HHAI 2026
M. Alimardani et al. (Eds.)

doi:10.3233/FAIA260504

Scaffolding the Scaffold: Co-Evolving Human-Centered Boundaries for GenAI in Education

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Abstract. Current educational approaches often treat GenAI access as binary, permit or prohibit, failing to accommodate learning's developmental nature. This one-size-fits-all approach risks either depriving students of valuable learning opportunities or enabling over-reliance that undermines skill development. While recent work explores instructor-configurable GenAI, no approach treats governance as an adaptive per-student scaffold based on demonstrated competency. We propose co-evolving boundaries: GenAI constraints that evolve dynamically with student competency. Grounded in pedagogical theories (Zone of Proximal Development, scaffolding, mastery learning) and technical capabilities (learning analytics, configurable GenAI), adaptive boundaries would evolve through three developmental stages negotiated among students, teachers, and GenAI systems: restrictive scaffolding for novices, selective access with over-reliance monitoring for intermediates, and open collaboration for advanced students. We present four research questions addressing boundary negotiation, competency detection, transparency, and evaluation. This transforms GenAI from a policy concern into a human-centered pedagogical instrument, enabling co-evolution of AI constraints and student competency while balancing personalization with equity, transparency with usability, and autonomy with guidance.

Keywords. AI in Education, Human-Centered AI, Adaptive AI, Human-AI Co-Evolution, Generative AI

1. Introduction

With the ever-increasing presence of GenAI, educators have been tasked with deciding its role in the classroom. They can choose to ban the use of GenAI entirely,

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but this risks losing pedagogical opportunities [1]. On the other hand, if they allow GenAI tools, there is a risk of student over-dependence and underdevelopment of foundational skills (e.g., writing, critical thinking, problem-solving) [2]. A study of the guidelines of the top 50 U.S. universities shows that 94% already advise their faculty to implement course-specific guidelines on GenAI [3]. As a result, many institutional guidelines address surface-level concerns like plagiarism while failing to address deeper ethical and governance challenges (e.g., transparency, accountability, student data protection), leaving educators without actionable policy support [4]. Lately, research is increasingly mediating student-GenAI interactions through configurable monitoring and output alignment, moving beyond “ban vs. allow” decisions [5]. For example, Ortega-Arranz et al. [5] enable teachers to pre-configure how GenAI responds, such as enforcing scaffolding instead of direct solutions, adding prompt modifiers to align answers with students’ curriculum, and setting constraints like answer length or controlled hallucination rates to shape pedagogical outcomes. However, the configuration of such monitoring and alignment tools is typically set at the course/teacher level rather than as a developmental scaffold that adapts per student as competencies emerge. Such one-size-fits-all policies fail to accommodate varying levels of expertise, which has been shown to negatively impact the learning process [6].

This one-size-fits-all approach reveals a conceptual gap in how we think about GenAI in education. Most policies are binary decisions enforced uniformly across all students [7,8], overlooking the developmental nature of learning. Previous research on scaffolding has demonstrated that effective support systems should adapt as the student progresses [9], thus staying within the student’s Zone of Proximal Development [10]. If we apply the same logic to GenAI, it should function less as a static tool to be permitted or prohibited and more as instructional support whose pedagogical value depends on how and when it is introduced.

Several recent developments suggest that adaptive approaches to GenAI governance are increasingly viable. First, GenAI has become widespread and is accessible to anyone with an internet connection. This leads many students to already use the technology, with or without permission. Second, recent UNESCO guidance calls for context-sensitive approaches to GenAI that account for different student levels instead of overly uniform or restrictive policies [11]. Third, technology has evolved to detect competency signals from interaction patterns [12], creating opportunities to scaffold more traditional learning content. At the same time, GenAI systems have evolved to provide more personalized interactions at a large scale [1]. We believe the combination of mature pedagogical theories, ever-advancing technological capabilities, and the recent institutional urgency provides the basis for a human-centered reconceptualization of GenAI in education.

In this paper, we explore this reconceptualization: what if GenAI boundaries in education were adaptive rather than fixed? What if access restrictions evolved with student competency, negotiated dynamically among students, teachers, and GenAI systems? Instead of asking “Can this student use GenAI?”, a binary question that ignores developmental context, we might ask “What interactions with GenAI serve this student’s growth right now?”

We explore this new concept across three sections. In Section 2, we introduce how adaptive boundaries can function as scaffolding that is reduced as the student's competency develops. Section 3 explains how this is now possible, drawing on mature pedagogical theories combined with emerging technological capabilities. Finally, we identify future research directions around detection, negotiation, transparency, and evaluation in Section 4.

2. Adaptive Boundaries as Pedagogical Scaffolds

We propose to reconceptualize GenAI policies as adaptive boundaries that can scaffold based on the students' demonstrated competency. Compared to static boundaries that either block or allow specific GenAI uses [7,8], adaptive boundaries regulate which GenAI uses are available to a student based on their current mastery of a certain skill or topic. We envision these adaptations as a human-AI collaborative negotiation between three parties: (1) students, who signal competency through their learning behaviors; (2) instructors, who define learning goals and pedagogical constraints; and (3) the GenAI system itself, which mediates between the two by adapting its available features.

2.1. How Adaptive Boundaries Function

A key part of the adaptive boundaries is the signals a system can use to inform boundary changes. These signals should inform the system of students' competency development and can take many forms. For example, the frequency and depth of questions asked to a GenAI system [13], patterns in task completion in online learning environments [14], and the ability to critically evaluate GenAI output [15]. Instructors complement these signals by setting pedagogical milestones that define minimum requirements for a given competency or learning objective before the boundaries evolve. For example, a writing instructor might require students to demonstrate proper argumentation before allowing GenAI-assisted writing, while a programming instructor might already allow immediate access to code generation but require students to explain and modify the output.

After instructors set these pedagogical milestones, (Gen)AI systems can serve as an adaptive layer that scaffolds available features based on students' detected competencies and the instructors' pedagogical plan. For example, a system might initially require students to attempt a problem before offering hints, then gradually shift to on-demand assistance as their competencies develop. Importantly, this adaptation should be bidirectional: boundaries can loosen, but they should also tighten again during assessments or when the signals suggest over-reliance [16]. With this mechanism, GenAI in education would shift from "Are students allowed to use GenAI?" to "What GenAI uses serves this student's growth right now?"

2.2. Boundary Adaptation Across Learning Stages

As explained above, the adaptive boundaries only change when the students develop sufficient competency. Based on established models for skill acquisition [17] and mastery learning [18], we discern three stages where GenAI serves fundamentally different purposes: a novice, intermediate, and advanced stage.

At the novice stage, boundaries are most restrictive, as early access to (excessive) GenAI risks undermining the development of foundational skills [2]. Furthermore, research indicates that the same tool can benefit some students while negatively impacting others [6]; therefore, the system should first build an initial model of the student before personalizing the learning process. Because of this, the novice-stage boundaries should ensure that GenAI exposes its reasoning, requires metacognitive reflection before providing answers, and only gives direct solutions after the student has made a meaningful attempt, which aligns with teachers' demand for pedagogical GenAI configurations [5]. Next, at the intermediate stage, boundaries become more flexible, allowing identification and targeted addressing of gaps in students' competencies. At this stage, the primary risk is the creation of an over-reliance on the newly unlocked tools by students, who use them to offload cognitive work rather than further develop their own competencies [16]. The system should monitor interaction patterns for signs of over-reliance, such as passive help-seeking without articulation of knowledge gaps, or uncritical adoption of AI-generated outputs [19], and should temporarily restrict access if such patterns emerge [15]. Finally, at the advanced stage, boundaries are largely open, and GenAI can function as a true collaborator, comparable with a professional tool or work colleague [1]. Even at the advanced stage, boundaries can tighten again during assessments in which students need to demonstrate competencies, for example, by applying them in new contexts [20]. Furthermore, boundaries should track demonstrated competency, but also include aspirational scaffolds that push slightly beyond it, preserving the productive challenge of the ZPD and avoiding the risk that strictly competency-gated access inadvertently caps growth at what the student has already shown. Together, these stages show that adaptive boundaries are not just access controls, but pedagogical instruments that co-evolve with the student, turning a policy constraint into a mechanism for guided growth.

3. Foundations for Adaptive Boundaries

The adaptive boundaries we describe in Section 2 build on components that already exist independently: decades of research on adaptive instruction, mature learning analytics pipelines, and, in recent times, increasingly flexible and available GenAI platforms. While combining these into a coherent system is nontrivial, the necessary foundations are already in place. In this section, we examine the pedagogical theories (Section 3.1) and technical capabilities (Section 3.2) that can serve as a foundation for future work on developing adaptive boundary systems.

3.1. Pedagogical Foundations

The pedagogical foundation for adaptive boundaries is that the appropriate level of (GenAI) support depends on a student's developmental stage. This starts with the Zone of Proximal Development (ZPD) [10], which shows that learning is most effective when the support system targets tasks that the student cannot yet accomplish independently, but can with appropriate guidance or collaboration. This was extended by Wood et al. [9] through the concept of scaffolding, in which support systems are gradually reduced as the student gains competence. We apply the same logic to adaptive GenAI boundaries, which scaffold not the learning content itself, but the student's access to GenAI.

This is further supported by mastery learning, which supports the idea of competency-based rather than time-based scaffolding [18]. Bloom showed that when students need to reach a predefined level of mastery before advancing, most can achieve results previously achieved only by top performers [18]. Similarly, the Dreyfus model of skill acquisition [17] describes a progression from rule-following novices to intuitive experts, with different support needs at each stage. The adaptive boundaries are based on these theories, defining different GenAI roles at each phase of competency development.

Finally, research on Intelligent Tutoring Systems (ITSs) demonstrates that fine-grained, competency-based adaptation is feasible at scale: step-based ITSs can rival one-on-one tutoring [21], and metacognitive ITSs help students regulate their own learning [22]. Adaptive boundaries, however, differ from ITSs in two ways. First, ITSs adapt content, hints, and problem sequencing within a closed, instructor-authored environment. Adaptive boundaries govern student access to external GenAI tools used independently across tasks and courses. Second, where ITSs treat the tutoring system as the adaptive instrument, adaptive boundaries treat governance itself as the adaptive variable. We therefore extend ITS-style adaptive logic from in-system content delivery to the cross-platform governance of student–GenAI interaction.

3.2. Technical Readiness

On the technical side, detecting student progression, personalizing tool access, and dynamically configuring boundaries each draw on established research areas. Below, we discuss how advances in learning analytics and GenAI platforms provide the technical basis for adaptive boundaries.

Previous research on learning analytics has already established that interaction patterns can contain reliable signals for student development: clickstream data from online learning environments can predict student performance [23,24] and reveal self-regulatory behavior [14]. Additionally, process mining techniques can identify how students approach learning [25] and language analysis of student-GenAI interactions can surface the nature of student questions [13]. Finally, machine learning classifiers have already demonstrated the ability to detect competency signals from technology-mediated interactions with reasonable accuracy [12]. Taken together, this prior work shows how signals from various interaction data can be modeled and acted upon. This can provide the technical foundation needed for adaptive boundaries that determine when a student should receive a different level of GenAI access.

The GenAI platforms themselves (e.g., ChatGPT, Claude, Ollama) already support the personalized interactions that adaptive boundaries require. These systems can adjust their behavior through a system prompt that contains instructions on what personality they should mimic, the expertise level they can expect from the student, answers they can provide, etc. This configurability and adaptability mean that a single GenAI system could implement all the boundaries through prompting, rather than designing a dedicated system for each stage.

In conclusion, we find that adaptive boundaries do not require exotic technology. Process-based grading that evaluates not just the final output, but also the steps leading to that output, is already common in learning platforms [22] and metadata-driven configuration, where systems adapt to the user, is more accessible than ever with the rise of GenAI tools. What is missing is not any individual capability, but the conceptual integration of these governance and configuration capabilities with developmental scaffolding: boundaries that are (i) student-specific, (ii) evidence-driven (e.g., via learning analytics), and (iii) designed to evolve over time as competency and contexts change.

4. Future Research Directions

In this section, we discuss four interrelated research questions (RQ) and their methodological approach to achieve adaptive pedagogical boundaries. These questions are designed to cover the entire lifecycle of systems integrating adaptive pedagogical boundaries. These questions cover the following topics: negotiating boundaries among stakeholders, detecting when students are ready for changes, making the logic transparent, and evaluating whether the approach achieves its pedagogical goals. These questions also surface risks: competency signals may perform unevenly across different student backgrounds, readiness is hard to standardize across disciplines, and what functions as a scaffold for one student may function as a ceiling for another.

RQ1 *"How should boundaries be negotiated among students, teachers, and GenAI systems to balance competing priorities?"*: This question aims to balance competing priorities such as teacher authority, student agency, and algorithmic assessment, or standardization for equity and personalization for effectiveness [26]. During the negotiation, teachers must set developmental goals aligned with their pedagogical philosophy, while students should be able to have input in the boundaries set with regard to how they can use GenAI, as it impacts their agency [27]. The negotiated boundaries can also change over time. They might need to loosen as competency develops, but could also tighten during high-stakes assessments or even reverse at mastery when students need to demonstrate independent capability. This question could be explored through participatory boundary negotiation methods, involving educators and students in collaborative sessions that use speculative scenarios to surface value conflicts and co-design activities to explore how boundaries might be configured across different educational contexts.

RQ2 *"What interaction patterns reliably indicate a student is ready for boundary shifts?"*: This question addresses the technical challenge of detecting competency development through observable behaviors. Since adaptive boundaries should respond to individualized learning progress, the system requires interaction data that indicate a student's mastery of a specific skill or topic. There are many signal types, such as clickstreams in online courses [14], question topics [13], and self-assessment accuracy [22], but detecting readiness remains challenging. When using too few metrics, we risk oversimplifying the situation (e.g., a student might demonstrate technical skills while lacking critical thinking skills, or vice versa). Furthermore, the temporal pattern of the data is also important: short-term performance spikes can indicate surface learning rather than deep understanding [28]. This question could be explored through process mining techniques applied to learning management system data [25], combining clickstream analysis [23,24] with qualitative methods such as think-aloud protocols to validate whether detected patterns actually correspond to meaningful competency development. Machine learning models could identify combinations of behavioral indicators that predict successful performance on transfer tasks, while longitudinal studies track how interaction patterns evolve as students develop expertise.

RQ3 *"How can boundary logic be made transparent without creating cognitive overload?"*: The goal of this question is to find a balance between explainability and usability in adaptive boundary systems. All parties should be able to understand why certain GenAI features are available or restricted at any given moment. Black-box systems that do not provide meaningful explanations for their outputs risk undermining trust and reducing the agency of the involved parties [29]. This is further complicated by the fact that excessive explanations can overwhelm users or distract from learning goals [30], and by the different needs of varying stakeholders: students need understanding of what they can currently do and what progress would unlock additional access, teachers need insight into the pedagogical rationale for boundary configurations to maintain instructional alignment, and administrators need accountability mechanisms to ensure fairness and consistency. The challenge of this research question thus not only lies in being able to fully explain a system, as it would possibly confuse its users, but also in finding an appropriate balance without oversimplifying too much [31]. Informed by previous frameworks on Explainable AI (XAI) in education [29], we envision a transparency mechanism that can include tiered explanations: from simple default explanations to justify decisions to all users, to very in-depth explanations for technical and/or curious users. These can be aided by visualizations showing the students' current position in a competency framework and the thresholds for boundary changes. This question could be investigated through comparative studies of different explanation interfaces, measuring comprehension, trust, perceived fairness, and cognitive load across designs [32]. Participatory design sessions with students and teachers could further surface which information they actually find useful versus what generates confusion or resistance.

RQ4 *"How should we evaluate whether adaptive boundaries achieve their pedagogical goals?"*: This final question aims to validate the outcomes of the other research questions by testing multiple aspects of the new boundary system: immediate learning outcomes (e.g., knowledge acquisition, skill development, task performance), and long-term learning outcomes to see whether students develop capabilities that persist when the GenAI support is reduced, removed, or when the knowledge has to be applied to new contexts [20,33]. Furthermore, the evaluation should assess whether students appropriately rely on GenAI and know when to rely on their own capabilities, thereby avoiding over-reliance or under-utilization [15]. Finally, the evaluation should look at affective and motivational outcomes, especially student agency and self-regulated engagement, which can be influenced by AI assistance [16]. All of these factors should be evaluated not only against no-GenAI conditions, which may be unrealistic given students' widespread adoption, but also against static-boundary conditions, as that is the system most institutions seem to be adopting [8], and self-regulated approaches that impose no restrictions on students. Such evaluations should also find a balance between short- and long-term studies. Short-term studies may show performance improvements, but mask long-term skill degradation, while long-term studies could be influenced by evolving GenAI capabilities or other external factors. Because of this, the RQ calls for a mixed-methods evaluation. Some examples include: randomized trials comparing adaptive boundaries against alternative policies within short assignments, longitudinal studies tracking students across multiple courses or academic years, and measuring retention and transfer. In these evaluations, metrics should not just be test scores, but also process measures (how students interact with GenAI), metacognitive assessments (students' awareness of their own learning strategies), and equity analyses examining whether adaptive boundaries benefit all students or inadvertently advantage specific students.

5. Conclusion

This paper proposes a reconceptualization of GenAI governance in education: rather than treating access as a binary policy decision applied uniformly across all students, we propose adaptive boundaries that evolve with student competency development. Drawing on proven pedagogical theories and emerging technical capabilities, we demonstrate that the foundations for such systems already exist. What is missing is not technological capability but conceptual integration: although ITSs have long adapted content inside closed environments and teacher-facing tools now configure GenAI at the course level, no approach treats access to GenAI as a scaffolded, student-specific variable that co-evolves with competency. Our four research questions provide a path toward realizing this vision, addressing how boundaries should be negotiated among stakeholders, how competency signals can reliably trigger boundary shifts, how transparency can be achieved without cognitive overload, and how outcomes should be evaluated. By answering these questions, adaptive boundaries can transform GenAI from a policy concern into a human-centered pedagogical instrument that co-evolves with the student, knowing when to help, when to challenge, and when to step back.

Acknowledgments

This work was supported by the Special Research Fund (BOF) of Hasselt University (BOF24OWB28 & R-15015).

Author Contributions

J.T. and Y.D. conceived the adaptive boundaries concept. J.T. led the manuscript preparation. All authors contributed to conceptual refinement, writing, review, and approved the final manuscript.

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