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The Illusion of Prompting: A Discourse Analysis of Epistemic Engagement in Student–AI Dialogue

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ABSTRACT

The rapid integration of generative artificial intelligence (AI) into education has intensified interest in how learners engage with AI-generated knowledge. While much research has focused on prompt engineering and output quality, less attention has been given to the epistemic work learners undertake after responses are generated. Drawing on sociocultural and dialogic perspectives on learning [1], [2], this study examines how graduate university students engaged with ChatGPT while completing a formative-assessment design task. Twenty-five student–AI transcripts were analyzed using discourse and thematic analysis, supported by an adapted Initiation–Response–Feedback (IRF) framework. Four interactional patterns were identified: Extraction, Confirmation, Negotiation, and Co-construction. Extraction involved information retrieval with limited visible evaluation; Confirmation involved presenting learner-generated ideas for AI validation; Negotiation occurred when students introduced contextual, pedagogical, or disciplinary criteria to evaluate and redirect AI-generated proposals; and Co-construction involved the progressive development and reformulation of ideas across successive turns. These patterns formed a continuum of epistemic engagement distinguished by the extent to which learners assumed responsibility for evaluating and developing generated knowledge. Neither prompt sophistication nor interactional length reliably indicated the quality of epistemic engagement. More consequential was how learners positioned themselves in relation to AI-generated content and whether that content became an object of scrutiny, judgement, and further inquiry. The findings suggest that AI literacy should extend beyond prompt competence to include evaluative judgement, dialogic engagement, and responsibility for knowledge development within human–AI interaction.

KEYWORDS Generative AI, student–AI dialogue, epistemic engagement, AI literacy, discourse analysis, formative assessment, evaluative judgement

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Introduction

Generative Artificial Intelligence (GenAI) has changed how students' access, evaluate, and produce academic knowledge [3-4]. Large Language Models (LLMs) now enable students to generate explanations, summaries, and arguments with unprecedented speed and ease [4-7]. Yet this capability raises a fundamental pedagogical question: Does the ability to produce a sophisticated academic response necessarily reflect the intellectual work required to understand it? Traditionally, academic learning has required students to search for information, evaluate evidence, synthesize ideas, and construct arguments. With generative AI, however, students can produce seemingly sophisticated responses without necessarily undertaking these processes themselves. Although LLMs offer valuable opportunities for explanation, feedback, and academic support [5], [8], they also create the possibility that intellectual tasks central to

learning may be delegated to the technology rather than undertaken by the learner [9-11]. The central concern, therefore, is not merely what students can produce with AI, but how critically they engage with what it produces.

These concerns have brought renewed attention to AI literacy as an educational priority. Beyond operational proficiency, AI literacy encompasses the ability to interpret, evaluate, and use AI-generated information critically, ethically, and responsibly [8], [12], [13]. Within this broader discourse, prompt engineering has gained prominence as a means of improving the quality of interactions with GenAI [5], [14], [15]. Through the deliberate and iterative use of techniques such as role assignment, contextual framing, and output specification, learners can guide LLMs towards more accurate, relevant, and pedagogically useful outputs [16], [17]. Yet this focus primarily concerns the conditions under which information is generated, rather than learners' intellectual engagement with that information once generated. Prompt engineering may improve what AI produces, but it does not, in itself, establish whether learners critically examine its claims, evaluate its evidence, or construct their own understanding.

The distinction becomes particularly important when considering what learners actually do with AI-generated information. Research on learning has long established that meaningful learning requires more than access to information; it depends on active interpretation, evaluation, elaboration, and knowledge construction [2], [18-19]. A carefully engineered prompt may yield a coherent and persuasive response that a learner accepts without scrutiny. Conversely, a simple prompt may initiate substantial intellectual engagement when learners question claims, seek evidence, challenge assumptions, compare alternatives, or revise their understanding. The sophistication of a prompt, therefore, cannot be taken as a measure of the intellectual work undertaken by the learner. What matters is not only what students ask AI to produce, but how they engage with, challenge, and build upon its responses [8], [12-13].

Productive engagement with AI-generated responses requires more than a willingness to question them. Learners must also possess the disciplinary knowledge, critical reasoning, and relevant literacy practices needed to assess the credibility of claims, evaluate evidence, and recognize the limits of an explanation. Bearman et al. [20] conceptualize this capacity as evaluative judgement - the ability to assess the quality of work against relevant standards. Crucially, such judgements are not made in isolation but are informed by disciplinary conventions, prior knowledge, and an understanding of what constitutes credible evidence and sound reasoning within a particular field [21-22]. Research further suggests that domain specific knowledge and evaluative skills are interdependent, with each informing the exercise of the other [18], [23-24]. This has particular implications for AI-mediated learning because a superficial response may appear coherent and convincing if the learner lacks the disciplinary knowledge or evaluative capacity to identify its weaknesses.

Sociocultural perspectives further suggest that these capacities are shaped by cultural frames, interactions and social practices through which learning occurs [25], [26]. In AI-assisted learning, generative models become part of this mediation, influencing the questions learners pursue, the explanations they consider, and the judgements they make. Dialogic theories further emphasize the role of explanation, challenge, and justification in the development of understanding [1], [24]. From this perspective, analytical attention shifts from the quality of AI-generated responses to the 'interactions' through which learners engage with them [2], [27]. How learners accept, question, challenge, or revise AI-generated ideas becomes particularly significant, as these exchanges offer insight into how disciplinary knowledge and evaluative judgement are exercised in practice.

Recent studies of multi-turn interactions with GenAI have begun to examine these processes more closely. Tang and Putra [28], for example, suggest that analyzing extended exchanges can reveal patterns of reasoning and elaboration that single-turn analyzes may overlook [2], [25]. However, two limitations remain. First, much of this research examines interactions within highly structured environments, where reflective prompts, prescribed tasks, or AI-generated scaffolds are deliberately designed to encourage critique and justification. While such approaches provide valuable insights into supported forms of engagement, they offer a less complete account of how learners independently question, evaluate, and negotiate AI generated ideas in the absence of explicit scaffolding [29-30].

Second, the presence of sustained dialogue does not necessarily indicate meaningful epistemic engagement. Extended exchanges may remain largely transactional, while brief interactions can involve substantial intellectual scrutiny [1], [24], [27]. Interaction length alone, therefore, offers limited insight into the nature of learners' engagement. What requires closer examination is how learners position themselves in relation to AI-generated knowledge - whether they accept claims at face value, seek confirmation, question underlying assumptions, negotiate interpretations, or construct new understandings through dialogue. This distinction calls for greater analytical attention to the nature of discourse within AI interactions, rather than the frequency or duration of those interactions.

These gaps highlight the need to examine how students engage with AI-generated knowledge in contextually situated ways. Pakistani higher education provides a particularly relevant site for such inquiry. Although English serves as the principal medium of instruction in many universities, students often navigate academic learning through multilingual repertoires and diverse educational trajectories [47]. They routinely move between English, Urdu, and regional languages, even in formally English-medium environments [48], and many report challenges related to academic literacy and disciplinary communication in English [49], [50]. At the same time, studies of higher education in Pakistan have noted the continuing influence of transmission-oriented pedagogies

and assessment practices that may provide limited opportunities for students to critically evaluate knowledge claims [51-53]. Within such contexts, AI-generated responses may acquire authority not solely because of their accuracy but because they are presented in fluent, academically recognizable forms. Prior research suggests that users frequently overestimate the reliability of large language model outputs [55], while linguistic fluency can increase perceptions of truthfulness and credibility [56], [57]. Students may therefore face the dual challenge of evaluating both the content of AI-generated responses and the cues through which authority is communicated. Examining these processes can deepen understanding of how learners interpret, evaluate, and negotiate knowledge in AI-mediated learning environments.

To address these needs, this study examines university students' interactions with ChatGPT during a pedagogical design task, with particular attention to the forms of discourse that emerge across successive conversational turns. Through discourse analysis, the study investigates how students position themselves in relation to AI-generated knowledge, including how they accept, verify, question, challenge, and extend AI-generated ideas. Rather than assessing learning through the quality of prompts or the accuracy of AI-generated responses, the study focuses on the interactional processes through which students engage with AI as a knowledge source. In doing so, it seeks to illuminate how epistemic engagement is enacted in real-time dialogue with AI and how learners negotiate the authority and credibility of AI-generated knowledge.

Methods or analytical approach

This study employed a qualitative exploratory design to examine how university students engaged with AI-generated knowledge during multi-turn interactions with ChatGPT [31]. The study was conducted at a private English-medium university in Karachi, Pakistan and involved 25 students enrolled in a bridging semester of an MPhil Education program. Data were generated through a course-based assignment in which students used ChatGPT-4 to address a pedagogical problem involving the *'design of a formative assessment strategy for a mixed-ability secondary classroom'*. The task was selected because it required participants to draw on disciplinary knowledge, evaluative judgement, and iterative reasoning. Students were encouraged to engage in sustained interaction with ChatGPT through follow-up questions, requests for clarification or justification, challenges, and alternative lines of inquiry. No explicit guidance on evaluating or critiquing AI-generated responses was provided, allowing patterns of epistemic engagement to emerge naturally. Upon completion, participants submitted anonymized transcripts of their interactions. The final dataset comprised 25 transcripts containing approximately 300 conversational turns. Transcripts were analyzed using a combination of discourse analysis and thematic analysis informed by sociocultural and dialogic theories of learning [1-2]. An adapted Initiation Response–Feedback (IRF) framework was used to examine the sequential organization of student–AI exchanges, with particular attention to how students responded to and acted upon AI-generated content across successive turns. Analysis proceeded in two stages. First, student contributions were coded according to their epistemic function, including clarification, evidence-seeking, challenge, elaboration, revision, and acceptance. These initial codes were informed by the adapted IRF framework and the study's conceptual focus on epistemic engagement, while remaining responsive to functions evident in the data. Second, coded exchanges were compared within and across transcripts to examine how these functions combined and developed across successive turns. Through iterative comparison, recurring configurations of epistemic functions were grouped and refined into four broader patterns: *Extraction, Confirmation, Negotiation, and Co-construction*. For example, sequences dominated by requests for information, clarification, or elaboration, without subsequent evaluation of the AI response, contributed to the category of *Extraction*. In contrast, sequences in which students challenged an AI generated proposal, introduced contextual or disciplinary criteria, and prompted its revision contributed to *Negotiation*. *Co-construction* was distinguished by sequences in which successive student contributions not only evaluated AI responses but also introduced, connected, or reformulated ideas that progressively shaped the developing solution. The resulting categories therefore reflected a combined deductive–inductive process: the initial coding was conceptually informed, while the four broader patterns were developed through iterative comparison of recurring interactional configurations across the dataset. Coding and category development were conducted by the researcher using NVivo 14, with categories repeatedly checked against the transcripts and refined to ensure that they adequately represented the interactional patterns evident in the data.

Results and findings

Analysis of the transcripts revealed four recurring discourse stances: *Extraction, Confirmation, Negotiation, and Co-construction*. These patterns were not mutually exclusive; students could move between them within a single interaction. The percentages reported below therefore indicate the proportion of transcripts in which each pattern was identified and are not expected to sum to 100%.

Extraction: Treating AI as a Source of Information

In this study, *Extraction* refers to sequences in which students elicited content from ChatGPT without subsequently evaluating, challenging, contextualizing, or substantively developing it. *Extraction* sequences were identified in 13 of the 25 transcripts (52%). *Extraction* was treated as an interactional pattern rather than a fixed learner characteristic, as students frequently moved between different forms of engagement within a conversation. Within the IRF sequence, the student's Initiation (I) elicited information from ChatGPT, which was followed by the AI Response (R). The Feedback move (F) often became a new Initiation by requesting clarification, elaboration, or another example, producing

repeated I–R cycles without placing the preceding response under evaluation.

In the data, *Extraction* occurred in three forms: *immediate extraction, specified extraction*, and *extended extraction*. *Immediate extraction* involved interactions that ended following the initial AI response. *Specified extraction* involved detailed prompts that generated contextually tailored responses but were not subjected to further evaluation. *Extended extraction* involved multiple conversational turns focused on clarification or elaboration rather than scrutiny of the generated content. These variations are analytically significant because they demonstrate that *Extraction* cannot be reduced to either brief interactions or poorly formulated prompts. In some cases, students engaged only minimally with ChatGPT before concluding the interaction. In others, they invested considerable effort in specifying contextual details or extending the conversation across multiple turns. Yet across these variations, AI-generated content remained primarily a resource for information retrieval rather than an object of evaluation, comparison, or critique. The defining feature of *Extraction* was therefore not interaction length or prompt sophistication, but the absence of visible evaluative engagement. Analytically, the distinction rests on the function of the learner's subsequent moves: requests for clarification, elaboration, or additional examples extend the informational sequence, whereas questioning assumptions, identifying limitations, contesting claims, or proposing alternatives transforms the generated response into an object of evaluation.

Student: I need to design a formative assessment activity for a Grade 7 mathematics lesson on fractions. The class has around 40 students with mixed ability levels and limited classroom resources. I want something that can be done during the lesson and can help the teacher identify students who are struggling with the concept. suggest a practical strategy which would work in this context
ChatGPT: One practical option is to use mini-whiteboards or response cards during the lesson. The teacher can ask short fraction questions and all students respond at the same time. This allows the teacher to quickly see who has understood the concept and where students are having difficulty.
Student: we don't have mini whiteboards
ChatGPT: In that case, students can use small pieces of paper or their notebooks. The teacher can ask students to write their answers and hold them up together. Another option is to use an exit ticket at the end of the lesson.
Student: exit ticket how?
ChatGPT: The teacher can give students two or three short questions before they leave the class. For example:
– Which is bigger ½ or ¼ ? – Write one fraction equivalent to ½.
– Explain how you know that ½ is greater than ¼.
The teacher can review the responses and identify which students need further support.
Student: but class is 40 students so checking all will take time no?
ChatGPT: Yes, checking every response in detail may take time. The teacher does not need to mark each response formally. The responses can be scanned quickly and grouped according to common patterns. For example, the teacher might identify students who understand the concept, students who made calculation errors, and students who show a misconception about fractions.
Student: okay then what teacher do next class
ChatGPT: In the next lesson, the teacher can use the responses to plan a short follow-up activity. Students who are still confused could work with visual examples, while students who have understood the concept could attempt more challenging fraction problems.
Student: visual examples like what
ChatGPT: The teacher could draw fraction bars or circles on the board. For example, the teacher could divide one rectangle into halves and another into fourths and ask students to compare ½ and ¼. This can help students understand equivalent fractions visually.
Student: any activity students can do themselves not teacher showing
ChatGPT: Students could draw their own fraction bars in their notebooks. The teacher can give them different fractions to represent and compare. They could also work in pairs and check each other's representations.

Fig. 1. Participant Excerpt 03 - Extended extraction

The excerpt illustrates an extended form of *Extraction*. The interaction develops across multiple conversational turns as the student requests alternative suggestions, practical details, and further elaboration. At several points, the student introduces contextual considerations, including the absence of classroom resources and the challenges of managing formative assessment in a class of forty students. Notably, the student identifies a legitimate feasibility constraint in relation to the use of exit tickets yet delegates the resolution of that concern back to ChatGPT. Rather than evaluating the adequacy of the proposed solution, comparing alternatives, or weighing pedagogical trade-offs, the student treats the constraint as a prompt for further recommendation. Consequently, the interaction becomes progressively more detailed without becoming more evaluative. In addition, this example highlights an important distinction between interactional extension and epistemic evaluation. Although the exchange expands the quantity and specificity of information generated, the AI's recommendations do not become an explicit object of scrutiny. The interaction is characterised by informational refinement rather than epistemic scrutiny; the student remains engaged in shaping and refining the information provided by the AI, but not in evaluating its underlying assumptions, limitations, or adequacy.

Across *Extraction* sequences, students exercised agency in determining what information to request and whether to continue the interaction. Less evident, however, was the application of independent pedagogical, contextual, or disciplinary criteria to assess the content once generated. Although the task required judgements concerning learner variability, feasibility, and pedagogical purpose, such considerations were rarely mobilised explicitly as grounds for accepting, rejecting, adapting, or refining AI-generated recommendations. Importantly, the absence of evaluative moves should not be interpreted as evidence that students accepted responses uncritically, regarded ChatGPT as authoritative, or lacked the capacity to assess the quality of the information provided. Such evaluation may have occurred outside the recorded interaction. The claim proposed here is therefore more limited as evaluation was not made visible within the discourse itself. Extraction identifies an interactional configuration in which AI generated content is obtained, and sometimes elaborated, without becoming an explicit object of scrutiny. Nor does the presence of extraction imply that a learner occupies this position throughout an entire interaction. Because the patterns identified in this study exist along a continuum, sequences may initially take an extractive form before shifting towards *Confirmation, Negotiation,* or *Co-Construction*. Extraction is therefore best understood as a local interactional accomplishment within an unfolding interaction rather than a stable characteristic of individual learners. Its analytical significance lies in identifying moments where information generation functions as an endpoint rather than a catalyst for further epistemic work.

Confirmation: Seeking Validation of an Existing Position

Confirmation refers to instances when students brought an existing idea, judgement, or proposed strategy into the interaction and sought ChatGPT's validation of that position.

Confirmation sequences were identified in 9 of the 25 transcripts (36%). Within the IRF framework, Initiation (I) in *Confirmation* sequences typically contained a student-generated proposition or strategy, which ChatGPT evaluated in its Response (R). The student's Feedback (F) generally indicated uptake of that judgement and, in serial forms, became a new Initiation (I) in which a further or revised proposition was returned to the AI for validation. In the data, *Confirmation* occurred in three forms: direct confirmation, qualified confirmation, and serial confirmation. *Direct confirmation* involved straightforward endorsement of a student-generated proposal. *Qualified confirmation* occurred when ChatGPT endorsed a proposal while introducing conditions, limitations, or implementation considerations. *Serial confirmation* involved successive cycles in which students presented revised or additional ideas for further validation. These variations demonstrate that *Confirmation* is not defined by the complexity of the interaction but by the direction of evaluation. Unlike *Extraction*, students entered the interaction with an identifiable position of their own. However, across all three forms, evaluative authority remained oriented towards the AI. Student-generated ideas became the object of validation, while the AI's judgement was typically accepted as the basis on which adequacy was established.

Student: I need to design a formative assessment activity for an MPhil research methods class where students are learning how to develop focused and researchable research questions. I want an activity that can help me see how they are judging the quality of a research question, not just whether they can remember the criteria. what kind of activity can I use?
ChatGPT: You could give students several sample research questions and ask them to identify which ones are well focused and researchable. They could justify their choices using features such as clarity, scope, and feasibility. This would help you identify how well they understand the characteristics of a good research question.
Student: I was actually thinking something similar. I can give 3 or 4 research questions and ask them which one is better and why. but I dont want to give criteria first because then they will just use the criteria to answer
ChatGPT: That would be a useful approach. If you want to identify students' existing understanding, asking them to make an initial judgement before providing the criteria would give you better evidence of how they are currently thinking about research questions.
Student: yes and maybe first they answer individually and after that discuss in groups? because if I start with group I will not know what each student actually thinks
ChatGPT: Yes, beginning individually would allow you to capture each student's initial judgement. The group discussion could then give students an opportunity to compare their reasoning and reconsider their choices.
Student: then after discussion I can introduce the criteria and ask them to look at their first answer again. I think this will show if their thinking changed
ChatGPT: Yes. Asking students to revisit their original response after seeing the criteria would make any revision in their thinking visible. You could also ask them to briefly explain why they retained or changed their original choice.
Student: I like that. maybe they write one line like "I changed my answer because…" so I can see what actually changed not only the final answer
ChatGPT: That would strengthen the activity. A short explanation would provide evidence of the reasoning behind the revision rather than only showing that the student selected a different answer.
Student: okay so I will do individual selection with reason, then group discussion, give criteria and then they revisit original answer and explain if they changed it. this works as formative assessment?
ChatGPT: Yes. The sequence works as formative assessment because it allows you to identify students' initial understanding, observe how their reasoning develops through discussion, and examine how they apply the criteria when reconsidering their original judgement.

Fig. 2. Participant Excerpt 11 - Serial confirmation

The excerpt illustrates the most extended form of confirmation. Throughout the interaction, the student presents successive ideas and returns them to ChatGPT for assessment. The student's contributions clearly demonstrate prior knowledge of the task and an emerging understanding of formative assessment. Unlike *Extraction,* the interaction does not begin with a request for the AI to generate a solution from scratch. Instead, the student contributes substantive content and uses the AI to determine whether that content is appropriate, feasible, or educationally sound.

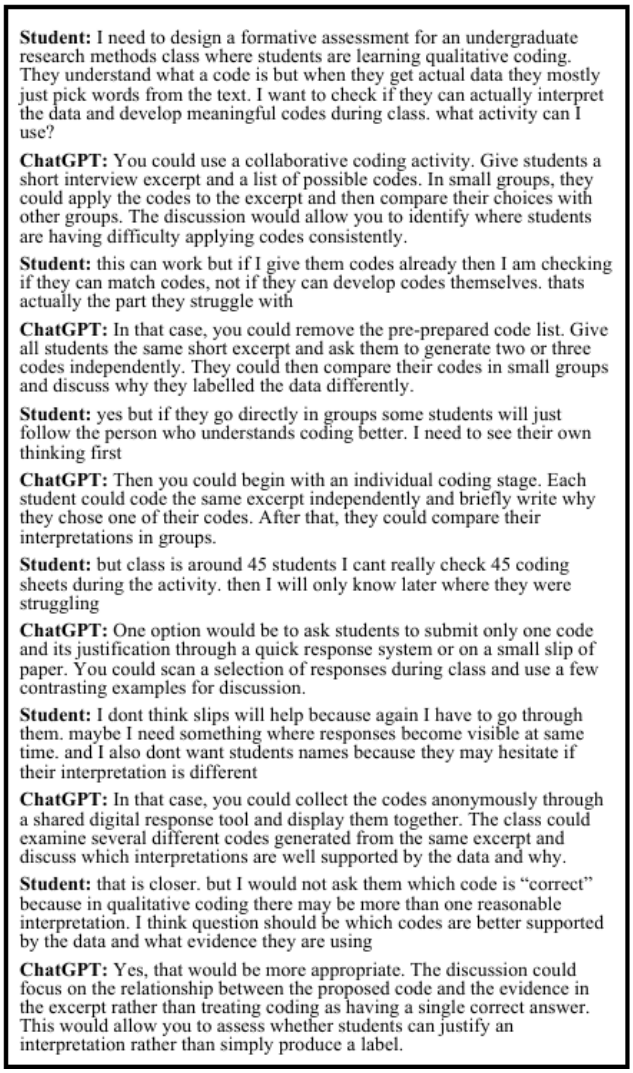
At first glance, such interactions appear more evaluatively sophisticated than *Extraction* because they involve learner-generated propositions rather than simple information requests. However, the evaluative work remains asymmetrical. The student seeks judgement, but primarily from the AI rather than through independent examination of the AI's reasoning. Even when ChatGPT introduces qualifications, conditions, or recommendations, these are rarely taken up as objects of inquiry in their own right. Instead, they become prompts for further validation. As a result, the interaction becomes more elaborate without substantially altering the location of evaluative authority. This distinction is important as it demonstrates that students are not relying exclusively on AI-generated content; they bring their own ideas, experiences, and disciplinary understandings into the interaction. Yet contributing an initial position and using that position to evaluate AI-generated claims remain distinct forms of epistemic engagement. The former establishes ownership of an idea, whereas the latter requires learners to subject both their own reasoning and the AI's reasoning to scrutiny.

As with *Extraction, Confirmation* should not be interpreted as evidence of uncritical reliance on AI. The transcripts cannot establish why students sought validation, how confident they were in their original proposals, or whether they subsequently verified the AI's responses using other sources. The claim advanced here is therefore more limited as student-generated ideas became visible objects of evaluation, but the AI's judgement rarely became an object of scrutiny within the interaction itself. Altogether, confirmation occupies an important position along the continuum of epistemic engagement identified in this study. It represents a movement beyond *Extraction* because learners contribute and test their own understandings within the dialogue. Nevertheless, the direction of judgement remains largely unchanged: adequacy is established primarily through AI evaluation. The transition to *Negotiation* begins when this relationship shifts and students increasingly draw upon contextual, disciplinary, and experiential knowledge to assess whether the AI's claims are acceptable to them.

Negotiation: Evaluating and Redirecting AI-Generated Content

Negotiation refers to instances in which students moved beyond requesting information or seeking validation and began evaluating AI-generated proposals against criteria derived from their own contextual, pedagogical, or disciplinary understandings. *Negotiation* sequences were identified in 7 of the 25 transcripts (28%). As with the preceding patterns, *Negotiation* was treated as an interactional position that emerged at particular moments within a conversation rather than as a fixed characteristic of either the learner or the transcript.

Within the IRF framework, in *Negotiation*, the Feedback move (F) became analytically consequential because the student evaluated the AI Response (R) against contextual, pedagogical, or disciplinary criteria introduced from outside the response itself. That Feedback frequently functioned as a new Initiation (I), requiring ChatGPT to revise, qualify, or replace its preceding proposal. In more extended forms, this produced successive I-R-F cycles in which learner judgement progressively shaped the direction of the interaction. Three broad forms of *Negotiation* were observed in the dataset. Some arose from perceived mismatches between AI-generated recommendations and classroom realities. Others focused on pedagogical adequacy, particularly whether a proposed strategy could achieve its intended educational purpose. A third form involved *recursive Negotiation*, in which students repeatedly evaluated and redirected successive AI responses across multiple turns. Although these forms differed in focus and complexity, they shared a common feature: the AI-generated response became an object of evaluation rather than a source of information or validation.



Student: I need to design a formative assessment for an undergraduate research methods class where students are learning qualitative coding. They understand what a code is but when they get actual data they mostly just pick words from the text. I want to check if they can actually interpret the data and develop meaningful codes during class. what activity can I use?

ChatGPT: You could use a collaborative coding activity. Give students a short interview excerpt and a list of possible codes. In small groups, they could apply the codes to the excerpt and then compare their choices with other groups. The discussion would allow you to identify where students are having difficulty applying codes consistently.

Student: this can work but if I give them codes already then I am checking if they can match codes, not if they can develop codes themselves. thats actually the part they struggle with

ChatGPT: In that case, you could remove the pre-prepared code list. Give all students the same short excerpt and ask them to generate two or three codes independently. They could then compare their codes in small groups and discuss why they labelled the data differently.

Student: yes but if they go directly in groups some students will just follow the person who understands coding better. I need to see their own thinking first

ChatGPT: Then you could begin with an individual coding stage. Each student could code the same excerpt independently and briefly write why they chose one of their codes. After that, they could compare their interpretations in groups.

Student: but class is around 45 students I cant really check 45 coding sheets during the activity. then I will only know later where they were struggling

ChatGPT: One option would be to ask students to submit only one code and its justification through a quick response system or on a small slip of paper. You could scan a selection of responses during class and use a few contrasting examples for discussion.

Student: I dont think slips will help because again I have to go through them. maybe I need something where responses become visible at same time. and I also dont want students names because they may hesitate if their interpretation is different

ChatGPT: In that case, you could collect the codes anonymously through a shared digital response tool and display them together. The class could examine several different codes generated from the same excerpt and discuss which interpretations are well supported by the data and why.

Student: that is closer. but I would not ask them which code is "correct" because in qualitative coding there may be more than one reasonable interpretation. I think question should be which codes are better supported by the data and what evidence they are using

ChatGPT: Yes, that would be more appropriate. The discussion could focus on the relationship between the proposed code and the evidence in the excerpt rather than treating coding as having a single correct answer. This would allow you to assess whether students can justify an interpretation rather than simply produce a label.

Fig. 3. Participant Excerpt 15 - Recursive negotiation

Figure 3 shows a clear instance of recursive negotiation. Rather than accepting the initial recommendation or simply requesting further explanation, the student repeatedly evaluates successive AI proposals against criteria drawn from their own pedagogical and disciplinary understanding. Each AI response generates a further point of scrutiny: whether the activity assesses code generation rather than matching, makes individual thinking visible, remains feasible in a large class, and reflects the interpretive nature of qualitative coding. Within the IRF sequence, the student's Feedback therefore repeatedly becomes a new Initiation, identifying a limitation in the preceding response while specifying conditions that the next proposal must address. In contrast to *Extraction* and *Confirmation*, where students sought information and validation, respectively, the direction of judgement shifts towards the learner. AI generated proposals become objects of evaluation against criteria that originate outside the AI response itself.

Negotiation was often selective rather than oppositional. Students frequently retained aspects of a proposal while questioning others. Responses such as *"That could work, but..."* acknowledged the potential value of a recommendation while opening it to revision. The issue at stake was therefore rarely whether a recommendation was simply right or wrong. More often, students considered whether it was appropriate for a particular educational context. A strategy that appeared reasonable in general terms could still be judged inadequate if it failed to account for learner variability, resource constraints, classroom realities, or the kinds of evidence needed for formative decision making. In such moments, students retained authority over the conditions under which a proposal could be regarded as feasible or educationally useful. As with the preceding patterns, the absence of *Negotiation* should not be interpreted as evidence that students lacked the capacity to evaluate AI-generated content, nor does effective engagement require learners to challenge every response they encounter.

Negotiation therefore marks an important shift along the continuum of epistemic engagement identified in this study. Whereas *Confirmation* leaves evaluative authority primarily with the AI, *Negotiation* positions learners more clearly as judges of the adequacy of AI-generated proposals. Nonetheless, the interaction remains centered on evaluating and revising proposals already on the table. Co-construction extends this process further. Rather than primarily assessing successive proposals, learners and AI become jointly involved in developing an evolving line of reasoning, with ideas progressively refined, extended, and reconfigured across turns.

Co-construction: Developing Understanding Across Turns

Co-construction refers to sequences in which the student and AI progressively develop a solution, with each turn contributing substantively to how the idea is reformulated. *Co-construction* sequences were identified in 4 of the 25 transcripts (16%). These sequences involved sustained cycles in which students introduced ideas, engaged substantively with AI-generated suggestions, reconsidered emerging problems, and progressively reformulated the assessment design. Within the adapted IRF framework, *Co-*

construction commonly appeared through recursive sequences such as I–R–F/I'–R–F/I"–R. Its defining feature, however, was not the number of turns or the recurrence of this structure. Rather, the student's Feedback/Initiation (F/I') contributed new substance to the developing solution. Ideas, constraints, experiences, and connections introduced in one turn became resources for subsequent turns. The developing design therefore changed across the interaction and could not be attributed solely to either the student's initial position or the AI's first response. This distinguishes *Co-construction* from *Negotiation*. In *Negotiation*, learner generated criteria are primarily used to evaluate and redirect an AI proposal. In *Co-construction*, such evaluation becomes part of a broader process in which the student also introduces, connects, revises, or synthesizes ideas that alter the direction of the developing solution.

Student: I need formative assessment for B.Ed class on research ethics. students know principles like consent confidentiality etc but when given actual research situation they find it difficult to decide what is ethical because sometimes there is no simple right answer. I want to see their reasoning not just if they remember principles. what can I do?

ChatGPT: You could use a short ethical dilemma. Give students a research scenario with competing concerns and ask them to decide what the researcher should do and justify their decision. You could then compare different responses in a whole-class discussion.

Student: dilemma is good. I was thinking maybe everyone should get same case first so I can see how differently they reason. but if I just ask what researcher should do they may jump to solution. maybe first ask what ethical issues they can see?

ChatGPT: That would give you two levels of evidence: whether students can recognize the ethical issues and how they use those issues to reach a judgement. You could therefore separate the activity into identifying concerns first and deciding on a course of action afterwards.

Student: yes. actually this gives me another idea. I can stop the case halfway. like first only give initial situation and they identify concerns. then give additional information which makes decision more difficult and ask if their position changes

ChatGPT: That could make the assessment more revealing because students would need to reconsider an earlier judgement when the context changes. You could ask them to record their initial position before receiving the additional information and then explain what, if anything, caused them to revise it.

Student: hmm and maybe different groups can get different second information? one group gets issue about confidentiality, and another gets issue about participant risk. then when groups compare they will see why same case can lead to different decisions

ChatGPT: Yes. That would shift the task from finding a single correct answer towards examining how ethical judgements depend on the information available and the relative weight given to different principles. The comparison between groups could become part of the formative evidence.

Student: right. then my original idea of checking if they know ethical principles is actually too limited. I think I want to see if they can identify the principle, use it in making a decision, and then reconsider decision when new information comes. maybe at end they should write what information changed their judgement and why

ChatGPT: That would give the activity a clearer progression. You would be assessing recognition of ethical concerns, application of principles, and revision of judgement in response to changing circumstances. The final explanation would also make the reasoning behind that revision visible.

Student: okay so instead of one dilemma question I now have staged case. first same incomplete case individually, identify issues and initial decision. then groups receive different additional information, reconsider decision, compare across groups, and at end each student writes what changed or did not change in their judgement and why. that is actually closer to what I want to assess

ChatGPT: Yes. The activity has developed from a single ethical-dilemma question into a staged assessment of how students identify, apply, and reconsider ethical principles as the research context changes.

Fig. 4. Participant Excerpt 07 - Co-construction

Figure 4 illustrates a clear instance of Co-construction. Across the interaction, the student does more than request information, seek validation, or identify limitations in AI-generated suggestions. Successive contributions build on preceding turns by introducing new considerations, connecting emerging ideas, and progressively refining the assessment design. Within the IRF sequence, Feedback repeatedly becomes a renewed Initiation. Unlike *Negotiation*, however, these F/I' moves do not simply identify deficiencies requiring revision. Instead, they contribute directly to the development of an evolving solution.

The cumulative nature of this process is centrally important. As the interaction develops, earlier ideas are revisited, modified, and connected to new considerations. Discussion may expand from selecting an assessment technique to broader questions of learner participation, evidence collection, feedback, feasibility, or instructional use. Interactional length alone was therefore insufficient for classification as *Co-construction*; what distinguished these exchanges was the extent to which successive contributions shaped a developing line of reasoning.

The IRF framework makes this distinction particularly visible. Similar recursive I–R–F/I'–R structures could occur across *Extraction, Confirmation, Negotiation*, and *Co-construction*, but the function of the student's Feedback/Initiation differed. In *Extraction*, F/I' primarily sought further information or elaboration. In *Confirmation*, it commonly registered uptake of the AI's judgement or introduced another proposition for validation. In *Negotiation*, it identified a limitation and established conditions for revision. In *Co-construction*, F/I' contributed directly to the emerging solution by proposing, connecting, reconsidering, or synthesizing ideas. The same structural position therefore performed different epistemic work across the interactional patterns. In addition, student-generated knowledge was also more visibly incorporated into the development of the solution during *Co-construction*. Students drew upon their understanding of formative assessment, knowledge of learners and classroom conditions, prior experience, and anticipated instructional consequences. These resources were not used only to judge whether an AI suggestion was acceptable. They were brought into relation with successive responses and used to develop the idea further. At times, this altered the AI generated proposal; at others, engagement with the AI- response prompted students to reconsider their own earlier position. *Co-construction* therefore involved development at the level of ideas rather than a succession of AI proposals followed by student evaluation.

The term *Co-construction* is used here in a deliberately limited sense. It does not imply equivalence between interaction with GenAI and collaboration between human participants, nor does it assume that student and AI contributions are comparable in status or origin. Rather, it describes an observable interactional process in which the eventual assessment design emerges through successive cycles of contribution, uptake, reconsideration, and reformulation. The analytical focus is therefore on the visible development of ideas across the interaction. *Co-construction* represents the furthest point on the continuum of epistemic engagement identified in this study. *Extraction* centres on obtaining information; *Confirmation* introduces a student position but primarily seeks its validation; and *Negotiation* uses learner-generated criteria to evaluate and

redirect AI-generated proposals. In *Co-construction*, the learner's own position also becomes open to reconsideration and development. Ideas are connected, revised, and recombined across turns, so that the assessment strategy becomes a developing solution rather than a product to be generated, validated, or corrected.

Discussion

The findings revealed substantial variation in how students engaged with AI-generated knowledge. Rather than representing fixed learner characteristics, the patterns identified in this study emerged as interactional positions that students could move between as conversations developed. Taken together, the findings suggest that the educational significance of student-AI interaction cannot be adequately inferred from prompt quality, response sophistication, or conversational length alone. More consequential is the extent to which learners assume responsibility for evaluating, questioning, and developing the knowledge generated during the interaction. Viewed in this way, the findings shift attention from the production of AI outputs to the epistemic work learners undertake in engaging with them.

Beyond Prompt Competence: Generating a Good Response Is Not Equivalent to Learning

A central implication of the findings concerns the prominence of prompt engineering within contemporary accounts of AI literacy. Previous research has shown that prompt quality influences the relevance, specificity, and usefulness of large language model outputs [14-17]. The present findings do not challenge the importance of prompt competence. Rather, they suggest that generating a high-quality response and engaging productively with that response are analytically distinct forms of activity [32]. This distinction was particularly evident in *Extraction* sequences. Students could formulate detailed prompts and obtain contextually relevant responses without subsequently examining the adequacy of what had been generated [33-35]. Conversely, relatively simple prompts sometimes gave rise to more substantive engagement when learners identified limitations, introduced contextual knowledge, or redirected the interaction. Prompt sophistication therefore provided only limited evidence of the epistemic quality of the exchange [32].

From a dialogic perspective, the educational significance of AI does not lie in response generation alone but in how learners subsequently question, evaluate, and develop the ideas those responses contain [1-2], [19], [24]. A response that appears coherent, authoritative, and contextually relevant may still require judgements concerning its accuracy, completeness, disciplinary validity, and practical usefulness [36]. Indeed, the fluency and plausibility of AI- generated content may make such scrutiny even more necessary [5], [20], [37-38]. The findings therefore support a broader conception of AI literacy in which prompt competence constitutes one component, rather than the endpoint, of effective AI use [8], [12-13], [39]. The critical educational question is not simply whether learners can obtain better responses from AI systems, but whether they retain epistemic responsibility for evaluating, questioning, and developing the knowledge those responses contain [40,41]. In this sense, prompting may shape the quality of information generated, but learning depends on how that information becomes an object of judgement, inquiry, and knowledge development.

What Learners Bring to AI Matters: From Possessing Knowledge to Mobilizing It

A second contribution of the findings concerns the role of learner knowledge within AI-mediated interaction. Across the patterns identified in this study, differences in epistemic engagement were closely associated with how students brought disciplinary, contextual, practical, and experiential knowledge into the exchange [41]. The findings suggest, however, that possessing relevant knowledge and mobilizing that knowledge as a basis for judgement are not equivalent [23]. This distinction was particularly evident in the transition from *Confirmation* to *Negotiation*. In *Confirmation* sequences, students frequently demonstrated prior understanding by proposing assessment strategies, articulating pedagogical positions, or relating classroom practices to formative-assessment principles. Yet these contributions were commonly presented to ChatGPT for validation [33], [35]. By contrast, *Negotiation* occurred when learners used their knowledge to assess AI-generated proposals. Considerations such as class size, resource constraints, learner variability, and assessment purpose became criteria through which recommendations were judged, challenged, or redirected.

The significance of prior knowledge therefore lies not simply in its possession, but in its capacity to support evaluative judgement. This aligns with Bearman et al.'s [20] conception of evaluative judgement as the ability to recognize quality and apply appropriate standards to work or information [42]. It also resonates with research demonstrating that critical evaluation depends upon the conceptual resources available to the evaluator [22], [24]. In the present study, students were better able to interrogate AI-generated proposals when they could articulate why those proposals were inadequate, incomplete, or misaligned with the instructional problem under consideration [18]. At the same time, the findings caution against equating productive AI engagement with disciplinary knowledge alone. Students drew on a wider repertoire of resources, including professional experience, knowledge of learners, contextual awareness, and practical understandings of classroom realities. What distinguished more substantive engagement was not the possession of these resources, but their mobilization through acts of comparison, critique, justification, and revision. Engagement became visible when learners brought what they knew into dialogue with what the AI had generated [19]. This interpretation is consistent with sociocultural perspectives on learning, which view knowledge not as a static possession but as something enacted through participation in meaning-making activity [1-2], [25]. From this perspective, learner

knowledge becomes educationally consequential when it is used to question assumptions, identify limitations, recognize contextual mismatches, and reshape emerging interpretations. The shifts observed within some transcripts reinforce this point as students occasionally moved from *Extraction* or *Confirmation* towards *Negotiation* when AI-generated responses conflicted with prior experience, failed to accommodate contextual realities, or introduced new issues requiring consideration. Such shifts suggest that epistemic engagement is not simply a stable learner disposition but is also shaped through interaction. The analysis indicates that productive engagement was associated not merely with students' prior knowledge or the information generated by AI, but with how learners drew upon their understanding to question, evaluate, and develop AI-generated ideas. From this perspective, the potential educational value of AI-generated responses lies not in the information they provide alone, but in the intellectual work learners undertake in examining, challenging, and reconsidering that information [18].

Multi-Turn Interaction Is Not Necessarily Dialogic Learning

The findings also have important implications for sociocultural and dialogic accounts of AI-mediated learning. Dialogic perspectives emphasize that learning develops not simply through participation in interaction, but through exchanges in which ideas are taken up, questioned, justified, challenged, and extended [1-2], [19], [24]. From this perspective, multi-turn interaction might initially appear to provide evidence of deeper engagement with AI. The present findings suggest that such an assumption is insufficient [43].

Across the four patterns identified in this study, similar interactional structures frequently performed very different epistemic functions [44]. Students could sustain extended exchanges by requesting clarification, elaboration, or additional examples while remaining primarily engaged in *Extraction*. Similarly, complete I-R-F sequences could function as *Confirmation* when feedback merely acknowledged or accepted the AI's judgement. By contrast, *Negotiation* and *Co-construction* were distinguished not by the number of conversational turns but by the work those turns performed. Feedback became epistemically consequential when it evaluated, redirected, connected, or reformulated preceding contributions. Theoretically, this distinction suggests that interactional structure and epistemic function should not be conflated [44]. A lengthy interaction is not necessarily dialogic in the educational sense, just as a brief interaction is not necessarily epistemically weak [43]. What matters is how contributions are taken up and transformed across the dialogue. Repeated requests for additional content may generate substantial interaction while leaving the learner's relationship to generated knowledge largely unchanged [18]. Conversely, relatively brief exchanges may involve considerable challenge, justification, evaluation, and revision. This finding resonates strongly with dialogic theories of learning. Mercer [1] argues that educationally productive dialogue depends upon the collective examination and justification of ideas, while Wells [2] emphasizes the progressive development of understanding through inquiry. Viewed through this lens, the educational value of AI interaction lies less in the quantity of interaction than in the extent to which generated ideas become objects of scrutiny and development. The critical issue is therefore not whether learners continue the conversation, but whether successive turns contribute to reasoning, judgement, and knowledge construction [24].

The findings also extend emerging research that examines student-AI dialogue beyond isolated prompt-response exchanges [28]. Rather than treating prompt quality, response sophistication, or turn count as proxies for learning, the present study highlights the importance of learner uptake. Whether learners elaborate, validate, challenge, compare, justify, or revise AI-generated content appears more educationally consequential than the number of conversational turns through which those actions occur [44]. Methodologically, this strengthens the case for treating unfolding discourse, rather than individual prompts or outputs, as the primary unit of analysis. It is through successive turns that epistemic engagement becomes visible, making discourse trajectories a more informative indicator of learning than interactional quantity alone.

Co-construction, but not symmetry: Who carries epistemic responsibility?

The *co-construction* sequences raise a broader theoretical question concerning the status of AI as a dialogic partner. In the most developed interactions, students' ideas changed through successive exchanges with ChatGPT. The final assessment design was neither fully specified in the student's initial contribution nor simply reproduced from the AI's first response. Instead, it emerged through cycles in which possibilities were proposed, reconsidered in relation to classroom knowledge and experience, revised, and eventually synthesized [2]. In this restricted interactional sense, describing these sequences as co-construction is warranted [45-46]. However, the findings also reveal an important asymmetry in how this development was sustained. Across *Negotiation* and *Co-construction*, substantive shifts in the direction of inquiry were predominantly initiated by students. Learners recognized when a suggestion was inadequate, introduced considerations that had been overlooked, determined which issues required further attention, and reconsidered their own emerging positions. ChatGPT responded by elaborating possibilities, generating alternatives, or revising earlier proposals, but it did not consistently assume equivalent responsibility for determining what warranted scrutiny. This distinction becomes particularly significant when viewed through sociocultural accounts of dialogue. Mercer [1] conceptualizes dialogue as a process through which participants make reasoning available for examination and use one another's contributions as resources for further thought [19]. While some student-AI exchanges displayed

these interactional qualities, responsibility for recognizing limitations, introducing new evaluative criteria, and redirecting inquiry remained largely with the learner [40]. ChatGPT could produce plausible alternatives, explanations, and revisions, but the trajectory of the interaction depended primarily on students recognizing when such moves were necessary [58].

Co-construction should therefore not be taken to imply symmetry between human and AI contributions [45]. A more precise interpretation is that ideas can develop through human-AI dialogue while responsibility for judging their adequacy remains disproportionately located with the learner [41]. The AI can contribute explanations, alternatives, representations, and revisions, but the learner remains centrally responsible for determining what should be accepted, questioned, connected, or developed further [20], [42]. Co-construction of ideas, in other words, does not necessarily entail co-distribution of epistemic responsibility. This distinction has important educational implications. The possibilities afforded by extended AI dialogue may depend partly on learners' capacity to recognize when an apparently plausible response requires further examination [32-33]. Students who cannot readily identify omissions, inconsistencies, or contextual limitations may have fewer opportunities to move the interaction beyond *Extraction* or *Confirmation* [34-35]. Supporting productive AI use may therefore require attention not only to how learners converse with AI, but also to the disciplinary and evaluative resources that enable them to assume responsibility for the direction of that dialogue [12], [39], [41], [54].

Overall, these findings suggest that a continuum of epistemic positioning may offer a useful complement to existing conceptualizations of AI literacy that emphasize technical competencies. The four discourse stances - *Extraction, Confirmation, Negotiation,* and *Co-construction* - illustrate differences in the extent to which learners assume responsibility for evaluating, questioning, and developing AI-generated knowledge. These stances do not represent fixed learner characteristics or a linear developmental sequence, as students may move between them within a single interaction. Rather, they highlight a dimension of AI literacy that neither prompt sophistication nor interaction length can adequately capture the extent to which learners exercise judgement over what constitutes credible, justified, and meaningful knowledge. The educational challenge, therefore, extends beyond teaching students to obtain better AI-generated responses to supporting their capacity to interrogate, contextualize, and develop those responses through critical inquiry.

Implications for AI Literacy and Pedagogy

At the classroom level, the findings suggest the importance of designing learning activities that make students' engagement with AI-generated content visible. Rather than assessing only whether learners can formulate effective prompts or obtain useful responses, educators might create opportunities for students to justify decisions, compare alternatives, identify limitations, and revise AI generated suggestions using disciplinary or contextual criteria. Such tasks position AI output as a starting point for intellectual work rather than its conclusion.

At the level of curriculum and teacher education, the findings suggest that AI literacy should be embedded within disciplinary learning rather than treated as a standalone technical skill. Students need opportunities to practise evaluating and revising AI-generated content in relation to the standards, evidence, and forms of reasoning valued within their field. This also has implications for teacher preparation and professional development, particularly in supporting educators to design tasks that make evaluative judgement and disciplinary reasoning visible.

At the level of AI literacy frameworks and educational policy, the findings support a broader conception of AI literacy than one centered primarily on prompt competence or technical proficiency. As GenAI becomes increasingly integrated into educational practice, greater emphasis should be placed on learners' capacity to evaluate, contextualize, and develop judgement, AI-generated disciplinary knowledge. Evaluative reasoning, and epistemic responsibility should therefore be treated as central dimensions of AI literacy rather than secondary complements to technical skill.

Limitations

Several limitations should be considered when interpreting these findings. First, the study involved 25 university students from a single institutional context in Pakistan. The relatively small, context-specific sample limits the transferability of the findings to other educational settings, disciplines, and student populations. Second, the analysis focused on a single pedagogical design task. Different tasks, disciplinary demands, or levels of familiarity with GenAI may give rise to different forms of discourse. Third, the analysis was confined to students' observable interactions with ChatGPT. Learners may have evaluated information, consulted other sources, or reconsidered their understanding without explicitly articulating these processes in the transcripts. The absence of visible critical engagement should therefore not be interpreted as evidence that no such evaluation occurred. Finally, the identification and interpretation of discourse stances involved qualitative researcher judgement, and alternative interpretations of particular exchanges remain possible. The four stances should consequently be understood as contextually situated analytical categories rather than fixed learner characteristics or a universal developmental sequence. Further research across different tasks, disciplines, and educational contexts could examine the applicability and refinement of these categories.

Conclusion

This study examined how university students engaged with ChatGPT during a pedagogical design task, with particular

attention to how they position themselves in relation to AI-generated knowledge. The findings suggest that understanding students' use of GenAI requires attention beyond the sophistication of prompts or the quality of generated responses. Of particular significance is the extent to which learners exercise evaluative judgement, question the authority of AI-generated claims, and assume responsibility for knowledge construction. By identifying the discourse stances through which these processes are enacted, the study shifts attention from AI use as a technical skill to AI engagement as an epistemic practice. This perspective extends current discussions of AI literacy by highlighting how learners negotiate, challenge, and develop knowledge in interaction with AI. For educators, the implication is not simply to teach students how to obtain better responses from AI, but to cultivate their capacity to question, evaluate, and contribute to the knowledge those responses present. Future research across different tasks and educational contexts can further examine how such forms of epistemic engagement emerge and the conditions that support them.

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