Chatbots for Dialogic Feedback during Self-Study: The Importance of Contextual Information

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ABSTRACT

Self-study often leads to impasses – getting stuck. Impasses can be a valuable learning opportunity if supported by timely feedback, especially dialogic feedback. LLM-based chatbots can provide timely, dialogic feedback for all students in a large cohort, however their use requires careful consideration. Two key challenges of LLM chatbots are aligning with educational values and ensuring technical accuracy.

This paper examines how providing chatbots with contextual information affects their educational value. Using a framework of impasse-driven learning, we introduce concepts of objective context (e.g. course materials) and subjective context (e.g. student's thought process). We theoretically analyse the risks and benefits of context-awareness in chatbots when supporting a student during an impasse.

To gain empirical insight, we deployed chatbots to students on a self-study learning platform (Lambda Feedback) that can provide objective context to the chatbot. Qualitative analysis of conversations from 23 students show that students frequently reference objective context in their queries, allowing the dialogue to focus on their impasse and reducing cognitive load.

Evidence provided here shows the benefits of contextual awareness for chatbots. We also discuss the potential risks, namely removing student agency and 'productive struggle'. We conclude that, on balance, chatbots are likely to be most educationally beneficial if context is available, but that chatbots should be configured to manage the risks. We outline future work on managing the risks.

INTRODUCTION

Self-study is a major part of higher education. An essential part of self-study is reaching an impasse (VanLehn, 1988), where the student cannot complete the task at hand. In the terminology of Vygotsky (1978), the student reaches their Zone of Proximal Development (ZPD) and requires external help, 'scaffolding', or 'feedback'.

This paper focusses on feedback at the moment of impasse. We treat the impasse as a path to learning – an opportunity, not a problem to be avoided (VanLehn, 1988). This approach is also known as 'desirable difficulties' (Bjork 1994), or 'productive failure' (Kapur, 2024, p.35-58). As well as educational evidence that impasses drive learning, basic neuroscience shows that effort is required to encode memories (Klein, 2014). A shortcut to the solution then omits the learning itself. Therefore, while feedback should offer enough support to overcome the impasse, it also risks ruining the learning opportunity.

Dialogic feedback, where the student can interact with the support being provided, is increasingly encouraged (Boud and Molloy, 2013). Dialogue allows students to negotiate meaning, build trust, manage emotions, and foster self-regulation, leading to deeper engagement (Yang and Carless, 2013). Effective feedback is also recognised as being timely (Shute, 2008; Yang and Carless, 2013).

Providing timely, personalised, dialogic feedback to every student at every impasse during self-study for large cohorts is practically challenging (Henderson et al., 2019). Automated 'chatbots' have the potential to provide timely dialogic feedback at such a scale (Labadze et al., 2023; Casebourne and Wegerif, 2024). In this paper we apply the principles of impasse-driven learning theory to focus on practical aspects of deploying chatbots based on Large Language Models (LLMs).

There are two key 'alignment' challenges in developing effective LLM-based educational chatbots: (1) technical accuracy in domain specific areas, such as avoiding hallucinations (Huang et al. 2025); and (2) alignment with educational values, such as allowing the student to resolve their own issues when completing a task (Wollny et al. 2021; Jurenka et al. 2024).

To address alignment challenges, LLM behaviour can be influenced using either fine-tuning or prompt engineering. Fine-tuning involves altering the model's underlying weights, leading to general behavioural changes, but is computationally intensive. Jurenka et al. (2024) fine-tuned a Google LLM for educational purposes. However, their follow-up report (LearnLM Team et al., 2024) found that the diverse demands of education could not be met by fine-tuning and recommended a focus on prompt engineering.

Prompt engineering involves crafting the prompt for the LLM by incorporating the student's message with additional content such as instructions, examples, or context. This paper focuses specifically on the provision of contextual information. Winkler and Söllner (2018) emphasised the importance of context awareness for educational chatbots before the modern era of LLM-based chatbots, and the issue has since become more important as the behaviour of LLMs depends strongly on the prompts – called instruction-following (Zhou et al., 2023; Wen et al., 2024). This paper contributes to best practice on providing contextual information for educational chatbots, which is an under-explored area in current practice and literature.

In this paper, we propose a theoretical framework that distinguishes between objective and subjective context. We then hypothetically analyse how integrating objective context in chatbots impacts impasse-driven learning during self-study. We describe a pilot experiment of an educational chatbot with objective context automatically provided. Results present initial evidence on how objective context influences student interaction patterns with an AI chatbot, focussing on references to contextual information. We conclude with recommendations on the use of context with educational chatbots.

AIM AND OBJECTIVES

This study provides practical recommendations on providing contextual information to educational chatbots for dialogic feedback on self-study during an impasse.

Our research question is:

"How does providing contextual information affect student-chatbot interactions during an impasse?"

THEORETICAL FRAMEWORK

This section outlines conceptual ideas for the study of contextual information and how it affects student-chatbot interactions. First, we define and distinguish objective and subjective context, then we critically analyse the potential effects of objective context on interactions.

Objective vs. Subjective Context

Subjective context refers to the internal knowledge and experience of the student, such as thought processes, problem-solving strategies, interpretations, and areas of confusion or struggle. Subjective context cannot be directly given to chatbots, and the student must articulate it for themselves.

Objective context is outside the mind of the student and, at least theoretically, available to the chatbot. It includes *course-specific knowledge* (e.g., learning materials, local norms, domain specific abbreviations or conventions, learning objectives) and *student-specific knowledge* (e.g., feedback received, student's progress and temporal position within the course).

Integrated Context: helps or hinders learning?

In the absence of models in the literature, we begin by hypothetically analysing the potential benefits or risks of automatically providing educational chatbots with objective context. This theoretical framework will then be used to interpret the results of an initial study, presented in the remainder of the paper. We refer in short to chatbots 'with context' when objective context is automatically provided. We consider the benefits and risks of chatbots with context, and the same for chatbots without context.

Chatbots with context have two key benefits: first, it obviates the need for a student to articulate background information, enabling the student to focus on the impasse itself; second, it helps chatbots tailor their responses, such as giving more specific scaffolding.

The principal educational risk of providing context is that the chatbots may become 'too' helpful, or prematurely helpful. For example, they may prematurely reveal the answer to a task, reducing the effort, and therefore the productive struggle, of the student.

For a balanced view, we also consider chatbots without context, such that the student explicitly provides contextual information. A potential benefit is that, by students providing objective context, they may practice knowledge recall and identify their own knowledge gaps – these are productive steps in reflective learning.

There are also risks with chatbots without context. Articulating the context may impose high extraneous cognitive load and lead to counter-productive frustration (Sweller, 1988). One recognised coping mechanism is to copy-paste objective context – such as the entire task description – with minimal additional instructions (Wang et al., 2024; Tassoti, 2024). Copy/pasting negates the potential value of chatbots 'without context' and adds unproductive steps.

Table 1: Summary of a hypothetical analysis of the effects of chatbots with or without context

	Benefits	***Risks***
With Context	• focus on the impasse (lower extraneous load) • more effective scaffolding • technical accuracy	• superficial engagement (over-reliance, avoid productive struggle) • lost opportunity to articulate and reflect • lower student agency
No Context	• active knowledge retrieval • identify knowledge gaps • higher student agency	• high extraneous cognitive load • misunderstanding the context, e.g. irrelevant or erroneous scaffolding • technical errors • effort bypass (copy/paste)

A summary of our hypothetical analysis is given in Table 1, where we note the correspondence between diagonally opposite cells – the benefits 'with' context correspond to the risks 'without'; and vice-versa. It is therefore not immediately obvious whether automatically providing context is educationally beneficial. The remainder of this paper is concerned with obtaining empirical evidence to inform recommendations about the automatic inclusion of objective context when prompting educational chatbots.

METHOD

In this section we report on a study conducted using Lambda Feedback, a platform for interactive self-study (Johnson et al. 2025). The chat feature tested is illustrated in Figure 1. An underlying 'chat function' was created as part of this study. The chat function is an external, independent microservice for general use and can be used by any platform.

The study was conducted at a research-intensive UK university, where Lambda Feedback is used across four faculties. Work presented here is from a second-year cohort of 185 'mechanical engineering' students using the platform regularly for self-study tasks, to submit answers for automated formative feedback, and view step-by-step worked solutions.

The self-study tasks were formative (not summative) but comprised the main course of study, i.e. they were not additional tasks but were the core activity directly relevant for summative examinations. The cohort that participated in this study used the platform for 7 simultaneous academic modules, one of which was 'Fluid Mechanics' where the chatbots were enabled as a pilot.

Figure 1 illustrates the platform interface for a specific task. In this case, the chatbot was equipped with 'objective context' comprising:

- Content of the active question including all sub-parts ((a), (b), etc.),
- Step-by-step worked solution,
- Guidance including a blurb, expected duration (range of time) and skill level (three-star scale),
- Student's prior attempts and any feedback received,
- Estimate of the student's time spent on the active question and part.

The underlying LLM for the chatbot was *gemini-2.0-flash* with a system prompt composed of:

- Chatbot's role as a highly skilled and patient AI tutor with specific educational goals (e.g., guiding step-by-step, treating mistakes as opportunities, fostering critical thinking and active engagement),
- "Objective Context" as defined above,
- Output structuring instructions (e.g., keeping answers short, directly addressing questions within the context).

The chatbot feature was not visible to students by default and could be optionally opened. Students were informed about the chatbot's awareness. Provision for ethical use of the conversations for research was included in the privacy notice students agree to.

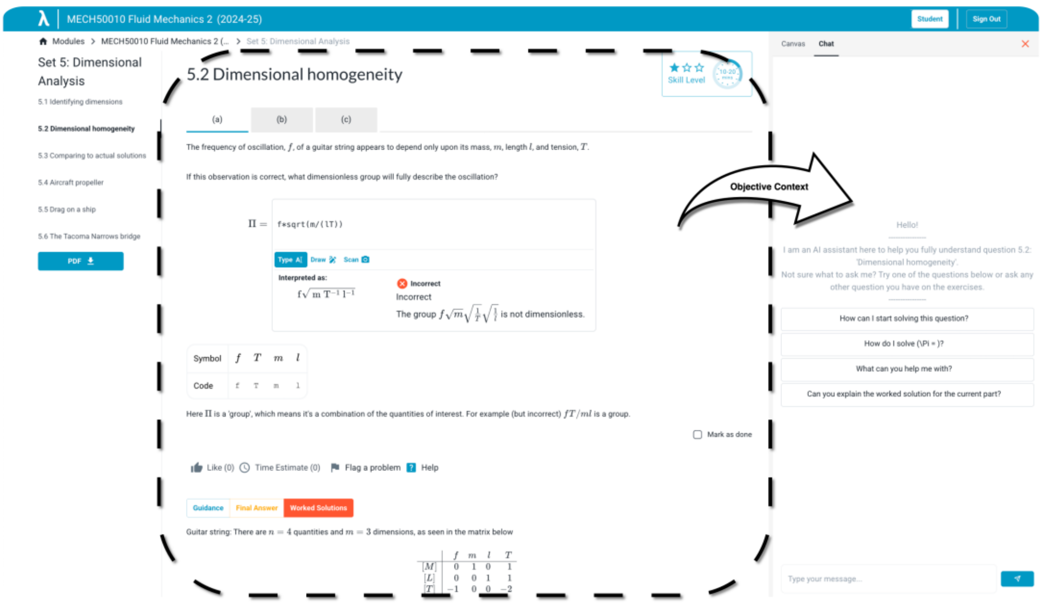

Figure 1: Student view of the chat functionality on Lambda Feedback

We conducted a qualitative analysis of conversations from 23 students across 37 exercises over one month, examining how students referenced the integrated context and how their conversations align with our theoretical framework.

RESULTS

This section presents key findings from our preliminary study on 65 conversations between a student and a context-aware AI chatbot. The main finding was that students often used direct references to the context, for example:

- *"can you explain part a",*
- *"can you explain the worked solution for the current part?",*
- *"for part d, we need a force equation for the bending moment. Can we use the momentum thickness for this?",*
- *"why can you use the Euler equations in part f?".*

The reference to contextual information by students contrasts sharply with more common interactions pattern for chatbots without context, where students would first need to manually provide the context before asking a specific question.

To quantitatively understand the referencing phenomenon, each of the 65 conversations was analysed. Figure 2 shows that 49 conversations (75%) included at least one reference to contextual information. Of those 49 conversations with references, in 38 cases (77%) the reference was in the student's first message.

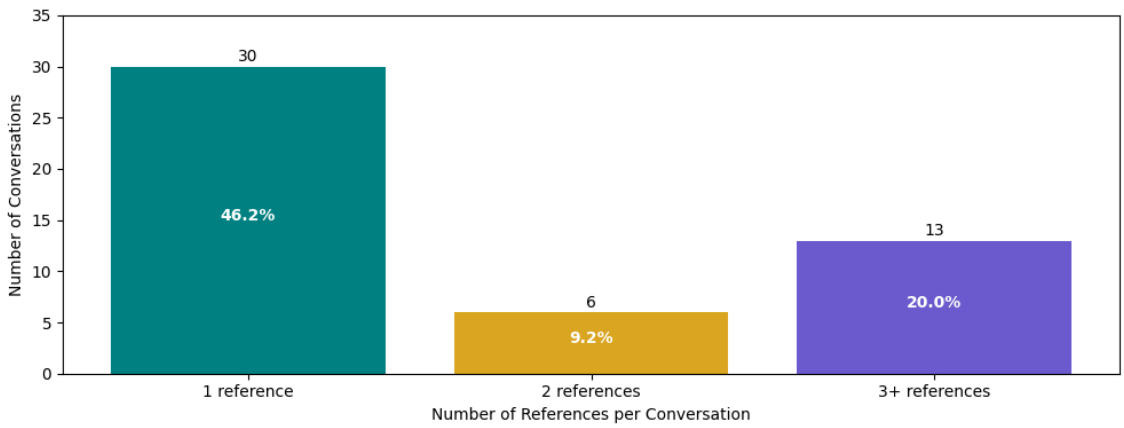

Figure 2: References to contextual information in 65 conversations

DISCUSSION

The pilot study of an educational chatbot 'with context' showed that in most conversations students referred to the context. These results validate one corner of Table 1 in our theoretical framework, namely that chatbots with context can help the dialogue focus on the impasse by removing extraneous load.

Our theoretical framework also identified potential risks of providing context, principally around the 'opportunity cost' of not articulating one's own problem. The study provided here does not directly provide evidence for the significance of this risk, because there was no control group using a chatbot without context. Such a controlled experiment would strengthen the evidence on the educational risks – the opportunity cost – of providing chatbots with context.

The absence of a control group 'without context' also limits the ability of the current study to inform conclusions on the benefits and risks of a chatbot without context. Studies in the literature do, however, confirm copy/paste behaviour that obviates any potential benefit of a chatbot without context (Wang et al., 2024).

Given the risks, established in the literature, that not providing context will simply lead to copy/paste behaviour, the more likely way to ensure that students own and articulate their problem – to the extent that it is educationally useful – is to use chatbots 'with context', through programming the chatbots to manage the support they provide. We used this approach here and we recommend this approach in future.

The study provided here is a pilot with several limitations. The theoretical framework of the research uses a constructivist approach embedded in WEIRD values, viewing learning as an active, individual journey. This lens shaped our interpretation of the data. The number of conversations (65) was large enough to reach qualitative conclusions but is only indicative of potential general trends. Therefore, while the empirical observations and our theoretical considerations are informative for any researchers developing educational chatbots, further research is required. Such studies would build more generalizable evidence, moving beyond initial insights. Nevertheless, the work presented here provides a valuable foundation for future research on the use of context by chatbots for education.

CONCLUSIONS & RECOMMENDATIONS

AI chatbots in education can be used for dialogic feedback at an impasse during self-study. In this paper we distinguished between 'subjective' and 'objective' context and focussed on the objective context. We studied the effects of automatically providing a chatbot with objective context about the specific task where the student is stuck and needs support. Our theoretical framework identified potential benefits and risks of providing context to the chatbot, in contrast to not providing context.

Our pilot study of chatbots with context showed that students usually refer to the context (49 of 65, or 75%, of conversations) and that this helps the dialogue focus on the impasse. This is key evidence to support the use of context with AI chatbots and is the main contribution of this paper.

We also discussed the opportunity cost of providing context, i.e. that students lose agency and the reflective benefits of articulating their context. While in theory a chatbot without context may insure against such a risk, literature shows that in practice students just copy/paste their context into a chatbot if needed. Therefore, we recommend chatbots with context, but with careful management of the educational risk of reducing student agency and losing the ‘productive struggle’ of articulating their context. Future research on chatbots should focus on this issue. Additionally, a controlled study of chatbots with/without context would enhance the evidence presented here.

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