Prompting Behavior and Human-AI Interaction: Insights Into Learning Dynamics and Critical Engagement in Higher Education

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Abstract

The increasing integration of generative Artificial Intelligence (AI) tools in higher education raises essential questions about how students engage with content, regulate their learning, and develop critical thinking skills in AI-augmented environments. This paper presents results from the second phase of a longitudinal, quasi-experimental study conducted in a dual study program in Germany. The first phase (N = 93) quantitatively examined the impact of AI-supported learning on knowledge gain, motivation, cognitive load, critical thinking, and reflective use across three measurement points (T1, T2, T3) conducted throughout the semester. These findings provided the empirical foundation for the second phase. In phase two, a particular focus was placed on prompting behavior as a potential behavioral indicator of underlying learning processes. At mid-semester (T2), one intervention group (N = 32) was systematically observed with regard to prompt behavior, frequency, preferred AI use-cases, and whether outputs were revised or adopted directly. These variables were descriptively analysed and explored in relation to the findings from phase one. Preliminary patterns suggest that prompting behavior may be meaningfully associated with deeper learning dynamics, including motivation, critical engagement, and over-reliance on AI tools. Students who revised AI outputs more frequently also tended to score higher in critical thinking and reflective use. These findings highlight prompting behavior as a meaningful indicator of student critical engagement with AI and self-regulated learning.

Keywords: generative AI, prompting behavior, human-AI interaction, higher education, self-regulated learning

Introduction

The increasing integration of generative Artificial Intelligence (AI) into higher education is fundamentally reshaping how students interact with knowledge, approach learning tasks, and regulate their learning processes (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). While AI systems provide immediate access to information, adaptive explanations, and support for complex problem-solving, their role in fostering meaningful learning remains critically debated (Kasneci et al., 2023; Mollick & Mollick, 2023). The central issue is no longer whether AI is used in educational contexts, but how students engage with AI systems and what this implies for learning dynamics and critical engagement (Darvishi et al., 2024).

Recent research increasingly suggests that AI does not inherently improve learning outcomes (Koedinger et al., 2023; Shang et al., 2024). Instead, its educational value appears to depend on how learners interact with AI-generated content and integrate it into their own cognitive processes (Darvishi et al., 2024; Tankelevitch et al., 2024). In this sense, AI can be understood less as an autonomous instructional agent and more as part of a dynamic human–AI interaction system in which learning emerges through the interplay between learner, task, and technology (Swiecki et al., 2022). This shift reflects a broader movement in educational research from outcome-oriented perspectives toward process-oriented approaches that emphasize interaction, regulation, and engagement (Järvelä & Hadwin, 2013; Winne, 2017).

Within this framework, learning dynamics in AI-supported environments are shaped by cognitive and metacognitive processes (Flavell, 1979; Zimmerman, 2002). Findings from the longitudinal phase of this research indicate that knowledge gains occur across conditions, but are not significantly enhanced by AI use alone. Instead, factors such as germane cognitive load and reflective use emerge as more decisive predictors of learning outcomes, highlighting the importance of productive cognitive effort and critical engagement (Sweller et al., 2019).

Cognitive Load Theory (CLT) provides a central theoretical foundation for interpreting these findings (Sweller, 1988; Sweller et al., 2019). While AI systems may reduce extraneous load by simplifying access to information, they may simultaneously reduce germane load if learners rely on AI outputs without engaging in deeper processing (Kalyuga, 2011; Tankelevitch et al., 2024). As a result, AI-supported learning environments create a paradox: they can facilitate access and efficiency while simultaneously risking superficial engagement. Meaningful learning therefore depends on whether learners actively process, evaluate, and integrate AI-generated information (Mayer, 2009).

Closely related to this is the concept of critical engagement, which refers to the ability to question, evaluate, and adapt information rather than accepting it uncritically (Ennis, 1989; Facione, 1990). In AI-supported contexts, this is operationalized through reflective use, defined as the capacity to critically assess and modify AI-generated outputs. Previous findings demonstrate that reflective use is positively associated with critical thinking and represents a key mechanism for productive AI integration (Darvishi et al., 2024). At the same time, the increasing accessibility of AI raises concerns about over-reliance, particularly when learners adopt outputs without modification, thereby bypassing deeper cognitive engagement (Bastani et al., 2024; Skjuve et al., 2021).

Despite these theoretical advances, a critical gap remains. Most existing studies rely on outcome measures or self-reported perceptions, while the interaction process itself remains largely unobserved (Shang et al., 2024; Swiecki et al., 2022). As a result, little is known about how students engage with AI systems in real time and how these interaction patterns relate to underlying learning processes (Darvishi et al., 2024).

To address this gap, the present study introduces prompting behaviour as a behavioural lens on human–AI interaction. Prompting behaviour captures how learners formulate prompts, interact with AI systems, and handle generated outputs. As the primary interface between learner and AI, it provides direct insight into interaction processes that are otherwise difficult to access (Lo, 2023; Mollick & Mollick, 2023).

From a theoretical perspective, prompting behaviour can be understood as a behavioural manifestation of learning dynamics and self-regulated learning (Zimmerman, 2002). Differences in prompting behaviour may reflect variations in interaction depth, intentionality, and cognitive engagement. While minimal interaction may indicate low engagement, iterative prompting and active revision suggest deeper processing and critical engagement (Chin & Brown, 2002; King, 1992).

Building on this perspective, the present study investigates prompting behaviour as an indicator of learning dynamics and critical engagement in higher education. By linking behavioural observations with previously measured constructs such as critical thinking and reflective use, the study contributes to a more comprehensive understanding of AI-supported learning as an interactional process (Darvishi et al., 2024; Swiecki et al., 2022).

Methodology

The present study represents the second phase of a longitudinal, quasi-experimental research project conducted in a dual higher education program in Germany. While the first phase focused on learning outcomes across a semester, the second phase adopts a behavioural perspective by analysing real-time student–AI interaction (Shadish et al., 2001).

A mixed-method design was employed, combining quantitative data from the longitudinal study with structured observational data (Creswell & Plano Clark, 2018). The observational phase was conducted with a subsample of 32 students drawn from one intervention group. All participants had prior experience with AI-supported learning tasks as part of the course design.

Data collection took place at mid-semester (T2) during a regular course session. Students were asked to complete a learning task using a generative AI system. During task completion, student–AI interactions were systematically observed in real time using a structured observation protocol (Bakeman & Gottman, 1997).

The analysis focused on three dimensions of prompting behaviour: prompt frequency, types of use cases, and output handling. Data were analysed descriptively and complemented by an exploratory pattern classification (Mayring, 2015). In addition, behavioural patterns were linked to previously collected quantitative data, particularly critical thinking and reflective use.

Results

The analysis reveals substantial variability in prompting behaviour, indicating that interaction with AI systems differs considerably across students. Prompt frequency was generally low, with a mean of 1.9 prompts and a median of one. The majority of students (65.6%) relied on a single prompt, while only a small proportion engaged in more extended interaction involving multiple prompts. This distribution suggests that iterative engagement with the AI system remained limited and that most students interacted with the system in a minimal and task-focused manner, consistent with findings on shallow AI use in educational settings (Darvishi et al., 2024; Shang et al., 2024).

Regarding functional use, AI was primarily used as a cognitive support tool. The most frequent use case was content explanation (56.3%), followed by idea generation (43.8%) and structuring support (34.4%). Less frequent were surface-level transformations such as paraphrasing (15.6%). These findings indicate that students predominantly used AI to support understanding and organize their thinking rather than to fully outsource task completion, aligning with observations by Mollick and Mollick (2023) on productive versus substitutive AI use.

A key distinction emerged in the handling of AI-generated outputs. A majority of students (59.4%) adopted outputs without modification, whereas 40.6% engaged in active revision. This difference suggests varying levels of cognitive engagement, with active revision reflecting deeper interaction and processing (Mayer, 2009; Sweller et al., 2019).

Descriptive comparisons with the longitudinal data indicate that students who actively revised outputs showed higher levels of critical thinking ($M = 3.8$) and reflective use ($M = 3.9$), while those who adopted outputs directly showed lower levels (critical thinking: $M = 3.2$; reflective use: $M = 3.1$). These patterns suggest a meaningful alignment between observed behaviour and learning-related outcomes, consistent with theories linking metacognitive monitoring to academic performance (Flavell, 1979; Zimmerman, 2002).

An exploratory classification of interaction patterns identified three types: minimal interaction, functional use, and active engagement. These patterns reflect increasing levels of interaction depth and cognitive engagement, ranging from single-prompt usage and direct adoption to iterative prompting and active revision, paralleling taxonomies of learning strategy use in technology-enhanced environments (Järvelä & Hadwin, 2013; Winne, 2017).

Discussion

The present findings provide strong evidence that learning in AI-supported environments is fundamentally shaped by the nature of human–AI interaction rather than by AI use itself (Darvishi et al., 2024; Koedinger et al., 2023). While previous research has already suggested that AI does not automatically enhance learning outcomes (Bastani et al., 2024; Shang et al., 2024), the present study advances this understanding by demonstrating how differences in interaction behaviour translate into differences in cognitive and metacognitive engagement.

From the perspective of Cognitive Load Theory, the results can be interpreted as a differentiation between superficial and productive cognitive processing (Kalyuga, 2011; Sweller et al., 2019). Students who relied on single prompts and directly adopted AI outputs likely experienced reduced cognitive effort, particularly in terms of germane cognitive load. While this may increase efficiency, it limits opportunities for deeper processing and knowledge construction. In contrast, students who engaged in iterative prompting and actively revised outputs likely invested more germane cognitive load, thereby supporting meaningful learning (Mayer, 2009). These findings reinforce the idea that learning is not enhanced by reducing cognitive effort per se, but by directing it toward productive processing (Sweller et al., 2019).

The results also align closely with theories of self-regulated learning (Pintrich, 2000; Zimmerman, 2002). Prompting behaviour can be understood as an observable manifestation of regulation processes, including planning, monitoring, and evaluation. Minimal interaction suggests limited engagement in these processes, whereas iterative prompting and revision indicate active regulation. In this sense, prompting behaviour provides a behavioural proxy for self-regulated learning in AI-supported environments, extending existing process-oriented frameworks to new technological contexts (Järvelä & Hadwin, 2013; Swiecki et al., 2022).

Furthermore, the findings highlight the central role of critical engagement (Ennis, 1989; Facione, 1990). The clear association between active revision and higher levels of critical thinking and reflective use suggests that learners benefit from engaging critically with AI-generated content. This supports the view that AI should not be understood as a substitute for cognitive processing, but as a tool that can amplify learning when used reflectively (Kasneci et al., 2023; Mollick & Mollick, 2023).

At the same time, the high proportion of direct adoption points to a significant risk of over-reliance (Bastani et al., 2024; Skjuve et al., 2021). Many students appear to use AI in a way that reduces cognitive engagement, potentially leading to superficial learning. This finding is particularly important in light of ongoing concerns about the impact of AI on critical thinking. Rather than diminishing critical thinking per se, AI may create conditions in which critical engagement becomes optional rather than necessary — a phenomenon Tankelevitch et al. (2024) describe in terms of shifting metacognitive demands in AI-mediated task environments.

Importantly, the results also extend the concept of scaffolding in AI-supported learning (Pea, 2004; Wood et al., 1976). While traditional scaffolding focuses on externally provided support, the present findings suggest that generative AI may provide elements of implicit scaffolding through explanations and structured responses. However, the effectiveness of this support depends on how learners engage with it (Puntambekar & Hübscher, 2005). External scaffolding alone may not be sufficient if learners do not actively process and adapt the provided information, highlighting the importance of internal regulation as a key mechanism in AI-supported learning (Zimmerman, 2002).

Taken together, the study advances a process-oriented understanding of AI-supported learning by demonstrating that prompting behaviour reflects underlying learning dynamics (Swiecki et al., 2022). It shifts the focus from access to AI toward interaction with AI, emphasizing that the educational value of AI depends on how it is used (Darvishi et al., 2024; Kasneci et al., 2023).

Limitations and Future Research

Despite the insights gained into the behavioral dynamics of human–AI interaction, several limitations must be acknowledged. First, the sample size of the observational phase () is relatively small and drawn from a specific dual study program in Germany. While this allowed for a detailed analysis of individual interactions, the generalizability of the findings to other disciplines or cultural educational contexts remains to be established. Future research should aim to replicate these patterns with larger, more diverse samples to increase the robustness of the exploratory pattern classification.

Second, the structured observation focused on a single measurement point (). While this provided a “snapshot” of real-time prompting behavior, it does not capture how interaction patterns might evolve as students gain more experience with generative AI over time. Longitudinal studies that track interaction data across multiple tasks could reveal whether students develop more sophisticated prompting strategies or, conversely, become more prone to automated over-reliance as the novelty of the tool wears off.

Third, while the study linked behavioral traces to psychometric constructs (critical thinking and reflective use), the underlying motivations for specific prompting choices remain partially inferential. Future studies could employ “think-aloud” protocols or stimulated recall interviews to gain deeper qualitative insights into the metacognitive reasoning behind students' prompt formulations and their decisions to either revise or adopt AI outputs.

Finally, the present study focused on a centralized university AI platform. Future research should investigate how different interface designs or the provision of specific “prompting scaffolds” (e.g., predefined templates or reflective prompts) influence interaction quality. Understanding these factors will be crucial for developing evidence-based instructional designs that move students from minimal interaction toward more active, self-regulated engagement with AI.

Conclusion

The present study demonstrates that prompting behaviour provides valuable insights into learning processes in AI-supported environments. The findings show that interaction patterns vary substantially and that these differences are meaningfully related to critical thinking and reflective use, consistent with broader theoretical accounts of self-regulated learning and cognitive engagement (Sweller et al., 2019; Zimmerman, 2002).

By introducing prompting behaviour as a behavioural lens, the study contributes to a deeper understanding of learning dynamics and critical engagement in higher education (Darvishi et al., 2024; Swiecki et al., 2022). The results highlight that it is not AI use itself, but the nature of human–AI interaction that determines learning outcomes (Kasneci et al., 2023; Mollick & Mollick, 2023).

Future research should further explore how prompting behaviour can be supported through instructional design and how it relates to long-term learning development, ideally drawing on larger samples and longitudinal interaction data (Järvelä & Hadwin, 2013; Winne, 2017).

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