Paper accepted for presentation at CONVERSATIONS 2025 – the International Symposium on Chatbots and Human-Centred AI, hosted at TU Lübeck, Germany, November 12-13, 2025.

Adaptive Scaffolding for Human-Centered AI in Education

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Abstract. Artificial intelligence (AI) is increasingly integrated into educational contexts, offering new opportunities for efficiency and accessibility. Yet, growing reliance on AI raises concerns about superficial learning and reduced cognitive engagement. Prior research has investigated strategies to limit overreliance in AI-supported environments, such as restricting guidance or introducing turbots, while studies in traditional settings have compared different scaffolding types. However, little attention has been given to how scaffolding can be dynamically adapted to learners' preparedness in AI-driven environments. This position paper outlines a study that will examine the balance between domain-specific and metacognitive support, and how fading strategies can be used to gradually reduce guidance as learners gain competence. The planned experiment systematically varies scaffolding conditions to evaluate their effects on learning outcomes. By presenting this research design, we aim to stimulate discussion and receive feedback on how adaptive scaffolding can contribute to human-centered AI in education and foster meaningful learning.

Keywords: Scaffolding, Adaptive learning support, AI-supported learning.

1 Introduction

Generative artificial intelligence (GenAI) is transforming education at a rapid pace, with systems such as ChatGPT being integrated into learning environments across institutions. These systems offer significant advantages, providing students with highly personalized learning experiences and offering educators efficiency gains through automated support and feedback [1, 2].

However, the widespread use of general-purpose AI in educational contexts has revealed significant limitations. Research shows that students are becoming overly reliant on these tools and developing superficial learning patterns that could undermine their long-term educational outcomes [3, 4]. When learners become dependent on AI for tasks that they should be mastering independently, the fundamental objectives of education, namely the development of autonomous thinking and problem-solving skills, are compromised [3, 4].

One way to address these challenges is to implement fading guidance, whereby AI systems gradually reduce their level of support as students become more competent [2].

This approach is based on the educational principle of scaffolding, whereby temporary support is provided to enable learners to complete tasks that are beyond their current capabilities, with this support being withdrawn as competence develops [6, 7]. Effective scaffolding operates within Vygotsky's Zone of Proximal Development, offering learners just enough support to facilitate learning without fostering dependency [8] . The challenge lies in translating these well-established pedagogical principles into the context of modern AI systems [2, 3]. While extensive research evidence exists for scaffolding in traditional educational settings [7] , most of this research predates recent advances in GenAI. Consequently, most existing research focuses on static categories of scaffolding that remain fixed throughout the learning process [9, 10] . However, generative AI systems offer the opportunity for dynamic, personalized scaffolding that can adapt in real time to the needs and progress of individual students [2].

This presents significant opportunities and research needs. In this study, we examine how scaffolding can be aligned with learners' preparedness in AI-supported environments. We concentrate on the balance between domain-specific and metacognitive support and explore how fading strategies might reduce guidance as competence develops. To investigate this, a quasi-experimental study with university students is planned, comparing students who naturally choose not to use AI assistance with those who utilize adaptive scaffolding that adjusts support to learners' progress.

While this experiment is in preparation, several methodological issues remain open. These include the appropriate frequency of adaptation, suitable metrics for assessing readiness, and the balance between ecological validity and experimental control. Addressing these questions will be essential for designing robust studies on adaptive scaffolding in AI-supported education.

2 Theoretical Background

2.1 Learning Theories and Scaffolding

Understanding scaffolding starts with how Cognitive Load Theory (CLT) works. As Kalyuga and Sweller (2005) describe, when learners face new or complex material, their working memory can easily become overloaded. Because this memory can only handle a few pieces of information at once, performance drops when the task feels too demanding. With experience, however, learners build mental structures—called schemas—that help them connect ideas and process information more efficiently. These schemas, stored in long-term memory, ease the burden on working memory by grouping information into familiar patterns [11]. Vygotsky's idea of the Zone of Proximal Development (ZPD) adds another important layer. He viewed learning as a social process and explained that real progress happens in the space between what learners can do on their own and what they can do with guidance from others. In this view, effective support depends not just on managing mental effort but also on understanding when and how help becomes meaningful [8]. Together, these two ideas show different but complementary sides of learning. CLT focuses on how the mind manages information, while the ZPD shows where support is most effective. Scaffolding works best when both come together—when the task is mentally manageable and the help fits the learner's current stage of growth. Good teaching keeps the balance. When cognitive load is managed well, learners have more capacity to think deeply and make sense of new ideas. Clear examples, prompts, or feedback can direct attention to what truly matters and prevent wasted effort. As learners grow more skilled, though, the same level of help can start to hold them back. Too much guidance can make tasks feel restrictive rather than supportive—a pattern known as the expertise reversal effect [11, 12]. Effective scaffolding, then, is not fixed. It adjusts as learners change, providing enough structure to guide them but not so much that it limits their independence. Over time, as learners internalize what they have practiced, external support fades and becomes unnecessary. This gradual shift—from supported to independent performance—is the core of meaningful learning [13] .

2.2 Forms of Scaffolding

Scaffolding can take different forms. Domain-specific scaffolding offers content-related guidance by providing learners with subject knowledge, highlighting which aspects should be considered, and illustrating how ideas can be connected in the process of problem solving [6, 14]. As Kim and Lim (2019) emphasize, this type of support helps novices construct more accurate representations of problems by directing them to identify and link key concepts. Research shows that this type of support is especially valuable for novices, as it directs students toward relevant concepts [6]. For instance, a novice working on a lesson plan might be given a template with predefined sections such as learning objectives or assessment methods, which provides the necessary content-related guidance to organize their ideas effectively [6].

Metacognitive scaffolding, in contrast, focuses on students' ability to regulate their own learning. Prompts that encourage planning, monitoring, and reflection help learners to organize and manage their strategies [6, 15]. This kind of support is particularly valuable in complex problem-solving settings, where multiple strategies must be coordinated and adapted to new challenges [9, 16]. For example, instead of providing a template, the system might ask the student questions such as "Have you considered alternative solutions?" or "How will you evaluate whether your plan works?", encouraging reflection on the process rather than supplying content [15].

Building on the previous discussion of how instructional support must evolve as learners gain experience, both domain-specific and metacognitive scaffolding face the same limitation—the expertise reversal effect. Instructional methods that effectively support novices, such as worked examples or step-by-step explanations, may lose their value as learners develop relevant schemas in long-term memory [11, 12]. In such cases, processing redundant information can impose unnecessary cognitive load and interfere with self-directed problem solving. In these cases, processing repeated or unnecessary information adds extra load to working memory and can slow down active knowledge construction [11, 12].

2.3 Adaptive and Fading Guidance

To address these challenges, scaffolding needs to be matched to the learner's level and then reduced as competence grows [2, 5]. Fading procedures offer a structured way to achieve this. Support is gradually withdrawn step by step, so that learners receive guidance when it is most useful, while at the same time developing the independence needed for autonomous learning [7] .

This gradual reduction can be implemented through adaptive scaffolding. Here, support is aligned with the individual's learning progress by providing hints at critical moments, offering guidance when difficulties arise, and withdrawing assistance once competence is demonstrated [9, 16] . By tailoring the fading process, adaptive scaffolding reduces redundancy, mitigates the expertise reversal effect, and fosters autonomy [5]. In contrast, static scaffolding maintains the same level of support throughout the learning process, without adapting to changes in competence [9]. This distinction is crucial when considering how scaffolding principles can be transferred into technology-enhanced settings.

2.4 Scaffolding in AI-Supported Learning Environments

The contrast between static and adaptive scaffolding becomes especially relevant once digital technologies are introduced into learning settings. Recent advances in artificial intelligence make it possible to deliver guidance that is immediate, personalized, and dynamically adjusted, thereby bringing scaffolding into real-time and large-scale educational practice [1, 17]. Yet studies caution that if such support is applied uniformly or too intensively, it can foster dependency and encourage superficial engagement [2–4, 18] .

To address these concerns, researchers have explored ways of regulating the timing and intensity of guidance, for example by limiting feedback or by using conversational tutor-bots that provide context-sensitive support [2, 19]. These efforts connect to the broader debate on human-centered AI, which emphasizes that efficiency should not come at the expense of meaningful learning and active engagement [4] .

By enabling adaptive scaffolding on a large scale, AI translates long-standing pedagogical principles into new technological contexts. At the same time, these possibilities also sharpen the need to regulate support carefully, since poorly calibrated guidance—whether too uniform or too intensive—can foster dependency and limit deeper engagement [2, 18] .

3 Research Questions

Against this backdrop, the study sets out to examine how scaffolding can be effectively designed and implemented in AI-supported learning environments. The focus is on when and how different forms of support should be applied, and how adaptive fading can sustain learner autonomy while preventing overreliance.

The primary research questions are:

- **RQ1:** How can scaffolding be dynamically adapted to learners' levels of preparedness in AI-supported learning environments?
- **RQ2:** What are the relative effects of domain-specific versus metacognitive scaffolding on learners at different stages of expertise?
- **RQ3:** How do fading strategies influence the balance between necessary support and learner autonomy in AI-assisted education?

Together, these questions frame a study that will provide feedback on the design of human-centered AI learning systems.

4 Proposed Method

The AI system to be used in this study will be implemented as a conversational agent based on large language model (LLM) technology. Rather than developing a model from scratch, we will employ an existing LLM interface that allows the integration of customized scaffolding prompts and feedback rules. This setup enables adaptive, context-sensitive support while maintaining transparency and replicability.

We will employ a quasi-experimental design with approximately 150 university students in an authentic course setting. To ensure fairness and ecological validity, participants will self-select into conditions based on their actual usage patterns of the AI support system:

1. Control group: Students who choose not to use AI assistance during their learning process. The control group will consist of students who, at the beginning of the semester, indicate that they do not intend to use AI assistance during the course. These students will complete the same learning tasks without support from the adaptive AI system under study. While it is not possible or desirable to fully prevent the use of other AI tools (such as ChatGPT) outside the experimental setting, participants will be asked to adhere to their declared learning strategy throughout the course. This self-selection approach reflects the natural diversity of student preferences regarding AI use and ensures that participation remains voluntary and ethically sound.
2. Adaptive scaffolding group: Students who use the AI system with dynamically adjusted support based on their preparedness levels. More precisely, the adaptive condition relies on a layered scaffolding approach. The system interprets diagnostic indicators to estimate each student's level of preparedness. When general support is required, it provides domain-general scaffolds, for example metacognitive prompts that guide planning, monitoring, and reflection. When content knowledge becomes the main obstacle, it shifts to domain-specific scaffolds, such as worked examples, targeted hints, visual concept maps, or structured templates. Interventions are regulated by control mechanisms: prompts are delayed until ineffective strategies appear consistently, a minimum interval is maintained between successive interventions, and critical problems are prioritized over minor ones. Finally, scaffolding is gradually withdrawn through backward-fading. Students begin with fully worked examples, then complete progressively larger parts of the task, until they can work independently.

While this self-selection approach limits our ability to make strong causal claims, it provides high external validity by examining how students naturally engage with AI support in real educational contexts. We will control for potential confounding variables such as prior knowledge of and experience with generative AI tools such as ChatGPT, motivation, and learning strategies based on a questionnaire students complete before and after using the AI-learning assistant. This design reflects the reality that in actual educational settings, students have autonomy over their tool usage, making our findings more applicable to real-world implementations. The learning task consists of Enterprise Resource Planning (ERP); module offered at Friedrich Schiller University Jena as part of the bachelor's curriculum.

To align scaffolding with learners' competence, support will be adjusted at three checkpoints that correspond to distinct proficiency levels: beginner, intermediate, and expert. This stratification of guidance follows prior work on adaptive fading and the expertise reversal effect, which emphasize that instructional support must vary according to learners' proficiency [12] . The use of discrete stages or checkpoints for adaptive guidance has been shown to help maintain an optimal balance between learner control and instructional support [20].

Participants will be dynamically classified into these categories based on diagnostic measures collected before and during the learning activity, consistent with approaches to adaptive tutoring that rely on continuous assessment of learner performance [21]. Classification will rely on a combination of indicators: pre-test performance, self-efficacy ratings, and process data such as response time, frequency of ineffective strategies, and efficiency indices that integrate performance and mental effort [9]. Together, these measures provide a dynamic estimate of cognitive efficiency, allowing learners to move between categories as their expertise evolves [12].

For beginner learners, scaffolding will focus on knowledge acquisition and comprehension, corresponding to the lower levels of Bloom's taxonomy [22]. Tasks in this phase will include worked examples, structured templates, and step-by-step prompts that reduce extraneous cognitive load while promoting schema construction [23] .Intermediate learners will engage with tasks situated at the application and analysis levels of Bloom's hierarchy [24]. At this stage, support will gradually shift from explicit instruction to metacognitive prompts that encourage planning, monitoring, and self-correction [9].

For advanced learners, scaffolding will emphasize evaluation and creation, the upper levels of Bloom's taxonomy [25]. Tasks will involve open-ended problem solving and project-based activities that require learners to integrate and apply knowledge across domains, reflecting the higher-order thinking skills outlined in the revised taxonomy [15]. Here, guidance will primarily take the form of reflective prompts that foster autonomy and self-regulation rather than direct instruction [8, 13] .

Progression between levels will depend not only on performance accuracy but also on a multidimensional assessment of cognitive efficiency and strategy use [26] . When learners demonstrate high performance with low mental effort and consistent self-regulation, external guidance will be reduced, signaling readiness to advance [11]. Conversely, when persistent inefficiencies or cognitive strain are detected, learners may temporarily return to a lower level of scaffolding to consolidate understanding before progressing further [9]. This adaptive mechanism ensures that instructional support remains contingent, data-driven, and pedagogically aligned with learners' evolving expertise [20].

The AI-learning assistant will be implemented as a conversational agent using an open-source LLM (e.g., LLaMA or Mistral 7B) hosted locally. The system employs three key components: Retrieval-Augmented Generation (RAG) to ground responses in verified course materials, persistent storage of learning dialogues to track individual progress patterns, and customizable scaffolding rules that implement fading guidance by adjusting support levels based on demonstrated competence. This architecture enables adaptive, context-sensitive support while ensuring data privacy.

While AI technologies hold significant potential for enhancing learning, critical scholars have pointed out that their integration in education also raises questions about human agency, deskilling, and overreliance on automated guidance. As Selwyn (2019) argues, the increasing use of AI systems in classrooms should be understood not only as a technological development but also as a sociocultural shift that may redefine the boundaries of teaching and learning. This study takes such concerns into account by focusing on how adaptive scaffolding can preserve learner autonomy within AI-supported environments [27].

5 Expected Contribution

This research will provide three key contributions:

1. Theoretical contribution: A framework for understanding when and how different types of scaffolding should be employed in AI-supported learning environments, extending current theories of the guidance fading effect to AI contexts.
2. Methodological contribution: A novel approach for measuring and responding to learner preparedness in real-time, combining performance metrics with metacognitive indicators.
3. Practical contribution: Evidence-based design guidelines for AI-learning systems that can dynamically adjust support, potentially improving learning outcomes while reducing overreliance.

6 Conclusion

We invite feedback from the CONVERSATIONS community. In particular, we seek input on how to best assess learner preparedness, whether our planned checkpoints for adjusting scaffolding are suitable, and how the study design could be extended to other contexts. Such feedback will help us refine the methodology and strengthen the contribution of adaptive scaffolding to human-centered AI in education. Future work will explore how cognitive load and ZPD principles can be jointly operationalized in adaptive AI systems, and how the proposed checkpoint model can be validated across diverse educational contexts.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article

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