

Cognitive Scaffolding: An AI-Generated Intelligent Tutoring System Advancing Bloom's Taxonomy in Distance Higher Education

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Abstract. *In distance learning courses for higher education, bridging the gap between passive reading and active knowledge construction is a critical challenge. This paper presents the design and large-scale deployment of a Cognitive Scaffolding Intelligent Tutoring System (CS-ITS). Unlike generic conversational agents or static signaling tools, CS-ITS operationalizes Bloom's Taxonomy as a control mechanism to orchestrate "upward cognitive scaffolding." The system detects key concepts in digital textbooks, anchors them with re-explanations at the learner's current cognitive level, and automatically generates follow-up questions at the subsequent higher Bloom level. This design transforms static reading into a dynamic inner loop of active learning. We report on a pilot study that involved 7,192 undergraduate students in four disciplines (Pedagogy, Administration, HR, and Logistics). The results indicate that while voluntary participation was 7%, the system achieved high user satisfaction (CSAT 4.7/5) and successfully guided 14% of the engaged users through higher-order cognitive tasks. Critically, the engaged students demonstrated gains in academic performance of up to 2.9%.*

1. Introduction

Distance education has expanded rapidly in higher education, increasing student access through flexible schedules and lower tuition costs [Qayyum and Zawacki-Richter 2019]. However, achieving adequate learning outcomes and addressing high dropout rates remain persistent challenges, particularly in large-scale distance programs where persistence and academic success are uneven across learners from diverse backgrounds. In Brazil, for example, more than half of distance-learning students leave their programs within the first year, and only a minority complete their degrees [Instituto Semesp 2025]. These patterns highlight the need for scalable instructional support that improves the quality of learning in text-heavy, self-regulated learning environments typical of distance education.

Academic reading is a central challenge in these contexts. While short video lessons often provide useful overviews, students are typically expected to deepen their

understanding through dense textbook materials with limited instructor mediation, making comprehension and sustained engagement difficult. One widely studied support strategy for reading is signaling, such as highlighting key passages to direct attention and reduce extraneous cognitive load [Beege et al. 2021]. Prior research shows that signaling can improve transfer performance, but its effects on retention and deeper understanding are limited when used in isolation. Studies on digital highlighting further indicate that system-provided highlights can support basic comprehension. Yet durable learning depends on follow-up activities that promote explanation, reflection, and application [Mason et al. 2024, Fowler and Barker 1974, Joshi and Vogel 2024].

To address this core challenge of supporting deeper reading comprehension with limited instructor mediation, Intelligent Tutoring Systems (ITS) provide a well-established framework that goes beyond passive signaling. It works by tightly coupling learner actions with adaptive explanations, questioning, and feedback [Nkambou et al. 2010, VanLehn 2006]. A key mechanism for this adaptation in ITS is cognitive scaffolding, which is temporary, targeted support that helps learners progress beyond their current level of understanding [Anderson et al. 1990]. While scaffolding has been extensively studied in problem-solving domains, its systematic application to reading-based learning remains limited, despite the central role of academic reading in higher education [Koedinger et al. 2015, Hooshyar et al. 2024]. Moreover, cognitive progression, even within the broader scope of instructional support, emerges as a critical concern.

While Bloom’s taxonomy is widely used to define learning objectives and align assessment with instruction [Bloom 1964, Anderson and Sosniak 1994], it is rarely operationalized as a control mechanism guiding moment-to-moment instructional decisions in AIED research [du Boulay 2016, Guo et al. 2021]. As a result, most reading-support tools emphasize comprehension checks at lower cognitive levels and provide limited support for structured progression toward higher-order thinking [Mason et al. 2024, Joshi and Vogel 2024]. This limitation is increasingly salient in LLM-based systems, where fluent language generation can obscure the pedagogical rationale behind explanations and questions [Dao and Williams 2025].

To address these gaps, this paper introduces a Cognitive Scaffolding ITS (CS-ITS) designed to support reading-based learning in distance education. The system integrates signaling with explicit upward cognitive scaffolding by anchoring interactions in highlighted textbook excerpts, re-explaining concepts at the current Bloom level, generating questions at the subsequent level, and providing immediate feedback. Bloom’s taxonomy is embedded as a first-class control signal in the tutoring logic, enabling principled cognitive progression within a classical ITS inner–outer loop architecture [VanLehn 2006, Kulik and Fletcher 2016].

Beyond presenting the CS-ITS design, we report results from a large-scale pilot deployment involving over 7,000 undergraduate distance-learning students across multiple programs. We examine student engagement, satisfaction, and academic performance, providing evidence of the system’s feasibility and potential learning benefits in an authentic institutional context. By combining theory-grounded system design with large-scale empirical validation, this work advances AIED research on scalable, cognitively principled support for reading-intensive learning environments.

2. Background

2.1. Theoretical Foundation

Classical ITS research converges on an architectural view comprising domain, learner, tutoring, and interface models [Nkambou et al. 2010]. Together, these models operate through inner (i.e., moment-to-moment instructional decisions such as hinting, prompting, or feedback) and outer (i.e., task selection and sequencing over time) loops [VanLehn 2006]. In this paradigm, effectiveness is often attributed to the tight coupling between learner actions, system diagnoses, and immediate, personalized feedback, with empirical studies showing that such systems can support deeper learning than those limited to static content delivery [Hillmayr et al. 2020].

Another concern is that many ITS have a background in cognitive scaffolding. Rooted in socio-constructivist theories of learning, scaffolding refers to the temporary support offered to learners to help them accomplish tasks just beyond their current level of competence, often operationalized through hints, worked examples, fading strategies, and adaptive feedback [Anderson et al. 1990]. However, most AIED research has focused on problem-solving domains such as mathematics or programming, where learner actions are well-defined and easily assessed, while little is known about how scaffolding principles can be systematically applied to reading-based tasks, despite the centrality of academic reading in higher education and distance learning [Hooshyar et al. 2024, Koedinger et al. 2015].

Moreover, while scaffolding is often discussed in general terms, comparatively little work has formalized how cognitive progression should be enacted at a fine-grained level. Many ITS adapt difficulty or provide remediation based on performance, failing to explicitly encode a theory of cognitive development [du Boulay 2016, Guo et al. 2021]. This gap becomes especially salient in the increasingly available LLM-based systems, where fluent language generation can obscure the pedagogical rationale behind explanations and questions [Dao and Williams 2025]. Meanwhile, Bloom’s taxonomy and its later revisions have been widely adopted as frameworks for articulating learning objectives and aligning assessment with instruction [Anderson and Sosniak 1994]. In AIED research, however, Bloom’s taxonomy has more often served as an analytic or evaluative lens than as an instructional guide [Rodrigues et al. 2024, Monteiro Santos et al. 2024]. As a result, upward cognitive scaffolding, where learners are intentionally guided from lower to higher-order thinking within a single conceptual thread, remains underexplored.

2.2. Related Works

The lack of upward cognitive scaffolding is particularly evident in reading-support tools, which often emphasize comprehension checks (e.g., remembering or understanding) but rarely orchestrate a structured transition toward application, analysis, or reflection [Joshi and Vogel 2024, Mason et al. 2024]. Besides the popularity of reading tasks, especially in distance learning, reading-support tools are prominent because research demonstrates the benefits of enhancing reading with signaling. For instance, signaling by highlighting central ideas or relevant passages while reading can help learners identify what is important, especially in dense or unfamiliar texts [Beege et al. 2021]. Additionally, highlighting a passage can serve not only as an attentional aid but also as an anchor

for explanation, questioning, and feedback, although few ITS explicitly integrate text signaling into a broader scaffolding cycle that links authentic curricular material to adaptive instruction [Hillmayr et al. 2020, Guo et al. 2021, du Boulay 2016].

Aligned with the idea of expanding highlighting's role, intelligent textbooks have gained traction by enabling digital textbooks to evolve from static repositories into interactive learning environments [Brusilovsky et al. 2022]. Prior work in this area has explored features such as embedded questions, adaptive explanations, and analytics-driven personalization [Sosnovsky et al. 2025]. More recently, LLMs have enabled conversational interfaces layered on top of textbooks, allowing students to ask free-form questions and receive natural-language responses [Xu and Jian 2024]. While these developments have greatly improved accessibility and responsiveness, they also raise concerns about pedagogical coherence [Sosnovsky et al. 2025, Brusilovsky et al. 2022, Xu and Jian 2024]. Accordingly, AIED research calls for stronger integration of learning theories into AI-driven tools [Xia et al. 2022]. For example, existing intelligent textbooks rarely implement explicit learner models or structured tutoring loops comparable to those of classical ITS and empirical evaluations frequently focus on usability or perceived usefulness, with fewer large-scale studies examining learning outcomes in authentic institutional settings [Sosnovsky et al. 2025].

2.3. Research Questions

This context reveals important gaps that motivate the current study. First, there is limited research on ITS that support reading-based learning through explicit cognitive scaffolding grounded in learning theory. Second, Bloom's taxonomy has not been widely operationalized as a first-class control mechanism guiding moment-to-moment instructional decisions and cognitive progression. Third, signaling and highlighting are seldom integrated into a full tutoring loop that connects attention guidance to explanation, questioning, and feedback. As such, our first research question is:

RESEARCH QUESTION 1 (RQ1):

To what extent does a reading-focused ITS that implements explicit, Bloom-driven cognitive scaffolding engage distance-learning students, and how do they perceive its pedagogical value?

Furthermore, despite rapid advances in LLM-based tutoring, there remains a need for more evidence of practical implications on a scalable real-world educational contexts. This study addresses this gap through the application of the proposed system on a cohort of 7192 undergraduate students. Thus, our second research question is:

RESEARCH QUESTION 2 (RQ2):

Does interaction with such a system lead to measurable improvements in academic performance and contribute to positive institutional outcomes?

3. The Cognitive Scaffolding Intelligent Tutoring System

The system was co-designed by professors, instructional designers, and AI engineers in iterative cycles, following the best practices of user-centered design to ensure its practical suitability [Barbosa et al. 2021]. This approach is similar to recent AIED studies [Rodrigues et al. 2025, Alfredo et al. 2025], corroborating recommendations from recent

literature reviews [Topali et al. 2025]. Accordingly, this process resulted in a pedagogically based user flow powered by our ITS.

As Figure 1 demonstrates, the system performs the five main steps once the student starts a reading task within the learning environment. *First*, starting from a textbook, the system identifies and highlights a key excerpt to anchor learning in authentic curricular material and reduce extraneous cognitive load. *Second*, the system provides a re-explanation at the same Bloom's level to consolidate understanding. *Third*, the system generates a question at the next Bloom's level, enacting upward cognitive scaffolding that promotes conceptual progression rather than rote rehearsal. *Fourth*, the student answers the question to close the learner action loop. *Fifth*, immediate feedback is provided to support timely error diagnosis, metacognitive regulation, and knowledge refinement.

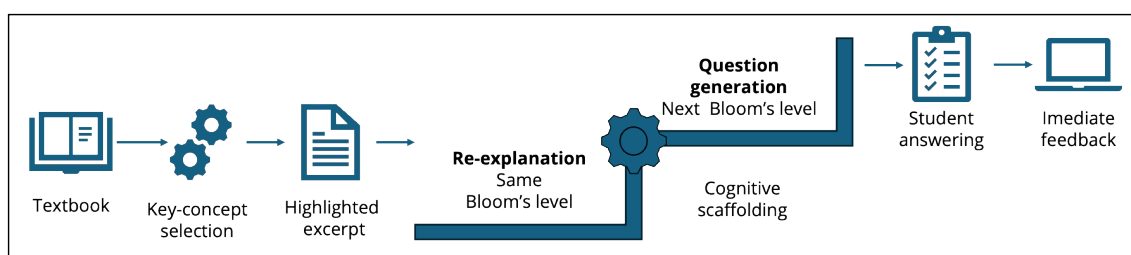


Figure 1. Architecture of the Cognitive Scaffolding ITS, showing concept detection, re-explanation in the same Bloom's taxonomy level, question generation in the next Bloom's taxonomy level and immediate feedback.

This approach integrates instructional alignment, adaptivity, and feedback immediacy into a workflow aligned with classical ITS systems [VanLehn 2006]. On the one hand, the *inner loop* operates at the micro-level of a single concept by coupling re-explanation, question generation at an incrementally higher Bloom's level, student response, and immediate feedback to support moment-to-moment knowledge construction and regulation. On the other hand, the *outer loop* governs progression across concepts and objectives by selecting curriculum-aligned excerpts and sequencing scaffolded interactions in accordance with institutional learning goals. Together, these loops enable fine-grained adaptation within particular queries and principled advancement across queries, reflecting established ITS design patterns while leveraging cognitive scaffolding to balance short-term performance support with longer-term conceptual development.

3.1. System Architecture

The system is structured according to a classical ITS architecture while embedding Bloom's Taxonomy as the main resource for control signals across instructional decisions. Figure 2 provides details of each model used in the proposed system.

The *domain model* is instantiated through a curated corpus of textbook excerpts, key concepts, and course-level learning objectives defined by the educational institution. Each learning objective is explicitly mapped to representative textual anchors and annotated with Bloom-level tags (from Remember to Create), enabling semantic alignment between curricular intent and system behavior. Content retrieval is handled via a hybrid storage and generation layer (MongoDB combined with Azure OpenAI), allowing the system to ground interactions in authoritative material while flexibly adapting explanations and prompts.

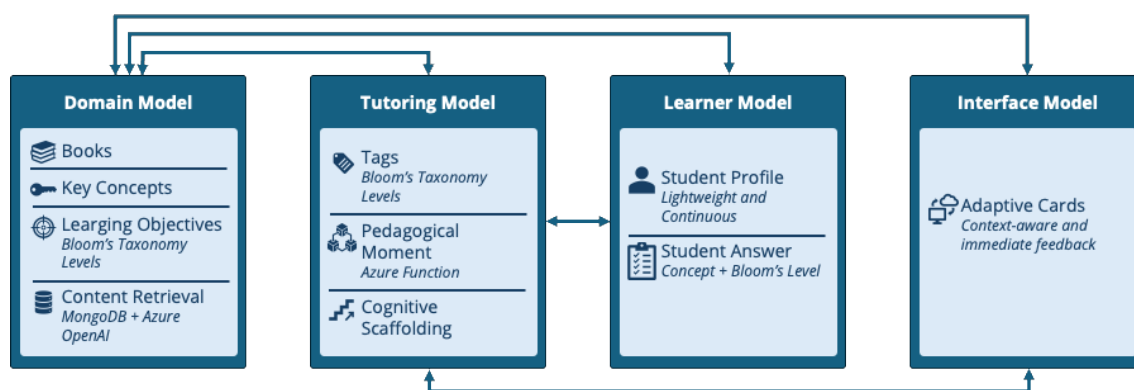


Figura 2. Overview of the architecture of the Cognitive Scaffolding ITS.

The *tutoring model* is implemented as a tag-driven pedagogical engine that operationalizes Bloom’s Taxonomy. An Azure Function serves as the interaction orchestrator, detecting the pedagogical “moment” encoded in each student query and routing it to the appropriate instructional strategy. When no key concept is detected, the system enters a low-structure *TEXT* moment, including possible yet non-mandatory queries, supporting exploratory dialog and learner agency. When a concept is present, the tutoring model activates the structured scaffolding sequence presented in Figure 2. This design reflects an explicit upward scaffolding policy, aligning micro-level instructional moves with cognitive progression rather than static content delivery.

The *learner model* is realized through a lightweight, continuously updated profiling mechanism. Each student response is logged as a proficiency signal associated with specific concepts and Bloom levels. Over time, these signals accumulate into learner profiles that can inform adaptive decisions, such as recommending remediation, advancing to more complex tasks, or redirecting learners to supplementary materials. While currently used primarily for post hoc analysis and rule-based adaptation, this layer is designed to support future data-driven personalization and mastery learning strategies.

Lastly, the *interface model* is implemented using adaptive cards that structure student interactions while preserving conversational flexibility. Immediate, context-aware feedback is generated following each student response, supporting error diagnosis, meta-cognitive regulation, and sustained engagement. This tight feedback loop constitutes the system’s inner loop, while concept selection and sequencing across objectives form the outer loop, aligning the architecture with established ITS control paradigms.

From an implementation perspective, the system is realized as a modular, cloud-based architecture. The Concept Orchestrator (Python + LangChain) coordinates flow control, the Bloom Taxonomy Engine encapsulates pedagogical logic via prompt engineering, and a multi-layered guardrail system enforces schema validation, content scope, language constraints (Brazilian Portuguese), and academic integrity protections. Logging and monitoring via Azure Functions enable traceability and learning analytics.

3.2. System Usage

Figure 3 demonstrates the user interface of the ITS, illustrating the interaction between a student (left-hand side) and the ITS (right-hand side). The figure exemplifies an interaction where a psychology student starts a reading task seeking help to understand the

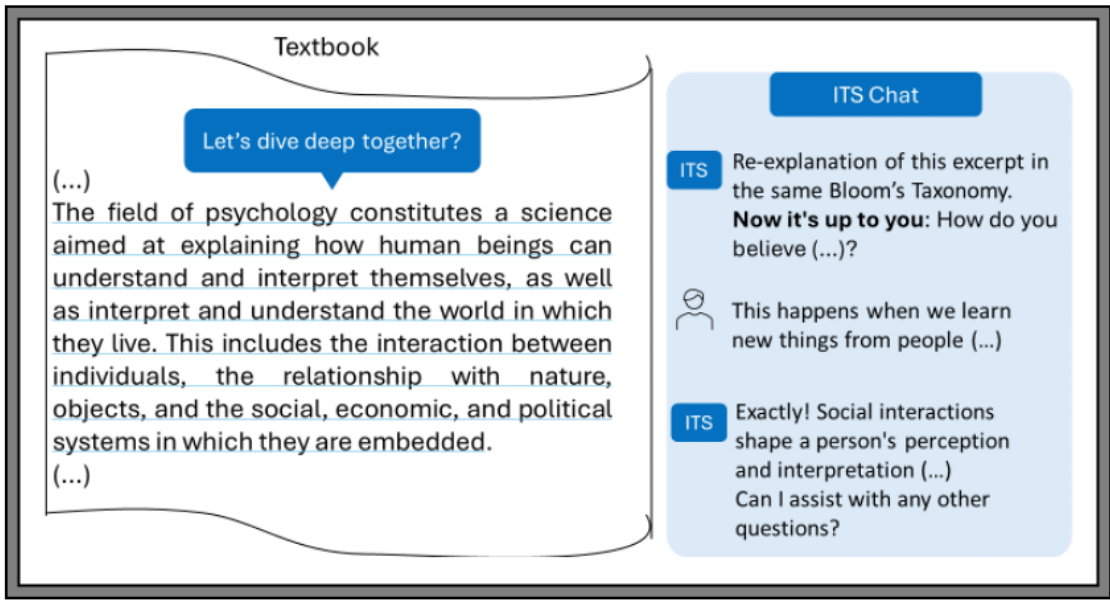


Figura 3. Design of the Cognitive Scaffolding ITS in the textbook being shown on a computer screen.

broader field, beginning with the system presenting a curated excerpt extracted from a textbook. In this context, Table 1 details the interaction according to the steps from Figure 1.

Table 1 demonstrates the step-by-step student-STI interaction. It highlights that the system i) presents a key concept extracted from a psychology textbook, then re-explains it to the student and poses a reflective question. Next, the table presents an example of a student's response, which is followed by immediate feedback from the ITS. This example demonstrates how the system facilitates understanding by guiding students through a structured cognitive progression, encouraging deeper reflection on social interactions and their influence on self-perception and worldview. Figure 3 shows a schematic drawing of the design that the student receives from the tool.

4. Method

Following the system development, we sought to understand how it contributes to distance learning through a large-scale pilot implementation in authentic learning contexts. For this, we deployed the Cognitive Scaffolding ITS into the learning management system of a nationwide network of universities and implemented it for one month to enhance the learning experiences of 7,192 students enrolled in undergraduate programs from four distinct learning domains: Pedagogy ($n = 2,829$), Administration ($n = 2,113$), Human Resources Management ($n = 1,111$), and Logistics ($n = 1,139$).

During the one-month implementation, the 7,192 students were exposed to the system as described in Section 3.2. Once the student highlighted an excerpt during a reading task within the learning management system, the ITS would present a tooltip with the prompt "Let's dive deep together" that, when clicked, triggered the remainder of the flow (see Figure 1). Therefore, this study considered a student to be engaged with the ITS when that tooltip was clicked.

Tabela 1. Demonstration of our Cognitive Scaffolding ITS Interaction Process.
Key-concept (an excerpt from the textbook)
“The field of psychology constitutes a science aimed at explaining how human beings can understand and interpret themselves, as well as interpret and understand the world in which they live. This includes the interaction between individuals, the relationship with nature, objects, and the social, economic, and political systems in which they are embedded.”
Re-explanation (provided by the Cognitive Scaffolding ITS)
“The field of psychology is a science that seeks to understand how human beings know and interpret themselves, as well as the world around them. This includes the analysis of interactions between individuals, their relationships with nature, objects, and the social, economic, and political systems in which they are embedded. The primary focus is the symbolic exchange that living beings establish with the environment, implying that the understanding of human beings is multifaceted and interconnected.”
Question
“Now it’s up to you: How do you believe social interactions influence the way a person perceives themselves and interprets the world?”
Student answer
“This happens when we learn new things from people.”
Immediate feedback
“Exactly! Social interactions shape a person’s perception and interpretation of the world, as they influence their experiences, values, and beliefs. When we interact with others, we exchange ideas and feelings, which can alter our view of ourselves and the reality around us. For example, a person who spends time with friends who value education may develop a greater appreciation for learning. To deepen your understanding, consider how your own social experiences have impacted your worldview. Remember that psychology studies these symbolic exchanges and how they affect behavior and consciousness.”

In that context, our study addressed two main objectives. To answer RQ1, we sought an overall picture of students’ perceptions regarding the ITS. To achieve this, we collected both behavioral and opinion data from all 7,192 students based on engagement (i.e., clicking the tooltip) and Customer Satisfaction (CSAT), with the latter being measured on a five-point Likert scale, where a higher value indicates a higher customer satisfaction rate.

For the second RQ, we sought to understand whether the ITS contributed to engaged students academic performance, where academic performance concerns the student overall grade at the end of the semester in which the ITS was implemented. For this, we compared the academic performance of two groups: i) a *not-engaged* group that could access the ITS but chose not to (i.e., the tooltip appeared but was never clicked); and ii) an *engaged* group, where students actively engaged with the ITS (i.e., clicked the tooltip).

Accordingly, we used descriptive and inferential statistics to analyze these data. First, we extracted descriptive statistics to understand overall engagement, CSAT, and academic performance. Then, we used inferential tests to compare whether engagement (Chi-

squared) and CSAT (Mann-Whitney) rates differed among programs, as well as Analysis of Variance (ANOVA) to compare academic performance among groups. In all cases, we used R to perform the tests and adopted the standard 95% alpha level to determine statistical significance.

5. Results

5.1. RQ1: System Viability and Adoption

The overall engagement rate, considering all 7,192 students, was 7% ($n = 519$). Nevertheless, note that this rate varied across programs, ranging from 4.8% for Logistics students to 9.1% for Administration ones. A chi-square test of independence reveals there is a statistically significant association between program and engagement ($\chi^2(3) = 27.86$, $p < 0.001$). However, the magnitude of this association is small (Cramér's $V = 0.06$). This finding indicates that while engagement rates differ across programs, the practical impact of program membership on engagement is minimal. Among these students, 14% answered the question proposed by the ITS.

Tabela 2. Engagement and CSAT results for our pilot study by program. Data shown as *Number of students (percentage)* for engagement; CSAT scores based on a five-point Likert scale.

Program	N	Engagement	CSAT
Pedagogy	2829	214 (7.6%)	4.6
Administration	2113	192 (9.1%)	5.0
Human Resources Management	1111	58 (6.1%)	4.8
Logistics	1139	55 (4.8%)	4.5

Furthermore, although the 7% overall engagement with the Cognitive Scaffolding ITS, the CSAT outcomes were notably high. Overall, the 519 students who interacted with the ITS reported an average CSAT of 4.7. Also, Table 2 demonstrates that the CSAT ranged from 4.5 for Logistics students to 5 for Administration students on the five-point Likert scale, indicating strong approval among the 519 students who interacted with the ITS.

5.2. RQ2: Learning and Institutional Impact

Table 3 show improvements of up to 2.9% in exam scores depending on the program. These findings suggest that the Cognitive Scaffolding ITS contributes to learning gains, thereby reinforcing its role as an equity-enhancing intervention that combines high satisfaction with measurable academic benefits.

Tabela 3. Summative tests scores of students with and without access to the Cognitive Scaffolding ITS (CS-ITS). Test scores could range from 0 to 100.

Program	Engaged	Not-engaged	Score Difference
Pedagogy	77.6	75.5	2.9%
Administration	83.4	83.2	0.3%
Human Resources Management	83.7	83.0	0.8%
Logistics	85.3	83.4	2.3%

6. Discussion

This study introduced a Cognitive Scaffolding ITS, an AI-Generated ITS that extends traditional signaling by re-explaining key concepts and generating Bloom-level progression questions. A pilot study was conducted with students in the second semester for one month. During this period, participation reached 7%, of which 14% responded to higher-order requests. Satisfaction was consistently high and performance gains of up to 2.9% were observed.

Although adoption was modest, the data demonstrate that a measurable subset of learners engaged not only with explanations, but also with who cognitively demanding follow-up tasks. This provides early evidence that AI tutors can stimulate higher-order reasoning when concept detection is combined with Bloom progression. In this context, Cognitive Scaffolding demonstrates that signaling, when combined with Bloom-level orchestration, can move beyond highlighting toward active learning. The observed responses show that AI tutors can foster vertical cognitive progression at scale, an especially valuable contribution in resource-constrained educational contexts.

To contextualize adoption, engagement rates were compared with leading platforms. Khan Academy's 2024 Annual Report [Khan Academy 2025] indicates that, among 4.1 million students in partnered programs, only about 3.7% achieved "Very Active Learner" status over the year, showing that deep engagement is challenging even at a massive scale. Duolingo, with more than 300 million users worldwide, maintains engagement through gamification, but research shows that not all interactions translate into durable learning outcomes [Hadi Mogavi et al. 2022]. Against this backdrop, the 7% of the students who participated in the Cognitive Scaffolding ITS is noteworthy. It is important to note that Khan and Duolingo students have profiles different from those evaluated in this study.

Cognitive Scaffolding ITS is not an isolated tool, but rather an integral component of a broader personalization strategy. By continuously capturing learner interactions, the system generates proficiency signals that accumulate into individualized learner profiles that can help inform future customization projects. In this way, cognitive scaffolding can also contribute to macro-level personalization, where recommendation engines can direct learners toward remedial content, advanced exercises, or interdisciplinary connections tailored to their needs. As part of an institutional ecosystem, the ITS reinforces equity by ensuring that personalized learning is systematically embedded in curricula, moving beyond isolated interventions to a data-driven sustainable strategy for student success.

The system's theoretical contribution lies in operationalizing Bloom's Taxonomy within an ITS pipeline that integrates signaling, intelligent textbooks, and active learning. By requiring learners to respond to progressively more complex questions, the system fosters cognitive progression while also generating proficiency data that enables future personalization efforts.

Practically, the results highlight that our ITS cannot only achieve engagement rates comparable to global EdTech leaders, but do so while also advancing cognitive depth. Early institutional evidence of reduced dropout suggests that cognitive scaffolding can serve as a dual lever to promote both learning and equity, especially for low-income students. Future research should investigate longitudinal trajectories, integration with institu-

tional analytics, and differential impacts across student subgroups to strengthen evidence on retention, equity, and sustained cognitive growth.

7. Limitations and Future Work

While the results of this pilot study provide encouraging evidence for the scalability and efficacy of AI-driven cognitive scaffolding, several limitations must be acknowledged to contextualize the findings and guide future research. The primary limitation is the study's quasi-experimental design. As participation in ITS was voluntary, triggered by students clicking on a specific tooltip, the engaged group can inherently consist of learners with higher intrinsic motivation or self-regulation skills. Consequently, the observed performance gains (up to 2.9%) may be partially influenced by self-selection bias, preventing a definitive causal attribution to the system alone. Second, the adoption rate of 7% highlights a challenge in interface design. The current system relies on a passive "tooltip" mechanism that requires explicit learner initiative. This design likely misses at-risk students who lack the metacognitive awareness to "dive deep" into complex concepts voluntarily. Third, the generalizability of the domain remains untested. The system was deployed in reading-intensive humanities and management programs. The applicability of this Bloom-based text-anchored scaffolding model to STEM disciplines, where learning often involves procedural problem-solving and symbolic manipulation rather than conceptual synthesis, requires further investigation.

To address these gaps, future research and development will focus on three primary axes:

1. **Experimental Validation:** We intend to conduct a semester-long Randomized Controlled Trial (RCT) to isolate the causal impact of the CS-ITS on learning outcomes and retention. This rigorous design will control for confounding variables such as prior student motivation.
2. **Proactive and Adaptive Interventions:** To improve engagement, future iterations will move beyond passive signaling. We plan to implement proactive "nudges," where the ITS autonomously triggers scaffolding based on reading behaviors (e.g., dwell time or rapid scrolling). Additionally, we aim to introduce downward scaffolding, providing simplified hints or remediation when a student struggles with a concept to complement the current upward progression and fully realize a mastery learning approach.
3. **Closing the Outer Loop:** As outlined in the system architecture, the current learner model accumulates proficiency signals but relies on rule-based progression. Future work will utilize this data to power a dynamic recommendation engine, suggesting personalized content paths and interdisciplinary connections based on the student's evolving cognitive profile.

Statement on the Use of Artificial Intelligence

Artificial intelligence tools, including *ChatGPT* and *Gemini*, were used to support the development of this manuscript, including brainstorming ideas, structuring the narrative, drafting and revising textual content, improving language clarity and presentation, and assisting with proofreading and formatting. All final decisions regarding content, interpretation, and conclusions remained under the authors' responsibility.

Ethical Concerns

This study uses secondary data within the field of Learning Analytics from Cogna Educational S.A. to support evidence-based institutional management. Data processing was conducted in strict compliance with the organization's information security policies, ensuring data anonymization and full adherence to applicable data protection regulations and ethical standards.

Artifacts Availability

This study's artifacts will be made available from the corresponding authors upon reasonable request and compliance to data protection regulations and ethical standards.

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