# CAN A ROBOT TEACH DESIGN? LARGE LANGUAGE MODEL BASED FEEDBACK TOOL FOR ENGINEERING DESIGN COURSES

**M. Lim**[1]
School of Chemical Engineering, The University of New South Wales
Sydney NSW 2052, Australia
ORCID: 0000-0001-7210-7083

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## ABSTRACT

This practice paper report the use of by Inflection AI's Pi chatbot and Azure OpenAI GPT-3.5-Turbo and GPT-4 APIs to provide insightful and timely feedback across written, oral, project-based and team-based assessment tasks in a level 2 capstone engineering design course. The Large Language Model (LLM) driven AIs can text and audio based artefacts submitted by students, including short written tasks, draft reports, pitch presentations and meeting transcripts. This in turn allows course instructors to address students' learning needs more efficiently and effectively. The present work further demonstrated there are still limitations and barrier to full implementation of AI-assisted feedback in the classroom. Unless trained on specific content, LLM-driven AI lacks nuanced contextual understanding. For some students, the AI generated feedback did not appear to develop or improve the student's metacognitive abilities or their self-regulation of learning. At the time, use of LLM-driven AI for feedback was hindered by an absent of toolchain for data capture and processing, as well as the lack of an institutional level AI strategy and roadmap, partnerships to bridge capability and capacity gaps, robust guiderail and policies around the use of AI in the classroom. The final section of this paper outlines strategies that can be used to address these limitations and how the needs of academics who intent to apply LLM-driven AI in feedback practice should be supported.

[1] *Corresponding Author (All in Arial, 10 pt, single space)*
*M. Lim*
*m.lim@unsw.edu.au*

## 1 INTRODUCTION

Design is generally considered a core competency in undergraduate engineering education and a main component in value creation. The modern engineer is also expected to possess the necessary technical, project management, communication, and teamwork skills needed to deliver the best design solution. As such, many engineering schools have introduced project-based design courses into their curriculum to better align engineering theory with practice. Students are given opportunities to work on authentic problems, and some recent developments include the teaching of user-centred approach such as design thinking (Charosky et al. 2022).

While authentic, real-world based design courses have been reported to engage and motivate students more effectively, their implementation in large class remains a challenge (Heller et al. 2010). Engineering students often have difficulty conceptualising and contextualising user-centred problems solving, particularly if it is their first exposure to the approach. Some students also had the tendency to switch immediately to solution mode, skipping or rushing through the user research stage of the design. Teaching strategies that are based on project and collaborative learning are also vulnerable to the students' lack of project management and teamwork skills. The issues that can hampered a student progress in a design course are also difficult to detect and address, particularly in large classes with high student to staff ratio.

A way to overcome the abovementioned issues and improve the learner experience in project-based design courses is to provide timely feedback that is aligned with the course learning outcomes and learner needs (Gülbahar and Tinmaz 2006). In recognition of this fact, engineering educators have embraced various feedback tools and strategies to improve student's feedback literacy in their practice (Coppens et al. 2023, Gilbuena et al. 2015). Peer feedback, for instance, have been shown to foster a culture of constructive criticism and continuous improvement among students, while enhancing their ability to provide and receive feedback effectively (Dong et al. 2023, Tai et al. 2018).

Another important development is the increase affordance of digital platforms. Learning analytics and educational data mining offer promises in enhancing students' learning in design courses through early intervention, individualized feedback mechanisms and improved workflow (Xing et al. 2023). Recent development in LLM-driven AI, as exemplified by ChatGPT, Open AI's widely accessible web based chatbot, further reshaped the landscape (Bauer et al. 2022).

Several investigators have reported the use of LLM-driven AI to generate feedback for written and programming tasks (Dong 2024; Escalante 2023; Mahapatra 2024; Husain 2024; Sun et al. 2024; Wilson et al. 2024; Xiao and Zhi 2023). Banihashem et al. (2024) found a statistically significant difference between the feedback generated by an AI and student peers for a written task. Using statistical methods, they showed the former was more descriptive while the latter was better at identifying deficiencies in the written task. Nonetheless, the quality of both types of feedback did not affect the quality of the written task. Instead, a positive correlation was found between the former and the affective features present in the AI-generated feedback.

So far, the consensus in the literature was that LLM-driven AI has the potential to alleviate the challenge of providing feedback to large classes and to promote self-regulating skills such as feedback seeking, goal-setting, and progress monitoring (Guo 2023; Hopfenbeck et al. 2023; Li and Kim 2024). Subtle variations remain in how students and teachers perceive the trustworthiness of AI-generated feedback. Barrett and Pack (2023) noted a disagreement between students and teachers concerning the acceptable use of LLM-driven AI tools for generating feedback for written tasks. Ding et al (2023) found physics students held misconceptions about the capability of LLM-driven AI, with nearly half of the students trusting LLM-driven AI generated answers even though the AI only has 85% accuracy. Contrarily, Tossell et al (2024) found students were not confident in the feedback generated by LLM-driven AI and did not trust its' use as an independent evaluation and feedback tool. Darvishi et al. (2024) found students tended to rely on, rather than learn from, AI. Moreover, supplementing AI assistance with self-regulated strategies did not yield significant advantages over relying solely on AI assistance.

Taken together, these findings suggest a complex dynamics between the use of LLM-driven AI to generate feedback, attainment of learning outcomes, and student's perception of the tool which requires further exploration and elucidation, and for learning tasks other than writing or programming. The present study examine how LLM-driven AI can be employed to monitor or evaluate the quality of formative written and oral assessment tasks, as well as team interactions and contributions in a 10-week long project based design course. The course was taught to level 2 chemical engineering students with the aims of developing the students' design thinking and professional skills. Outputs from the LLM-driven AI were also used to provide tailored and immediate feedback to individual students (class size = 54 students). The use of AI generated feedback as a complement to instructor and peer feedback was also explored.

## 2 METHODOLOGY

Due to the rapidly evolving nature of LLM-driven AI technologies in 2023, a design-based research methodology was applied in this study (Holland et al. 2019). Instead of pre-defining and controlling all variables in the study, a variety of LLM-driven feedback mechanisms were introduced to support students in different formative tasks at various stage of the course delivery (see Figure 1). The outcome of each intervention which were then used to guide subsequent feedback mechanisms design.

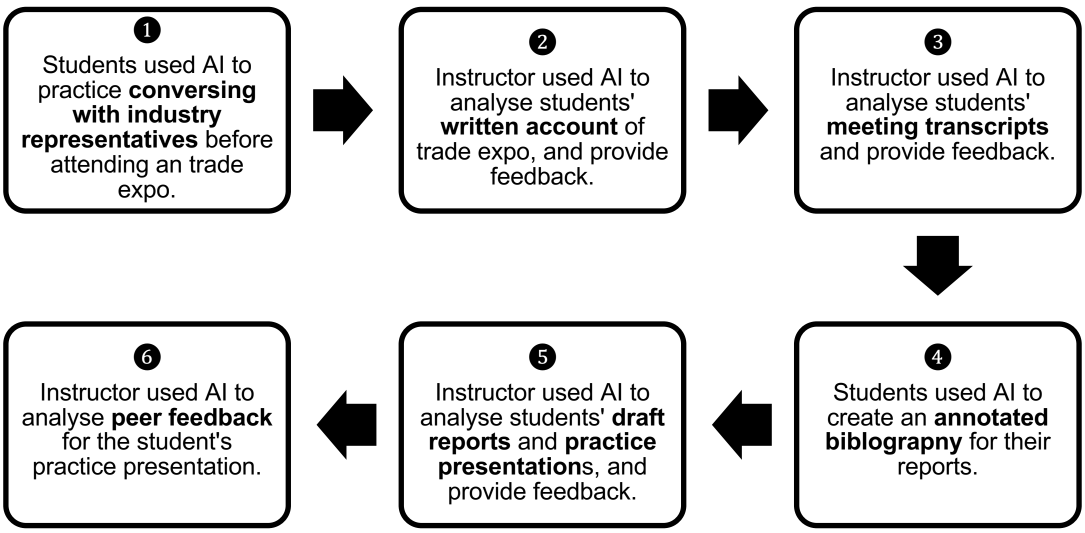


*Fig. 1. Schematic of the design-based approach.*

At the start of the course, students role-play conversation with industry representative at a trade show with Pi, a chatbot by Inflection AI's, via a web interface (see text box marked '1' in Figure 1). Based on Inflection's proprietary LLM Inflection-1, Pi was designed to maintain an interactive text or voice-based dialogue with a human user in personable manner. It was for this reason which Pi was selected over other chatbot at the time.

The students then attend a trade show that is related to the course. The students were assigned the task of sharing their experience, observations and conversations with industry representative at the trade show on Padlet, a virtual bulletin board. The instructor downloaded the student's accounts of their interactions at the trade show as a CSV file and summarised the submission using Azure Open AI's gpt-35-turbo model via the API (see text box marked '2' in Figure 1).

Throughout the course, the students who were assigned to teams of six students. The student teams held regular online meetings on Microsoft Teams outside of class time. In these meetings, collective sensemaking, brainstorming, planning and decision making about the design solution occurred. The meetings were setup to automatically record and generate a transcript at the end. The transcripts were analysed periodically using Azure Open AI's gpt-4 model via the API (see marked '3' in Figure 1).

Mid-way through the term, the students had to submit draft of their reports and practice pitching their design solution individually as formative tasks for end-of-term summative assessments that are worth 60% and 20% of the total mark, respectively. As part of the report writing process, the students were instructed on how to use elicit.org, an AI research tool which can create annotated bibliography from articles the students have found (see text box marked '4' in Figure 1). It should be noted here that the use of elicit.org is not mandatory, but students were evaluated based whether they can accurately gauge the quality and relevancy of the articles they have selected for their report. The draft reports were all written 'from scratch' on Microsoft Word documents that were saved to a SharePoint library.

The practice pitches were recorded during class time in the same way as the students' meeting. Both type of submissions were summarised by the instructor using Azure Open AI's gpt-35-turbo model via the API (see text box marked '5' in Figure 1). When a student was practicing their pitch in class, other students who were in the audience were required to provide peer feedback on the quality and content of the pitch on Padlet. The instructor downloaded the students' feedback as a CSV file and summarised them using Azure Open AI's gpt-4 model via the API (see text box marked '6' in Figure 1).

A survey with two sets of questions was developed for this study. The first set of questions, derived from the work of Brookhart (2017), Haughney et al. (2020), and Carless and Boud (2018) surveyed students' feedback literacy and experiences of feedback practice. The second set of questions explored students' experiences and perceptions of AI-assisted feedback. This includes comparing the perceived quality of feedback generated by or with the assistance of AI, to that of their instructor, and peers. A total of 17 students' responses were received (32% of cohort). This is typical in an academic setting, and is due to the fact that the students were only invited twice to complete the survey in order to reduce the number of inauthentic responses.

The survey data was complemented by autoethnographic account of the instructor's experiences of implementing the LLM-drive AI interventions in their course. Here, 'auto' relates to a focus on personal experience; 'ethno' relates to the study of a culture; and 'graphy', refers to a systematic process for describing and analysing both personal and cultural experience arising from the study (Ellis et al. 2011). The act of self-enquiry by an author-instructor who had designed the present design course from scratch and has good insight into the support needs of their students can lead t0 a deeper and more nuanced understanding of LLM-driven AI use in teaching practice (Mao et al. 2023).

## 3 RESULTS

### 3.1 Instructor's Account of Developing AI Feedback Tools for a Design Course

In an essay on constructionism, Harel and Papert (1991) described two styles of solving problems. One is the methodical and analytical method of problem solving that is familiar to many engineers. The other is 'bricolage', which is a way to learn and solve problems by tinkering, that is, trying, testing, learning, and iterating. More recently, the term bricolage was used when referring to an innovation practice that is based on using the least amount of immediately available resources, usually in a resource-constrained context (Bouvier-Patron, 2021).

The instructor was first exposed to LLM-driven AI in early December of 2022, immediately after ChatGPT was launched. The disruptive and somewhat unpredictable nature of LLM tools has generated excitement and academic integrity concerns among the education community on social media. The ensuring Christmas break afforded time for the author-instructor to tinker with ChatGPT and Open AI's APIs. At this stage, the instructor found their prior expertise in the subject matter, experience in learning design, and intuition on what will or will not work in the classroom is critical. For instance, the instructor soon realise some of the response generated by the LLM-driven AI is superficial and unreliable. The instructor experience at this stage is akin to traditional bricolage as defined by Papert.

It later became clear that the toolchain needed to deploy AI tools and apps in a manner that met the institution's data, privacy, cybersecurity policies are not immediately unavailable to teaching staff. The cost of Open AI's premium subscription and APIs needed to process large volume of input is also prohibitive. Through their professional network, the instructor was able to secure access to non-production Azure Open AI GPT-3.5-Turbo and GPT-4 APIs via their institution's Microsoft O365 tenancy. Using a citizen development approach, i.e. simple Python scripts and in-built speech-to-text (STT) function of the Office suite applications (e.g. meeting transcript in Teams), the instructor deployed basic LLM-driven feedback tool in their course (McHugh et al. 2023). Here, the instructor felt their experience aligns more with contemporary bricolage where resource constrain necessitate the use of resource that are already available.

Towards the end of the development cycle, it became clear to the author-instructor that any LLM-driven AI tools developed in-house for education purposes or otherwise will not scale easily. For innovation around LLM-driven AI to thrive, the institution will have to develop the following: (1) Short and long term AI strategy and roadmap; (2) internal or external partnerships that bridges the institution's capability and capacity gaps; (3) robust guiderail and policies around the use of AI in the classroom; (4) program to identify and upskill teaching staff wanting to upskill; and (5) process for scaling and translating successful implementations.

### 3.2 Student Experience and Perception of AI Assisted Feedback

Figure 2 shows students' responses on a Likert scale to questions on receiving (top-left) and giving feedback (bottom-left). Both chart shows in general, students are comfortable with giving and receiving feedback. The more negative response appeared to be related to managing affect.

The responses to the open question "**Can you describe your experiences with giving feedback?**" contained a mixture of positive and challenging experiences. Most individuals expressed difficulty and anxiety over the process, highlighting concerns about the time required, difficulty in evaluating tasks against guidelines, and potential negative outcome for the reviewee due to incorrect feedback. Only one individual was appreciative of peer feedback, noting the mutual learning aspect as an inherent benefit.

The open question "**Can you describe your experiences with receiving feedback?**" resulted in a range of responses. Some individuals reported the feedback they received was beneficial, aiding in improvement and learning. There are also instances where feedback is seen as non-constructive or substandard. Complaints include feedback being vague, shallow, too brief, not enough justification for marks given, or that it didn't align with the student's expectations.

The responses to the open questions "**What guidance have you received to date on giving feedback?**" indicate students have received inconsistent levels of guidance on how to give feedback. The response  ranging from "none" to needing to several individuals noting that they were instructed to adhere to a rubric, and to provide feedback that were actionable, specific, and constructive.

Taken together, these response suggested the negative affect maybe due to quality of feedback received by the students. Carless and Boud (2018) reported that feedback can have varied affective effects depending on the student's self-confidence, motivation, and emotional management skills. The feedback's tone and feedback provider expressed care for students also significantly influences student reaction. Here, the student may have perceived a lack of care after receiving poor quality feedback, i.e. feedback that are generic or unconstructive. This in turn maybe due to poor instruction received by students and graders on how to give constructive feedback.

Figure 2 further shows student's responses on a Likert scale to questions around receiving AI assisted feedback (top-right), and perception of the feedback quality relative to feedback provided by course instructor and peers (bottom-right).

It is interesting to note in that while the responses to AI generated feedback is generally positive, the students did not perceive the feedback to be better (or worst) than feedback provided by their instructor or peers. This response can be explained by the fact that most of the feedback produced by the LLM-driven AI will lack nuanced contextual understanding is unless it is trained on specific content (which it is not in this study). Hence, the utility of the feedback is similar to that produced by a human.

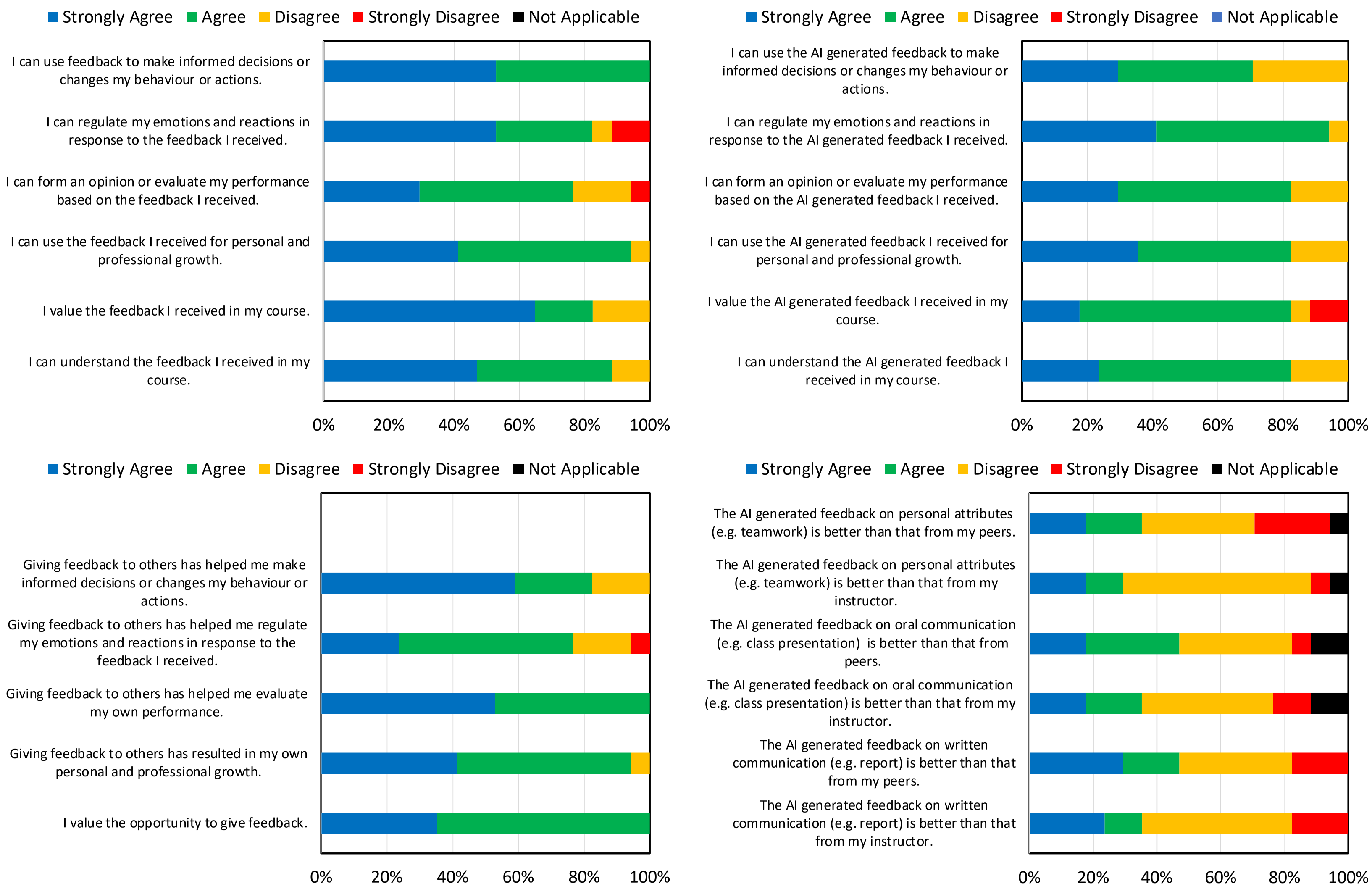


*Fig 2. Students' responses on a Likert scale to questions around receiving feedback (top-left), giving feedback (bottom-left), receiving AI assisted feedback for different formative task (top-right), and their perception of the feedback quality relative to feedback provided by course instructor and peers (bottom-right).*

The responses to the open question “**What guidance have you received to date on AI generated feedback?**” was peculiar in the sense that there was huge variability in experiences with guidance on AI-generated feedback. Some student indicated that they have received no direction at all. Other student noted that they have been advised by the instructor to view AI feedback critically, not to take the AI generated feedback too seriously, which suggest the student was aware of the limitations of AI and the need for human judgment.

Finally, the responses to the open question “**Can you describe your experiences with AI generated feedback?**” provide insights into the student’s varied experiences involving AI-generated feedback. Some students found AI feedback valuable, helping them enhance their work through recommendations. Others, however, reported negative experiences where the AI failed to accurately assess their work, as discussed previously. There appeared to be a recurring theme in the response regarding how the AI had failed to recognise some sections of reports, or failed to capture certain aspects of team contribution.

## 4 SUMMARY AND ACKNOWLEDGEMENTS

LLM-driven AI can improve student learning in design courses by offering tailored and immediate feedback on written, oral, and team-based formative tasks. However, integrating AI-generated feedback into courses presents some challenges. It involves an ongoing process of tinkering, iterating and adapting, often within a resource-constrained context. Expertise in the subject matter and experience in learning design are important factors for successful implementation. Moreover, scaling the use of AI in feedback practices would require an institution-wide strategic approach. This includes developing an AI strategy and roadmap, forming partnerships and innovation pathways to bridge capability gaps, establishing robust policies and guardrails for AI use in classrooms, identifying and upskilling teaching staff, and creating processes for scaling and translating successful implementations.

Students' experiences with AI-generated feedback further reveal a complex interplay of factors influencing their perceptions and reactions. While students generally have good feedback literacy, and are comfortable receiving AI-generated feedback, the quality of the AI-generated feedback can significantly impact their experiences. Future development should include fine-tuning the LLM-based AI to produce more nuanced feedback.

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