

UNDERSTANDING GENAI USE IN STUDENT ENGINEERING DESIGN WORK: INSIGHTS FROM A PILOT INTERVIEW STUDY

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ABSTRACT

Generative AI (GenAI) tools are increasingly capable contributors to design work, though human judgement in design ideation and decision-making remains essential. Design learners' use of GenAI tools is shaped by characteristics of the design task, their own skills and attitudes, and the broader learning context. Student-AI interactions unfold within a complex "jagged frontier" - a boundary where AI excels in some areas but may degrade design process and outcomes in others. For design educators, helping students navigate this frontier through guided, hands-on experience is an emerging pedagogical challenge. This pilot study investigated how three undergraduate engineering students used GenAI in the early stages of design, and its perceived benefits and limitations. Using an adaptation of the echo interview method, each student was interviewed twice – following individual and group projects respectively - during a third-year engineering "pre-capstone" design course that explicitly integrated instruction on effective GenAI use. Students used GenAI primarily for research, ideation, and writing support, citing efficiency as the key benefit. They developed verification practices and prompting strategies largely through peer learning and individual experimentation rather than formal instruction; this over-reliance on peer networks may not benefit all students equally. A perceived negative impact on creative exploration also emerged, with students tending to settle for "good enough" AI outputs under time pressure. Findings offer preliminary recommendations for design educations seeking to integrate GenAI in ways that foster effective, critical, and inclusive design practice.

Keywords: Problem definition, design projects, Generative AI, qualitative, student experience

1 INTRODUCTION AND MOTIVATION

Organisations are rapidly integrating AI across operations including product design, making AI proficiency a baseline expectation for employees and new hires. Generative AI (GenAI) tools now match or surpass human performance in many design tasks, though human oversight in design ideation and decision-making remains essential [1]. Integrating AI into design work introduces a complex "jagged frontier" [2] - a boundary where AI excels in some areas but may degrade decision making in others. Understanding these limits is critical given limited formal AI education in design curricula [3] and evolving AI capabilities [4, p. 142]. Becoming "expert designers in the loop" - thoughtfully integrating AI tools while maintaining critical oversight - requires practice and reflection.

Design practice is shaped by the socio-technical context in which design unfolds [5]. As such, student adoption of GenAI in design is shaped by characteristics of the task, the student, and their broader context [6]. Navigation of the jagged frontier is thus unlikely to be uniform; variation in prior AI exposure, confidence, and access may introduce new forms of inequity into design learning.

This research investigates how undergraduate engineering students use GenAI in early stages of design, and how this use affects their design thinking, behaviours, and self-efficacy. Specifically, we ask:

- 1) In what ways do students integrate GenAI into early-phase design tasks?
- 2) What benefits and limitations do students perceive?
- 3) How do socio-technical contextual factors shape the nature and extent of GenAI use?

Findings of a pilot study highlight student-identified use cases and inform recommendations for design educators seeking to integrate GenAI in ways that foster effective and responsible practice.

2 METHOD

The study setting was a 13-week third-year management engineering design course at the University of Waterloo, Canada, in fall 2025. The course acts as “pre-capstone” and serves two primary roles in the curriculum: 1) offer training in engineering design methods, especially those most relevant to the early phases of the design process, and 2) provide multiple structured opportunities for students to develop skills in problem finding, analysis, and conceptual design. Students are encouraged to take an analysed problem from this course into their capstone design courses in fourth year. Capstone projects in this discipline are typically software-based decision support tools that leverage AI, analytics, and optimisation approaches. The instructor explicitly integrated instruction on effective use of GenAI tools throughout the course, providing examples of how AI can support key tasks (e.g., publication research, developing interview questions). Figure 1 shows the complete course timeline.

This study (REB #47748) was designed as a pilot to establish and test the interview protocol with a small participant pool. Three students – all male – were recruited to participate. While each had some prior experience with GenAI tools, the nature and extent of that experience varied considerably – from personal use (e.g., to study) to intensive professional use on industry internships, providing a range of perspectives within a small sample. Each student was interviewed twice in the term, at the conclusion of two cycles of open-ended problem finding and analysis (highlighted in pink in Fig. 1) – the individual project in weeks 1 to 6, and the group project in weeks 7 to 13. This design enabled the capture of changes in design reasoning and GenAI tool engagement over time.

Week	1	2	3	4	5	6		
In class instruction	Course intro	Problem finding	Analyzing needs	Research with secondary sources	Research with primary sources	Problem framing & conceptual design	Design Comms	Design thinking
Project	-----Individual project-----							
				M1	M2			M3
		7	8	9	10	11-13		
		Requirements analysis		Design impact				
		-----Group Project-----						
		Group formation, topic selection		M1	M2 - peer critiques		M3-design reviews	
		First set of interviews					Second set of interviews	

Figure 1. Course overview and alignment with two sets of study interviews

The six interviews (each 60 min to 90 min in length) were conducted by 2-3 members of the research team and were structured in three parts. In *part 1* participants assessed their prior experience and confidence in both design and GenAI use, relative to their peers. In the first interview this was framed around starting a new design project; in the second, participants reflected on how their skills and perceptions had developed over the course and looked ahead to future academic and co-op (industry internship) experiences. In *part 2*, participants described their current design problem, key tasks performed, challenges encountered, and any resulting plan changes. As they spoke, interviewers noted elements in the students’ context (influences), including people (e.g., instructor, TA, peers) and social and technical factors (e.g., course materials, technologies, project instructions). In *part 3*, an adaptation of the echo interview method (as described in [5]) was used to investigate how elements in the students’ socio-technical context influenced the nature and extent of GenAI use in their design tasks. Participants identified actions or decisions that made the task more challenging, then ranked the socio-technical factors described in part 2 according to impact on their task. For each influence, they provided examples of the ways these influences had been helpful or unhelpful.

The six transcripts were coded by the first author using a mix of deductive and inductive analyses. Deductive coding was guided by the questions in the interview protocol (e.g., self-assessed confidence in GenAI use, contextual influences), while inductive codes captured other topics or patterns that emerged in the interviews. This process resulted in 283 unique codes applied across 622 excerpts, which were iteratively grouped into eight themes. Coding and thematic grouping were then verified by a second member of the research team. One of the themes (46 codes over 148 excerpts) comprised all excerpts that related to GenAI use, and is the focus of this paper, as detailed in the next section.

3 RESULTS

Two sub-themes illustrate how students incorporated GenAI into their workflows and how they responded to the tools' limitations, as detailed below. Student quotes have been minimally edited for clarity and brevity.

3.1 GenAI uses cases and benefits

Students described GenAI as a practical support tool integrated into their design workflow rather than an all-purpose solution. In line with the scope of the course (viz. early stages of design) students used GenAI primarily in three areas: 1) in problem research (to identify related problems, generate initial research directions, develop search queries, identify sources, and summarise lengthy reports or technical documents, 2) in ideation and prototyping (to generate low-fidelity concepts as inspiration, or preliminary user interfaces from text prompts, and 3) as writing support and quality assurance (to review drafts against deliverable criteria, generate outlines, refine tone and clarity, and reduce word count). Students selected tools based on task needs: Copilot for coding tasks, ChatGPT for writing and general reasoning, Gemini for image generation or tasks requiring numerical precision, and Perplexity for consolidating research information. Some described preferring to rely on AI tools they personally found more effective rather than built-in platform assistants – *“we all have our own AIs that we prefer using ... what we're comfortable with and what we think will give us a better output.”*

Students described several ways GenAI supported their course and project work. The most common benefit was increased efficiency. They noted that time pressure influenced when they turned to GenAI: *“I think GenAI wasn't something initially that we had in mind... the time crunch we had for our second milestone [is] why the GenAI was incorporated”*. Participants noted different ways that LLMs helped them expedite their research workflow, including screening large sets of materials, extracting potential quotes, and compiling sources, which allowed them to spend more time on verification and synthesis:

“I do think it does make a lot of these processes more efficient because it does that initial like processing step for, not necessarily for you because you still have to verify that the information is correct, but for you in the way that you don't have to look through a million sources that Google search presents to you ... Now LLMs check if they're relevant and then give you a list so that you can check if they're correct or not.”

One participant noted that Gemini supported their design tasks by speeding up early concept development and reducing repetitive work they had to do with Figma (a user interface prototyping tool): *“...having that initial idea from the conceptual design created using Figma in a [smaller] amount of time was very efficient for us”*. Another participant described how GenAI helped them broaden their research, identify new research directions when they felt stuck, and notice important details they might otherwise overlook:

“I think before I used AI... I felt a little bit overwhelmed because I was kind of stuck on where I should go next or what should I use for my potential solutions... that's when I started moving to Chat [GPT] and then with [it] I was able to kinda get myself back on track.”

Students developed their GenAI practices through a combination of peer learning and individual experimentation. Participants described sharing workflows, recommending tools to teammates, and adopting new models after seeing how classmates used them: *“I'm continuously learning by like having conversations with ... classmates as well as like friends from other [engineering programmes] ...learning how they're using it in their fields”*. Students described improving their prompting through *“trial and error”*, learning not only to adjust prompts but also to guide the model toward desired outputs – *“I have to kind of structure it sometimes in a certain way to kind of push it into the right answer that I want”*. Two participants reported relying primarily on prompting styles that felt natural to them, one noting that their informal approaches often worked as well as the structured prompting guidance provided in class: *“[instructor's way of prompting] was only different with the structure, so hers were a lot more like professional... but when I talked to Chat[GPT], it's very like scrappy... I don't think in quality... there is much of a difference”*. While instructor guidance may have served as useful background knowledge, students' own habits and preferences ultimately shaped their prompting strategies.

3.2 Recognising and responding to GenAI limitations

Students frequently encountered problems such as hallucinated citations, broken links, inconsistent answers, and numerical errors. There were also noted limitations stemming from model training data,

with noted difficulties in finding recent or rapidly evolving information: *“some of [the new articles] won’t be there because the data have been trained up on them and they are fairly new. So [Chat]GPT tends to give out the ones that are not yet updated”*. The rapid pace of model updates introduced another layer of uncertainty: *“as the model’s improving, it’s trying different outputs as well. So, you could ask the same thing in like two different Chat histories and then it might output different results.”*

To address these concerns, students relied on multiple ways of verification. One participant described cross-checking outputs across different models to assess consistency and reliability:

“I have used like Gemini to compare to [Chat]GPT and then in terms of code I know Claude is like one of the top performing models for coding, so I’d use that to compare to like traditional GPT models, etc. To see which one’s more efficient, which one’s easier to use, and which outputs are more consistent.”

This cross-checking extended to validating AI-generated findings against original sources:

“...then once Chat [GPT]... give us a list of things or a list of quotes that we can use and then we’d go back, make sure that all the quotes are there and then just do a quick skim to make sure everything’s fine and then ... use that as a source for a lot of our research.”

Verification thus became a routine part of their workflow, adding additional time to refine prompts and confirm the accuracy of GenAI-generated information - *“it just wasn’t understanding what I wanted and it outputted something like completely random...[which required] more time kind of fixing my prompt to get it back to where I want it to be”*. For source credibility specifically, one student noted that asking ChatGPT for credible sources could double the time needed to find one.

Despite these challenges, students did not believe GenAI use affected the overall quality of their work, given that they still verified sources: *“As long as you have that like initial structure in mind, I don’t think the quality will dip because you’re still vetting the information and you’re still like synthesising your conclusions from it individually...”*

Students also faced uncertainty about acceptable use of GenAI, especially when expectations varied across courses. Even as GenAI has become more normalised, students were still navigating unclear boundaries around what was academically appropriate: *“I couldn’t tell if maybe I was using too much AI or too little AI, so I feel like that fine line is still really fine on what is morally right to use for this and what’s not”*. They were thus attentive to aligning their use of GenAI with course expectations, noting that these rules had loosened over time:

“I remember earlier on they were very strict on no AI and then the more that it’s developing, the more they’re like OK, maybe we can kind of shift how we structure it. So, you can use it more... another example is my last STAT [course] ... [the professor] said do all the math by hand...the write up you can make AI do it. I don’t care.”

Students also grappled with how they perceived AI use affected their design thinking and behaviours. For example, one described feeling that relying heavily on AI-generated visual concepts reduced their creative exploration, noting a tendency to settle for outputs that looked “good enough” rather than generating alternative concepts, particularly when teams were working quickly:

“Oh, I think it sort of takes our creativity as, away from us at some point, because we might not come up with things on our own..., it sort of restricts our creativity at like a certain level, I guess that would be a drawback that I would say...I think it sort of creates a mindset of it’s enough like this sort of looks OK, so we don’t try to go above and beyond...”

One way in which students described retaining some of their agency in the design process was by evaluating GenAI outputs selectively rather than adopting them wholesale. For example, in front-end design work, they explained keeping AI-generated elements that aligned with their design goals and discarding parts that did not fit. GenAI’s usefulness thus varied depending on the complexity of the task:

“...in the broad aspect of things, for example where our navbar should be ... or like where our search button should be ... it was pretty similar, but for example how our graph should look like or how our accountability page or like the peer pressure aspect ... was completely different. So, it completely depends on the complexity of things.”

Here, GenAI served as a mid-process aid for exploring layouts rather than a substitute for careful design refinement. It was helpful for generating initial directions, but the student remained selective in what they adopted. While broader layout suggestions were often usable, more complex or context-specific elements required human intervention.

4 DISCUSSIONS

4.1 Key findings and implications

This pilot study set out to understand how undergraduate engineering students integrate GenAI into early-phase design tasks, what benefits and limitations they perceive, and how socio-technical contextual factors shape the nature and extent of their GenAI use. The results broadly align with other research exploring undergraduate engineering students' use of GenAI in design. Findings about the use of GenAI in the early stages of design [7], [8], [9] and writing [10] are consistent, as are those reporting on perceived improvements in efficiency [11], [12] and quality of work [10], [13], and the challenge of verifying GenAI output [10]. Acknowledgement of whether the use of GenAI is acceptable is noted - while a previous study indicates that students do consider the ethical considerations and design authenticity, they are "secondary to perceived functional advantages" [7]. Notably, students in this study developed prompting strategies and verification practices largely through peer learning and individual experimentation rather than relying on the available formal classroom instruction on effective AI use in the design process - suggesting that AI literacy in design education may be emerging unevenly, shaped by students' social networks and prior exposure as much as by curriculum.

There are two key areas where the current study strays from previous research. First, students in this study perceived a negative impact on their creativity – settling for “good enough” AI outputs rather than exploring alternatives. This is counter to students in other studies who are motivated to use GenAI to improve their creativity [10] or who experience a positive impact on their creativity [11]. In this study, the risk appears most acute in visual ideation tasks under time pressure, where AI-generated outputs can appear convincing enough to discourage further exploration. Educators may be able to mitigate this by requiring students to generate and document their own concepts independently before engaging GenAI, preserving the divergent thinking that early ideation is meant to develop. A second point of divergence from the literature was noted in the reported verification of GenAI results during the design process, which appears counter to studies that report students frequently accept GenAI responses without rigorous verification [7] and develop an over-reliance on unverified GenAI output [8]. This may reflect the explicit attention given to verification in this course - pointing to the value of directly teaching critical evaluation of GenAI outputs as a core design skill, alongside prompting and tool selection.

The shared findings and new insights reflect the everchanging landscape of GenAI use in the engineering design process and its highly contextual nature [5], [6], and reinforce the need for design educators to move towards actively shaping how students engage with GenAI across diverse learning contexts.

4.2 Limitations and future work

This research was a pilot study, and as such there are important limitations to consider. First among them is the small participant pool (three students, each interviewed twice). Compounding this issue, two of the students were in the same project group for the second half of the course, potentially limiting the breadth of experiences/perspectives captured in the study. This limitation was evident as each interview continued to unearth new insights with limited repetition between participants. Clearly, the study would have benefited from including a larger sample population. Finally, the course the students were recruited from was focussed on the early stages of the design process, and so the uses of GenAI were limited to those stages as well. So, while there was mention of using GenAI to quickly develop prototypes of user interface designs, GenAI uses in code generation (for example) were outside the scope of the study.

This study was conducted in an engineering programme which typically generates software-based solutions to problems. This limited the applications of GenAI tools to use cases that aligned with this context. Future research could utilise a similar research approach to look for novel applications to other engineering domains (e.g., mechanical or electrical design). More generally, future studies could also intentionally recruit across diverse student populations – varying in prior AI exposure, demographics, and institutional context - to explore how these factors influence the nature and extent of GenAI use in design, and how students evaluate different trade-offs that may emerge [5].

Future studies could also explore student uses of GenAI tools with more depth. For example, study designs with verbal protocol analysis could investigate student uses during a live design task instead of relying on self-reports. Additionally, analyses of generated artifacts/assignments/AI chat logs may provide a broader perspective on the uses of GenAI tools across an entire student cohort.

5 CONCLUSIONS

This pilot study aimed to capture engineering students' use of GenAI during the early stages of design, and how it affected their design thinking and behaviours. Students integrated GenAI pragmatically, primarily for research, ideation, and writing support. They developed prompting strategies and verification practices largely through individual experimentation and peer learning, rather than formal instruction. Notably, students showed critical awareness of GenAI's limitations, including outdated training data and the risk of loss of creativity under time pressure. Findings suggest that educating "expert designers in the loop" may require not only introducing GenAI tools into the curriculum but also attention to how students develop AI literacy, including the ability to evaluate AI output, and ensuring these opportunities are accessible across diverse student populations and socio-technical contexts.

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