Characterising Student Behaviours with AI-Generated Feedback in Higher Education

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Abstract. The increasing use of Generative AI (GenAI) in educational feedback has prompted growing interest in understanding how students interact with AI-generated feedback. However, most existing research examines student–AI feedback interactions through the lens of writing revision outcomes, self-reported perceptions, or conceptual theorisation, leaving the real-time behavioural processes largely underexplored. This study investigates the range of student behaviors that emerge during multi-turn conversational interactions with a GenAI tool implemented in a university-level machine learning course. Using inductive qualitative coding of 2,128 conversational messages between students and AI, we developed an empirically grounded behavioural coding scheme comprising 24 indicators organised across 8 dimensions: Feedback Orientation and Engagement, Cognitive Externalisation, Iterative Dialogue Management, Metacognitive Monitoring, Epistemic Positioning Toward AI, Self-Regulatory Persistence and Progression, Strategic AI Use Orientation, and Relational Framing Toward AI. Our findings reveal that students display a diverse range of behaviours that extends well beyond simple answer-seeking, ranging from minimal answer submission to extended self-explanation, and from managing dialogue depth to strategically using AI for forward learning plans. This coding scheme provides a systematic tool for researchers and practitioners to analyse and understand the complexity of student–AI feedback interactions in conversational settings.

Keywords: AI-generated feedback · student-AI interaction · Generative AI · AI in education · Qualitative Coding.

1 Introduction

The rapid adoption of GenAI in higher education has fundamentally shifted how students interact with feedback. Recent surveys indicate that the proportion of students using generative AI tools for their studies has risen sharply, with usage becoming a routine part of their academic experience [4]. While a growing body of research examines AI-generated feedback quality [5, 8] and student perceptions

[14], comparatively little work has systematically investigated what students actually *do* when they interact with AI-generated feedback in real time.

This gap matters because the pedagogical value of feedback depends not on the information provided, but on what learners do with it [3, 10]. Feedback research has moved away from a transmission model towards a process-oriented view, emphasising feedback as an active process in which learners interpret information about their work, evaluate it against standards, and use it to enhance subsequent performance [2]. Accordingly, understanding student behaviours during feedback interactions is essential for designing effective AI-mediated learning environments.

A growing body of research has begun to examine how students interact with AI-generated feedback. Several studies have investigated student engagement with GenAI-generated (e.g., ChatGPT) feedback in writing contexts, revealing patterns such as superficial prompting, predominantly one-off interactions, and high uncritical uptake of AI suggestions [13]. Others have proposed conceptual frameworks theorising how GenAI may influence feedback engagement across stages of eliciting, processing, and enacting feedback [12]. Meanwhile, research on AI-mediated feedback tools has examined how AI-generated comments affect revision quality compared to human feedback, finding that even when GenAI produces high-quality feedback, students do not necessarily revise more effectively [6]. Work on a GenAI-powered feedback management tool found declining student engagement over time despite positive initial perceptions, suggesting a mismatch between GenAI outputs and student expectations [7]. However, these studies primarily examine student engagement through the lens of writing revision outcomes, self-reported perceptions, or conceptual theorisation, leaving the real-time conversational behaviours through which students orient to and act upon AI feedback largely unexplored.

This study addresses this gap by developing a fine-grained, empirically grounded coding scheme for characterising student behaviours with AI-generated feedback in a conversational assessment context, guided by the following research question (RQ):

RQ: *What behaviours do students exhibit when interacting with AI-generated feedback?*

The contribution of this paper is an empirically grounded behavioural coding scheme that provides researchers and practitioners with a systematic tool for analysing student–AI feedback interactions, moving beyond broad categorisations to capture the fine-grained behavioural processes through which students orient to, make sense of, and act upon AI-generated feedback.

2 Method

2.1 Context and Participants

This study was conducted in the context of a GenAI-powered conversational assessment tool, Blinded, deployed in a university-level machine learning course.

The tool generates quiz questions – both multiple-choice and open-ended – on machine learning topics. Students receive AI-generated feedback on their responses through a conversational interface before moving to the next question. Students engaged with the tool across four quiz sessions throughout the semester. Since these were designed as formative assessments and the purpose was to support learning through engagement and feedback-seeking, the correctness of students' responses was not graded, and only their engagement was.

The dataset comprises time-stamped, dyadic chat logs between the AI and individual students. There were 43 students enrolled in the course. The number of students engaging with the tool across the four quizzes varied, with 41, 34, 39, and 32 students participating in each quiz, respectively. Throughout these quizzes, a total of 2,128 conversational messages between students and the AI tool were collected for analysis.

2.2 Data Analysis

We adopted an inductive qualitative coding approach following established methodological procedures [11]. The analysis proceeded through five phases. In Phase 1, two coders independently examined Quiz 1 data, listing all observed student behaviours, then met to discuss their observations and collaboratively developed an initial codebook of behavioural indicators. In Phase 2, both coders independently applied the codebook to Quiz 2 data to examine whether any new behaviours emerged beyond those captured in the initial codebook. Each coder flagged any new behaviours encountered during coding, which were then discussed and incorporated into the codebook where agreed upon. Inter-rater reliability (IRR) for this round reached a Cohen's kappa (k) of 0.77, indicating substantial agreement [9]. The same process was repeated in Phase 3 with Quiz 3 data, where coders again independently coded and flagged potential new behaviours (k = 0.87, indicating almost perfect agreement [9]). Phase 4 involved inviting four domain experts to review the behavioural indicators. Based on expert feedback, two codes were renamed for improved clarity and representativeness. In Phase 5, a final validation round was conducted using Quiz 4 data to confirm the stability of the codebook (k = 0.88, indicating almost perfect agreement [9]). Across all coding phases, each message was assigned at least one code, with multiple codes applied when a single message exhibited more than one distinct behaviour. This iterative process ensured both the comprehensiveness and stability of the coding scheme.

3 Results and Discussion

The inductive coding process yielded a behavioural coding scheme comprising 24 indicators organised across eight dimensions (A–H). Fig. 1 presents a mind map of the coding scheme. Rather than presenting all dimensions separately, we describe each dimension alongside its theoretical significance.

Fig. 1. Student behavioural indicators with AI-generated feedback

Feedback Orientation (A) and Cognitive Externalisation (B). Students ranged from providing minimal answer attempts (A1: "C") to requesting elaborated feedback on evaluations (A4: "Where is that 1 missing?"). The depth of reasoning they externalised (B) similarly varied, from answers with some reasoning (B1) to proposing reasoning for AI to check (B2: "I have done temperature data analysis using R. The processes I have done, including data preparation, cleaning, removing missing values... are data mining process?") to extended self-explanation with multiple justifications (B3). This spectrum resonates with Zhan and Yan's finding [13] that students' engagement with ChatGPT feedback ranged from superficial prompting to more substantive interaction. However, our fine-grained coding reveals intermediate forms of cognitive investment, such as proposing reasoning for verification (B2) and requesting numerical ratings (A3: "If you want to give me marks out of 10 then how much it would be?"), which have not been differentiated in existing studies.

Dialogue Management (C), Metacognitive Monitoring (D), and Self-Regulatory Persistence (F). These dimensions can be understood through the cyclical feedback engagement framework proposed by Zhan et al. [12]. Students' clarification-seeking (C1: "Could you explain this a bit more before we move on?") and explicit expressions of uncertainty (D1: "Honestly, I'm not sure how a decision tree could be used for regression problems") correspond to the feedback control stage. Self-regulatory persistence behaviours, such as continuing by requesting the next question (F1), checking whether they could stop

(F2), or delegating session closure (F3), reflect how learners manage ongoing engagement. While Zhan et al. [12] identify this as a critical dimension, it has mainly been discussed conceptually rather than examined through behavioural indicators.

Epistemic Positioning Toward AI (E) and Strategic AI Use (G). These dimensions highlight behaviours that appear specific to AI-mediated feedback contexts. Students probed AI capabilities and boundaries (E3: "How many quiz questions are you capable of generating?"), questioned its responses (E2: "You didn't provide summary for the last two questions"), and used it strategically for forward learning plans (G3: "I'll need to read more on Gradient Boosting Tree and XGBoost"). These findings align with recent studies [1] identifying meta-cognitive engagement and conversational repair as key categories of student–AI interaction. Our scheme extends such findings by situating these behaviours within a feedback-specific context. Notably, the range from uncritical acceptance (E1) to epistemic vigilance (E2), and from completion-oriented (G2: "How can I mark this quiz complete?") to learning-oriented use (G1: "Give me a real world problem where can I apply data mining techniques"), offers a possible explanation for Farrokhnia et al.'s finding [6] that higher-quality GenAI feedback does not necessarily lead to more effective revision: what students do with feedback varies considerably and may mediate the relationship between feedback quality and learning outcomes.

Relational Framing Toward AI (H). Students introduced themselves (H1: "Hello, my name is [name]"), used polite social expressions (H2: "Hi"; "Cheers"; "Bye bye"), and shared their learning identity and motivation (H3: "I'm currently pursuing a Master of Data Science at the [university name], I am very curious about data analysis... that's the reason for me to enrol in Predictive Analytics"). These behaviours resonate with findings that students regularly anthropomorphise ChatGPT, positioning it as a social actor. In our structured feedback context, such relational framing may serve a functional purpose: establishing rapport that supports willingness to engage deeply with feedback, consistent with feedback literacy research emphasising affect and motivation in feedback engagement [3, 10].

4 Conclusion

This study developed an empirically grounded behavioural coding scheme comprising 24 indicators across eight dimensions that captures how students engage with AI-generated formative feedback. By providing more fine-grained behavioural distinctions than existing approaches, this scheme offers researchers and educators a systematic tool for analysing how students engage with AI feedback. It shifts the focus beyond what feedback AI provides to how students interpret and act on it. Limitations include the single-course context and relatively small sample, which constrain generalisability. Future work should apply the scheme across diverse disciplinary and institutional contexts, examine how behavioural patterns relate to learning outcomes, and investigate whether targeted interventions can shift students toward more productive feedback engagement behaviours.

Disclosure of Interests. The authors declare no conflict of interest.

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