International Society of the Learning Sciences

Designing AI to Scaffold Learners' Cognitive Engagement in Generative Learning

Zhenyao Cai, University of California, Irvine, zhenyaoc@uci.edu
Minchun Lai, University of California, Irvine, minchul@uci.edu
Shiyao Wei, Florida State University, sw22b@fsu.edu
Shayan Doroudi, University of California, Irvine, doroudis@uci.edu

Abstract: Recent advances in AI have raised concerns about students' overreliance on automated systems that may complete learning tasks without requiring meaningful cognitive effort and engagement. This paper explores how AI can be designed to scaffold and sustain cognitive engagement in generative learning activities. Drawing on generative learning theory and scaffolding, we present a conceptual account of how AI can guide learners through generative processes such as selecting, organizing, and integrating information, while gradually fading support as competence develops. We illustrate this through the design of an AI-assisted system that helps children (aged 8–13) create educational science videos --- a task that embodies generative learning but poses cognitive challenges for young learners. Our work sheds light on how to integrate scaffolding to foster but not replace meaningful engagement with AI in generative learning.

Introduction

One growing concern of using AI in education is what some researchers describe as *overreliance* or *overdependence* on AI, where students use AI systems to complete tasks that require personal effort and thinking (Han et al., 2024; Cai et al., 2025a). While AI tools can solve problems and provide answers quickly and often accurately, they may diminish learners' active participation and engagement in the mental processes involved in these tasks, which are essential for understanding and actual learning.

This issue is especially salient in generative learning tasks**.** Generative learning theory was first proposed by Wittrock (1992)**,** who viewed learning as an active process in which learners generate relationships between new information and their prior knowledge to make sense of experience. Later research has proposed cognitive models to explain the mechanisms of generative learning and the tasks that support it. Notably, Fiorella and Mayer (2016) describe the SOI model, where learners deepen understanding by *selecting* relevant information, *organizing* it into coherent structures and *integrating* it with existing knowledge. They also proposed eight types of tasks that promote such learning, such as teaching others or self-explaining, as these tasks would strength and support the SOI process involved (Fiorella & Mayer, 2013, 2016). However, AI systems can now automate many of these generative tasks, which means students may complete them without engaging in the underlying cognitive work. For example, instead of explaining a concept in their own words, a student might ask AI to generate the explanation, resulting in a finished product but limited cognitive engagement (Cai et al, 2025b).

This challenge, however, is not unsolvable. The solution can be framed as how to design AI systems that support these mental processes rather than allowing students to avoid them. Many researchers have attempted to do this. In the field of Human–Computer Interaction (HCI), which focuses on the design of systems, many studies have used approaches based on behaviorism, such as adding friction or nudges to influence user behavior and many showed positive results (Buçinca et al, 2021; Bo et al, 2025). For example, some systems intentionally add small difficulties or interruptions to have users wait or slow down, prompting them to think more carefully. Some systems embed nudges in the interface that reinforce positive behaviors (Caraban et al, 2019). As mentioned in some of the studies, one problem with such approach is reduced user satisfaction and productivity, as they are obtrusive than supportive (Buçinca et al, 2021; Bo et al, 2025). A different approach, which is also what we propose in this paper, can be drawn from Vygotsky's Zone of Proximal Development (ZPD) theory (1978), where AI functions not as an automation but as a form of guidance to guide them through the cognitive tasks they would not be able to accomplish alone. The AI decomposes the overall task into subtasks that fall within the student's ZPD and acts as a temporary scaffold that supports their progression in key mental processes such as organizing, reflecting, and integrating information (Van de Pol et al, 2010). Over time, the AI gradually reduces its support as the learner gains competence and confidence, allowing the student to internalize these processes and perform them independently (Wood et al, 1976).

In this paper, we contribute a conceptual understanding of how AI can be designed to scaffold and foster generative learning, drawing on theoretical perspectives from both generative learning theory and scaffolding. We demonstrate this through the design of an AI-assisted system that supports children in creating educational

 © ISLS

science videos. We focus on this case because science video creation is a generative learning task that requires learners to comprehend content by actively constructing their own explanations and narrations, yet it remains a challenging activity for children to accomplish independently (Cai & Wei, 2024). Our work sheds light on how scaffolding strategies can be incorporated into the design of AI systems to support generative learning activities.

Theoretical framework

Generative learning through learning by teaching

Generative learning theory builds on cognitive constructivism and highlights that learning occurs when learners organize and integrate new content with prior knowledge (Wittrock, 1992; Fiorella & Mayer, 2016). Many models explain the mechanism of generative process. According to the SOI model, learners deepen understanding by selecting relevant information, organizing it into coherent structures, and integrating it with existing knowledge. A different model ICAP framework (Chi & Wylie, 2014), further emphasize that learning outcomes depend on the level of cognitive engagement, with *constructive and interactive* activities (e.g., discussion or peer teaching) producing the deepest understanding.

Among the many generative activities, learning by teaching has been shown to be particularly effective because it requires learners to externalize knowledge. Research identifies two main stages in the learning-by-teaching process: preparing to teach and actually teaching (Fiorella & Mayer, 2014). Preparing to teach helps learners select and organize, while the act of teaching itself deepens comprehension by prompting learners to elaborate and monitor their own understanding (Roscoe & Chi, 2007). Empirical studies have shown that the preparation phase leads to immediate comprehension gains, whereas the act of teaching supports delayed comprehension (Fiorella & Mayer, 2014). Recent work also examines teaching through video as a non-interactive but effective learning-by-teaching activity. Teaching to a camera allows learners to experience a moderate level of social presence that lower the anxiety or distraction that may accompany live audiences (Wang, Cheng, & Mayer, 2023).

However, generating their own explanations or teaching based on science content is a difficult task for novices (e.g. children with limited experience) to accomplish independently. A study by Cai and Wei (2024), which analyzed YouTube science educational videos created by children, found that children who made videos without parental involvement often produced superficial explanations that focused on describing observable phenomena rather than engaging with underlying scientific principles. This is where AI can add meaningful learning experiences (Cai et al, 2025b), but it must be designed to navigate the stages of learning by teaching and to support the generative processes involved rather than completing the task for the learner.

Scaffolding to support generative learning

Scaffolding can be used to support generative learning, especially when learners find it difficult to engage in complex cognitive processes without guidance. The concept comes from Vygotsky's (1978) theory of the Zone of Proximal Development (ZPD), which refers to the distance between what a learner can accomplish independently and what they can achieve with assistance from a more knowledgeable other. Within this zone lies the optimal point for learning, where tasks are challenging but achievable with guidance. A scaffolder provides temporary and adaptive support to help learners operate within this zone, and the support is gradually withdrawn as learners gain competence and independence.

From a functional perspective, scaffolding allows learners to progress through what Bickhard (1980) describes as a series of "manageable points of stability," where complex problems are broken down into smaller, attainable steps. Scaffolding is also not static assistance but a dynamic and contingent process**.** Van de Pol, Volman, and Beishuizen (2010) identify three characteristics of effective scaffolding: contingency, which refers to responsiveness to the learner's current understanding and needs**;** fading**,** which involves gradually reducing support as the learner's skill improves; and transfer of responsibility, which occurs when learners take increasing control of their own cognitive and metacognitive processes.

In the context of generative learning, scaffolding supports learners' engagement in core cognitive processes such as selecting, organizing, and integrating information. Core design considerations of the AI scaffolder are (1) identifying and breaking large problems into smaller, manageable subproblems within learner's ZPD, (2) guiding learners not only to complete each subtask but also to engage in the underlying process of constructing knowledge and (3) gradually fading the level of support and transferring responsibility to the learner once they demonstrate sufficient capability.

Design case: AI-assisted science video creation

Building on generative learning theory and scaffolding, the AI system was designed to help children (aged 8–13, as aligned with our prior studies) learn science through the process of teaching on video. The design is grounded in two main considerations: (1) Guiding learners through structured generative cognitive processes involved in video creation, including connecting to prior knowledge, selecting key information, organizing content, and integrating ideas into existing knowledge through coherent explanations and personal reflections; and (2) Embedding scaffolding mechanisms within each subprocess, including contingent prompting and modeling, targeted feedback, and fading or sharing responsibility as the learner gains competence. Figure 1 provides a user scenario of the system.

Supporting the generative learning process

Step 1: Connecting to prior knowledge

The AI begins by asking general prompts such as "What do you already know about this topic?" or "Can you think of something similar you've seen or experienced?" This stage activates learners' prior knowledge, helping them build connections between new and existing concepts.

Step 2: Selecting information

Next, the AI guides learners in identifying key scientific ideas from source materials. It asks learners to summarize what is most important or relevant to their topic. When learners overlook critical information, the AI offers contingent hints ("Which part explains why it happens?") or models selection strategies. Feedback helps learners evaluate the accuracy and completeness of their selections. Over time, the AI fades assistance, allowing learners to identify and articulate the important and relevant information from the source material.

Step 3: Organizing content

In this phase, learners are prompted to structure their explanations for an audience --- for example, by outlining an introduction, main body, and conclusion. The AI provides models of effective organization ("You could start by explaining what happens, then describe why") and gives feedback on clarity and coherence. As learners improve, the AI reduces explicit modeling and instead asks reflective prompts such as "How could you make your explanation easier to follow?"

Step 4: Integrating ideas

Finally, learners are guided to synthesize their understanding into their own words and reflect on their explanations. The AI asks deeper prompts like "Why does this happen?" or "How would you help someone else understand this idea?" Feedback reinforces conceptual connections and encourages independent expression.

Scaffolding strategies in each step

Within each step, the AI provides scaffolding through three core mechanisms:

- Contingent prompting and modeling: The AI begins each step with open-ended prompts to elicit the learner's initial ideas. If the learner struggles or gives incomplete responses, the AI offers follow-up questions, examples, or simplified versions of the task to model the reasoning process.
- Feedback: The AI evaluates learners' responses in real time and provides targeted feedback that points out missing elements, logical gaps, or opportunities to elaborate.
- Fading and transfer of responsibility: As the learner demonstrates understanding and self-direction, the AI gradually reduces the amount of guidance, allowing the learner to take more ownership of the cognitive process.

Figure 1 in the Appendix illustrates how the AI system scaffolds children's engagement in generative with "Stella": (A) Article Upload. Stella uploads a short science article. The AI extracts key information and identifies the topic and main ideas that form the foundation for learning. (B) The bot sets the learning goal ("teach others about Earth's orbit and seasons") and prompts Stella to recall what she already knows. When Stella initially says "I don't know," the AI provides contingent hints ("Tell me anything about it you knew"), helping her activate relevant prior knowledge. (C) Information Selection. The AI guides Stella in identifying and explaining essential scientific ideas from the learning material. When she misunderstands "tilt," the AI models reasoning through guided questioning ("Does tilt mean leaning?") and gradually fades support as she finds a comprehensive and accurate list information. (D) Script Organization: The AI helps Stella structure her script with an introduction,

 © ISLS

main content, and conclusion, providing feedback on transitions and coherence, then transferring responsibility by prompting self-evaluation ("How can you make it clearer?").

Discussion and future work

This paper offers an initial theoretical account of how the problem of outsourcing essential cognitive processes in generative learning to AI can be addressed through the design of AI scaffolding. Our design is grounded in two core ideas derived from generative learning and scaffolding theory: (1) structuring complex learning tasks into manageable subprocesses, and (2) embedding contingent support within each subprocess to sustain cognitive engagement. Although we conducted a small pilot study with children to explore the feasibility of this design, data cannot be reported due to IRB restrictions. Future empirical work is therefore needed to examine the effectiveness of this scaffolding approach in promoting both short-term learning and long-term retention.

Beyond video creation, we envision extending this framework to other generative learning contexts, such as concept mapping or argument construction. Future work could include a more comprehensive review of scaffolding strategies to identify which types of supports are most effective for different generative tasks and subprocesses, as well as to examine which forms of scaffolding are feasible for AI to implement effectively.

References

Bo, J. Y., Wan, S., & Anderson, A. (2025, April). To rely or not to rely? evaluating interventions for appropriate reliance on large language models. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-23).

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. *Proceedings of the ACM on Human-computer Interaction*, *5*(CSCW1), 1-21.

Cai, Z., & Wei, S. (2024, June). From Viewers to Teachers: Child-Led Teaching Strategies and Family Participation in YouTube How-Tos. In *Proceedings of the 23rd Annual ACM Interaction Design and Children Conference* (pp. 396-407).

Cai, Z., Han, A., Zhou, X., Gazulla, E. D., & Peppler, K. (2025a). Child-AI Co-Creation: A Review of the Current Research Landscape and a Proposal for Six Design Considerations. *Proceedings of the 24th Interaction Design and Children*, 916-922.

Cai, Z., Wei, S., Han, A., & Peppler, K. A. (2025b). " Hi Kids, Let's Talk About How Snakes Hunt": Understanding the Process of Children's Instructional Video Creation through a Workshop Study. In *Proceedings of the 24th Interaction Design and Children* (pp. 684-698).

Caraban, A., Karapanos, E., Gonçalves, D., & Campos, P. (2019, May). 23 ways to nudge: A review of technology-mediated nudging in human-computer interaction. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-15).

Fiorella, L., & Mayer, R. E. (2013). The relative benefits of learning by teaching and teaching expectancy. *Contemporary Educational Psychology*, *38*(4), 281-288.

Fiorella, L., & Mayer, R. E. (2014). Role of expectations and explanations in learning by teaching. *Contemporary educational psychology*, *39*(2), 75-85.

Fiorella, L., & Mayer, R. E. (2016). Eight ways to promote generative learning. *Educational psychology review*, *28*(4), 717-741.

Han, A., Zhou, X., Cai, Z., Han, S., Ko, R., Corrigan, S., & Peppler, K. A. (2024, May). Teachers, parents, and students' perspectives on integrating generative AI into elementary literacy education. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (pp. 1-17).

Roscoe, R. D., & Chi, M. T. (2007). Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. *Review of educational research*, *77*(4), 534-574.

Van de Pol, J., Volman, M., & Beishuizen, J. (2010). *Scaffolding in teacher–student interaction: A decade of research. Educational Psychology Review, 22*(3), 271–296.

Wang, F., Cheng, M., & Mayer, R. E. (2023). Improving learning-by-teaching without audience interaction as a generative learning activity by minimizing the social presence of the audience. *Journal of educational psychology*, *115*(6), 783.

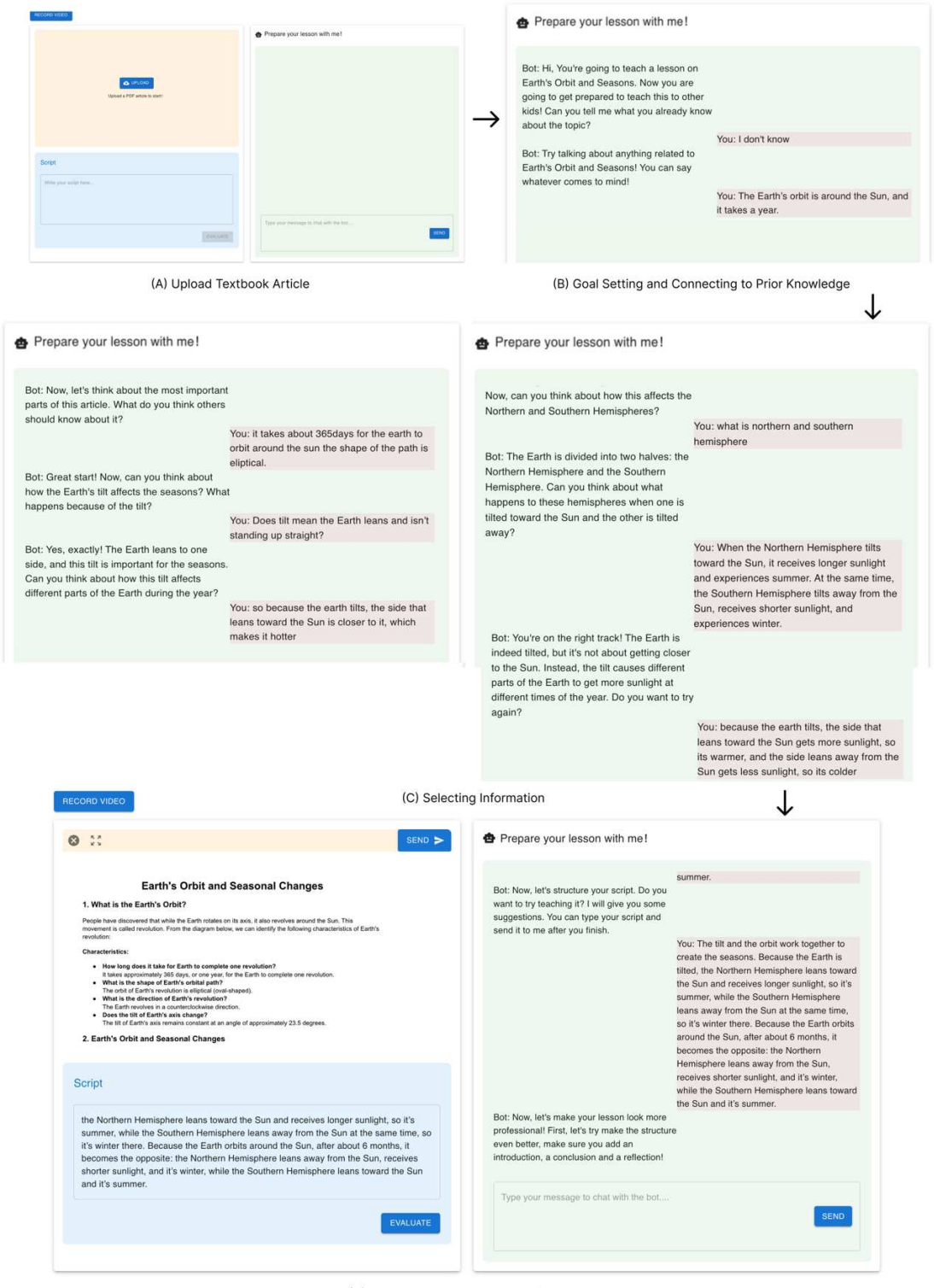
Wittrock, M. C. (1992). Generative learning processes of the brain. *Educational psychologist*, *27*(4), 531-541.

Wood, D., Bruner, J. S., & Ross, G. (1976). *The role of tutoring in problem solving. Journal of Child Psychology and Psychiatry, 17*(2), 89–100.

Appendix

Figure 1

The AI Scaffolder Workflow



Note: For a higher-resolution image, please access: https://www.figma.com/proto/9p8rKJA4C09ozFo1vebmek/Untitled?node-id=1-2&t=BoiThn2NVGcH73j7-1&scaling=min-zoom&content-scaling=fixed&page-id=0%3A1

 © ISLS