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How do students regulate their learning with a genAI chatbot?

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Self-regulated learning (SRL) is essential for effective learning, yet students often struggle to regulate in digital environments, including suboptimal learning tool use. The rapid integration of generative AI (e.g., ChatGPT) into learning settings raises questions about their role in supporting or hindering SRL. This exploratory study investigated how students' SRL in a technology-enhanced learning environment with a genAI tool was associated with learning processes and performance. Thirty university students were tasked to read texts and write an essay within 45 minutes. Learning performance was measured using knowledge and transfer tests, and the essay. SRL processes were measured using trace-based SRL event analysis and learner-genAI interaction with chatbot log events and coded queries. Most students (73%) used the chatbot voluntarily, primarily for seeking information. Chatbot users achieved higher essay scores than non-users. Chatbot interaction frequencies correlated positively with high cognitive activities; durations of chatbot use and high cognition negatively correlated with reading time. Qualitative data indicated reliance on the chatbot to summarisee and extract key points, suggesting offloading of learning. Findings highlight potential performance benefits but also risks of outsourcing critical SRL processes to genAI. Implications point to instructional and tool design that align technological advances with educational fit.

Keywords: generative AI, higher education, self-regulated learning

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Introduction

Self-regulated learning (SRL) is a dynamic process in which learners actively monitor and control their learning activities to pursue their goals (Winne & Hadwin, 1998) Although a robust body of research has linked SRL to improved learning outcomes (Dent & Koenka, 2016; Schunk & Greene, 2017), learners have been found to often struggle with effective learning regulation, particularly in digital settings, leading to missing learning outcome effects (e.g., Azevedo & Feyzi-Behnagh, 2011; Lim et al., 2021). The rapid adoption of generative artificial intelligence (genAI) tools (e.g., non-educational tool, ChatGPT), into learning settings warrants the need to investigate how to facilitate meaningful human-AI collaboration in order to foster SRL (Järvelä et al., 2023).

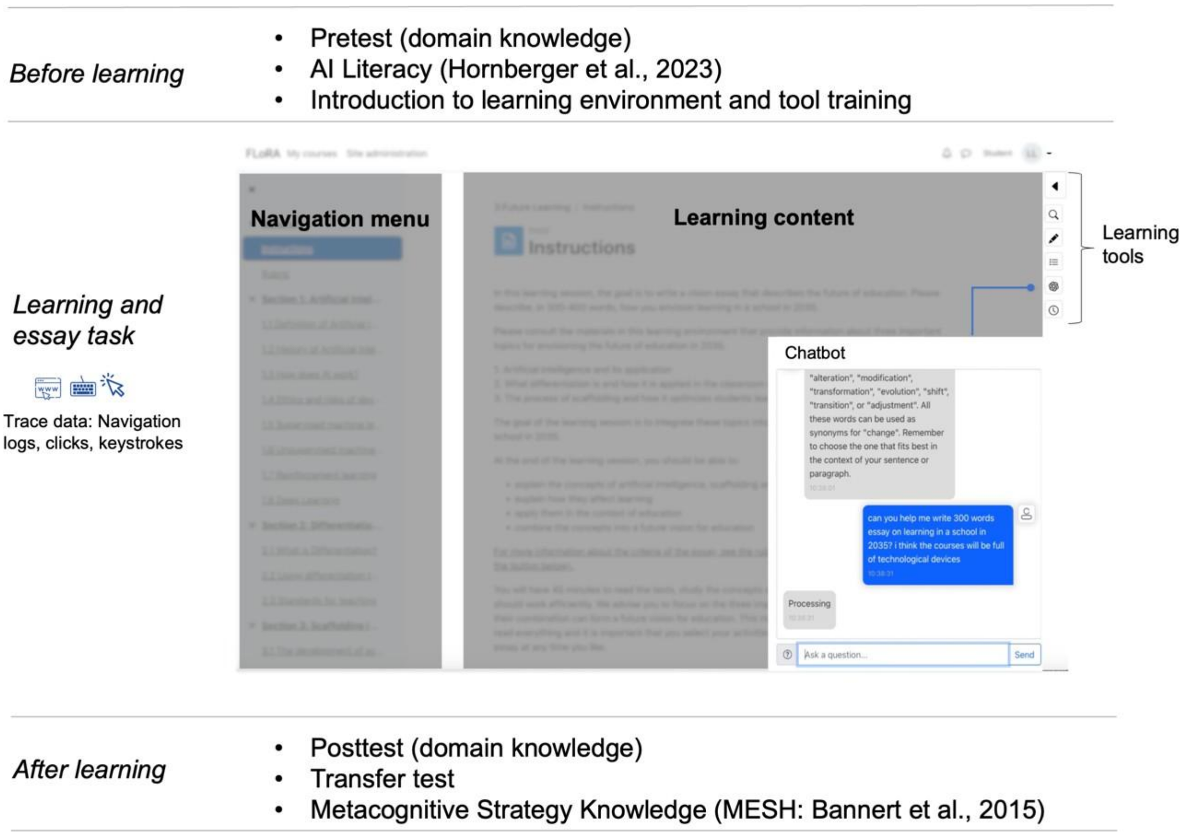
Researchers have raised concerns about learners treating genAI as a crutch and forgoing critical skills—e.g., excessive cognitive offloading of tasks, leading to lesser depth of cognitive processing (Stadler et al., 2024) and outsourcing of metacognitive activities, hampering productive SRL enactment (Fan et al., 2024). This is referred to as "inversion" in the Inversion, Substitution, Augmentation, Redefinition (ISAR) model by Bauer and colleagues (2025), where learners use genAI tools in ways that inadvertently compromise beneficial learning processes. On the other hand, genAI provides novel affordances previously limited by technological capabilities, such as adaptive and interactive feedback (Bauer, Richters, et al., 2025; Neshaei et al., 2025). Therefore, scholars have acknowledged that more research needs to be conducted to critically assess learning effects and establish guidelines for genAI integration in learning (Weidlich et al., 2025; Yan, Greiff, et al., 2025; Yan, Pammer-Schindler, et al., 2025). Previous empirical studies have investigated system-driven adaptive SRL tools which are more structured (i.e., less learner control), such as personalised scaffolds, to support SRL (Lim et al., 2023) as well as on-demand, learner-driven tools, which are less structured (i.e., higher learner control) (Azevedo et al., 2022; Herold & Seufert, 2025). Yet, regardless of design, a recurring challenge has been learners' suboptimal interactions with these tools, such as when and how to use them to support learning. For example, poor scaffold usage has been repeatedly found in research, suggesting the need to support learners' regulation with tools (Saint et al., 2024). Moreover, learners who make productive use of support tools through active and consistent engagement with them demonstrated higher learning outcomes (Bannert, Sonnenberg, et al., 2015; Zheng et al., 2023). This highlights the importance of providing support tools and fostering learners' productive interaction with them.

In light of these challenges and opportunities, this exploratory study aimed to advance understanding of how students spontaneously regulate their learning in a technology-enhanced environment with an integrated genAI tool: a ChatGPT chatbot. By analysing SRL processes including chatbot interactions using both quantitative and qualitative approaches, we sought to contribute evidence-based insights for the design of tools that promote SRL in the age of genAI. Hence, we posed the research question: *How is students' regulation of learning in a technology-enhanced learning environment with an integrated genAI tool associated with learning processes and performance?*

Methods

The present exploratory study was integrated in a university seminar about social science research methods (n = 30, M_{age} = 25.70, SD_{age} = 2.88). All participants reported prior experience with genAI use, particularly ChatGPT, for gathering information, writing and language support, and so forth. Participation was voluntary, and all students provided active consent prior to data collection. The study was approved by the university ethics committee. Students were provided with learning materials about the topics: AI, differentiation in the classroom, and scaffolding. They were instructed to read the texts and write a 300 to 400 word essay about the future of education. Learning took place in a technology-enhanced learning (TEL) environment with integrated tools, including a chatbot powered by ChatGPT (see Fig. 1). Training and instructions were provided for all integrated tools, including the chatbot, prior to the learning task. The training included information about where to find the tools in the TEL environment and general best practices (e.g., always reviewing and evaluating the chatbot's response, being specific with queries, etc.). Students were not explicitly instructed nor obligated to use the chatbot. We pre-configured the chatbot with a custom prompt: 1) The chatbot should not write the essay for students, 2) Responses should be succinct, 3) Suggestions should be based on provided information. We provided the chatbot contextual information about the learning texts, task instructions and essay rubric. We assessed learners' prerequisites with an AI literacy test (Hornberger et al., 2023; Cronbach's α, internal consistency = 0.70) and a metacognitive strategy knowledge questionnaire (Bannert, Pieger, & Sonnenberg, 2015; Cronbach's α = 0.79). Learning performance was measured via pre-post domain knowledge tests (Cronbach's α = 0.78), a transfer test (Cronbach's α = 0.58), and the essay (Cohen's κ, inter-rater reliability = 0.88). We measured SRL processes via trace data with Fan et al.'s (2022) approach, using an SRL process library (see Appendix A) that parsed raw data into sequences of learning actions representing SRL activities. The SRL activities were metacognition (orientation, planning, monitoring, and evaluation), high cognition (elaboration and organisation), and low cognition (reading, rereading). Chatbot interaction was classified by interaction events—all chatbot log events (e.g., Ask_Chatbot, Close_Chatbot) and queries—and student inputs such as questions, clarifications, requests and so forth. Students' chatbot queries were coded *post hoc* (κ = 0.72) into the categories: Generating Idea (GI), Seeking Information (SI), Language Support (LS), and Correction/Repetition (CR) (see Appendix B for descriptions and examples).

Figure 1: Research design and example of chatbot tool in the learning environment



Results

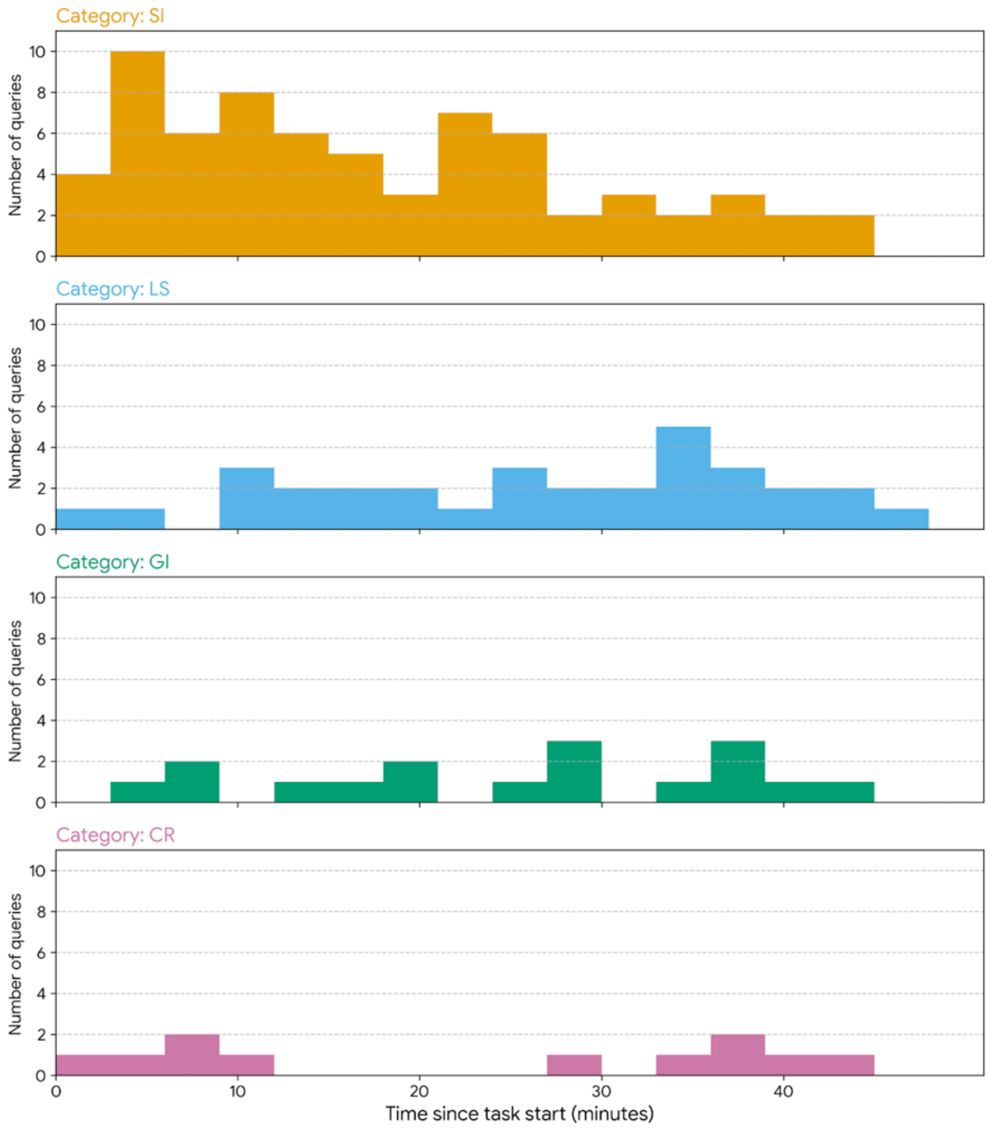
Results indicated that students had moderate AI literacy (*M* = 49.50%, *SD* = 14.30%) and sufficient metacognitive strategy knowledge (*M* = 75.80%, *SD* = 11.10%). All students learned significantly from the task (pre-post learning gain), $t(29) = 4.90$, $p < .001$, $d = .89$. The majority of the students voluntarily used the chatbot (73%; *n* = 22). As we were interested in how students regulated their learning in the TEL environment, including whether or how they used the chatbot, we focused our analysis mainly on the chatbot-users, with the non-users (*n* = 8) presented only for reference.

We first investigated how students engaged with the chatbot (see Table 1). Students used the chatbot on average 11.90% of the learning time. There was a total of 381 interaction events, about one-third of which were queries posed by students to the chatbot ($n_{queries}$ = 129). Other interaction events included reading chatbot responses, opening/closing the chatbot. Figure 2 shows the declining trend of queries posed over time, with students seeking information from the chatbot more intensively in the first half of the learning session. Queries for seeking information constituted the largest proportion (53%), followed by language support (25%), generating ideas (13.18%), and lastly, correction/repetition (8.53%).

Table 1: Descriptive table of chatbot interaction

	M	*SD*	Min	Max
Interaction events	17.30	14.60	2	55
Duration proportion (%)	11.90	9.49	2.53	33.90
Queries	5.86	4.73	1	15

Figure 2: Number and distribution of query categories in learning session



Note. SI = Seeking information, LS = Language support, GI = Generating ideas, CR = Correction/Repetition

We conducted a comparison among chatbot users and non-users regarding their learning processes and outcomes (see full descriptive statistics table in Appendix C). Generally, all students—whether or not they were chatbot users—engaged in both high and low cognitive activities at high frequency and duration. but they engaged in almost no planning and monitoring. Interesting differences between the groups are that chatbot users showed higher rereading frequencies, and trended towards better performance in the essay, $t(28) = 2.14$, $p < .05$, $d = .88$. No other notable between-group trends were found. We conducted two distinct correlation analyses with frequency-based (36 pairwise comparisons) and duration-proportion-based (28 pairwise comparisons) chatbot interaction and SRL process measures within the chatbot user group. To control for multiple comparisons, we applied the Benjamini-Hochberg false discovery rate correction (Benjamini & Hochberg, 1995) using the p.adjust function with method = “BH” in R version 4.4.1 (R Core Team, 2024). Correlations with adjusted p-values < .05 were considered significant. Results revealed that higher frequencies of chatbot interactions were linked to higher cognitive activities, such as writing the essay (chatbot events: $r_s = .70$, $p_{adj} < .05$; chatbot queries: $r_s = .62$, $p_{adj} < .05$). High cognitive activities were not significantly associated with rereading activities after p-value adjustment ($r_s = .49$, $p_{adj} > .05$). Negative correlations were found between duration proportions of reading and high cognition ($r_s = -.74$, $p_{adj} < .05$), as well as chatbot use and reading ($r_s = -.61$, $p_{adj} < .05$). Looking into students’ chatbot queries, we found that students often did not engage in deeper processing of the learning materials on their own, but rather, asked the chatbot to highlight the key points in the text. For example, students pasted sections of the learning material and asked the chatbot, “Summarise the paragraph into 3 sentences” or “Extract only the main ideas.”

Discussion and conclusion

The exploratory study examined how students regulated their learning in a genAI-integrated learning environment. Through the examination of learner-chatbot interaction and its association with learning processes and outcomes, this study sought to contribute to evidence-based insights for ongoing research that promotes SRL in the age of genAI.

Contrary to previous research (e.g., Bannert, Sonnenberg, et al., 2015; Clarebout et al., 2010) which found that students were less willing to use provided tools—especially tools with higher learner control—in their learning process, the majority of students in the present study voluntarily used the chatbot. This contrast could reflect the unique affordances and students’ familiarity with commercially available genAI tools such as ChatGPT. However, students had highly varied chatbot interaction; there was large variance in frequency and duration of usage. Nevertheless, the results point to the chatbot being mostly an information source for learning content as well as fulfilling surface-level tasks, such as language support. Chatbot users had higher essay scores than non-users, which suggests that the tool benefits performance. We observed that students adopted strategies driven by a performance-driven approach in order to complete the task efficiently. As indicated by the negative correlations between the duration proportions of reading and high cognition, along with chatbot use and reading, the findings suggest that students prioritised task completion over deeper learning with the provided texts. The qualitative analysis of chatbot queries lends support to this finding—many queries requested summaries or key points from the learning text. Hence, for some students, the chatbot potentially replaced reading, which is a core learning activity to build an initial knowledge base. Although students offloaded the more superficial learning activity (reading) for a deeper learning activity (high cognition), they outsourced comprehension and synthesis activities to the chatbot (e.g., identifying and synthesising relevant parts of the reading text). While such chatbot use can support task completion efficiency, the qualitative analyses indicated that students relied on the chatbot to make important regulatory decisions, such as evaluating the relevance of the text, deciding what to read and why, and integrating new information with prior knowledge. Conversely, students who focused on reading the text used the chatbot less, and at the same time, engaged in high cognitive activities to a lesser degree.

Therefore, the results suggest that a genAI-integrated environment potentially supports the learning task, but it could also hamper productive SRL processes, particularly metacognitive processes (i.e., low enactment of planning and monitoring). The findings reflect a well-documented phenomenon where students possess sufficient SRL knowledge and skills but fail to spontaneously engage in SRL during their learning (i.e., production deficit; Veenman et al., 2005). This highlights the need to provide scaffolds to stimulate students to engage in regulation. Taken together, the mixed approach of process analysis and qualitative coding of chatbot queries led to better understanding of students' learning regulation with a genAI chatbot. However, given the study's exploratory nature and small sample size, causal interpretations should be avoided. Nevertheless, the exploratory insights provide the foundation for our development of genAI interventions in upcoming studies that address both the dynamics of learner–genAI interaction and the SRL gaps that require support. Moving forward, genAI interventions should embed SRL scaffolds that guide students to reflect on their learning process. For example, when students' chatbot queries indicate potential offloading (e.g., asking the chatbot to extract main points without prior reading of the text), students should first be prompted to reflect on their reading and comprehension as a monitoring scaffold.

In conclusion, the findings highlight the need to support students' learning regulation skills to mitigate their outsourcing of critical processes while using genAI tools. There is also a need to improve learner-genAI interaction in order to foster learning and not just efficiency in task completion. Furthermore, we need to improve the instructional design of both tasks and tools in order for students to be guided to use genAI meaningfully for enhancing learning processes, thereby aligning technological advances with educational fit.

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Lyn Lim leads the ATLaS (Adaptive Teaching, Learning, and Support) junior research group. She investigates how advanced learning technologies can optimise learning and teaching. Her work combines theory-driven, process-oriented assessment with multimodal data and learning analytics to understand learning processes and translate insights into adaptive support. A particular focus of her research is fostering self-regulated learning and meaningful human–AI partnerships in technology-enhanced learning environments.

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Appendix A

Coding categories of SRL activities based on Fan et al.'s approach (2022)

SRL activity	Description	Example of learner action sequence
Metacognition		
Orientation	Learner orientates to the task, such as reading the task instruction and essay rubric.	GENERAL_INSTRUCTION/RUBRIC -> (NAVIGATION*) -> RELEVANT_READING
Planning	Learner plans learning activities by arranging activities, determining strategies, and proceeding to the next topic.	PLANNER -> (NAVIGATION*) -> RELEVANT_READING
Monitoring	Learner monitors and checks the reading and writing process, such as checking on progress according to instruction or plan.	GENERAL_INSTRUCTION/RUBRIC <-> PLANNER* (after the first 15mins)
Evaluation	Learner evaluates the learning process, such as checking the content-wise correctness (e.g., essay content) of learning activities.	READING -> (NAVIGATION*) -> GENERAL_INSTRUCTION*/RUBRIC*/READ_ANNOTATION* -> (NAVIGATION*) -> READING
High Cognition		
Elaboration/Organisation	Learner elaborates by connecting content-related comments and concepts when writing the essay; organising content by creating an overview or writing down information point by point in notes or essay window, or summarising or adding self-generated information, and editing information by rephrasing or integrating information with prior knowledge.	GENERAL_INSTRUCTION/RUBRIC -> (NAVIGATION*) -> WRITE_ESSAY -> (WRITE_ESSAY)
Low Cognition		
Reading	Learner reads learning materials for the first time.	(IR)RELEVANT_READING -> (NAVIGATION*) -> (IR)RELEVANT_READING
Rereading	Learner reads learning materials that have been previously read.	RELEVANT_RE-READING -> (RELEVANT_RE-READING)

Appendix B

Coding categories of students' chatbot queries

Coding category	Code	Description	Examples	Frequency
Seeking information	SI	Asking for factual info or conceptual clarifications	*What is convergence in an educational context?*	69
Language support	LS	Asking for language-related help, e.g., translation, proofreading, etc.	*Please correct grammar and spelling in my essay: …*	32
Generating ideas	GI	Asking for ideas and outlines	*Give me a quote that I can start my essay with*	17
Correction/Repetition	CR	Clarifying or revising earlier queries	*But this is a new text, I need it in relation to the first task I gave you*	11

Note. Number of chatbot users = 22. Inter-rater agreement, κ = 0.72

Appendix C

Descriptive statistics of learning variables for chatbot users and non-users

	users (n = 22)		non-users (n = 8)	
	M	*SD*	*M*	*SD*
Learning performance scores				
Pretest[a]	16.40	3.36	14.80	5.12
Posttest[b]	19.40	4.04	17	7.09
Transfer[c]	10.30	3.12	9.63	3.29
Essay[d]	11.20	3.29	7.75	5.44
Learning process frequencies				
Orientation	13.00	7.63	12.80	3.54
Planning	1.18	2.36	0.13	0.35
Monitoring	2.73	1.42	2.38	1.41
Evaluation	5.36	5.02	8.50	7.41
High cognition	41.00	18.50	32.40	18.90
Reading	42.60	21.90	45.60	30
Rereading	8.82	10.10	1.75	3.28
Learning process duration proportion				
Orientation	5.59	2.93	6.42	1.85
Planning	0.65	1.37	0.01	0.02
Monitoring	0.68	1.34	0.20	0.16
Evaluation	0.97	1.57	1.75	1.88
High cognition	49.70	14.50	54.10	24.10
Reading	23.60	16.90	29.90	21.00
Rereading	2.33	2.96	1.39	2.91

Note. Maximum points: [a,b]30 points. [c]22 points. [d]21 points.