Ask Better, Learn Better: An Adaptive Metacognitive Support System for Enhancing Student Prompting with LLMs

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Abstract

Large Language Models (LLMs) increasingly shape students' everyday learning practices, yet many learners employ them in ways that prioritise quick solutions over deep understanding. Rather than constraining or fine-tuning LLMs, we propose a complementary approach: supporting students in developing the self-regulated learning (SRL) skills required to learn with commercial LLMs. Drawing on SRL theory and Learning Analytics (LA), we developed a browser-based adaptive metacognitive support system that classifies student prompts using an in-context learning classifier and provides real-time, SRL-aligned feedback on prompt quality. The system highlights low-quality help-seeking prompts and suggests more reflective alternatives, aiming to foster elaboration, strategic inquiry, and metacognitive awareness during LLM-mediated learning. In a preliminary evaluation with nine STEM students, results show that students were more than twice as likely to produce high-quality prompts when using the tool compared to baseline. Survey responses indicate perceived improvements in prompt formulation and SRL awareness, while also identifying needs for greater context sensitivity, balanced feedback, and personalization. This work demonstrates the potential of lightweight, LA-driven scaffolds to promote SRL-for-LLMs practices and outlines design considerations for more adaptive and learner-centered support systems.

Keywords

Generative AI, STEM, Higher Education, Metacognitive Adaptive Support, Prompting

1. Introduction

Large Language Models (LLMs) offer opportunities to support educational tasks, facilitate learning activities, and adapt education to individual needs [1]. At the same time, emerging research highlights lurking risks: students often use LLMs to ask for direct solutions rather than seek a deeper understanding [2]. Although technically constrained or fine-tuned LLM have been developed to support students, they do not equip students to engage effectively with widely used popular LLM-based chatbots, such as ChatGPT or Claude, which already shape students' everyday learning practices [3]. This work proposes a complementary approach: instead of redesigning the tool, we focus on supporting students in developing the self-regulated learning (SRL) skills needed to interact with popular commercial LLMs in ways that are conducive to student learning.

In this study, Learning Analytics (LA) provides a crucial foundation. By capturing and analyzing process data from student-LLM interactions, LA enables us to trace how students employ or fail to employ SRL strategies when using LLM during learning [4, 5]. By doing so, LA informs the design of targeted interventions that scaffold SRL in LLMs'-mediated learning practices. Guided by SRL theory

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[6, 7] and prior work [2, 8], we developed a tool using LA, a proof-of-concept adaptive metacognitive support system to help students engage more effectively with commercial LLMs during studies.

2. Development of the support system

The support system's design is based on the feedback mechanism commonly used in writing assistants: inline highlighting with on-demand suggestions, as exemplified by commercial tools such as Grammarly. Student-LLM interactions are logged and classified using a custom few-shot in-context learning classifier based on Google Gemini. The classifier was designed to serve two primary functions: 1) to categorize student prompts according to established SRL strategies [9] within the programming education setting [10, 2], and 2) to provide real-time, adaptive feedback tailored to students' individual prompts by differentiating between rudimentary help-seeking prompts from the other SRL strategies such as elaboration. The feedback provides metacognitive support by highlighting the quality of each student prompt in relation to the SRL strategies and by suggesting ways to rephrase prompts for more reflective learning when interacting with commercial LLMs.

2.1. Classifying SRL Strategies and Providing Adaptive Metacognitive Support

Figure 1 shows the deployment of the adaptive metacognitive support system. To encourage students to develop deeper understanding rather than seeking direct solutions, prompts classified as 'help-seeking' were considered low-quality and paired with guiding feedback in red pop-ups, suggesting reframing, such as "What is WebAssembly?" received the feedback, "Instead of just asking for a definition, try describing what you think it is and what confuses you." Prompts that might lead to vague or misleading LLM responses were regarded as suboptimal. These prompts were accompanied by guiding feedback in yellow pop-ups. For example, "Is AI always right?" received the feedback, "This question is too broad and might lead to vague answers. Try narrowing it down."

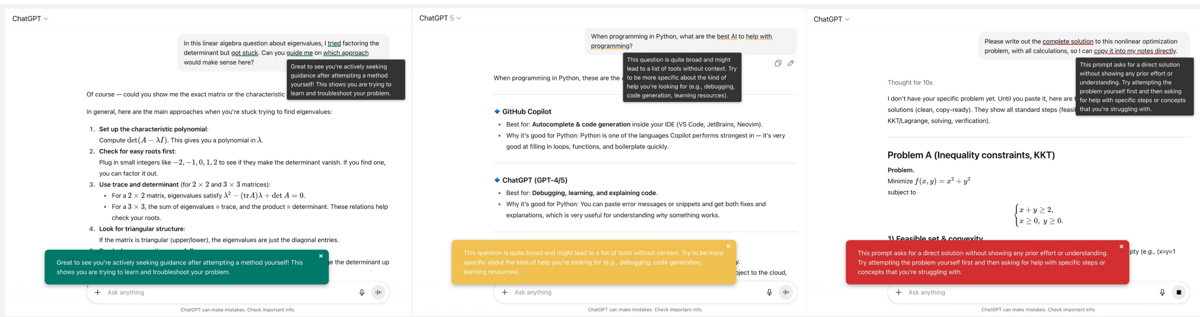

Figure 1: Figure 1: Example of feedback from the system

3. Preliminary Evaluation

3.1. Participants and Analytical Procedure

Participants were 10 STEM students from a large technological university in Europe. Data from one participant was excluded as interaction logs were not study-related. Each participant received a 15 euros gift voucher. Participants provided written informed consent and uploaded links to their daily LLM interactions for two weeks. They then used the system when interacting with ChatGPT for another two weeks, during which their interactions were automatically logged. Afterward, participants completed an online survey regarding their perceived impact of the metacognitive support system on their SRL behavior when interacting with ChatGPT in their university studies.

3.2. Impact of the System as an Adaptive Metacognitive Support Tool

Results from a generalized linear mixed-effects model (GLMM) with a binomial distribution and logit link indicated a significant effect of time, $\beta = 0.81$, $SE = 0.10$, $z = 8.02$, $p < .001$. This corresponds to an odds ratio of 2.25 (95% CI [1.85, 2.74]), suggesting that students were more than twice as likely to produce high-quality prompts when using the system compared to baseline. Model-based estimates indicate an increase in the probability of high-quality prompts from 49% at baseline to 68% during system use.The survey results indicate that students viewed the tool positively for improving how they formulate future prompts when interacting with popular LLMs. The strongest perceived impact concerned prompting practices and metacognitive reflection, as reflected in the relatively high ratings for *rephrasing prompts to promote deeper understanding* ($M = 4.30$) and *knowing which types of prompts help learning* ($M = 4.10$).

Coding of students' open-ended survey responses identified several areas for improvement. First, students raised concerns about the tool's limited conversation-level awareness. They noted that the system assessed prompts in isolation and sometimes misclassified simple but appropriate follow-up turns (e.g., "yes," "no," "thanks") as suboptimal. Students suggested that improved context-awareness for follow-up prompts would make the evaluation less repetitive and more nuanced. Second, students commented on the motivational implications of the color-coded feedback. They cautioned against feedback overload and emphasized the need to balance both the frequency and tone of feedback to avoid a punitive feel. Some reported that while green feedback could feel motivating, red feedback was perceived as overly harsh for minor issues. Third, students highlighted a need for greater personalization and adaptivity based on learner profiles, for example by calibrating feedback to academic level (e.g., first-year vs. master's) and differentiating between exploratory and targeted inquiry.

4. Discussion and Conclusion

The current work addresses the urgent need to foster student SRL strategies when using LLMs in STEM higher education. We introduced a proof-of-concept browser-based adaptive metacognitive support tool that delivers SRL-aligned feedback on prompt quality. Our preliminary finding suggests that lightweight scaffolds, delivered in the flow of authentic study practices, can help students reflect on their inquiry behavior when using commercial LLMs in learning practices, shifting from basic help-seeking to more instrumental ones to support their learning. However, when providing such support, there is a need to balance adaptivity and learner agency [11]. Students reported that the tool's turn-level evaluations sometimes felt irrelevant or overly harsh, suggesting that rigid scaffolds insensitive to dialogue flow and dynamics can undermine student agency. Similarly, the uniform feedback strategy was perceived as repetitive and occasionally punitive, which constrained its impact on higher-order goals such as fostering critical thinking and deeper understanding. These results resonate with evidence that one-size-fits-all supports do not meet the evolving SRL needs of learners in AI-mediated learning settings [12]. Future work should thus focus on enhancing the support system's adaptivity. Specifically, LA pipelines could integrate temporal modeling of dialogue histories to improve context awareness and differentiate between exploratory inquiry (broad, open-ended questioning) and convergent inquiry (targeted problem solving). Moreover, calibrating feedback intensity to students' academic levels and goals would personalize support, aligning with evidence that SRL interventions must be tailored to learner profiles to be effective [13, 8]. Interactive visualizations, e.g., dashboards that show trends in prompt quality, depth of inquiry, or shifts in SRL strategies when using LLMs, could further increase transparency and strengthen students' SRL capacity when interacting with LLMs during their studies.

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