2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #53923

Turning Chatbot Conversations into Learning Analytics for Troubleshooting in an Undergraduate Engineering Lab

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BCSER: Learning Analytics from Chatbot-Supported Troubleshooting:

Using Coded Interactions to Inform Learning Design Decisions

Abstract

This NSF-funded project (NSF BCSER Project, Award #2422510) explores a systematic approach to analyzing chatbot conversation logs and translating them into concrete learning design decisions for an undergraduate engineering experimentation course. We deployed a purpose-built Socratic troubleshooting chatbot within a seven-week laboratory module on metrology, sensing, and data acquisition. Over two academic terms, we captured and analyzed 80 distinct student-chatbot sessions comprising 884 coded questions. Our learning analytics framework centers on a codebook aligned with stages of engineering work, extended with three diagnostic indicators: divergent options, option uptake, and root-cause heuristics. Key findings reveal that troubleshooting dominated usage (37%), with substantial demand for conceptual clarification (29%). A spot audit showed divergent options in 75% of troubleshooting micro-episodes, with configuration/gain-setting heuristics appearing in 58%. We demonstrate how these analytics can inform specific course improvements, contributing a framework that enables instructors to use conversational traces as a design resource for instructional improvement..

1. Introduction

As AI-powered conversational agents emerge in engineering education, there is growing interest in understanding how these tools support student learning and how interaction data can inform instructional improvement. Recent research suggests that large language models can support divergent idea generation, a capability relevant to troubleshooting tasks (Hubert et al., 2024), while the visualization of learning activities encourages more student-centered course designs (Rienties & Toetenel, 2016). Yet learning analytics dashboards have shown limited impact, with most rarely grounded in learning theory or rigorously evaluated (Schwendimann et al., 2017), revealing a persistent disconnect between analytics and actionable pedagogy.

Troubleshooting presents a critical site where learning design can benefit from data-informed refinement. As a diagnosis-solution type of problem-solving, troubleshooting requires domain knowledge, the capacity to distinguish abnormalities, and divergent exploration of possible causes (Jonassen, 2004; Doggett, 2005). Root-cause analysis frameworks emphasize structured heuristics—such as checking configurations, comparing signals against expectations, or testing with known references—that can be explicitly scaffolded in dialogue (Andersen & Fagerhaug, 2006).

This study examines chatbot-supported troubleshooting in an undergraduate engineering laboratory, guided by two research questions: (1) In what capacity does the chatbot support divergent thinking for troubleshooting, specifically in root-cause analysis? (2) How can insights from chatbot interactions inform learning design decisions about materials, scaffolds, and instructional orchestration?

2. Methods

2.1 Setting and Chatbot Design

The study was conducted at a Worcester Polytechnic Institute, a mid-sized R1 university, in a seven-week engineering laboratory sequence introducing metrology, sensing, and data acquisition. We deployed a purpose-built Socratic troubleshooting chatbot configured to promote divergent thinking by offering multiple hypotheses rather than single solutions, prompting students to test alternatives and reflect on outcomes. The agent was configured to avoid direct code generation; when students asked for code fixes, it returned algorithmic plans or stepwise procedures to keep reasoning foregrounded.

2.2 Data Collection and Analysis

Over two academic terms, we captured 80 distinct student-chatbot sessions through secure turn-level logging, de-identification, and export. Sessions were analyzed using NVivo 14 qualitative data analysis software, where each session was created as a case with attached attributes. Each session corresponds to a single student's contiguous dialogue with the chatbot during one help-seeking episode. The codebook classified student questions into categories mirroring stages of engineering work: Troubleshooting, Scientific and Engineering Concepts, Integration, Analysis and Simulation, Design, Optimization, and Process Documentation.

2.3 Diagnostic Indicators

We extended the base framework with three diagnostic indicators that characterize the quality of troubleshooting support: (1) **Divergent options**—agent replies proposing multiple pathways; (2) **Option uptake**—student selection and follow-through; and (3) **Root-cause heuristics**—structured diagnostic moves including isolating variables, checking configurations, and comparing to expected ranges. These indicators are straightforward to compute and pedagogically interpretable.

3. Results

3.1 Category Distributions

Across 884 coded questions, troubleshooting dominated usage (330 questions, 37%), followed by Scientific and Engineering Concepts (256, 29%), Analysis and Simulation (119, 13%), Integration (86, 10%), Design (40, 5%), Process Documentation (40, 5%), and Optimization (13, 1%). Within Troubleshooting, Software questions accounted for 145, Experimental Progress for 137, and Hardware for 48.

Table 1. *Category and subcategory counts across two terms*

Category	Total	Subcategory	Count
Troubleshooting	330	Hardware	48
		Software	145
		Experimental progress	137
Scientific and Engineering Concepts	256	Scientific phenomenon	64
		Tool inquiries	37
		Scientific equation	155
Integration	86	System	45
		Device	41
Analysis and Simulation	119	Data analysis	39
		Hypothetical scenarios	44
		Mathematical tool	36
Design	40		
Optimization	13		
Process documentation	40		

3.2 Conversational Depth

Many sessions involved sustained diagnostic work: 36% (29 sessions) included ten or more student turns, indicating extended back-and-forth rather than simple fact-lookup. An additional 48% (38 sessions) contained 2–9 turns, while only 16% (13 sessions) were single-turn interactions. Deep sessions almost always involved multistep diagnostic decision making, while single-turn interactions typically sought conceptual clarifications.

3.3 Diagnostic Quality

A spot audit of twelve troubleshooting micro-episodes revealed: divergent options in 75% of cases (9/12), option uptake in 58% (7/12), configuration/gain-setting heuristics in 58% (7/12), and expected-range reasoning in 50% (6/12). Additionally, heuristics observed included isolated variables (5/12), signal-chain check (4/12), device identity/orientation (3/12), and reference test (3/12). These patterns demonstrate that the chatbot routinely produced multi-option replies, and students frequently converted these options into action.

Table 2. Spot-audit presence of diagnostic constructs in twelve troubleshooting micro-episodes

Construct	Operationalization	Presence (episodes)
Divergent options	Agent proposes two or more hypotheses or next steps in one turn	9 of 12
Option uptake	Student selects one option and advances with evidence or targeted follow-up	7 of 12
Configuration or gain setting	Checks of amplifier gain, ADC range, pin capability	7 of 12
Compare to expected range	Reference to expected voltages, counts, or temperature spans	6 of 12
Isolate variable	Hold one factor constant or test one component	5 of 12
Signal-chain check	Trace power, ground, and measurement path	4 of 12
Device identity or orientation	Verify polarity, pin mapping, part identity	3 of 12
Reference test	Ice bath, shorted input, or other known condition	3 of 12

4. Discussion and Implications

4.1 Translating Analytics to Design Decisions

The framework bridges the persistent gap between analytics outputs and instructor action. Based on interaction patterns, we propose specific course improvements (not yet implemented): (1) **Pre-lab preparation activities** that shift configuration and expected-range reasoning into planned preparation (e.g., “Compute the expected sensor voltage and ADC counts for your thermistor divider at 20–30°C and select the gain that keeps the node inside the readable range”); (2) **Visual scaffolding materials** at bench level showing thermocouple polarity, differential channel mapping, and PWM-capable pins; and (3) **Protocols for allocating teaching assistant support** based on session depth—repeated shallow hurdles can trigger brief modeling demonstrations, while deep sessions with documented option uptake warrant higher-order conceptual support.

4.2 Theoretical Contribution

This work links generative AI to learning design through operational constructs that are theoretically motivated and practically interpretable. The constructs translate classic insights from diagnostic reasoning and problem-solving research into analytics that make sense to educators, extending work that connects dialogue moves to learning processes (Graesser et al., 2005; VanLehn, 2011).

5. Conclusion

This work demonstrates a coherent pathway from chatbot conversation logs to learning-design decisions in an authentic engineering laboratory. The learning-design-aligned codebook and diagnostic constructs provide measures that instructors can understand and use, directly addressing calls in learning analytics for tools that close the gap between data and pedagogy. Conversational traces from AI support are not merely logs of help-seeking—they are a decision resource. Limitations include reliance on perception data rather than performance measures, and the agent's no-code configuration, which shaped question distributions. Future work should link conversational constructs to lab artifacts and track whether proposed design changes alter depth distributions across offerings.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Award No. 2422510 (NSF BCSER). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. We thank the undergraduate student researchers and teaching assistants who participated in and supported the course.

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