistic paradigm in education.," Humanist. Psychol., vol. 19, no. 1, pp. 88–104, 1991, doi: 10.1080/08873267.1991.9986754.
[17] D. F. Brown, "Urban Teachers' Use of Culturally Responsive Management Strategies," Theory Pract., vol. 42, no. 4, pp. 277–282, Nov. 2003, doi: 10.1207/s15430421tip4204_3.
[18] C. Weinstein, M. Curran, and S. Tomlinson-Clarke, "Culturally Responsive Classroom Management: Awareness Into Action," Theory Pract., vol. 42, no. 4, pp. 269–276, Nov. 2003, doi: 10.1207/s15430421tip4204_2.
[19] C. E. Hmelo-Silver, R. G. Duncan, and C. A. Chinn, "Scaffolding and Achievement in Problem-Based and Inquiry Learning: A Response to Kirschner, Sweller, and Clark (2006)," Educ. Psychol., vol. 42, no. 2, pp. 99–107, Apr. 2007, doi: 10.1080/00461520701263368.
[20] C. E. Hmelo-Silver, "Problem-Based Learning: What and How Do Students Learn?," Educ. Psychol. Rev., vol. 16, no. 3, pp. 235–266, Sep. 2004, doi: 10.1023/B:EDPR.0000034022.16470.f3.
[21] M. S. Kleine, K. Zacharias, and D. Ozkan, "Contextualization in engineering education: A scoping literature review," J. Eng. Educ., vol. 113, no. 4, pp. 894–918, 2024, doi: 10.1002/jee.20570.
[22] H. Arksey and L. O'Malley, "Scoping studies: towards a methodological framework," Int. J. Soc. Res. Methodol., vol. 8, no. 1, pp. 19–32, Feb. 2005, doi: 10.1080/1364557032000119616.
[23] Z. Munn, M. D. J. Peters, C. Stern, C. Tufanaru, A. McArthur, and E. Aromataris, "Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach," BMC Med. Res. Methodol., vol. 18, no. 1, p. 143, Dec. 2018, doi: 10.1186/s12874-018-0611-x.
[24] C. T. Schimpf et al., "Board 394: Supporting Secondary Students' Engineering Front-End Design Skills with the Mobile Design Studio," presented at the 2024 ASEE Annual Conference & Exposition, Jun. 2024. Accessed: Dec. 16, 2024. [Online]. Available: https://peer.asee.org/board-394-supporting-secondary-students-engineering-front-end-design-skills-with-the-mobile-design-studio
[25] M. Petticrew and H. Roberts, Systematic Reviews in the Social Sciences: A Practical Guide, 1st ed. Wiley, 2006. doi: 10.1002/9780470754887.
[26] M. Borrego, M. J. Foster, and J. E. Froyd, "Systematic Literature Reviews in Engineering Education and Other Developing Interdisciplinary Fields," J. Eng. Educ., vol. 103, no. 1, pp. 45–76, Jan. 2014, doi: 10.1002/jee.20038.
[27] M. Cutumisu, D. B. Chin, and D. L. Schwartz, "A digital game-based assessment of middle-school and college students' choices to seek critical feedback and to revise," Br. J. Educ. Technol., vol. 50, no. 6, pp. 2977–3003, Nov. 2019, doi: 10.1111/bjet.12796.
[28] J. Sanabria-Z, B. Alfaro-Ponce, A. Argüelles-Cruz, and M. S. Ramírez-Montoya, "AI-Based Platform Design for Complex Thinking Assessment: A Case Study of an Ideathon Using the Transition Design Approach," Comput. Sch., vol. 40, no. 4, pp. 391–411, Oct. 2023, doi: 10.1080/07380569.2023.2256711.
[29] H. Huang, "Promoting students' creative and design thinking with generative AI- supported co-regulated learning: Evidence from digital game development projects in healthcare courses," Educ. Technol. Soc., vol. 27, no. 4, pp. 487–502, 2024, doi: https://doi.org/10.30191/ETS.202410_27(4).TP04.

[30] T. Hirashima, “Computer-Based Intelligent Support for Moderately Ill-Structured Problems,” 2017.
[31] K.-A. Lee and S.-B. Lim, “Designing a Leveled Conversational Teachable Agent for English Language Learners,” Appl. Sci., vol. 13, no. 11, p. 6541, May 2023, doi: 10.3390/app13116541.
[32] C.-C. Liu, W.-J. Chen, F. Lo, C.-H. Chang, and H.-M. Lin, “Teachable Q&A Agent: The Effect of Chatbot Training by Students on Reading Interest and Engagement,” J. Educ. Comput. Res., vol. 62, no. 4, pp. 1122–1154, Jul. 2024, doi: 10.1177/07356331241236467.
[33] G. Biswas, H. Jeong, J. S. Kinnebrew, B. Sulcer, and R. Roscoe, “MEASURING SELF-REGULATED LEARNING SKILLS THROUGH SOCIAL INTERACTIONS IN A TEACHABLE AGENT ENVIRONMENT,” Res. Pract. Technol. Enhanc. Learn., vol. 05, no. 02, pp. 123–152, Jul. 2010, doi: 10.1142/S1793206810000839.
[34] Leelawong, K., & Biswas, G. (2008). Designing learning by teaching agents: The Betty's Brain system. *International Journal of Artificial Intelligence in Education, 18*(3), 181–208.
[35] D. Song, “Designing a Teachable Agent System for Mathematics Learning,” Contemp. Educ. Technol., vol. 8, no. 2, Apr. 2017, doi: 10.30935/cedtech/6194.
[36] N. Matsuda, W. Weng, and N. Wall, “The Effect of Metacognitive Scaffolding for Learning by Teaching a Teachable Agent,” Int. J. Artif. Intell. Educ., vol. 30, no. 1, pp. 1–37, Mar. 2020, doi: 10.1007/s40593-019-00190-2.
[37] A. Silvervarg, R. Wolf, K. P. Blair, M. Haake, and A. Gulz, “How teachable agents influence students’ responses to critical constructive feedback,” J. Res. Technol. Educ., vol. 53, no. 1, pp. 67–88, Jan. 2021, doi: 10.1080/15391523.2020.1784812.
[38] B. Tärning, A. Silvervarg, A. Gulz, and M. Haake, “Instructing a Teachable Agent with Low or High Self-Efficacy – Does Similarity Attract?,” Int. J. Artif. Intell. Educ., vol. 29, no. 1, pp. 89–121, Mar. 2019, doi: 10.1007/s40593-018-0167-2.
[39] M. B. Weaver et al., “Improving Engineering Sketching Education Through Perspective Techniques and an AI-Based Tutoring Platform,” Int. J. Eng. Educ., vol. 38, no. 6, pp. 1836–1850, 2022.

APPENDIX A
PICOS FRAMEWORK

Population	K-16 students in the United States Education
Intervention	Learning interactions in the environment of Artificial Intelligence are used for design thinking for open-ended problems
Comparison	Roles and Responsibilities of Students and Artificial
Outcome	Learning interactions and learning discussion
Study Design	Synthesizing all the empirical and theoretical studies discussing AI interventions for learning in open-ended problem space