The Representational Divide: A Qualitative Usability Analysis of an Adaptive AI for Atypical Learners

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***Abstract*—This paper explores how an adaptive Artificial Intelligence (AI)-based mathematics platform is experienced by a group of learners who are often overlooked—students who learn at a slower pace. Using a qualitative usability approach, the study does not aim to produce broad generalizations. Instead, it provides an "existence proof", showing how certain design choices can unintentionally create barriers to learning. Rather than presenting sweeping conclusions, the study offers a detailed look at where and how interactions with the platform break down, giving a nuanced picture of the challenges slow learners may face. By placing learners at the center of our study and using think-aloud protocols alongside participant observation, we were able to uncover key design flaws that directly hinder the learning process. Our findings point to two main patterns of failure. The first is what we call a "Frustration–Disengagement Loop". Here, the platform's punitive approach to gamification pushes students away from genuine learning. Instead of staying focused on understanding the material, they shift their goals toward simply trying to outmaneuver or bypass the system. The second failure pattern we observed is what we term a "Representational Divide". While the platform makes effective use of visual aids, it falls short in helping learners make the crucial connection to symbolic understanding. This gap often leaves students with only a surface-level sense of competence, reinforced by procedural hints that mask deeper misunderstandings. To address these issues, we propose a set of evidence-based design heuristics, along with visual redesigns, intended to support more inclusive, effective, and ethically responsible educational technologies.**

***Keywords*—Human-Computer Interaction (HCI), inclusive design, educational technology, cognitive walkthrough, slow learners**

I. Introduction

Designing intelligent tutoring systems remains a persistent challenge within Human-Computer Interaction, as it touches on core principles of multimedia learning and the management of cognitive load [1]. This dilemma becomes even more pressing for atypical user groups, such as slow learners, whose cognitive and emotional needs are often overlooked by one-size-fits-all system designs. While many studies assess the effectiveness of AI platforms through quantitative performance metrics, the actual user experience—the "how" and "why" of interaction—tends to remain a black box. As a result, the complex metacognitive and self-regulatory processes that shape learning often go unseen [2]. This study takes a qualitative usability approach to open that "black box". We ask: Which specific design choices in an adaptive AI platform create barriers for slow learners, and how do these barriers show up in the way they approach problem-solving? By tracing these flaws in detail, our goal is to contribute insights that can guide the development of more inclusive, user-centered educational technologies.

II. Literature Review

A. The Assistance Dilemma and Scaffolding in Educational Technology

At its heart, an intelligent tutoring system is designed to provide scaffolding—temporary, personalized support that helps learners accomplish tasks they would struggle to complete on their own. Yet putting this idea into practice is far from straightforward. One of the most well-known challenges in this area is the "assistance dilemma", which captures the tension between offering enough guidance to support progress and withholding enough to encourage independent problem-solving [3]. This tension is underscored by recent research. For example, research on AI-driven feedback systems [4] shows that while providing immediate, corrective feedback can boost performance on individual tasks, it often falls short in nurturing the metacognitive skills learners need to transfer knowledge over the long term. In these cases, the system ends up doing most of the "heavy lifting", leaving students without the chance to engage in productive struggle—a vital part of deep learning where knowledge is built through challenge and feedback. Without this struggle, learners may develop an "illusion of competence", a serious usability flaw in which both the system and the student believe that real learning has taken place, when in fact the student has only learned to mimic procedures without genuine understanding. Our study builds on this discussion by looking closely at how the problem plays out for slow learners—a group especially at risk of becoming overly dependent on procedural aids.

B. The Dark Side of Gamification and Its Impact on Motivation

Gamification—the practice of adding game-like elements to non-game settings—has become a dominant trend in educational technology, often promoted as a way to spark engagement and motivation. Yet, research increasingly warns that when these mechanics are applied uncritically, they can backfire. Instead of supporting learning, poorly designed gamification can introduce a "dark side", creating effects that are counterproductive to the very goals it seeks to achieve. For instance, a systematic review showed that although gamification can enhance learning, features such as points and leaderboards often redirect motivation. Instead of learning for its own sake, students may begin to focus on earning rewards. This shift from intrinsic to extrinsic motivation can erode their sense of autonomy and, in the long run, weaken genuine engagement with the learning process [5, 6]. The risks become even greater when gamification relies on punitive mechanics. Khaldi *et al*. [7] show that systems which penalize users for mistakes can heighten anxiety and lower self-efficacy—effects that are especially harmful for students who are already struggling academically. Our research provides an empirical case study of this "dark side", modeling how a specific punitive mechanic triggers a negative behavioral loop.

C. Inclusive Design and Usability for Atypical Learners

Our study evaluates the platform through the lens of Universal Design for Learning (UDL), focusing on how its narrow approach to representation—most notably the abrupt shift to symbols—and its reliance on punitive engagement run counter to UDL principles, creating real obstacles for atypical learners. In the realm of AI, this highlights the need to move beyond one-size-fits-all models. Many current AI tutors are designed with a neurotypical "average" user in mind, which can unintentionally exclude or disadvantage learners who fall outside that norm [8]. This points to the need for AI systems that adapt not only to a learner's knowledge level, but also to their cognitive and emotional states. Achieving this requires a qualitative understanding of how different user groups actually experience technology in practice. For slow learners in particular—who may need more processing time and rely on concrete representations—design decisions around language, pacing, and feedback are not small details. They are central factors that determine whether a system is truly usable and supportive. Going beyond cognitive adaptation, some researchers argue that effective gamified systems must be dynamically adaptive, moving beyond static user profiles [9]. They challenge the "one-size-fits-all" model, in which the user experience is fixed at the outset, and instead propose a framework where the system continuously learns and adapts to a learner's changing preferences and engagement style over time. Building on this perspective, our study adopts a user-centered and inclusive lens, evaluating the AI platform specifically through the experiences of an often-overlooked group: slow learners.

III. Methods

This section explains the methodological approach used in the study. The procedures are described with enough clarity and detail to allow a knowledgeable reader to conceptually replicate the research process.

A. Research Approach: Qualitative Usability Testing

To better understand the user experience, we carried out a qualitative usability study. Rather than relying on quantitative metrics alone, this approach allowed us to dig into the underlying reasons behind user behaviors and interaction breakdowns. In doing so, we aligned our work with established heuristics in usability engineering.

B. Participant Recruitment and Profile

We recruited four (N = 4) sixth-grade students from a public school in Toraja, Indonesia. The participants fit the profile of "slow learners", a specific user group that requires additional time to grasp abstract concepts but does not have a formal intellectual disability. Participant selection followed a two-step purposive sampling process. First, classroom teachers nominated students based on their long-term observations of academic pace. Then, to confirm suitability for the study, a team member with expertise in educational psychology conducted a cognitive screening.

C. Data Generation and Triangulation

Over a four-week period, data was generated using a triangulation of three established User Experience (UX) research methods:

1) In-Context Observation: We observed each user session closely, taking field notes on non-verbal cues—such as signs of frustration or moments of insight—as well as overall interaction patterns. For example, we noticed that codes linked to negative emotions and avoidance strategies often clustered together. From these, we developed the theme of a "Frustration–Disengagement Loop", which captured learners' intentions and reactions as they interacted with the AI platform. This method, grounded in foundational cognitive psychology [10], provided direct access to their real-time cognitive and affective processing.
2) Post-Task Debriefing Interviews: After completing key tasks, we held semi-structured interviews to revisit specific events from the sessions. This gave participants the chance to reflect on their experiences and share their perspectives in their own words.

D. Data Synthesis and Interpretation

All data—including transcripts and field notes—were analyzed thematically using NVivo. Our approach resembled an affinity diagramming process, beginning with open coding of individual user actions and direct quotes (e.g., user resets page after error, user misinterprets term "value"). These codes were then gradually synthesized into broader themes that highlighted key usability breakdowns. This systematic process of coding and theme development allowed us to trace meaningful patterns across the qualitative data [11].

1) Open Coding: We carefully reviewed the interview transcripts, field notes, and think-aloud logs multiple times to identify meaningful units of data. From these, we created initial codes to capture specific incidents, emotions, or strategies (e.g., frustration at reset, looking for pictures, exit–re-enter strategy).
2) Axial Coding and Theme Development: Next, the initial codes were clustered into broader categories, and we examined how these categories connected with one another to form major themes. For example, codes capturing negative emotions alongside avoidance strategies were brought together to shape the theme we call the Frustration–Disengagement Loop.
3) Conceptual Modeling: The themes we developed were then translated into process models, shown in Fig. 1 and Fig. 2, and Table 1. These models illustrate the dynamic relationships between the platform's design features, the students' cognitive processes, and the behaviors that emerged as a result.

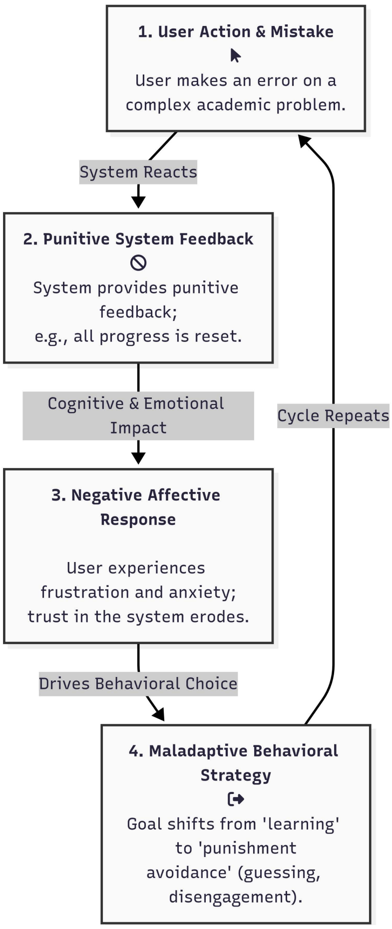

Fig. 1. The frustration-disengagement loop.

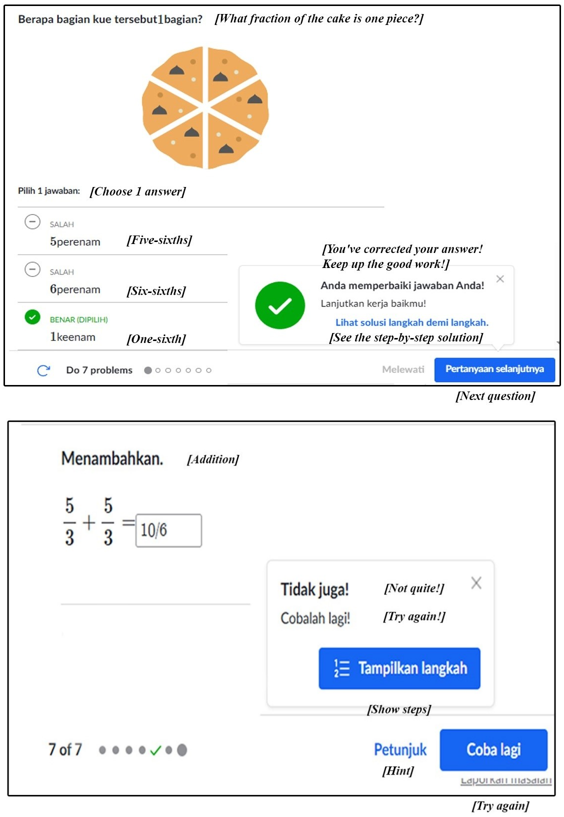

Fig. 2. A comparative analysis of the user interface demonstrating the "Representational Divide". (a) The "Visual Bridge": The student successfully solves a problem using concrete, iconic representations. (b) The "Symbolic Divide": The student is unable to solve a similar problem when presented in abstract, symbolic notation and is offered unhelpful procedural feedback, highlighting a critical failure in instructional scaffolding.

Table 1. Usability breakdown of AI language mismatch

Analysis Category	Content and Interpretation
AI Instruction (Formal Language)	"Perbesar nilai pecahan" *[Increase the value of the fraction]*
User's Cognitive Interpretation (from Think-Aloud Data)	"Disuruh dibesarkan gimana sih? Gedein gambarnya kah?" *[How am I supposed to 'make it bigger'? Do I enlarge the picture?]*
System's Intended Meaning	Perform a mathematical operation to make the fraction's value greater.
Resulting Usability Breakdown	Semantic Disconnect: The student defaulted to the most literal, concrete interpretation of the word "perbesar" *[enlarge]*, applying it to the visual object on the screen (the picture) rather than the abstract mathematical concept (the value). This is a critical failure of semantic correspondence.

IV. Result and Discussion

Our qualitative usability study of the adaptive AI platform uncovered several critical design flaws that pose serious barriers for slow learners. The results point to a clear disconnect between the platform's intended pedagogical goals and the reality of the user experience. This gap emerges in three main areas: motivational designs that backfire, inadequate scaffolding for abstract thinking, and usability problems caused by linguistic mismatches. This section discusses these findings in detail, interpreting them through the lens of established HCI and educational technology literature.

A. The Backfire Effect: When Punitive Gamification Undermines Learning

One of the most striking findings was a systemic flaw in the platform's motivational design. The AI used a "mastery bar" that reset a student's entire progress after just one mistake. Although this feature was likely meant to promote mastery, in practice it triggered what we call a "Frustration–Disengagement Loop"—a negative cycle of behavior that repeatedly derailed the learning process. This pattern was clearly visible in the "survival strategies" students developed. For example, one participant repeatedly exited and re-entered the system in hopes of being given an easier problem—an attempt to bypass the challenge altogether rather than engage with the learning task.

This behavior offers a vivid, real-world example of what scholars have described as the "dark side of gamification" [5]. The design choice to penalize failure directly contradicts the principles of fostering a growth mindset, which posits that intelligence can be developed and that failure is an opportunity to learn [12]. Rather than promoting persistence, the system tended to heighten anxiety and encourage avoidance, supporting concerns that such mechanics can undermine the self-efficacy of students who are already academically vulnerable [7]. Our findings extend this theory by modeling the process through which this damage occurs.

The cycle starts when a user makes a mistake and instead of receiving helpful guidance, they are met with harsh or punitive feedback. This strong negative response can be understood through behavioral economics, particularly the idea of loss aversion—the fact that the frustration of losing all progress feels far more intense than the satisfaction of making any gain [13]. The decision to reset the "mastery bar" is particularly demotivating, sparking strong emotional reactions like frustration or anxiety. Research shows that in AI-driven learning—especially in rural settings—these emotional experiences play a crucial role, often shaping how satisfied students feel with the technology and how engaged they remain in their learning [14]. These negative emotions can trigger a harmful shift in thinking: instead of focusing on understanding the material, the user becomes preoccupied with avoiding mistakes or punishment, disrupting their ability to regulate their own learning effectively [15]. This suggests that for this user group, the design of feedback systems must prioritize psychological safety over simplistic, game-like progress metrics that can inadvertently punish the very act of trying.

In contrast, other adaptive platforms show how a different design philosophy can produce far better results. For instance, a study of the KuisQ platform found that its differentiated learning features—adjusting question difficulty and offering personalized, real-time feedback—significantly boosted both student engagement and academic performance [16]. The KuisQ platform adapts the difficulty of its questions to match a student's performance in real time, keeping them in a "sweet spot" of productive challenge without triggering the stress of harsh resets. By doing so, it sidesteps the Frustration-Disengagement Loop we observed in our study and instead nurtures a sense of competence, confidence, and ongoing motivation. Looking at this through a theoretical lens, KuisQ follows a growth-oriented approach, subtly adjusting the difficulty to keep students in a productive zone of challenge. In contrast, the platform we studied relies on a rigid, punitive model that feeds into loss aversion, causing students to abandon their goals and shift focus away from learning.

B. The Representational Divide: A Failure in Scaffolding Abstract Thought

The second major finding reveals a critical gap in the AI's instructional scaffolding, a phenomenon we term the "Representational Divide". The platform worked exceptionally well when mathematical concepts were presented through tangible, visual aids—participants approached these tasks with ease and confidence. But as soon as the platform shifted from these visual representations to abstract symbols, a noticeable gap emerged, leaving learners struggling to bridge the conceptual leap. At this critical juncture, where learners most needed conceptual support, the AI's scaffolding regressed to offering flawed procedural hints that guided them to the right answer without building any transferable, abstract understanding.

This design choice encourages what researchers call an "illusion of competence", where both the system and the learner might think real learning has occurred, even though only procedural mimicry has taken place. The irony is striking: while AI has the potential to nurture higher-order thinking, this particular implementation ends up suppressing it. This contrasts sharply with other pedagogical approaches where AI is used to foster higher-order thinking. For example, one study explored how generative AI can explicitly support "generative thinking"—the ability to create hypotheses and generate diverse ideas—showing that AI can act as a cognitive scaffold rather than merely a procedural aid [17].

This finding directly engages with the "assistance dilemma", a foundational challenge in educational technology that questions how much help a system should provide [3]. In our study, the AI addressed this dilemma in the least helpful way possible: by offering too much of the wrong kind of assistance. This flood of poorly designed guidance can overwhelm learners, creating unnecessary cognitive load that actually hinders rather than supports the learning process [18]. Its procedural prompts relieved students of the productive struggle necessary for schema construction, a finding that echoes other work noting that such systems often fail to build the metacognitive skills required for long-term knowledge transfer [4]. This problem extends to how the system delivers feedback. Instead of allowing students time to reflect, it pressured them to move quickly—a common issue in poorly designed gamified tools. Research comparing popular platforms like Kahoot and Quizizz shows that features such as self-pacing can greatly improve the effectiveness of feedback, with students often benefiting more when they can process feedback at their own speed [19]. Our study extends this work by showing that the problem is most pronounced at the critical transition from concrete to abstract representations. The AI's failure to provide a "conceptual bridge" at this point highlights a key design flaw. This difficulty in scaffolding learners from concrete to abstract ideas mirrors challenges identified in the principle of "concreteness fading" [20].

C. Semantic Voids: The High Cost of Decontextualized Language

Finally, our analysis uncovered usability breakdowns rooted in a semantic mismatch between the system's formal language and the learners' real-world vernacular. As detailed in Table 1, a standard instruction in Bahasa Indonesia, "Perbesar nilai pecahan" *[Increase the value of the fraction]*, was consistently misinterpreted by participants. Rather than performing a mathematical operation, students defaulted to the most literal, concrete interpretation of the word "perbesar" *[enlarge]*, leading them to ask if they were supposed to enlarge the picture on the screen. This breakdown, captured in think-aloud data, is not a simple translation error but a fundamental failure of semantic correspondence between the system's intent and the user's cognitive interpretation.

This semantic gap is a clear violation of the long-standing HCI heuristic to "match between the system and the real world". For these students, the "real world" is a classroom where teachers use informal, contextualized, and often visual language to explain abstract concepts. This aligns with the personalization principle in multimedia learning, which suggests that learning is enhanced when instruction is delivered in a conversational, rather than formal, style [21]. As argued by Shabadurai *et al.* [9], many AI systems are inadvertently optimized for a generic, "average" user, which creates unforeseen cognitive barriers for atypical learners.

Our findings show how these manifests in practice: the formal, decontextualized language imposed a superfluous layer of cognitive load, a classic example of the expertise reversal effect, where instructional guidance that is effective for experts can be detrimental for novices [22].

D. Implications for Design and Practice

To improve learning and keep students motivated, educational platforms should avoid punishing designs and use growth-focused models. For example, instead of a "mastery bar" that resets progress after a mistake, systems could treat errors as learning opportunities, following a growth mindset approach [12]. The success of platforms like KuisQ, which adaptively adjust difficulty to keep learners engaged at just the right level, offers a clear, evidence-based example of how this approach can work in practice [16]. Shifting from a fixed view of ability—like "You failed, start over"—to a dynamic perspective—"With effort and strategy, you can improve"—can be put into practice by providing diagnostic feedback or tailored remedial paths. The focus moves from merely marking answers as right or wrong to guiding students through the learning process itself [23]. Designers should also consider implementing dynamic user models that adapt to a learner's evolving preferences and strategies over time, moving beyond static, one-time profiling [9]. Additionally, platforms should offer dynamic conceptual scaffolding that goes beyond simple procedural hints. Adaptive "conceptual bridges", such as animations connecting visual and symbolic representations, can help learners who struggle with abstract ideas. At the same time, content should be made more accessible through localization and usability features, like interactive visual glossaries and simplified language options, which reduce the cognitive load caused by formal, decontextualized text. Together, these strategies create learning experiences that are more inclusive, engaging, and effective.

In this context, the role of the teacher shifts towards a diagnostic one. Educators should be empowered to use interaction data (e.g., time latency, error patterns) as a cognitive diagnostic instrument to detect issues like the "illusion of competence", where procedural success masks conceptual failure. This allows for timely, targeted human intervention. This aligns with the core principles of formative feedback, which is designed to be timely and actionable [24]. Furthermore, teachers can use these observable patterns to initiate metacognitive dialogue with students about their strategies and learning processes. To truly empower educators in their diagnostic role, platforms should offer a Teacher Dashboard that visually highlights students' struggle patterns. For instance, the dashboard could notify a teacher when a student repeatedly resets their progress on a skill or spends an unusually long time on a single problem. This kind of insight allows teachers to step in efficiently, providing timely guidance and support where it's most needed. For educators to effectively take on this diagnostic role, they first need a solid understanding of AI. In other words, helping students cross the "Representational Divide" also requires addressing an "Algorithmic Divide" among teachers—giving them the knowledge and critical skills to grasp and question how AI shapes learning [25].

V. CONCLUSION

This study sheds light on the "black box" of student-AI interactions for slow learners, showing how certain design choices can create real obstacles to learning. By mapping the "Frustration-Disengagement Loop" and the "Representational Divide", we offer a detailed, evidence-based view of how usability failures play out in a real-world adaptive platform. The main contribution of this work is a set of process-focused models that question the effectiveness of one-size-fits-all AI designs and provide a strong case for a more user-centered, inclusive approach.

While the small, culturally-specific sample limits statistical generalizability, this study's primary contribution is not to measure the prevalence of these failure patterns, but to provide a powerful 'existence proof'. We present a detailed model illustrating how these usability issues can arise in real-world settings. Future research should examine how well these models apply across different populations and platforms. Additionally, studies should explore how demographic factors, such as gender, shape user experiences, since evidence suggests these variables can influence how learners perceive educational technologies [26]. Quantitative studies could examine how punitive versus growth-oriented feedback affects students' anxiety and persistence, while qualitative research could explore how AI tools can be co-designed with atypical learners to better support their unique needs. For AI in education to fulfill its promise for all learners, a vision of personalized learning at scale [27], the field must move from systems that merely deliver content to platforms that mindfully scaffold the human cognitive, metacognitive, and affective experience.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Topanus Tulak served as the principal investigator, coordinating with school partners and overseeing the classroom intervention. Andi Kaharuddin, the corresponding author, developed the research framework, conducted think-aloud protocols and classroom observations, analyzed qualitative data using NVivo, and took the lead in writing, revising, and creating visual representations of the findings. Harmelia Tulak carried out psychological screenings of participants, offered expert insights into the cognitive characteristics of slow learners, and helped interpret students' behavioral responses during the intervention. All authors actively participated in research discussions and approved the final manuscript.

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