ASCILITE 2026

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Collaboration, Creativity and Compassion in a Digital Society

Beyond conversation length: Conversation openings, cognitive engagement, and support orientations in student-AI chatbot interactions

Xiaoyu Zhuang, Aneesha Bakharia

The University of Queensland

Generative AI is increasingly used in learning environments, yet sustained interaction does not necessarily indicate cognitively engaged learning. This exploratory study examined how conversation openings related to cognitive engagement levels and the support orientations reflected in student messages during student-AI interactions. Cognitive engagement was classified by an adapted ICAP framework, openings were organised into a descriptive typology, and semantic thematic analysis was conducted on student messages. Openings oriented towards strategy guidance, conceptual explanation, error understanding, and resource review feedback were more often associated with moderate or deep engagement, whereas resource-evaluation openings were often associated with longer interactions despite limited cognitive depth. Semantic patterns revealed overlapping orientations towards questioning, improvement, examples, feedback, and concepts, spanning clarification, answer checking, revision, application, and task-focused support. These findings distinguish interaction persistence from cognitive engagement and suggest that conversation design should support students to articulate their reasoning and co-construct knowledge with AI, rather than prioritising continued interaction alone.

Keywords: Cognitive engagement, ICAP framework, student-AI interaction, semantic analysis, conversation openings, educational chatbot, exploratory study

Introduction and motivation

Educational chatbots powered by generative AI are increasingly used by students to request explanations, make sense of feedback, and seek task support (Chen et al., 2025; Darvishi et al., 2024; Heung & Chiu, 2025; Uzun et al., 2026; Yang et al., 2025). When chatbots are embedded in learning platforms, how conversations are initiated, whether through free-text input or predefined starters, is a design choice that may shape how students articulate uncertainty, reasoning, and support needs. Observed opening messages provide one trace of how students take up these affordances (Alfredo et al., 2024; Chen et al., 2025).

Educational chatbot studies commonly examine user perceptions, usage frequency, and broad engagement measures, while conversation length offers a readily observable indicator of persistence at scale (Debets et al., 2025; Uzun et al., 2026). Interaction persistence is informative and easily observable, but it cannot by itself show whether students are explaining, revising, or co-constructing understanding (Yang et al., 2025). This distinction matters for help-seeking and scaffolding. AI-mediated help-seeking can function as an active learning strategy, although its educational value depends on how learners articulate uncertainty, evaluate assistance, and retain agency (Alfredo et al., 2024; Chen et al., 2025; Uzun et al., 2026; Yang et al., 2025).

The ICAP framework proposed by Chi and Wylie (2014) offers a suitable lens because it conceptualises cognitive engagement through observable learner contributions, distinguishing the receipt of information from the manipulation, generation, explanation, and collaborative development of ideas. Continued interaction is therefore not equivalent to cognitively engaged contribution (Chi & Wylie, 2014; Yang et al., 2025). Nevertheless, it remains unclear how first message opening types correspond to cognitive engagement and what broader support patterns recur across students' messages. Accordingly, this study addresses the following two research questions:

RQ1. To what extent are different types of observed conversation openings associated with whole-thread cognitive engagement in student-AI chatbot interactions?

RQ2. What recurring semantic patterns are evident in student messages during student-AI interactions?

Context and methods

This study used an exploratory mixed methods design with two units of analysis: RQ1 examined conversation threads to assess associations between observed openings and whole-thread cognitive engagement; RQ2 examined individual student messages to identify recurring semantic patterns in the retained corpus.

Research context and data

To answer the above research questions, we collected 2,212 student-AI conversation threads from RiPPLE (Khosravi et al., 2019), an online learning platform where students engage in a cyclical process of resource creation, peer evaluation, and practice across multi-disciplinary courses at the University of Queensland (UQ). Generative AI chatbots are embedded within these activities, allowing students to seek real-time feedback and personalised support while completing learning tasks. UQ ethics approval (Approval No. 2023/HE001453) and informed consent were obtained before data collection. All data were anonymised.

Cognitive engagement coding

Cognitive engagement was coded at the whole-thread level using an adapted ICAP framework summarised in Table 1. Classification was based on observable contributions across all student messages in a thread. AI responses supplied conversational context but were not treated as direct evidence of student engagement. A human-led ICAP codebook was translated into structured instructions for the OpenAI GPT-5.5 model. Two human coders and the model independently coded 200 sampled threads. Agreement was assessed using Cohen's κ, and discrepancies were used to refine the coding instructions before automated classification of the full dataset and subsequent manual review. Between the two human coders, κ was 0.96 for Off-task, 0.88 for Passive, 0.83 for Active, 0.93 for Constructive, and 0.95 for Interactive. For the automated classifications, the corresponding κ values were 0.85, 0.70, 0.62, 0.79, and 0.77 against the first human coder, and 0.82, 0.76, 0.66, 0.76, and 0.71 against the second human coder.

Table 1.
Adapted ICAP-based coding framework for student-AI conversations

Category	Definition	Typical patterns
Off-task	The thread primarily concerns non-academic content, platform mechanics, chatbot testing, or unintelligible input.	Social conversation, interface questions, prompt injection, content unrelated to the learning task.
Passive	Student contributions are learning related but generic and show minimal cognitive processing.	Acknowledgement, generic review requests, basic assistance, requests for a complete answer without a specific contribution.
Active	Student contributions address specific content or procedures without explanation or reasoning.	Factual questions, selected answers, values, concept checks, requests for a specific next step.
Constructive	The student generates reasoning, interpretation, critique, reflection, or explanation.	Justifying an answer, diagnosing an error, comparing alternatives, correcting a representation, articulating a hypothesis.
Interactive	Understanding is developed through sustained uptake and mutual contribution across multiple turns.	Iterative refinement, collaborative debugging, testing explanations, building directly on earlier AI feedback.

Analysis of conversation openings

To answer RQ1, the first student message in each thread was extracted and normalised for HTML, typography, case, whitespace, and trailing punctuation, yielding 471 unique openings. Using a human-developed fixed-order rule set and face-validity review, openings were classified into 10 mutually exclusive categories: *Resource Evaluation* (existing-resource assessment), *Resource Review Feedback* (own-work feedback), *Peer*

Review Feedback (feedback on the student's peer review), *Error Understanding* (errors or answers), *Strategy Guidance* (approach or reasoning), *Conceptual Explanation* (concepts or relationships), *Content Generation* (resource-content creation), *Clarity Improvement* (wording, focus, or flow), *Social or Open* (minimal/social openers), and *Other* (no confident fit). This descriptive, dataset-specific typology reflected recurring functions across the platform's resource-creation, peer-evaluation, and practice activities. ICAP labels were collapsed into low (Off-task/Passive), moderate (Active), and deep (Constructive/Interactive) cognitive depth. Chi-square tests examined associations of opening type with cognitive depth and, separately, with interactions of at least four turns; Cramér's V reported association magnitude.

Semantic analysis of retained messages

To answer RQ2, the initial corpus contained 7,988 student messages. Exact matches to five primary system-generated conversation starters were removed, excluding 4,217 messages. A further 80 messages identified as non-English by the preprocessing rule were excluded. The resulting corpus comprised 3,691 messages from 1,340 threads and 687 students, including 848 retained first messages and 2,843 follow-up messages. Leximancer was used to identify recurring concepts, concept co-occurrences, and themes within the retained corpus (Smith & Humphreys, 2006). We interpreted the themes through their constituent concepts and representative text segments, describing them as nonexclusive support orientations rather than behavioural categories.

Results and analysis

Conversation openings and cognitive engagement

The 2,212 threads contained 471 unique normalised openings across ten categories. *Resource Review Feedback* was the most frequent category (n = 493, 22.29%), followed by *Resource Evaluation* (n = 480, 21.70%) and *Peer Review Feedback* (n = 321, 14.51%). A further 298 openings (13.47%) were classified as *other*. As shown in Figure 1, conversation-depth profiles varied across opening types. *Strategy Guidance* had the largest combined proportion of moderate depth (Active) and deep depth (Constructive and Interactive) conversations (47.79%), closely followed by *Conceptual Explanation* (47.37%) and *Error Understanding* (46.63%). *Resource Review Feedback* also had a comparatively large Active, Constructive, and Interactive share (40.97%). By contrast, 98.96% of threads initiated by *Resource Evaluation* were classified as low cognitive depth (Off-task or Passive). The association between opening type and the three conversation depth levels was significant, $\chi^2(18) = 370.17$, $p < 0.001$, Cramér's V = 0.289. Interaction persistence displayed a different pattern. Although resource evaluation had the largest low cognitive depth thread proportion, 37.50% of these threads contained at least four turns. Opening type was associated with interactions of four or more turns, $\chi^2(9) = 47.43$, $p < 0.001$, Cramér's V = 0.146. This association was smaller than that observed between opening type and the conversation depth levels.

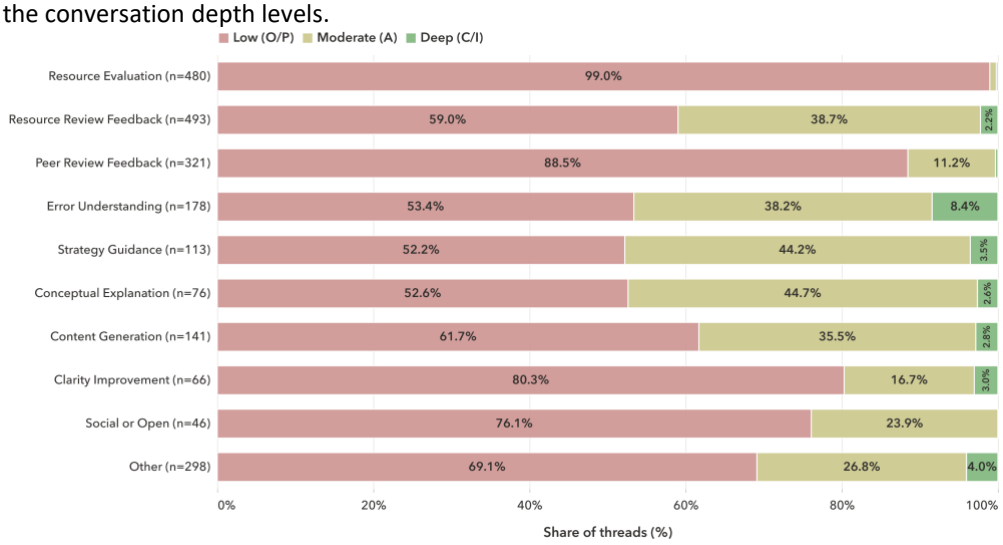


Figure 1. Conversation opening type by conversation depth

These findings indicate that observed opening types corresponded to distinct whole-thread engagement profiles, although they cannot be regarded as determining those profiles. Openings framed around strategy guidance, conceptual explanation, error understanding, and resource review feedback more often coincided with discourse with deeper cognitive engagement than several generic or evaluative openings. At the same time, resource evaluation frequently sustained four or more turns despite being overwhelmingly associated with low cognitive engagement depth. Interaction persistence and cognitive engagement thus represented related but distinguishable dimensions in this dataset: continuing a conversation did not necessarily entail specificity, reasoning, revision, or collaborative knowledge construction in students' contributions.

Semantic patterns in retained student messages

Leximancer semantic thematic analysis of 3,691 retained student messages identified five themes: *question* (1,448 hits), *improve* (1,110 hits), *example* (789 hits), *feedback* (182 hits), and *concept* (130 hits). Theme hits were treated as overlapping occurrences rather than mutually exclusive counts. Figure 2 shows substantial proximity between *question* and *improve*. The *question* region grouped concepts concerning answers, correctness, clarity, options, distractors, understanding, and checking. The *improve* theme was organised around explanation, suggestions, writing, resources, clarity, wording, structure, and specificity. The *example* theme occupied a broad adjacent region containing application-oriented and domain-specific concepts, including code, data, SQL, database, and article. The *concept* theme was positioned near the lower boundary of the question and example regions, while *feedback* formed a smaller peripheral cluster dominated by feedback and submit.

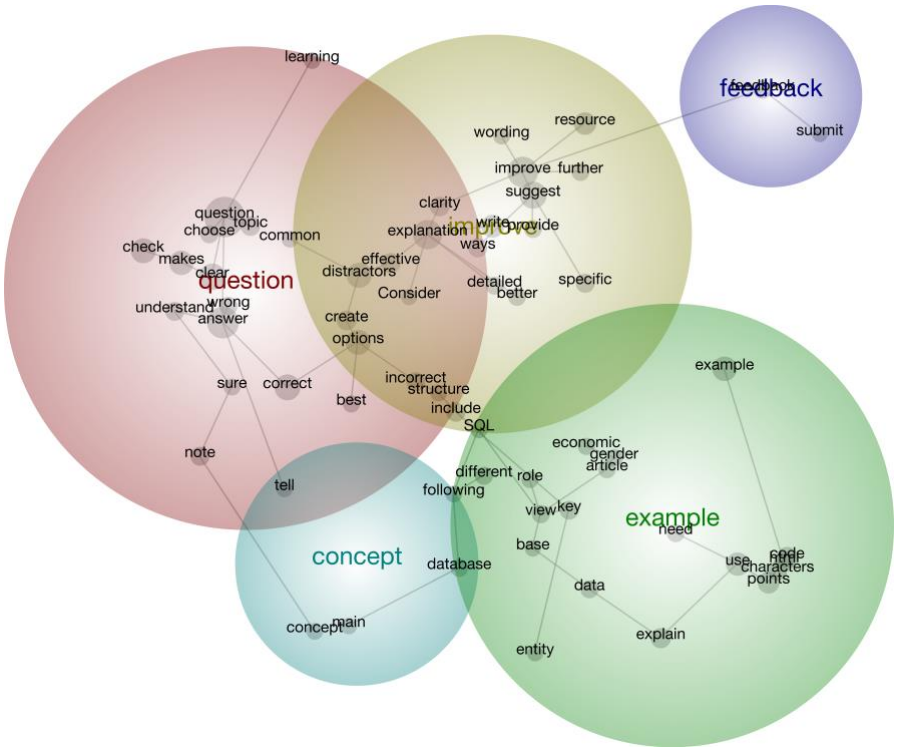


Figure 2. Concept map of retained student messages

These patterns reflected multiple, non-exclusive support orientations within the retained discourse. The prominent *question* and *improve* themes encompassed clarification, answer checking, wording, structure, and revision, while the *example* theme combined references or requests for examples with substantial domain-specific content. The smaller *feedback* and *concept* themes added procedural and task-focused patterns to the broader semantic landscape. These orientations contextualise the ICAP profiles by situating opening-level engagement differences within broader support-seeking around checking, revision, explanation, and application. As co-occurrence-based interpretations, they do not establish causal order, participant intention, mismatches between generic starters and student needs, or that removed starters constrained expression.

Limitations and future directions

Overall, opening types showed substantively different ICAP engagement profiles, whereas their association with interaction persistence was weaker, reinforcing that sustained interaction does not imply cognitively engaged discourse. Together with the semantic orientations, these findings suggest embedding scaffolds at chat initiation within learning platforms, such as “What are you uncertain about, and why?” or “Revise your answer using this feedback and explain the change.”

These findings should be interpreted in light of several limitations. The observational and associational design precludes causal inference, and repeated threads from individual students were not modelled. Automated whole-thread ICAP coding may compress within-conversation variation, and model–human agreement was lowest for Active ($\kappa = 0.62–0.66$), indicating greater uncertainty in this classification, while collapsed categories further simplify engagement profiles. The rule-based opening typology may retain boundary uncertainty, and the data do not identify whether openings were interface-selected, manually entered, or adapted by students. Semantic thematic analysis depends on concept co-occurrence and researcher interpretation cannot directly represent student intention, and was derived from one platform and learning context, limiting wider generalisation.

Future research could extend this work from conversation-level associations to sequential learning-process analysis. By integrating chatbot interactions with student activity logs, such as resource editing, feedback selection and adoption, and submission events, we could compare how learning pathways vary across different cognitive engagement levels. This would situate different forms of cognitive engagement with AI within students’ broader processes of task completion.

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