How AI Literacy Shapes Students' Engagement Goals in LLM-Assisted Writing

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Abstract

Large language model (LLM)-assisted writing is increasingly integrated into higher education, transforming how students construct and refine argumentative writing. While prior studies have examined writing outcomes and usage patterns, limited attention has been given to theoretically grounded interpretations of students' engagement during interaction with LLMs. In particular, few approaches connect linguistic features in chatbot prompts to established cognitive engagement frameworks or examine how AI literacy shapes these engagement processes. This paper presents an ongoing study proposing the chatbot prompt verb–intent–engagement goal model for interpreting chatbot prompt in LLM-assisted writing. This structure links observable action verbs in prompts to functional intents and maps these intents onto engagement levels. Our design involves collecting chatbot prompt logs from argumentative writing, identifying prompt verbs and intents, and modeling engagement goals indicators in relation to AI literacy. By integrating cognitive engagement framework, prompt-level linguistic analysis, and AI literacy, this work advances a process-oriented approach to modeling engagement in human–AI collaborative writing. The study aims to contribute a theoretically interpretable and scalable framework for evaluating how students think and reason in AIED environments.

Keywords

LLM-assisted writing, cognitive engagement, AI literacy

1. Introduction

Large language model (LLM)-assisted writing, in which students collaborate with chatbots such as ChatGPT, Gemini, or Claude to plan and refine texts, has rapidly entered educational contexts [1]. Argumentative writing is particularly relevant because it requires constructing claims, justifying them with evidence, and addressing counterarguments—core components of critical thinking [2, 3]. LLMs can support these processes by generating drafts, summarizing sources, and improving clarity, functioning in some respects as intelligent writing assistants [4, 5].

As LLM use becomes routine, the key issue is not whether students use these tools but how they engage with them [6]. Some iteratively refine arguments and deepen understanding, whereas others rely on chatbots to complete tasks efficiently. Because chatbots cannot reliably distinguish reflective engagement from superficial dependence, concerns have emerged that uncritical reliance may weaken independent reasoning [7, 8]. Even recent features designed to promote active learning struggle to capture diverse engagement patterns [9].

Analyzing students' prompts offers a process-oriented lens on engagement. Prompts are in-situ traces of students' intents, and verbs such as write, explain, or suggest signal underlying goals [10]. For example, requests to write a paragraph may indicate outsourcing, whereas prompts that clarify or challenge ideas suggest deeper collaboration. These linguistic patterns can be mapped onto ICAP-based distinctions, enabling a fine-grained interpretation of engagement during LLM-assisted writing.

Students' AI literacy further shapes how they interact with LLMs. AI literacy encompasses understanding AI capabilities, limitations, and responsible use [11, 12]. Students with higher AI literacy tend

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to use LLMs strategically and critically, whereas those with lower AI literacy are more prone to passive acceptance [13, 14]. However, its role in shaping engagement processes during argumentative writing remains underexplored. This study therefore examines how AI literacy relates to students' prompts, inferred intents, and engagement goals in LLM-assisted argumentative writing.

- RQ1: What engagement goals and underlying intents are reflected in students' chatbot prompts during LLM-assisted writing?
- RQ2: How does AI literacy level (high vs. low) influence students' engagement goals in LLM-assisted writing?

2. Theoretical Basis: Cognitive Engagement Framework, AI literacy

2.1. Students' Engagement in Writing Education

This study conceptualizes students' engagement in LLM-assisted writing through the ICAP framework, which differentiates cognitive engagement into four hierarchically ordered levels: Passive, Active, Constructive, and Interactive [15, 16]. ICAP provides a theoretically grounded lens for distinguishing observable learning behaviors based on the depth of cognitive processing they entail [16]. By adopting ICAP framework, this study interprets students' chatbot prompts not merely as usage traces, but as indicators of qualitatively different engagement evidence. Illustrative descriptions of each engagement mode are as follows:

- Passive Engagement. Receives chatbot outputs with minimal cognitive processing; prompts are primarily for answer retrieval.
- Active Engagement. Manipulates or organizes information without generating new ideas; uses the chatbot as a resource.
- Constructive Engagement. Generates new understanding by elaborating on or reorganizing prior knowledge based on chatbot feedback.
- Interactive Engagement. Co-constructs knowledge through dialogic exchange; responds to and challenges the chatbot's ideas to advance reasoning.

Based on these definitions, this study analyzes students' chatbot prompts to characterize their cognitive engagement during argumentative writing.

2.2. AI literacy

To account for individual differences in how students engage with chatbots, this study adopts Walter (2024)'s conceptualization of AI literacy [17]. This framework is particularly appropriate because it was developed in relation to writing practices and engagement in education contexts. In this study, this framework extends beyond technical familiarity and foregrounds strategic, epistemic, and ethical dimensions of AI use in writing. Specifically, it includes the following components:

- Applicability and Best Practices. Ability to apply LLMs strategically to support writing processes, including knowing when and how to use chatbots to enhance thinking rather than replace it.
- Limitations. Awareness of the strengths and limitations of LLMs, including their probabilistic nature, susceptibility to errors or hallucinations, and inability to reason or verify facts independently.
- AI Ethics. Capacity to use LLMs responsibly in academic writing by considering issues of authorship, fairness, transparency, and appropriate attribution, and by aligning AI use with institutional and disciplinary norms.

Based on these components, this study codes post-task interviews to classify students into AI literacy groups, and examines how these groups relate to engagement patterns in chatbot conversations.

3. Related work

3.1. Understanding students' engagement through chatbot conversation log

Recent study has increasingly used interaction logs to infer students' engagement in digital learning environments [9, 18]. In LLM-assisted writing contexts, chatbot prompts have been analyzed to identify patterns such as prompt frequency, revision cycles, help-seeking behaviors, and discourse moves [19]. These studies treat conversational traces as observable indicators of students' learning processes.

Moreover, cognitive engagement is often operationalized at the behavioral level, for example through clickstream or surface-level prompts [19, 20]. While such approaches provide descriptive insight into how students use chatbots, they rarely differentiate the depth of cognitive processing underlying similar linguistic actions. As a result, chatbot prompts are analyzed as behavioral patterns, but limited systematically interpreted through established cognitive engagement frameworks such as ICAP. Therefore, to gain a deeper understanding of students' engagement, studies are needed that investigate chatbot prompts at a more fine-grained linguistic level, such as examining action verbs that signal underlying engagement goals.

3.2. The effect of AI literacy in LLM-assisted writing

Alongside engagement, AI literacy has emerged as a critical competency in contemporary education, particularly as generative AI tools reshape how students learn and produce knowledge [12, 21]. In the context of LLM-assisted writing, AI literacy should be understood not only as what students know about AI, but as how they enact this knowledge during writing tasks [17]. Specifically, AI literacy shapes how students decide when to rely on LLMs, how critically they evaluate generated outputs, and whether they use chatbots to extend their thinking or to offload cognitive effort. Therefore, understanding AI literacy is essential for explaining variation in students' engagement patterns during LLM-assisted writing.

However, existing studies have largely examined AI literacy in relation to outcomes such as performance, writing quality, or intention to use AI, rather than focusing on engagement processes during writing [18]. In particular, little is known about how AI literacy shapes students' prompts, underlying intents, and engagement goals in cognitively demanding writing tasks such as argumentative writing.

4. Proposed Solution: Verb-Intent-Engagement Goal Models

4.1. Key idea

We propose a verb-intent-engagement goal model for understanding students' engagement in LLM-assisted writing. This model is a three-layer structure: (1) Verb (observable action), (2) Intent (functional purpose), and (3) Engagement Goal (cognitive orientation). The model assumes that linguistic actions in prompts provide entry points for inferring students' underlying engagement levels. However, the mapping between a verb and its cognitive engagement level may not always be unambiguous. To address this, we elicit participants' underlying intents through semi-structured interviews conducted immediately after the writing. Based on the identified intent, the most appropriate verb is then selected to represent each prompt. By presenting both the verb and the interview-derived intent together, the model is designed to resolve such ambiguity and support more grounded interpretations of engagement.

It is important to note that verbs serve as initial analytical anchors, not direct proxies for cognitive states; the intent layer is always established through interview-based clarification, guarding against the conflation of surface-level linguistic form with underlying cognitive engagement.

4.2. Proposed methods

We will recruit over 40 university students. And this study is structured in two phases. In the writing phase, participants provide short background materials and write a 100–300 word argumentative essay within 25 minutes on the topic: "Do you agree or disagree with the introduction of AI in professional fields?" based on our LLM-assisted writing platform. This platform can collect data including students' chatbot prompt, chatbots' responses, and final essays.

In the interview phase, participants and the first and second authors jointly review the full chatbot prompt logs. Intent is established by reviewing the entire chatbot session log with each participant, preserving conversational context.

To rigorously assess AI literacy, we will design a coding rubric grounded in Walter (2024)'s framework, encompassing three components: Applicability and Best Practices, Limitations, and AI Ethics [17]. Two authors independently code each participant's post-task interview responses using this rubric and reach consensus through discussion; inter-rater reliability is reported via Cohen's kappa. Although various methods exist for measuring AI literacy, such as self-report questionnaires, we adopt this interview-based coding approach to capture how students enact AI literacy within the specific context of LLM-assisted writing. This approach is useful for contextual assessment [22].

4.3. Proposed data analysis

We will employ a qualitative, process-oriented approach to identify participants' underlying intents for each chatbot prompt. Interview recordings will be transcribed, and segments related to prompt usage will be extracted and collaboratively refined to establish prompt–intent mappings. Chatbot prompt verbs will then be identified through independent review by two authors, followed by discussion to reach consensus.

Next, intents will be clustered into broader engagement goals using affinity diagramming [23]. Affinity diagramming was selected because it supports emergent categorization without pre-imposed codes, enabling collaborative, data-driven negotiation of intent-engagement goal mappings grounded in the behavioral data. This is particularly appropriate for an exploratory study in which engagement goal categories are not pre-defined but derived inductively from participants' actual prompting behaviors [20]. Based on this approach, for each prompt, its verb and corresponding intent will be paired and grouped according to ICAP engagement levels. Discrepancies will be resolved through discussion until full agreement is achieved, resulting in clearly defined engagement goal categories.

To examine the influence of AI literacy (RQ2), we will calculate the frequency of each engagement goal per participant and compare distributions between high and low AI literacy groups using independent-samples t-tests.

5. Expected results and challenges

The study anticipates identifying distinct engagement goals, such as clarify, revise, and co-construct. It is hypothesized that higher AI literacy will correlate with engagement patterns associated with deep processing and improved writing quality.

The expected result is a validated model that enables educators and researchers to infer students' cognitive engagement levels from their chatbot prompt logs within LLM-assisted writing contexts. For example, in LLM-integrated educational settings, the model could support real-time identification of students' engagement patterns, enabling timely nudges or interventions for students who may need additional support.

However, several challenges remain. Inferring cognitive states from linguistic traces involves construct validity risks. Intent classification may suffer from contextual ambiguity. In addition, it remains unclear whether focusing solely on argumentative writing is sufficient, or whether broader educational contexts, such as academic writing more generally, should also be examined. We will iteratively refine the study design and the proposed model through pilot studies and cross-context validation [24], as the value of such iterative improvement has been well recognized in educational research.

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Declaration on Generative AI

During the preparation of this work, the author(s) used GPT-5 and Claude Sonnet 4.6 in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication’s content.

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