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A GAI-Based Chatbot for Scaffolding Self-Regulated Learning: Insights from a Design-Based Research Approach

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Abstract

Generative AI (GAI) is increasingly integrated into education, particularly through chatbots that support students without direct human intervention. While these tools show promise as personalized learning companions, concerns persist about their potential to foster overreliance, limit creativity, and hinder the development of critical thinking. These risks highlight the need to strengthen students' metacognitive skills and promote structured self-reflection. This paper presents the design and iterative development of a GAI-based chatbot aimed at scaffolding self-regulated learning. Through three design cycles involving 276 students in 10 courses, the chatbot evolved from a static assistant into a dynamic, course-integrated tool capable of supporting personalized, Socratic-style dialogue. Thematic analysis of diverse qualitative data sources revealed that students seek scaffolded support, such as human tutoring, and require explicit guidance to engage meaningfully with AI. Findings emphasize the importance of dialogic competence, personalization, and educator involvement in shaping effective AI-mediated reflection. This study underscores the need for pedagogically grounded AI tools that position chatbots as collaborative agents, complementing rather than replacing the roles of teachers and learners. It advocates for reflective teaching practices that clearly define the responsibilities of students, educators, and AI systems to ensure that GAI enhances deep learning and independent thought.

Notes for Practice

- Educational chatbots should be designed to foster reflective dialogue through Socratic-style prompts, as this approach encourages deeper learning and reduces student overreliance on automated answers.
- This study employed a design-based research approach to iteratively develop and refine a GAI-based chatbot, capturing lessons learned from real-world classroom use.
- GAI-based chatbots can be most effective when thoughtfully integrated into course design, supported by instructor guidance, and well aligned with learning activities.

Keywords: Higher education, learning analytics, generative AI, design-based research, self-reflection

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1. Introduction

The convergence of artificial intelligence (AI) and learning analytics (LA) is creating new opportunities to generate actionable insights that support personalized teaching and learning. A key driver of this transformation is the emergence of generative AI (GAI) tools—particularly chatbots—which offer scalable, adaptable support for both students and educators (McDonald et al., 2025). Students increasingly rely on these tools as personal tutors, seeking targeted guidance and skill development (Ortega-Arranz et al., 2025), while instructors use them to enhance instructional design and support professional growth. GAI has shown strong potential to enrich learning by facilitating content-related discussions, supporting mastery learning, and reducing the burden of repetitive or time-intensive tasks (Sharef et al., 2021). Moreover, these technologies are proving effective in extracting insights from educational data to better understand and support learning processes (Sjöström & Dahlin, 2020).

One of the most prominent applications of GAI in education is the development of chatbots that support students without direct human intervention (Gounder et al., 2024). When used ethically and with pedagogical intent, these tools can serve as personalized self-assessment guides, fostering the development of higher-order thinking skills and deeper inquiry. In particular, GAI has shown effectiveness in writing support, where its appropriate use is linked to improved student performance and the acquisition of foundational skills such as text generation and revision (Fischer et al., 2024). Beyond writing, GAI-based tools have also been shown to enhance students' metacognitive awareness and engagement with their own learning processes. Studies across various domains—including language and science education—report improved learning outcomes and deeper cognitive engagement (Chu et al., 2025; Lee et al., 2025). Goyal (2025) highlights the role of GAI-based tools as cognitive partners that promote self-reflection, critical thinking, and self-regulated learning. Still, Fischer et al. (2024) caution that appropriateness in AI use goes beyond mere access or technical proficiency; it requires intentional design that encourages critical engagement and avoids reductionist approaches that limit learning to surface-level outputs.

Teaching staff have raised additional concerns about the use of chatbots, as it is perceived that they may limit creativity and foster excessive dependence (Nuñez-Canal et al., 2024). For instance, tools like ChatGPT may lead some learners to become overly reliant on technology (Buckingham Shum, 2024), hindering the development of critical thinking skills and reducing their ability to make informed decisions when faced with complex or ambiguous problems (Goyal, 2025). These concerns are amplified when students use GAI-based tools to offload assignments, leading to issues such as plagiarism, unreliable responses, and hallucinations—false yet seemingly coherent information that can mislead learners and propagate misinformation if undetected (Dang & Nguyen, 2025; Nuñez-Canal et al., 2024; Ortega-Arranz et al., 2025). Educators have also reported that GAI-generated content can undermine teacher autonomy, making it difficult to ensure alignment with course objectives and pedagogical intent (Ortega-Arranz et al., 2025). For this reason, the integration of AI into teaching and learning must be approached with caution (Goyal, 2025). Reflective teaching practices are essential to guide students in using these tools responsibly and meaningfully. Through structured self-reflection, higher education learners can develop strategies to overcome challenges to sustain learning interest in a task when using AI (Guan et al., 2025). Therefore, it is crucial to establish clear pedagogical roles for teaching staff in guiding AI use, ensuring that these tools support—not replace—deep learning and independent thought.

In this context, LA dashboards can play a central role in the LAK vision by visualizing learner data to support human sense-making and informed decision-making (Verbert et al., 2020). Many LA studies have focused on understanding how user-interaction data can be transformed into actionable indicators. This body of work provides a well-established methodological and conceptual foundation for the design of teacher-facing dashboards to support the interpretation of students' learning behaviours, engagement, and regulation processes (Verbert et al., 2020). Current research on GAI–based tools can build upon these insights by extending analytics approaches to student–GAI interactions, enabling the generation of dashboards that make learners' dialogic and reflective processes visible. Analytics such as message counts, conversation duration, and access to verbatim dialogue transcripts can offer instructors concrete mechanisms to monitor, interpret, and regulate the integration of GAI within their course designs through indicators derived from student–GAI interactions. These analytics support informed pedagogical decision-making, rather than opaque or unguided use of AI systems. This paper presents the design and iterative development of a GAI-based chatbot aimed at fostering self-reflection as a core component of metacognition and self-regulated learning. Grounded in the understanding that metacognitive processes could be scaffolded through structured dialogue, the chatbot was developed to support learners in planning, performing, and reflecting on their learning experiences in hybrid teaching environments. By hybrid environments, we refer to educational settings where AI does not completely replace teaching tasks but rather complements and augments them (Molenaar, 2022). Using a design-based research approach, the chatbot was conceptualized and developed over three iterative cycles involving 276 students in 10 courses taught by different instructors. The resulting tool leverages interaction data and user feedback to adapt its responses in real time, enabling personalized, course-aligned conversations that promote reflective thinking. By examining how students and instructors engage with the chatbot, this study explores its potential to serve as a pedagogically grounded AI partner that supports meaningful self-reflection and personalized learning while maintaining educators' central role in guiding its use.

2. Background

Self-regulated learning (SRL) refers to a cyclical process in which students set learning goals, implement strategies to achieve them, and monitor their progress through ongoing self-reflection (Panadero, 2017). Several prominent theoretical models have shaped our understanding of SRL, including those proposed by Zimmerman (2000), Pintrich (2000), and Winne and Hadwin (1998, 2008). While these models share a common structure—goal setting and strategic planning, performing and monitoring, and evaluation and self-reflection—they emphasize different aspects of the SRL process. Zimmerman (2000) presents a comprehensive framework that integrates cognitive, affective, and behavioural dimensions within a dynamic system influenced by personal and environmental factors. Pintrich (2000) highlights the simultaneous regulation of cognitive, motivational, behavioural, and contextual domains across SRL phases. In contrast, Winne and Hadwin (1998, 2008) focus on the central role of metacognition, emphasizing how learners monitor and control their learning through recursive evaluation and strategic adjustment. Together, these perspectives underscore the complexity of SRL and the importance of supporting learners in developing adaptive strategies for managing their learning processes across SRL phases.

Self-regulated learners tend to be more aware of their learning processes and, as a result, often achieve better academic outcomes. Developing SRL capabilities is therefore a key objective in higher education. However, fostering SRL is not without challenges. Many students enter university without prior exposure to environments where self-regulation is explicitly taught or modelled (Bjork et al., 2013). This is particularly concerning given that social guidance and scaffolding play a crucial role in helping learners develop these skills. As Zimmerman (2000) notes, students require substantial support before they can effectively and adaptively apply self-regulatory strategies. However, despite its importance, providing such scaffolding is often constrained by institutional realities—such as large class sizes and competing demands on instructors' time—which can limit the availability of individualized support (Kumar et al., 2024).

In recent years, the integration of large language models (LLMs) into educational contexts has opened new avenues for promoting and scaling SRL. Among the most prominent applications are educational chatbots, which leverage the natural language generation and comprehension capabilities of models like GPT-4 to simulate human-like dialogue (Guan et al., 2025). These chatbots can deliver instant, personalized feedback and reflection prompts, making them particularly effective for supporting SRL development at scale and addressing the challenge of individualizing support in diverse learning environments (Yuan & Hu, 2024). Given the persistent gap between available human resources and the need for social guidance in learning processes, there is growing interest in the use of chatbots to scaffold SRL.

An emerging body of research has begun to explore this potential across different instructional modalities, including online and face-to-face learning environments supported by technology. In online settings—where autonomy and self-regulation are especially critical—chatbots have been positively received by students, particularly for supporting goal setting, behavioural engagement, and reducing feelings of isolation (Hew et al., 2023; Huang & Hew, 2024). Similarly, in face-to-face courses with technological support, Lee et al. (2025) found that chatbot-assisted reflection improved students' performance, motivation, metacognition, and SRL when compared to traditional teacher-led reflection. These findings underscore the value of timely and meaningful feedback in fostering reflective learning. However, other studies highlight the importance of tailoring chatbot interactions to individual learner characteristics. For example, Han et al. (2025) found that students with low prior SRL benefited significantly from chatbot support, while those with high SRL showed decreased engagement and performance—suggesting that over-scaffolding may hinder autonomous learners. Lai et al. (2025) similarly observed divergent interaction patterns based on students' prior knowledge, reinforcing the need for adaptive chatbot design that accounts for learners' varying needs and preferences.

When more specifically considering SRL phases, a literature review by Guan et al. (2025) employed Winne and Hadwin's (1998) phases to map the reviewed articles. They found that chatbots tended to support only one or two phases of this model; few studies address the entire SRL cycle. Most chatbots helped students with the enactment of the study tactics and strategies phase associated with the particular tasks addressed by each investigation, followed by task definition and goal setting. Fewer studies addressed the metacognitive phase, fostering students' self-reflection. Studies with this component reported increased student performance (e.g., Chang et al., 2022; Lin & Chang, 2020), reaffirming the importance of metacognition in SRL processes. Moreover, while most of the reviewed studies indicated that chatbot use was beneficial for SRL, some reported non-significant or mixed outcomes. For example, while there were positive effects in several disciplinary subjects (e.g., ESL, obstetrics, physical education, science, and accounting), limited or no effects were found in chemistry, math, computer science, and geography.

It is also important to acknowledge metacognition as a key element of SRL (Pintrich, 2000; Winne & Hadwin, 1998, 2008). Recent research has demonstrated that self-reflection can be effectively scaffolded through structured learning activities. For example, Liu et al. (2025) found that scaffolded reflective learning—particularly when aligned with specific task phases—significantly improved student teachers' design performance and reflective thinking. These findings underscore the pedagogical value of intentional scaffolding, which can promote deeper understanding and more adaptive knowledge application across diverse educational contexts.

In parallel, researchers have emphasized the importance of designing LLMs with clear pedagogical intent to guide students through reflective processes and mitigate risks such as **c**ognitive offloading and hallucination (Dang & Nguyen, 2025; Buckingham Shum, 2024; Urban et al., 2024). Emerging empirical evidence suggests that pedagogically grounded LLMs can foster metacognitive development and enhance learning outcomes. For instance, Kumar et al. (2024) conducted a comparative study showing that both LLM-assisted and questionnaire-based reflection led to significant improvements in assessment performance compared to passive review, though no significant differences were found between the two active methods. Complementary findings by Yuan and Hu (2024) demonstrated that strategically crafted prompts enabled LLMs to achieve

82% inter-rater reliability with human tutors when evaluating reflective responses. While many of these approaches have been tested in synthetic scenarios, they show promise for scaling personalized feedback and reflective support. Nevertheless, these findings also highlight the need for careful design of LLM-based tools, ensuring they incorporate valid metacognitive cues, safeguard against misinformation, and promote critical thinking and responsible use among learners.

Despite growing interest in the use of LLMs and educational chatbots to support self-regulated learning (Guan et al., 2025), several research gaps remain. While existing studies have shown that LLMs can facilitate structured reflection and improve learning outcomes (Kumar et al., 2024; Yuan & Hu, 2024), most have been conducted in controlled environments or small-scale studies, with limited exploration of their effectiveness in authentic, hybrid learning contexts (Liu et al., 2025). Moreover, there is a lack of research examining how LLM-based tools can scaffold the full cycle of SRL—supporting students in setting goals, taking action, and reflecting on both past and future learning (Guan et al., 2025). A critical gap also lies in the underdefined pedagogical role of instructors in designing, facilitating, and evaluating AI-mediated reflection (Goyal, 2025; Ortega-Arranz et al., 2025). As Goyal (2025) emphasizes, there is an urgent need for empirical research that investigates how these tools function in real-world settings and how they can be meaningfully integrated into instructional design. To ensure pedagogical relevance and effectiveness, AI tools must be co-designed with educators—who bring expertise in structuring reflective learning—and with students whose everyday practices and needs shape tool adoption and engagement. This study addresses these gaps by foregrounding students' perspectives in the design of a GAI-based chatbot and illustrates how learner input informed the development of a tool tailored to support reflective learning in context.

3. Methods

This 3-year study addressed the following research question: *How can a GAI-based chatbot scaffold the full cycle of SRL in higher education?* To answer this question, we followed a design-based research (DBR) approach. According to Barab (2014), DBR consists of a series of interventions in which different research methods are used to capture lessons learned, aiming to derive a theory or a tool in a real-world setting. DBR is well-recognized within the technology-enhanced learning community for its potential to inform the design of pedagogically grounded technological solutions (Pérez-Sanagustín et al., 2016, 2022; Roschelle et al., 2010; Villagrán et al., 2024). The application of this approach has been associated with improvements in students' outcomes and attitudes (Anderson & Shattuck, 2012) and has recently been applied to evaluate GAI-based tutoring systems (Schmohl et al., 2022). In this paper, we adopt the DBR approach as a guiding framework to propose a situated solution grounded in existing knowledge of GAI-based chatbot use, exploring its potential to support the development of self-reflection as a higher-order cognitive skill.

Specifically, this study was conducted between 2022 and 2024. Throughout this period, every participant provided informed consent in accordance with the relevant ethics committee (ID protocol PUC210426026). We structured our work across three iterative design cycles, each grounded in the understanding of self-reflection as a key component of SRL. Given the common structure across SRL models (see the background section), each cycle in this study was inspired by a three-phase conceptualization of SRL (planning, task execution, and post-task reflection) and focused on developing and evaluating tools aligned with a specific phase. In the first cycle, we created and tested a proof of concept aimed at supporting the planning phase, helping learners set goals and develop strategies informed by their student approaches to learning (SAL)—a framework that distinguishes between deep, surface, and organized learning approaches (Richardson et al., 2012; Fryer & Vermunt, 2018; Postareff et al., 2017). The second cycle focused on building a functional prototype to assist students before and during task execution. In the third cycle, we deployed a web-based chatbot to guide learners through post-task reflection, enabling them to assess their performance and current understanding of a topic or mastery of a specific skill. This final iteration also empowered instructors to design tasks that incorporated guided reflection prompts, encouraging students to evaluate what they had learned, the effectiveness of their strategies, and the relevance of their learning to broader academic, personal, or professional goals (Russell et al., 2022).

Based on the guidelines of Lewis et al. (2020), each cycle followed a building-testing logic, aiming to ensure the implementation of deliberate iterations that systematically link design decisions to lessons learned by enabling purposeful tool development based on evidence. First, we conducted a tool development stage to design and deploy the tool with real users. Then, we conducted a testing stage to evaluate the tool's perceived usefulness and usability and to capture lessons learned for the next cycle (see Figure 1). Finally, a broad evaluation stage was conducted to integrate and discuss the findings from the three cycles. For this integration, we discussed the implications of using the chatbot for different phases of SRL. The following sections describe each cycle and present the main results.

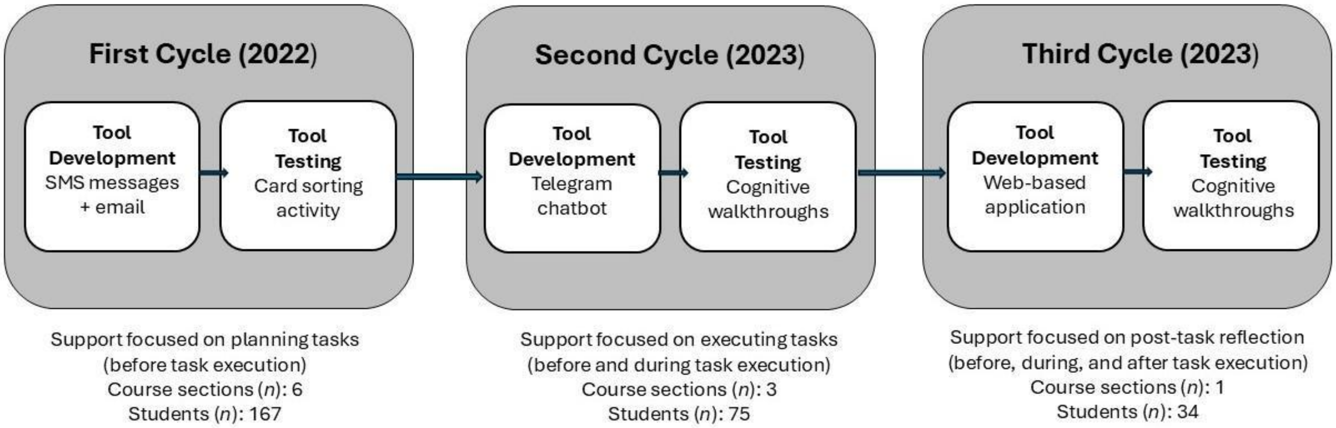

Figure 1. DBR Approach to Develop a Chatbot for Supporting Student Self-Reflection in Three Phases

4. First Cycle (2022)

4.1. Tool Development: SMS Messages and Emails

The first cycle of the DBR approach focused on supporting students to plan their learning tasks. To achieve this, a series of reflective prompts—adapted from the work of Zavaleta Bernuy et al. (2022)—were delivered to students via email and SMS, with informed consent. These prompts were distributed at different points throughout the academic term to encourage timely engagement with learning goals (see Table 1). The intervention was implemented across two contrasting institutional contexts (see Table 2). In U1, prompts were sent via email to align with institutional communication norms, as this leading private university is known for its strong academic tradition and selective admissions within Latin America. In contrast, at U2, one of the oldest and most prominent public universities in the region, SMS messages were used to increase accessibility and immediacy of engagement with a diverse student population. This dual-site implementation enabled exploration of how institutional context and communication channels influence students' responsiveness to reflective scaffolding in the early stages of learning.

Table 1. Prompts Sent to Students During an Academic Period of 16 Weeks (Based on Zavaleta Bernuy et al., 2022)

Academic Week	Prompts Focused on Planning Learning Tasks
Week 5	• Take a few minutes to plan your upcoming class weeks: What activities and assessments do you have in your courses? • Setting a reminder/alarm or adding an event to your agenda/calendar can be a useful strategy. • If you feel that you have made progress as expected, take some time to celebrate your progress.
One-week break (Week 8)	• Plan ahead so you can enjoy your one-week break, whether it's resting, celebrating, or spending time with loved ones.
Week 11	• The semester is well underway, and these weeks of the semester tend to be more demanding, so it's important to maintain a work pace. It's also important to maintain schedules for sleeping, resting, and engaging in non-study-related activities. • Pay attention to the distribution of your assessments during this period. Consistent work tends to be more effective than intensive study, so it's important not to leave submissions and studying until the last minute. • Remember to attend classes and promptly request assistance from the teaching staff if you need support with your studies.
Week 14	• We're approaching the end of the course, and this is the last message with planning recommendations. We hope they help you with the final stretch! • You should carefully review class materials, forums, and other resources. This can help you understand the content and clarify any questions you may have. • We are approaching the final exams. Using other texts or materials for further study can also be a good strategy.

Table 2. Courses Included in This First Intervention

University	Field	Course Name	Course Enrolment	Accepted Informed Consent
U1	Education	Education and Society	35	23
	Engineering Design	Anthro-Design	16	15
U2	Engineering	Leadership and Social Innovation	26	23
	Physics	Introduction to Modern Physics	62	50

4.2. Tool Testing: Card-Sorting Activity

To evaluate the perceived usefulness of the SMS and email prompts implemented during the first cycle, card-sorting activities were conducted in three of the four participating courses (see Table 3). This technique was chosen for its effectiveness in capturing participants' subjective categorizations and preferences in a structured yet flexible format, allowing researchers to identify patterns in how students interpreted and valued the reflective prompts. We followed the steps suggested by Spencer (2009) for designing and implementing these card-sorting sessions:

(1) *Deciding what you want to learn.* This study aimed to examine whether students could make sense of the different prompts described in Table 1 to plan their learning tasks.
(2) *Selecting the method.* Students received a predetermined set of prompts and numeric indicators on individual paper cards and were asked to organize the cards according to their level of actionability and interpretability. We conducted in-person sessions lasting 1 hour and 30 minutes, using laminated paper cards and bid sheets to sort the cards according to these two parameters. One researcher led the activity, while two research assistants took notes and pictures. All sessions were audio recorded.
(3) *Choosing the cards' content:* Although we mainly used text prompts, which students prefer for feedback (see Table 1), we also included cards with textual and visual representations to capture lessons learned for the next cycle.
(4) *Choosing and inviting participants.* Study participants were selected through convenience sampling from students at two universities: U1 and U2 (see Table 3).
(5) *Running the card-sorting and recording the data.* Three card-sorting sessions were held; one per course (see Table 3). Each session was organized into five phases following guidelines suggested by Spencer (2009) (see Appendix A).
(6) *Analyzing outcomes*. To analyze the qualitative outcomes (i.e., transcriptions of audio sessions), we conducted a thematic analysis as proposed by Nowell et al. (2017):
    i. Getting familiarized with the data (the researcher and the two research assistants involved in the card-sorting sessions read each transcript individually).
    ii. Generating initial categorical codes concerning the types of code evaluated (see Table 1): (a) text versus visual, (b) absolute versus relative, (c) social versus non-social reference frames, and (d) temporal versus non-temporal.
    iii. Searching for themes: The three researchers met to discuss potential themes based on the categorical codes established in step (2).
    iv. Reviewing themes' adequacy by extracting quotes from the raw data.
    v. Naming themes: (a) Preferences regarding visual representation, (b) Interpretability, (c) Prioritized indicators, (d) Relationship between indicators and academic performance, and (e) Self-monitoring support interventions.
    vi. Producing a report. The two research assistants wrote a seven-page manuscript presenting the principal findings for each theme, including quotes extracted from the session transcripts.

Table 3. Courses Included in This First Intervention

University	Field	Course Name	Course Enrolment	Card-Sorting Participants
U1	Education	Education and Society	35	6
	Engineering Design	Anthro-Design	16	2
U2	Engineering	Leadership and Social Innovation	26	8

4.3. Main Findings and Lessons Learned

The first implementation cycle revealed important lessons that shaped the design of the second cycle. Most notably, students described diverse patterns of planning and study habits, requiring the personalization of prompts. From the students' perspective, text-only messages with dates or absolute scores proved insufficient to support meaningful reflection or action. Participants from both U1 and U2 found prompts accompanied by visual elements—such as bar or pie charts—more actionable and easier to interpret than those presented as plain text, emphasizing that visual indicators helped them better understand their progress and plan future study actions. *"Pure text, like it really bothered me a lot. It's hard to interpret, and therefore it's not actionable or even actionable for me, because I can't really take advantage of the information" [Student, U2].*

Additionally, students valued receiving timely reminders and supportive messages, which they perceived as helpful for staying on track. Despite these strengths, the communication channels used in the first cycle had clear limitations: they lacked the depth of personalization and interactivity needed to foster deeper engagement with course content. The advice provided was often too generic to support actionable planning or self-reflection. Student feedback, such as the desire to customize content to personal preferences, highlighted the need for more flexible, user-centred interfaces in a subsequent cycle. These insights underscore the importance of designing reflective tools that are not only informative but also adaptable to individual learning contexts within a subject. *"Let's see if we think of a platform where we have like a lot of subjects. Then I would like the main page to be with the subjects one, I could change the colours, customize it and in my own case, I would really like to move it around. In Canvas, you can, that's what I like because you can move it around, and I like things in alphabetical order" [Student, U1].*

Temporal recommendations and indicators, such as weekly progress, were appreciated by some students for enabling time-based planning, though others found them confusing due to variability in individual study habits. Overall, students valued clarity, personalization, and contextual relevance, suggesting that prompts should be visually engaging, easily accessible from mobile devices, and tailored to their learning rhythms. These insights informed the design of a tool in the subsequent cycle, emphasizing the importance of personalization and motivational framing to make reflective learning tools easier to use.

5. Second Cycle (2023)

5.1. Tool Development: Telegram Chatbot

In the second cycle of this DBR approach, researchers addressed two key lessons identified during the first cycle: the need for an easy-to-use tool on mobile devices that provides students with more targeted support within a specific course context. This iteration was implemented in the course Education and Society at U1, across three sections: one offered to 28 students during the first semester of 2023, and two additional sections in the second semester, with 2 and 47 students respectively. Unlike the first cycle, where researchers manually crafted the content, this phase transitioned content generation to a chatbot powered by the ChatGPT API. The chatbot was deployed via Telegram, a widely used messaging platform among students, to ensure accessibility and ease of use.

Initially, the chatbot used the GPT-3.5-Turbo model during the first semester and was later upgraded to GPT-4 in the second semester to improve interaction quality and accuracy. All conversations were stored in Firebase, capturing student queries, chatbot responses, and timestamps for each interaction. In this cycle, the chatbot was specifically designed to support students during the task execution phase of self-reflection—that is, while they were actively engaging with course activities. To do so, it was enriched with course-specific information, including test dates and required readings. This information was updated weekly based on the course instructor's input, enabling the chatbot to provide timely, context-aware responses. Students could ask free-form, personalized questions about upcoming assessments or course logistics without needing to consult the institutional LMS. In turn, the chatbot offered tailored tips and reflective prompts that helped students before and during learning task execution, clarifying expectations to make informed decisions while completing academic tasks.

5.2. Tool Testing: Cognitive Walkthroughs

To evaluate the usability and perceived usefulness of the chatbot implemented during the second cycle, researchers conducted three cognitive walkthroughs with undergraduate students enrolled in the Education and Society course at U1, involving 12 participants in total. The cognitive walkthroughs consisted of in-person group interviews moderated by one researcher, with two research assistants recording audio and taking notes. Based on Dishman (2003), we followed a protocol that included activities to be performed, observations, and questions to be answered regarding the use of the chatbot (see Appendix B), aiming to gather insightful feedback for the third cycle.

The cognitive walkthroughs were organized around three key dimensions. First, participants were asked contextual questions about their interaction with the chatbot during the semester. This included whether they used it, their motivations for doing so (or not), the devices they used (e.g., mobile or desktop), and the types of actions they performed (e.g., downloading, messaging). In the second phase, students observed a brief demonstration of the chatbot's functionality via the Telegram platform. They were then encouraged to replicate the demo and engage in free-form interaction with the chatbot, while researchers collected feedback on the relevance and satisfaction with the responses received. Finally, the third phase focused on broader reflections regarding the chatbot's ease of use, the relevance of the information provided, and data privacy concerns. As in the first cycle, all sessions were audio-recorded, and the audio transcriptions were examined using a thematic analysis as proposed by Nowell et al. (2017). The two research assistants who supported the implementation of cognitive walkthroughs wrote a seven-page report with the main themes that emerged from the analysis, including quotes extracted from the sessions' transcripts. Themes included perceived usefulness and usability, types of requests, barriers to use, and suggestions for chatbot improvement.

5.3. Main Findings and Lessons Learned

The second implementation cycle revealed a nuanced picture of student engagement with the Telegram chatbot. While the tool was initially met with enthusiasm—largely driven by its novelty—its use declined over time. This drop was attributed to several factors, including the perception that Telegram, the platform hosting the chatbot, was not widely used among students and that downloading an additional app for a single course-specific function felt unnecessary. As one student noted, *"I did download it because it was something very new for me... but it was like the first two weeks that it was presented to us. After that, I didn't continue using it" (Student, U1).*

Among those who did engage with the chatbot, it was generally perceived as easy to use and helpful for administrative tasks, such as checking reading assignments, evaluation dates, and course logistics. Students appreciated the convenience of accessing this information directly from their phones, especially outside of class hours. However, limitations quickly became apparent. The chatbot lacked knowledge of specific academic information. While the chatbot provided links and general guidance, its responses were often perceived as overly pragmatic and impersonal, lacking the warmth or conversational tone expected in sensitive contexts. Several students suggested that the chatbot should adopt a more human-like communication style, similar to virtual assistants like Siri, and offer more direct, actionable information for self-reflection rather than simply redirecting users to course learning tasks: *"And maybe, I kind of thought of it like that, like the answers were more like if you were talking to a person, not like so much to a machine, because if we're talking like something maybe about health, mental health, like something more like a person than a machine" (Student, U1).*

In terms of suggestions for improvement, students expressed a desire for the chatbot to offer text analysis support and help with understanding course materials, as well as to include interactive features such as voice messages and name personalization. Therefore, for the chatbot to fulfill this potential, it must evolve into a more context-aware, emotionally intelligent, and integrated support tool that aligns with students' academic needs.

6. Third Cycle (2024)

6.1. Tool Development: Web-Based Application

The third cycle of this DBR was conducted during the first semester of 2024 in the course Education and Society at U1, involving a single section of 34 students. Building on insights from the previous cycle, this cycle aimed to strengthen support for students across all phases of SRL—before, during, and after task execution—with a particular focus on enhancing the chatbot's design. To improve accessibility and reduce friction, the chatbot was reimagined as a standalone, web-based platform that did not require students to download additional applications (Ferrettini et al., 2026). This iteration replaced the earlier Telegram-based version and was powered by OpenAI's Assistants API using the GPT-4o-mini model. It also integrated a file search tool to deliver responses enriched with course-specific content, including both administrative information and the substance of assigned readings.

The chatbot operates as a secure, login-based application with two distinct user roles. Instructors access a dedicated interface to design learning activities, which are automatically converted into structured prompts that constrain the LLM to function as a Socratic tutor (see Appendix C). Each activity generates a unique URL that instructors can share with students, who then engage with the chatbot in a guided, conversational format. To align with students' preferences for a warm and context-sensitive tone, instructors can specify the chatbot's communicative style—friendly, informal, or formal. These configurations were designed to promote reflective dialogue rather than direct answer provision, aligning with the principles of Socratic tutoring and the broader goal of fostering critical engagement across SRL phases (Hilliger et al., 2026). All interaction data, from both students and instructors, is securely stored in a database for future analysis of usage patterns and learning behaviours, contingent on prior informed consent.

To operationalize support across the phases of SRL, the course instructor designed four chatbot-based activities focused on learning strategies in higher education, aligned with course content. These activities were introduced progressively throughout the academic period and intended to complement traditional instruction by encouraging autonomous interactions outside the classroom. Each activity was configured using the chatbot's flexible prompt template, which allowed the instructor to tailor variables such as communication tone, teaching style, level of answer disclosure, and integration of supporting documents. A detailed description of the prompts and the specific variables used in each activity is provided in Appendix C.

To support the course instructor in analyzing student engagement, the tool included a built-in LA dashboard with four complementary tabs: *Conversation Stats*, *Student Stats*, *Engagement*, and *Raw Data*. These tabs aim to transform raw dialogue data into interpretable metrics. Aggregated indicators such as message count, average message length, and conversation duration could be visualized alongside individualized metrics that allow comparisons between student-level and cohort-level data. The dashboard also included summaries of student messages produced by GPT-4o-Mini, word clouds highlighting frequently used terms, and customizable scatterplots that display variables such as lexical diversity and vocabulary size. The instructor could also access verbatim transcripts of student–chatbot interactions to offer qualitative insights into reflective engagement. Together, these features aimed to offer a multifaceted view of student participation and discourse patterns, so any instructor could monitor engagement and adapt instructional strategies in alignment with LA goals (Nascimento et al., 2026).

6.2. Tool Testing: Cognitive Walkthroughs

Of the 34 students enrolled in the Education and Society course during the first semester of 2024, 15 interacted voluntarily with the GAI-based chatbot. According to the analysis of the interaction logs, a small subset of students (8 out of the 15) interacted continuously throughout the academic period, producing on average 23.6 messages (95% Confidence Interval = [1.89, 45.36]), participating in 10.9 conversational runs (95% Confidence Interval = [0.17, 21.58]). The rest of the users only interacted superficially (7 out of 15), with an average of 1.3 messages (95% Confidence Interval = [0.59, 1.98]) and almost no conversational runs (messages = 0.14, 95% Confidence Interval = [–0.21, 0.49]).

To evaluate this new version of the tool, five out of the eight active users participated in cognitive walkthroughs. In this cycle, cognitive walkthroughs were carried out individually, so one research assistant interacted with one student at a time. As in the previous cycle, the researcher followed a protocol that included activities to be performed, observations, and questions to be answered regarding the use of the chatbot (see Appendix D).

Specifically, the cognitive walkthroughs focused on how the chatbot supported self-reflection, specifically targeting the weekly readings. Given that the course syllabus included complex texts by both classical and contemporary authors in the sociology of education, students were directed to the chatbot to ask questions about a specific reading each week. In this way, the chatbot functioned as a complementary tutor, helping students better understand and engage with the course content.

As in prior cycles, the individual cognitive walkthrough sessions were audio-recorded, and the five audio transcriptions were examined using a thematic analysis as proposed by Nowell et al. (2017). The research assistant who supported the implementation of cognitive walkthroughs wrote an eight-page report with the main themes that emerged from the analysis, including quotes extracted from the sessions' transcripts. Themes included perceived understanding of the chatbot's purpose, use cases, motivation for adoption, quality of interactions, data privacy, and opportunities to improve the tool.

6.3. Main Findings and Lessons Learned

During the third cycle, the Socratic tutor was primarily used as a study aid for required readings: "It was designed to help us during the course and also had built-in activities so we could connect them, just like looking at the content (Student 4, U1)." Students engaged with it in various ways, from collaborative study sessions to targeted queries about specific text details.

"I remember using it a couple of times. I don't know if directly from my account, but I do remember studying with my friends" (Student 3, U1).

However, usage varied significantly. One particularly relevant use case—especially for students at the beginning of their academic journey—was learning study methods and planning strategies.

"Because in a more university-like context, you need to figure out which study method works best for you—the one that helps you save time and suits you the most" (Student 2, U1).

"It helped guide me on how to get started, because as a student, it's sometimes really hard to know where to begin" (Student 1, U1).

Concerning self-reflection, students valued the chatbot's ability to help identify key concepts and clarify complex content, particularly when struggling with summarization or comprehension. Additionally, its counterpart—ChatGPT—had significant limitations at the time regarding uploading files, either due to file-size restrictions or the general nature of its responses.

"(...) if you asked ChatGPT, maybe it would be more general, like it didn't know much about the topic. And the professor told us that the more you asked it, the more the algorithm would improve on its own" (Student 5, U1).

In many cases, the chatbot was even perceived as a study companion, because the chatbot fit more naturally into the routines of students or groups who were already engaging in dialogic or interactive study practices:

"[I] remembered that I had classmates who really studied like that [dialoguing] with the chatbot, and they would say things like, 'ask me a question about this topic,' and so on" (Student 3, U1).

"I feel like there are people who are really comfortable studying with someone else, or in a group, or through discussion—it's like the chatbot becomes another person to talk to about the subject" (Student 2, U1).

Regarding access to the chatbot, students mentioned different devices, such as tablets, cell phones, and computers, but mobile devices were preferred, most comfortable, and the most accessible. Although generally perceived as helpful, the quality of responses was inconsistent—some were detailed and useful, while others were overly brief or vague, especially when dealing with multiple texts or planning-related queries.

"Yes, they were very long, and other times short. When it was about how to look for the main ideas within the same text, then it was a little bit shorter" [Student, U1].

"(The chatbot) had like a program error, so to speak. It threw me an error, and I couldn't use it. After that, I didn't really use it again" [Student, U1].

Students suggested improvements such as enhanced personalization, integration with the institutional LMS, and additional features like dark mode, audio interaction, and concept mapping. They particularly appreciated the chatbot's specialization in course content, which distinguished it from more general tools like ChatGPT. While the integration of AI with course texts was seen as a major strength—described as a kind of "ChatGPT of the course"—its use did not necessarily align with the intended Socratic model. Instead, students primarily used it to answer questions in line with their individual study habits.

7. Broad Evaluation and Discussion

Across the three cycles of this DBR effort, a central lesson emerged: while students value GAI-based tools for supporting SRL, their effectiveness depends heavily on how well they are scaffolded within the specific context of a course. The final version of the chatbot, meaningfully integrated into course activities, was more likely to foster self-reflection. Conversely, when AI tools operated in isolation or lacked contextual alignment, students perceived them as less useful or even burdensome. This finding underscores a critical consideration for any use of GPT-based tools in education: their value is not inherent, but contingent on thoughtful integration into the learning environment. Without this alignment, even advanced AI systems risk being perceived as generic or disconnected, failing to meet learners' expectations for relevance and support. In particular, the use of AI-based chatbots revealed students' expectations for personalization and emotional closeness, often likening the ideal interaction to that of a human tutor. Rather than accepting generic or transactional responses, students sought conversational, empathetic, and context-aware support that could guide them through both academic content and the emotional challenges of learning. These findings extend prior work on the pedagogical potential of GAI-based tools for fostering metacognitive reflection (Goyal, 2025; Kumar et al., 2024; Yuan & Hu, 2024).

These findings align with and extend prior research on the role of AI in education. Building on Goyal's (2025) work, which positions AI tools as potential cognitive collaborators in learning environments, our study demonstrates how such tools can support SRL when embedded within course-specific structures and responsive to students' evolving needs. This is consistent with findings from previous studies that call for considering different students' profiles when designing chatbots for SRL development, given that not all students may benefit in the same way (Han et al., 2025; Lai et al., 2025). However, as Urban et al. (2024) emphasize, the effectiveness of such tools depends on the quality and intentionality of the metacognitive cues and tasks they offer. Our findings illustrate how different phases of SRL can be scaffolded through structured, dialogic interactions with AI. Over time, the chatbot evolved from a static, profile-based assistant into a more dynamic, responsive tool capable of engaging students in Socratic-style conversations grounded in course content. This transformation supports Molenaar's (2022) argument for shared regulation with AI, underscoring the importance of designing tools that adapt to learners' individual rhythms, goals, and study preferences. These developments demonstrate the potential of chatbots as effective tools for scaffolding SRL, particularly considering the constraints currently affecting teaching in higher education settings (Kumar et al., 2024).

A key contribution of this work lies in its empirical examination of the instructor's role in shaping AI-mediated reflection—an area underexplored in the current literature. While instructors were not directly addressed as study participants, students' perceptions allude to the instructor's role in adopting the chatbot, informing both its benefits and limitations. So far, there is a critical gap in how educators can design, facilitate, and evaluate these AI-based tools in alignment with pedagogical goals (Ortega-Arranz et al., 2025). This study reduces that gap by demonstrating how instructor-led design decisions—such as integrating course-specific prompts, using scaffolds, and adapting chatbot tone—can significantly influence student engagement and reflective depth.

A second contribution is that, throughout the iterative cycles, we addressed the three SRL phases, as described by Zimmerman (2000). Our approach was to incorporate SRL phases as cycles advanced. In this manner, we were able to test how students used the developed tool to plan, execute, and reflect on their learning as development progressed. Thus, adjusting and improving in each cycle. Most studies focused on supporting one or two phases (Guan et al., 2025). Therefore, this work extends prior research by explicitly testing a chatbot across SRL phases.

Moreover, our findings shed light on a growing concern: students' tendency to over-rely on AI tools when these are perceived as emotionally intelligent or human-like. This dynamic, while potentially supportive, may also hinder the development of critical thinking and independent decision-making (Buckingham Shum, 2024; Goyal, 2025). By documenting how students interacted with increasingly personalized AI tools, this research provides insight into the fine balance between support and dependency and underscores the importance of educator oversight to mitigate risks such as plagiarism, misalignment with learning objectives, and the erosion of learner autonomy (Nuñez-Canal et al., 2024; Ortega-Arranz et al., 2025).

What is particularly novel in this work is the identification of dialogic competence as a prerequisite for meaningful engagement with LLMs. Students struggled to initiate and sustain purposeful interactions, revealing a gap in AI literacy that extends beyond technical familiarity. This finding echoes recent calls in the technology-enhanced learning community to prepare students not just to use AI, but to collaborate with it critically and effectively (Urban et al., 2024; Buckingham Shum, 2024). As Gomez et al. (2025) note, GAI users often accept or reject generated responses rather than engage in deeper, co-constructive dialogue. Our study suggests that explicit instruction in prompting, goal-setting, and reflective questioning is essential to unlocking the full potential of AI-supported reflection.

The iterative design process also surfaced key design principles. First, personalization must go beyond static user profiles to support real-time, context-sensitive dialogue. Second, presentation matters—students responded positively to warmer, more conversational language, and suggested further enhancements such as visual elements and audio interaction. Third, platform integration is crucial; tools that require unfamiliar platforms or disrupt habitual workflows (e.g., switching to Telegram) risk abandonment. Finally, the chatbot's content integration—linking directly to course materials and assessments—was a major factor in its perceived value, transforming it from an administrative assistant into a learning companion.

8. Conclusion and Future Work

This study contributes to the growing body of research on LLMs in education by providing empirical evidence on how a GAI-based chatbot can support SRL processes in higher education. While the study does not aim to demonstrate causal effects on students' SRL, the findings suggest that chatbots have the potential to assist learners across different SRL phases when they are context-aware, pedagogically grounded, and emotionally attuned to students' needs. Drawing on a three-year DBR process, we identified four key insights that can inform both the design of intelligent chatbots and the development of student competencies for engaging with them:

1. Enable real-time, context-sensitive personalization.
2. Use warm, conversational language and support diverse pedagogical practices.
3. Integrate seamlessly into students' existing platforms and workflows.
4. Embed course content and assessment links to function as learning companions.

On the learner side, the study highlights the importance of cultivating dialogic competence—the ability to engage in meaningful, reflective conversations with AI. This includes explicit instruction in prompting, goal setting, and metacognitive questioning, which are essential for critical and collaborative interaction with AI tools.

These insights have several implications. For educators, the findings underscore the need for pedagogical guidance in AI use. Instructors play a crucial role in helping students develop the reflective and dialogic skills necessary to engage productively with AI. For designers, the study emphasizes the importance of flexible, adaptive systems that support both personalization and pedagogical alignment, ensuring that both teachers and students remain actively involved in the learning loop. For researchers, this work calls for further empirical studies in authentic learning contexts, particularly those that examine the long-term impact of AI-supported reflection on learning outcomes, student agency, and academic integrity.

Despite these promising findings, several limitations must be acknowledged. The study was conducted with a relatively small and homogeneous sample, which may limit generalizability. Additionally, while the chatbot was tested in real classroom settings, its use was often short-term and concentrated around assessment periods, limiting insights into its sustained impact. Although a recent study (Nascimento et al., 2026) found that higher engagement with the chatbot correlated with improved course performance, further research is needed to explore this relationship in depth. Moreover, students' interactions with the chatbot were shaped by their existing study habits and digital preferences, which influenced both the depth and frequency of engagement. Technical limitations—such as delayed responses, occasional inaccuracies, and the absence of multimodal features—also affected user experience and may have constrained the tool's perceived usefulness.

In sum, this study shows that when thoughtfully designed and pedagogically integrated, chatbots powered by LLMs can serve as effective partners in scaffolding SRL and deeper learning. However, realizing this potential requires more than technological innovation; it demands a collaborative effort to develop students' reflective capacities and to ensure that AI tools align with human-centred educational values. As the sophistication, reliability, and adoption of AI tools in higher education continue to grow, future research should be supported by larger samples and longitudinal data collection (Goyal, 2025). Quantitative analyses will be especially valuable in identifying the impact of scaffold-oriented AI tools on student learning outcomes. For example, large and standardized courses such as introductory physics could provide quasi-experimental opportunities to examine effects on academic achievement, lab reports, conceptual understanding, and patterns of online behaviour (Kim & Steiner, 2016). Because these tools elicit and structure students' responses, subsequent studies might also investigate content-specific learning using analytical strategies such as clustering or classification. Further research is needed to advance the analysis of conversational transcripts beyond descriptive indicators—such as those implemented in the chatbot presented in this paper—towards learning process models that capture how knowledge is constructed through student–GAI interactions over time. This includes the application of established LA methods, sequence analysis (Villalobos et al., 2024), and complex dynamical systems (Poquet et al., 2021) to model the temporal, dialogic, and regulatory dynamics through which student–GAI interactions evolve into effective forms of collaborative learning.

Finally, as generative AI advances toward multimodality, research methods in LA will need to evolve accordingly, incorporating multimodal approaches to capture and interpret increasingly complex forms of student interaction (Di Mitri et al., 2018).

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Appendix A. Protocol for Card-Sorting Activity Carried Out During the First Cycle

The activities will last a maximum of one hour and follow the structure below:

Before the workshop:
— The team arrives 15 minutes early.
— Research assistants handle the pizza purchase.
— Role check:
— One research assistant is responsible for the introduction and contextual questions at the beginning of the workshop.
— The researcher oversees the card-sorting activity on indicators.
— One research assistant is responsible for collecting informed consent, placing two audio recorders in the room, and taking notes during the activity.

Materials:
— White or kraft paper (around A2 size)
— Printed and laminated cards

Timing and Activities

Time	Activity
10 min	Workshop Introduction: • Description of the workshop's objective • Explanation of the context and instructions • Request for informed consent
20 min	Evaluation of the Experience
30 min	Study on Interpretability and Actionability of Indicators and Prompts

---

Part 1 — Introduction and Consent

"Good afternoon, my name is ___________, and my colleagues are __________and _______. We are part of a research project from the _____________, focused on university students' learning experiences. The results aim to contribute to a better understanding of students' learning experiences in hybrid learning environments.

This workshop will last approximately one hour. First, we'll conduct a brief interview to evaluate your experience with the recommendations, followed by an activity led by __________.

Please note that all information shared will be kept confidential and later anonymized. We ask for your full honesty in responding, as your answers will have no impact on your grades or academic standing. For research purposes, we would also like to inform you that the session will be recorded so it can be analyzed in greater detail later."

Part 2 — Questions on Experience (20 min)

— Students arrive in groups and introduce themselves.
— They will be asked if they have any additional comments about receiving the feedback emails.

Contextual Questions:

Study Habits
— Let's start by talking about your study habits. What strategies did you use in this course (e.g., studying alone or in groups, studying regularly or only before exams, summarizing or just reading, etc.)?

Study Resources
— What resources did you use to study (e.g., class notes, required readings, digital resources provided by the university, external resources, etc.)? What was your goal (e.g., deeply understanding the content, becoming a good professional, getting good grades, passing the course, etc.)?

Use of LMS
— Now let's talk about the course website. How do you use it (e.g., to download materials, ask questions, participate in discussion forums, etc.)?
— When do you use it (e.g., throughout the semester, near evaluations, etc.)?
— Why do you use it that way (e.g., to catch up on missed classes, complement class content, participate in forums, contribute to a wiki, etc.)?

Semester Intervention
— Did you receive the emails/SMS? Did you read them? Were they helpful?

Part 3 — Usability Study of Prompts Indicators (30 min)

To design a support intervention for the upcoming semester, we will conduct an activity to understand how certain indicators could support your study habits.

— A fictional scenario will be presented to the group both orally and in writing:

"You are a student in a course with 30 students and 1 professor. The course includes both in-person and online activities, synchronous and asynchronous. It is conducted through the Canvas platform, which tracks your interactions with course resources and can generate indicators to support your learning. The goal of this activity is…"

Card-Sorting Activity:
— Students are presented with cards showing different prompts indicators, categorized as per a predefined classification.
— The experience is introduced as follows:

"Next, you will see a series of cards, each showing prompts and indicators. We ask you to classify these cards based on two criteria: how interpretable and how actionable each indicator is."
— *Interpretable* means how well you understand the information the card conveys about your behaviour on the platform.
— *Actionable* means how clearly you can identify the next steps to improve your study habits based on the indicator.

— Each student will place the indicator cards on a grid of interpretability and actionability.
— Students will be invited to voluntarily explain the reasoning behind their card placements. Meanwhile, ________ will take photos of each grid.

Closing Questions

To conclude the activity, students will be asked how they would prefer to access this information:
— Always through a visualization?
— At critical moments via email?
— Other formats?

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Appendix B. Protocol for Cognitive Walkthroughs Carried Out During the Second Cycle

Objective:
To test the usability and perceived usefulness of the chatbot piloted during 2023, in order to gather information to improve its adoption in the first semester of 2024.

Methodology:
Cognitive walkthrough.

Participants:
Students from courses where the pilot was implemented, whether they used the chatbot or not.

Initial Steps
Introduce the activity and obtain informed consent

Thank you very much for joining us today. My name is XXX, and I'm here on behalf of the research project. The goal of this project is to gather information to understand and support students' experiences in higher education. Today, we'd like to ask for your help in providing feedback on the virtual assistant that was available in your course.

Start recording and take field notes

Context Questions

1. Did you interact with the chatbot during the past semester?
a. For those who say no:
— Why did you decide not to interact with the chatbot?
b. For those who say yes:
— What motivated you to interact with the chatbot?
— Through which device did you interact (e.g., PC or mobile)?
— Could you describe the types of actions you performed, such as downloading or messaging?

Activities

Brief demo of how the chatbot works
1. Download Telegram.
2. Click on the chatbot link.
3. Ask a sample question: "What is this course about?"

— Observe and record the students' reactions during the demo in the field notes.

Participant Interaction with the chatbot

1. Have participants replicate the demo (on mobile or PC).
2. Encourage each participant to ask the chatbot at least one question.

— Observe and record the student's reactions during the interaction in the field notes. Ask:
— Why did you ask that question?
— What do you think of the chatbot's response? Would you have preferred a different answer?

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Questions on Usability and Perceived Usefulness

— How easy or difficult was it to interact with the SIMBA chatbot?
— What kind of information is relevant to ask the chatbot?
— What kind of information would be useful to receive through the chatbot?
— What features did you value? What features would you like to see added?
— What aspects would you improve in its implementation (e.g., use of Telegram, installation process, etc.)?
— This chatbot interacts with you through your mobile phone. What aspects should be made transparent regarding data handling? And regarding privacy?
— Thank you very much for your time. Is there anything we haven't asked that you would like to add?

Appendix C. Prompt Construction for Web-Based Chatbot Used in the Third Cycle

This section describes the methodology used to construct the base prompt that configures the behaviour of AI Agents generated with the GAI Chatbot. This prompt template was co-designed in a team with teachers and researchers, giving feedback about using the tool in several courses.

Base Prompt Template

The AI agents are instantiated with a structured prompt defined by the following template:

```
You are a {adj1} {teaching_adj} tutor for the course '{courseName}'.

Your name is [Name of the tool] 😺 and you were created by the [Projet name] and the [Research Team name] team.
Respond in a {adj1}, concise and proactive way{emojis}.

Help the student answer the following questions:

{questions}

{subjects}

{answers} {teaching_type}

{documents}

Your first message should begin with ‘Hello! 😺 I am [Name of the tool], and I will help you reflect on the following questions:’ Followed by the questions to answer.

{limits}
```

Prompt Variables and Their Generation

Each variable in the prompt is generated or configured according to user settings:

- **`{adj1}` (Tone):** Sets the communication tone. Chosen from the list `[“friendly”, “informal”, “formal”]`.
- **`{teaching_adj}` (Role Style):** Determines the tutoring style. Options include `“socratic”` (emphasizing guided inquiry) or `“other”` (standard teaching).
- **`{courseName}`:** The name of the course, entered by the user.
- **`{questions}`:** The questions are entered by the user. Each question is labeled and appended in the form:

  ```
  Question 1 : …
  Question 2 : …
  ```

- **`{subjects}`:** Specifies the academic topics for reflection. When a subject list is provided, it is embedded between tags:

  ```
  You should help the student to reflect in depth on the following course
  subjects :
  <Beginning of the course subjects>
  [subjects]
  <end of the course subjects>
  {Restricted}
  ```

- **{Restricted}** The user can select a "restricted" mode. If it is selected, the following string is appended to {subjects}:

  ```
  You should only speak of those listed subjects{files}. Avoid as much as
  possible speaking of other subjects, and steer back the student to the course
  subjects if he tries to deviate from them.
  ```

  If files are uploaded to the assistant, {files} is replaced with this additional part:

  ```
  and the ones in your provided files
  ```

- **`{answers}`:** Controls whether the assistant should provide direct answers. If disabled, the assistant guides the student without revealing answers:

  Enabled:
  ```
  You can provide an answer to the provided questions if the student asks for it.
  ```

  Disabled:
  ```
  You should not give the answer, but guide the student to answer.
  ```

- **`{teaching_type}`:** Appended text that contextualizes the assistant's approach (e.g., Socratic versus standard teaching), generated based on the teaching style selected:
  Socratic:
  ```
  Act as a Socratic tutor, taking the initiative in getting the students to
  answer the questions.
  ```
  Other:
  ```
  Act as a standard teacher.
  ```

- **`{documents}`:** When enabled, the assistant encourages students to consult attached documents. If a URL is also provided, it is included to support accessibility:

  ```
  Encourage them to go and read a section of the provided documents to answer.
  {url}
  ```

- **`{url}`** `If a URL to the documents is provided, this is appended:`

  ```
  If they do not have access to the text, they can find it at [provided url].
  ```

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- **`{emojis}`:** If activated, prompts the assistant to use emojis in responses:

  `, using emojis where possible.`

- **`{limits}`:** Specifies a word limit for responses, entered by the user:

  `Your answers should be [entered limit] words maximum.`

Example of a complete prompt:

```
You are a friendly socratic tutor for the course ‘Computational Thinking and Digital Skills.’

Your name is [Name of the tool] 😸 (Sistema Inteligente de Medición, Bienestar y Apoyo) and you were created by the [Projet name] and the [Research Team name] team.

Respond in a friendly, concise and proactive way, using emojis where possible.

Help the student answer the following questions:

Question 1: Which practices do you use to make yourself safe on the internet?

Question 2: Have you encountered fraud or spam sites in your interactions on the internet in the last six months?

Question 3: Do you know what phishing is? Have you encountered any?

You should help the student to reflect in-depth on the following course subjects:

 <Beginning of the course subjects>

* Common attacks to users on the internet

* Safety practices on the internet

* How to discriminate if content is real or fraudulent

<end of the course subjects>

You should not give the answer, but guide the student to answer. Act as a Socratic tutor, taking the initiative in getting the students to answer the questions.

Your first message should begin with ‘Hello! 😸 I am [Name of the tool], and I will help you reflect on the following questions:’ Followed by the questions to answer.
```

Appendix D. Protocol for Cognitive Walkthroughs Carried Out During the Third Cycle

Objective:
To test the usability and perceived usefulness of the chatbot piloted during the first semester of 2024, in order to gather information to improve its adoption in the second semester of 2024.

Methodology:
Cognitive walkthrough.

Participants:
Students from courses where the pilot was implemented, whether they used the chatbot or not.

Initial Steps
Introduce the activity and obtain informed consent

Thank you very much for attending today. My name is XXX, and I'm here on behalf of the research project. The goal of the project is to gather information to understand and support students' experiences in higher education. Today, we would like to ask for your help in providing feedback on the virtual assistant that was available in the course *Education and Society*.

Start recording and take field notes

Context Questions

1. Did you interact with the chatbot during the past semester?
a. For those who say no:
— Why did you decide not to interact with the chatbot?
b. For those who say yes:
— What motivated you to interact with the chatbot?
— Through which device did you interact (e.g., PC or mobile)?
— Could you describe the types of actions you performed, such as downloading or messaging?

Activities

**chatbot Link: https://simba-refact.irit.fr/

Brief demo of how the chatbot works:
1. Click on the chatbot link.
2. Ask a sample study habits question in chatbot: "How can I organize my study?"

— Observe and record the student's reactions during the demo in the field notes.

Participant Interaction with SIMBA — "Study Strategies"

1. Have participants replicate the demo (on mobile or PC).
2. Encourage each participant to ask chatbot at least one question.

— Observe and record the student's reactions during the interaction in the field notes. Ask:
— Why did you ask that question?
— What do you think of SIMBA's response? Would you have preferred a different answer?

Participant Interaction with chatbot — “Activity”

1. Show students an example activity.
2. Encourage each participant to interact with SIMBA for at least 5–10 minutes.

— Observe and record the student’s reactions during the interaction in the field notes. Ask:
— Why did you ask that question?
— What do you think of SIMBA’s response? Would you have preferred a different answer?

Questions on Usability and Perceived Usefulness

— How easy or difficult was it to interact with the SIMBA chatbot?
— What kind of information is relevant to ask the chatbot?
— What kind of information would be useful to receive through the chatbot?
— What features did you value? What features would you like to see added?
— What aspects would you improve in its implementation (e.g., enhancing the web app, etc.)?
— What aspects should be made transparent regarding data handling? And regarding privacy?
— Thank you very much for your time. Is there anything we haven’t asked that you would like to add?