MetaCues: GenAI-Supported Exploratory Learning Guided by Metacognitive Cues

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Abstract. Generative AI (GenAI) tools are increasingly used for information seeking. However, using these tools effectively—particularly for meaningful learning—requires metacognitive engagement. This includes crafting effective prompts, verifying AI outputs, critically engaging with information, and monitoring and regulating search behaviors and associated learning. In this paper, we describe the design and development of *MetaCues*, a novel GenAI-based interactive tool for exploratory learning that delivers metacognitive cues alongside AI responses, along with a note-taking interface to guide learners' thought processes and interactions with GenAI. We conclude with outlining directions for future analyses of learners' interaction behavior and inquiry patterns within MetaCues to evaluate the impact of metacognitive cues on critical thinking and learning outcomes.

Keywords: Metacognition, Generative AI, Exploratory Learning

1 Introduction

Generative AI (GenAI) tools are being widely used for information seeking, given their speed, convenience, and the ability to synthesize information from multiple relevant sources into coherent responses (30). Among students, this trend is particularly notable: around 86% of students now use GenAI for studying, out of which 69% use it for information seeking (3). However, the growing use of GenAI for information seeking has raised several concerns. The design of GenAI tools inherently encourages cognitive offloading (20), which refers to the delegation of cognitive processes to an external system, such as AI (17). In particular, using GenAI for information seeking can bypass the cognitive processes of understanding, applying, analyzing, and evaluating information, potentially undermining learning and critical engagement with information (15; 20). Research suggests that information seeking with GenAI can lead to passive engagement and limit exposure to diverse perspectives (1; 15; 22).

Given these challenges, effective use of GenAI tools for information seeking requires metacognitive engagement. Metacognition involves being aware of and regulating one's thinking (27; 24). It is essential for both effectively prompting GenAI, which requires monitoring task goals and planning, and for being vigilant

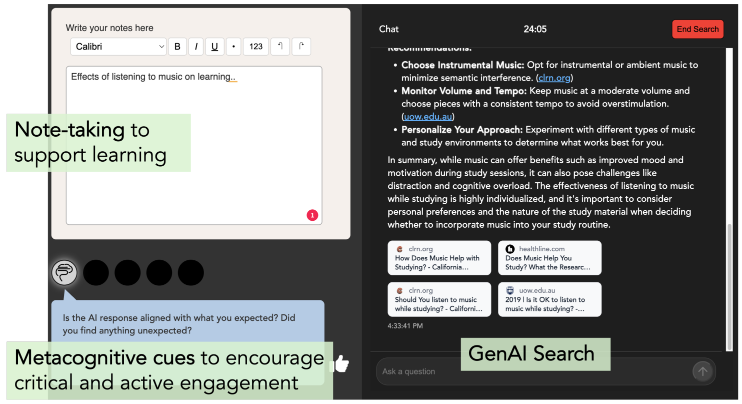

Fig. 1: A snapshot of the MetaCues interface.

of potential inaccuracies and biases in AI-generated responses (24). Further, critical evaluation of GenAI responses requires well-calibrated confidence in one's domain's knowledge, along with metacognitive flexibility to refine prompting strategies as needed (24).

Our recent work (19) shows that metacognitive cues—that prompt learners to pause, reflect, assess their comprehension and consider multiple perspectives—delivered while searching with GenAI tools can foster active engagement, broader exploration, and more thoughtful follow-up questioning. However, in that study, we employed a Wizard-of-Oz setup, where researchers manually delivered cues while monitoring participants' search behavior.

With the goal of automatically delivering metacognitive cues to guide learners' information seeking and learning, we build upon our previous study to design and develop **MetaCues** (Figure 1), an interactive GenAI-based tool featuring three panels: a chat interface on the right where learners query the AI and view responses with linked sources, and a notepad on the left, below which automatically generated metacognitive cues are displayed. MetaCues analyzes learners' questions, AI responses, notes, and clickstream data to proactively deliver tailored cues that encourage active and critical engagement during the information seeking process.

This work describes the design and development of the MetaCues system and reports the interaction data we logged to capture learners' behavior and engagement patterns. We also outline the study we conducted to examine the impact of metacognitive cues on learners' critical thinking and learning outcomes, and discuss our ongoing research for analyzing the data collected from this study.

2 Related Work

2.1 Information Seeking with GenAI

GenAI tools promise efficiency and interactivity for information seeking by generating synthesized, context-aware responses, and supporting conversational and adaptive user engagement (25; 29). However, the fluent and confident nature of their responses can obscure inaccuracies and biases, which can cause overtrust and misinformation (1; 11). Over-reliance on GenAI tools can cause cognitive offloading, reducing learners' active engagement and critical evaluation of information (17; 6; 12). Consequently, GenAI interactions have been found to reinforce existing beliefs (18) and marginalize alternative viewpoints (1). Given these concerns, the design of GenAI systems imposes metacognitive demands on users (24) and effective interaction with GenAI systems requires metacognitive engagement (8; 27). For GenAI-assisted information seeking, effective evaluation of AI responses requires users to accurately judge their topic knowledge and adapt prompting strategies as needed (24). However, this can be challenging for users who have misplaced confidence in their knowledge of a topic or prompting abilities (19; 24).

Recent work shows *metacognitive cues* can significantly support information-seeking and associated learning by promoting reflection, broadening exploration, and deepening inquiry (19). Metacognitive cues draw on the concept of metacognitive prompting, an established instructional approach that has been found to support metacognition in educational contexts (2; 14) and improve information seeking with traditional search engines (10; 23). Metacognitive cues are designed to direct learners' attention toward their own thought processes and toward understanding the activities in which they are engaged (13). Such cues are typically framed as thoughtful questions that are intended to support learners' monitoring and control of their information processing by inducing metacognitive and regulative activities, such as orientation, goal specification, planning, monitoring, and control as well as evaluation strategies (2).

More recently, emerging GenAI tools have begun to incorporate reflective scaffolds (4; 9) and Socratic dialogue mechanisms (7) to increase learners' awareness of their reasoning processes, promote critical engagement with information, and support the detection of misinformation. Building on this body of work, the present work investigates the automatic generation of metacognitive cues within the *MetaCues* system.

2.2 Search as Learning

The Search as Learning (SAL) framework reconceptualizes search systems as rich, interactive learning environments where learning occurs over the course of search sessions (16). This framework characterizes the interplay between three dimensions: search behaviors (e.g., query patterns, navigation), learning processes (e.g., information synthesis, critical evaluation), and learning outcomes (e.g., changes in conceptual understanding or attitudinal shifts) (26). The SAL framework is grounded in Self-Regulated Learning (SRL) theory, which emphasizes that effective learners actively monitor and control their cognitive processes to achieve specific goals (31). In a search context, SRL manifests as a metacognitive feedback loop where learners evaluate retrieved information against their current knowledge state and dynamically adjust their search strategies (28). The search interface serves as a critical scaffold; without explicit support for metacognitive monitoring, learners may fail to recognize knowledge gaps or overlook diverse perspectives.

As learners increasingly turn to GenAI for information seeking, the nature of the "search session" is changing. Traditional search engines require users to sift through diverse sources, a process that naturally encourages information analysis, evaluation and synthesis. In contrast, GenAI tools that provide a single, synthesized response, can undermine learners' active engagement and inquiry. Consequently, designing GenAI interfaces through the lens of SAL requires moving beyond efficiency to prioritize interventions that stimulate the metacognitive engagement necessary for effective information seeking and learning.

3 MetaCues System Design

MetaCues is designed for GenAI-based information seeking and exploratory learning with metacognitive guidance, and is served as a web application (Figure 1). It not only provides answers to a learners' questions on a given topic, but also guides the information seeking and learning process through metacognitive cues that are generated based on learners' chat history, notes and click-stream data. We designed MetaCues for a study (21), described in Section 4, where participants were *assigned* a topic to learn, however this design can be readily adapted to allow learners to input their own topics. A demo of the MetaCues system can be viewed here[3].

3.1 Chat Interactions and Search

The conversational AI interface uses OpenAI GPT-4o model with web search capabilities. Temperature is set to 0.8 to balance focus and diversity. Search context size is kept low to minimize response time. The chat uses an instructional LLM prompt[4] that defines the role of AI as a teaching assistant for providing comprehensive academic information. We prompt GPT to: (i) provide responses with clarity, conciseness, and minimal jargon, (ii) mandatorily use information from web search with 5+ sources and include citations, (iii) frame the response at a technical level of a Bachelor's degree student, and (iv) structure the response in alignment with major themes in a Markdown format with headings, lists, and emphasis. We also prompt the model to respond with 'Sorry I can't help you with that' for off-topic queries to promote safety. Additionally, responses include visual link cards at the end to provide a compact summary of sources provided in the response.

3.2 Cue Generation Process

The cues implemented in MetaCues were informed by prior work on metacognitive support in GenAI-based search and learning (19). Building on insights regarding the metacognitive demands of GenAI tools (24), GenAI-assisted search

[3] Demo: https://tinyurl.com/2sm72j4x

[4] Supplementary material with LLM prompts and Cue Messages

(18; 15), and search as a learning process (16), Singh et al. initially proposed five types of metacognitive cues: Orienting, Monitoring, Comprehension, Broadening Perspectives, and Consolidation. Each cue was delivered according to predefined criteria based on observable user behavior. Following data collection, Singh et al. identified measurable indicators of critical thinking, called Persistent Inquiry, Independent Thinking, and Source Engagement, and recommended tailoring cues to support these behaviors.

Guided by these insights, we adopted four cue types directly from Singh et al.—*Orienting, Monitoring, Broadening Perspectives (BP), and Consolidation*—and introduced three additional types of cues aligned with their identified indicators of critical thinking: *Source Engagement* (SE), *Persistent Inquiry* (PI), and *Independent Thinking* (IT). We now describe the purpose of each type of cue:

1. **Orienting**: Helping establish evaluative criteria for GenAI responses.
2. **Monitoring**: Prompting learners to compare AI-generated information with prior knowledge and expectations.
3. **Persistent Inquiry (PI)**: Encouraging follow-up questions in pursuit of depth of understanding.
4. **Source Engagement (SE)**: Promoting active engagement with sources cited in the AI responses
5. **Independent Thinking (IT)**: Stimulating reflection and synthesis through note-taking to identify new questions or make connections ideas.
6. **Broadening Perspectives (BP)**: Encouraging consideration of overlooked perspectives.

The SE, PI, IT, and BP cues can be instantiated in two variants:

- **Regular**: Encouraging under-exhibited desirable behaviors e.g., "Are there parts of the AI response for which you need more details or evidence? Consider going through the sources, which are your key to confirming facts and uncovering nuances."
- **Reinforcement:** Acknowledging and strengthening desirable behaviors that are already demonstrated, e.g., "Great job engaging with the sources! This is helpful for going beyond surface level understanding.".

This design choice was informed by feedback from pilot studies, in which participants expressed a preference for cues that recognized ongoing effective behaviors rather than redundantly prompting actions they believed they were already performing. While we prompt GPT-5[4] to determine which of these variants to deliver, the actual cue messages are predefined[4], for consistency and preserving the integrity of metacognitive support—guiding learners' thinking and search behavior without offering explicit search recommendations (2). We explored dynamically generating cue messages via LLM prompting, but this approach produced noisy outputs that did not consistently meet established criteria for effective metacognitive scaffolding. Future work may investigate more advanced prompting strategies to support reliable dynamic cue generation. Figure 2 shows

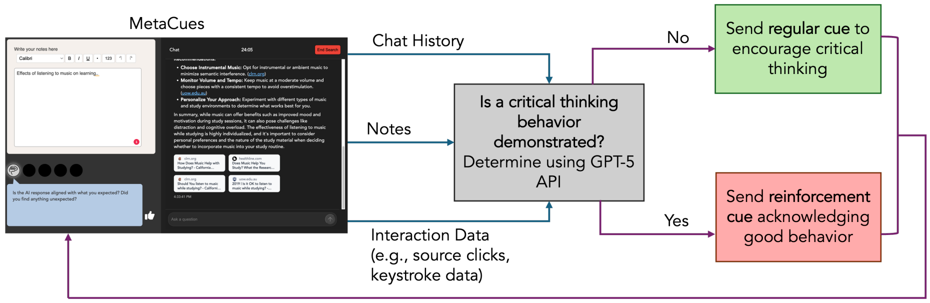

Fig. 2: The process underlying the generation of metacognitive cues.

the process underlying the generation of SE, PI, IT and BP cues, where "critical thinking behaviors" correspond to the behaviors each of these cue types are designed to promote.

The regular variant of the **SE cue** is sent if any AI response containing sources has zero source clicks, else its reinforcement variant is sent. If there are no sources in any of the responses so far, a special message is sent to encourage engagement with sources when they do appear.

For the **PI cue**, MetaCues identifies if a learner is asking relevant follow-up questions by prompting GPT with the chat history and topic along with positive and negative examples of relevant follow-up questions. The regular variant is sent if it is determined that the learner has not asked any relevant follow-up questions thus far, otherwise the reinforcement variant is sent.

For the **IT cue**, MetaCues prompts GPT to compare the learner's notes with AI responses and content scraped from the sources in these responses, to determine if the notes contain novel viewpoints, such as questions the learner may have about the information obtained from searching. If no novel viewpoints are found, the regular variant is sent, else the reinforcement variant is sent. If notes are empty, a special message is displayed to encourage the user to take notes and reflect on their prior knowledge and note any unanswered questions.

Finally, for the **BP cue**, which promotes exploration of overlooked perspectives, we currently do not include a reinforcement variant, as achieving comprehensive exploration within the brief study duration (25 minutes) is unlikely and we wanted to encourage as broad exploration of the topic as possible.

MetaCues operationalizes cue timing using fixed, time-based intervals rather than adapting to user actions. Cues are delivered in a predetermined sequence: an Orienting cue at session start, a Monitoring cue after the first query, followed by SE $\rightarrow$ IT $\rightarrow$ PI $\rightarrow$ BP. These four dynamic cues cycle in this order until the session ends. The initial SE cue is delivered 3-minutes after a session begins, and subsequent cues are triggered at 2.5-minute intervals. These interval durations were informed by pilot studies and our prior Wizard-of-Oz study (19). We observed that, due to the cognitively intensive nature of searching and note-taking, participants attended to cues only when they had sufficient mental bandwidth, rather than immediately upon the appearance of a cue. Accordingly, we designed cue timing to align with approximate phases of the session rather than precise, state-dependent triggers. This approach also simplifies cue generation and reduces computational overhead by avoiding dependence on real-time modeling of the search process. Future work may explore more adaptive cue scheduling strategies, including dynamically adjusting cue timing and gradually fading cues as learners internalize desirable behaviors.

3.3 Displaying Cues to Capture User Attention

Once a cue is triggered, it is queued to be displayed in an activity-aware process. MetaCues waits for natural pauses in user activity (3-second idle), and displays a new cue only when the interface is visible to the user, and there has been some recent user activity within the last 5 minutes. In case such an opportunity is not found, the cue is shown 60 seconds after generation. This approach minimizes distraction while ensuring that the cues are not missed. When a new cue is displayed, a pulsing glow around the cue icon draws attention. The pulsing effect stops when the user acknowledges the cue by clicking the thumbs-up button next to it.

3.4 Data Logging

We computed the following behavioral measures from system logs: (1) *search duration*, (2) *time spent outside the interface*, (3) *total typing time*, (4) *number of queries*, (5) *average words per query*, (6) *number of sources clicked*, and (7) *click-through rate*. Measure (2) estimates the time participants spent on the linked sources, which opened in a new tab. Measure (7) captures the ratio of unique sources clicked to the number of all unique sources linked in all AI responses during the session.

4 Conclusion & Future Work

We presented MetaCues, an interactive system that automatically generates metacognitive cues to support GenAI-based information seeking and associated learning. MetaCues was developed for and evaluated through an online between-subjects study ($N = 146$), where we compared it to a baseline system without cues to examine its impact on learning outcomes, critical thinking, and search behavior. Participants used one of the two systems to research a given topic while taking notes in preparation for writing an essay. They were randomly assigned to conduct research on one of two topics and, following the task, answered post-test questions about the topic, reported their informed judgments and confidence in those judgments.

To assess participants' learning outcomes and gather evidence of critical thinking, we will rely on the behavioral measures outlined in Section 3.4, the notes taken by participants while searching, and their responses to the post-test questions. In particular, the post-test required participants to provide arguments in favor of and against the topic on which they were required to make an informed judgement, as well the reasoning behind their informed judgement. We are currently analyzing the data through the lens of the integrated critical thinking framework for the 21st century (5) to understand how MetaCues shapes search behavior and, in turn, learning outcomes, informed judgments, and confidence, relative to the baseline.

In terms of system design, MetaCues currently employs fixed, study-driven cue timing; future work should explore more adaptive cue delivery as well as the gradual fading out of cues as learners gain experience and demonstrate desirable behaviors. It would also be valuable to explore whether the cues can be integrated into learners' workflows more seamlessly, such as by investigating optimal placement within the interface.

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