Exploring the Influence of Generative AI on Engineering Students' Learning Experience

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1. Introduction

Engineering Education (EE) is facing a substantial change with the integration of advanced tools like Artificial Intelligence (AI) [1]. Generative AI (GenAI) offers interactive learning environments where students can have dynamic conversations [2]. GenAI functions as an invaluable learning aid that gives students immediate and personalized feedback that is tailored to their specific requirements. This instant help enables students to quickly clear up misunderstandings or resolve difficult concepts on their own schedule while working alongside the comprehensive and in-depth feedback instructors provide [3]. As GenAI adoption grows, its effective integration holds the potential to improve personalized learning experiences and enhance engagement [4]. Several studies have presented GenAI's potential in education [5-8], yet there remains a notable gap in understanding its effective integration into *engineering* education. Existing studies [9-11] do not fully capture student experience and there is a lack of deep understanding. Mainly on *how* and *why* they choose to use these tools, as well as the personal tactics they employ to weigh the benefits against the potential drawbacks. Such a lack of insight is a concern to engineering education because it is a shift from the end-product (code/solution) to the process. As the learning process is unclear due to GenAI, the insights the educators gained are being obscured. Recent research warns that this 'cognitive offloading' can lead to 'cognitive debt', where students increasingly delegate reasoning to the tool at the expense of their own critical skill development [12]. There is a need to understand the mechanisms so that the basic engineering skills are not being undermined. This study seeks to address this gap by examining the rich experiences of three engineering students to explore the research question of *How do engineering students at different curriculum levels perceive GenAI-assisted learning as support for their academic needs?* with the following sub-questions:

RQ1: How do engineering students perceive the specific benefits of GenAI in enhancing learning and academic performance?

RQ2: How do engineering students describe and justify their active strategies for interacting with GenAI tools to ensure accuracy and critical engagement?

RQ3: What are the perceived risks, challenges, and necessary curriculum adjustments associated with the integration of GenAI in EE?

2. Theoretical Frameworks

This study is guided by two complementary psychological frameworks to analyze the "why" and "how" of student interactions with GenAI. A macro-theory of human motivation the Self-Determination Theory (SDT) [13] framework was used that focuses on the degree to which an individual's behavior is self-motivated and self-determined. The core of this theory posits that satisfying three basic psychological needs that foster intrinsic motivation, high-quality learning, and well-being are autonomy, competence, and relatedness. This research investigates the capacity of GenAI to satisfy three core motivational needs within engineering education. We expect that GenAI supports *autonomy* by granting students agency over problem-solving approaches. It supports this particularly by allowing students agency over *when, where, and how* they seek assistance while removing social friction and scheduling barriers. It builds *competence* by improving the efficiency of technical execution. Such as coding or solving problems faster. Finally, it facilitates *relatedness* by bridging gaps in academic understanding and providing a sense of support when human instructors are unavailable. As illustrated in Figure 1, we conceptualize these interactions not merely as technical exchanges, but as a psychological mechanism where specific GenAI affordances directly satisfy these three motivational requirements to foster an enhanced learning experience.

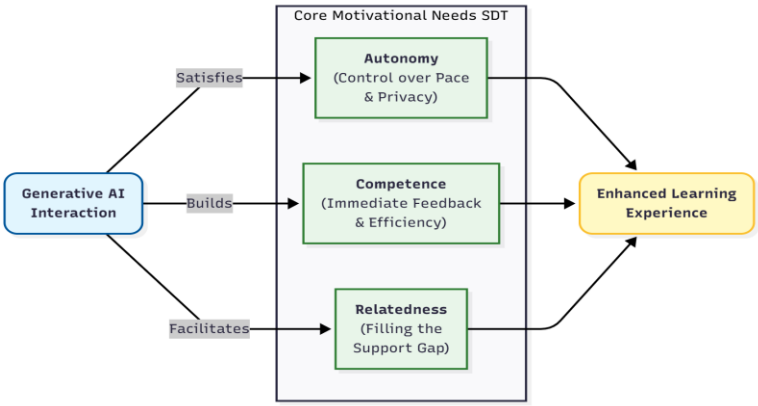

Figure 1: Application of Self-Determination Theory revealing how GenAI interactions satisfy the student's core motivational needs (Adapted from [13])

Self-Regulated Learning (SRL) involves active and strategic management of one's own cognition and motivation as well as behavior toward educational objectives [14]. It is necessary to adopt this lens to help shift the debate into a form that will enable the teacher to move the conversation from plagiarism to the growth of students as agents. It allows us to investigate *how* students actively strategize and manage their use of GenAI (i.e., handling known limitations like inaccuracy, how they plan and monitor, their reflections on its output) to maximize its instructional value, rather than assuming they are passive recipients. This recursive dynamic is depicted in Figure 2, which maps the student's active journey through the cyclical phases of forethought, performance monitoring, and self-reflection when engaging with GenAI tools.

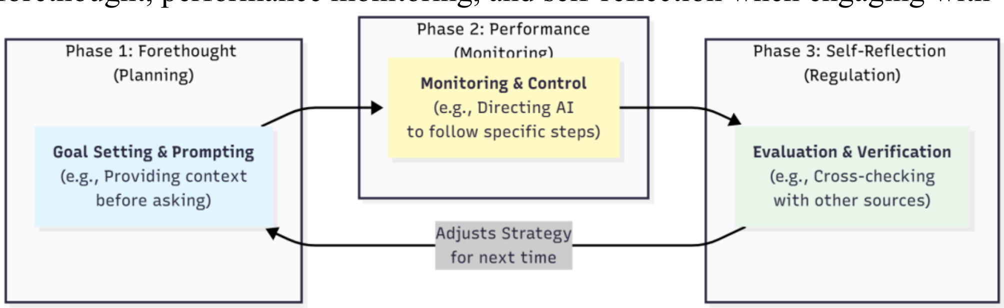

Figure 2: The cyclical phases of Self-Regulated Learning of student interactions with GenAI (Adapted from [14])

3. Methods

Research Methodology: This study employs a qualitative, multiple-case study approach [15]. This methodology is ideal for exploratory research, as it allows for an in-depth, nuanced investigation of a contemporary phenomenon (GenAI use) within its real-world context [16]. Each of the three participants is treated as a single case. This allowed for rich within-case description and subsequent cross-case analysis.

Participant Selection: Participants were recruited in Fall 2024 using a purposeful sampling strategy following IRB approval. Emails were sent to engineering students at a large, public R1 university in the Southwestern United States. The criteria for selection were that participants be current engineering students who had used and are using GenAI tools for their learning where we aimed for maximum variation sampling. Three participants were purposively sampled to reflect a variety of engineering specializations and academic levels. From this pool of volunteers, these particular cases were selected because they represent different degrees or extremes of adoption for GenAI, ranging from a *daily power user* to a *highly cautious skeptic*. We present three participants, who have been given pseudonyms (Alpha, Beta, Gamma) to protect their anonymity. Their demographic and academic details are summarized in Table 1. **Alpha (P1)** is a graduate student in Data Science. As a daily user of GenAI, he is a "power user" who leverages multiple platforms (ChatGPT-4, Claude, Gemini) and even builds his own tools. He differentiates between using GenAI for "development" (coding) and "learning" (research). **Beta (P2)** is a junior in Mechanical Engineering, who is an *older, non-traditional student* transferred from a community college. He uses GenAI weekly and brings a mature, reflective perspective, explicitly comparing his current experiences at a large university to his previous college. **Gamma (P3)** is a sophomore in Environmental Engineering who is a light user ("once a month or less") and is highly cautious. Their primary experience with GenAI was in a first-year Python programming course and they remained skeptical of its abilities in core engineering subjects like math and physics.

Table 1. Participant Demographics

Pseudonym	Major	Year	Race	Gender	GenAI Use (Learning)	Months of Use
Alpha	Data Science	Graduate	Black/African American	Male	Daily	14
Beta	Mechanical Engineering	Junior	White	Male	Once a week	24
Gamma	Environmental Engineering	Sophomore	White, American Indian/Alaska native	Gender Non-Conforming	Once a month or less	15

Data Collection: Data was collected through one-on-one semi-structured interviews which were audio-recorded over Zoom. Each interview lasted between 50 to 60 minutes. The interview protocol was aligned with research questions that were designed to extract participants' specific experiences that demonstrate their strategies for learning and perceptions regarding GenAI tools.

Data Analysis: Interview transcripts were analyzed using a systematic multi-cycle coding process. To ensure deep immersion in the qualitative data, coding was conducted manually using structured spreadsheets to organize and track emerging themes. A first cycle of open coding was conducted [17]. The initial codes were structured deductively based on the three sub-research questions (Benefits, Strategies, Risks). In the *second cycle*, an inductive thematic analysis was used to connect and group the initial codes [18]. This approach ensured a hybrid deductive-inductive approach for credibility and consistency. The data strongly aligned with the theoretical frameworks of SDT and SRL during this phase. Finally, a cross-case analysis was conducted to identify the key patterns and variations in experience across the three participants. This formed the basis of the Findings section. Table 2 presents the final coding framework that maps emergent themes to theoretical constructs and identifying the specific codes that ground the analysis.

Table 2. Emergent themes, descriptions, and associated codes

#	Theme	Description	Codes
1	Supporting Student Needs (SDT)	This theme explores how GenAI satisfies the three core psychological needs of Self-Determination Theory. It delves into students' use of the tool for autonomous control over learning pace and social safety, overcoming immediate competency barriers, and filling gaps in institutional support.	– Autonomy (Control) – Autonomy (Social Safety) – Competence (Efficiency) – Relatedness (Logistical)
2	Perceived Risks of GenAI Dependency and Inaccuracy	This theme addresses the reservations students have regarding the long-term impact of GenAI on their learning. It highlights the tension between short-term performance and deep mastery, as well as anxieties surrounding academic integrity systems.	– Competence-Dependency Paradox – Institutional/Systemic Fear – Delayed Gratification Deficit
3	Enacting Self-Regulated Learning Strategies (SRL)	This theme explores the active strategies students employ to mitigate the risks of AI. It examines how students move beyond passive consumption to actively direct the tool and verify its outputs to manage the "hallucination" risk through specific workflows.	– Directive Prompting – Skeptical Integration – Verification Stack

Quality and Trustworthiness To ensure the trustworthiness of this qualitative study, we employed several methods [19]. The primary researcher, who conducted all interviews, engaged in analytical memoing after each session to capture initial thoughts and identify potential biases. The findings were triangulated by comparing the interview data to these researcher memos. Finally, the use of two theoretical frameworks (SDT and SRL) provided a robust structure for analyzing and interpreting the data, moving beyond simple description.

Researcher's Positionality The primary researcher in this study is a doctoral student in Engineering. This perspective of an *insider* [20] provided a foundational understanding of the engineering curriculum and its challenges. The researcher began this study with a *mixed view* on GenAI. This investigation was catalyzed by the dichotomy between the enthusiasm for GenAI-driven efficiency and the skepticism surrounding academic rigor. Specifically, it addresses the friction between enhanced learning velocity and the risk of shallow comprehension. It should be noted that the researcher possessed no pre-existing academic or personal affiliations with the selected participants.

4. Findings

Our analysis identified three primary themes aligning with our research questions. Each of them contains distinct sub-themes as well. These sub-themes reveal important nuances in the student experience. They move the story beyond simple tool use. Instead, they show how students navigate issues of safety, support, and self-regulation.

Theme 1 - Supporting Student Needs (SDT)

While we were trying to answer RQ1, a significant theme that emerged in the analysis was ***'Supporting Student Needs'*** (Theme 1). The most significant finding was that GenAI's perceived benefits mapped directly to the three core needs of Self-Determination Theory. Students felt *enhanced* not just because the tool was fast, but because it satisfied these psychological needs. The strongest support was for *Autonomy* - the need to control one's own learning. All participants valued the tool's immediacy and privacy. The cautious sophomore Gamma explained that they preferred GenAI to an instructor when they were stuck on a programming assignment:

> *"It's really nice because I'm able to say that I have this line of code and It's not working for me. I can go to ask ChatGPT and it can give me an understandable answer, or I can*

ask it to rephrase... and I don't have to be afraid of offending a professor or I don't have to plan to go to office hours."

This quote powerfully illustrates GenAI as a tool for autonomous learning. It removes the social friction and scheduling barriers of traditional help-seeking. This autonomy is deeply linked to a sub-theme of **Autonomy as social safety**. Gamma noted that sometimes human explanations can be difficult to parse if they are too formal, but they hesitated to ask for clarification in person. They appreciated that GenAI allowed them to bypass the anxiety of feeling incompetent in front of an instructor, stating: *'It's kind of nice to just have ChatGPT right at your fingertips... and not having to plan around the professor's schedule'*. For novice engineering students, the tool acts as a judgment-free zone where they can ask 'stupid' questions without social risk. Thus, giving the student complete control over their learning pace.

Second, students used GenAI to build *Competence* - the need to feel effective. For Alpha (the graduate student), this meant expanding his capabilities. He used it to learn new skills outside his domain:

> *"He needs something that he can deploy as a web app. I'm not a front-end engineer or front-end developer... But because I know I have ChatGPT... to kind of like help me and give me the code... I agree to help him do it."*

For Gamma (the sophomore), GenAI was a motivator that built their competence *within* a difficult subject: *"Yeah, it was kind of motivating for me to be able to understand my mistakes immediately. And have that immediate feedback."*

Finally, and most surprisingly, one student used GenAI to satisfy his need for *Relatedness* - the need for support. Beta, the junior transfer student, contrasted his current R1 university with his previous community college, where he felt *"a lot more support from the professors."* He stated: *"[At the university] it is harder to get a hold of professors... I do feel ChatGPT has helped with kind of filling that gap when I can't get a hold of somebody."* For Beta, GenAI was not just a knowledge tool; it was a *support tool*. He used it to fill a perceived gap in human connection and institutional support, allowing him to persist in his work. This need for support was magnified by his transition between institutional contexts, revealing the sub-theme of Relatedness as an 'Institutional Bridge'. Beta explicitly contrasted his current experience at a large R1 university with his previous community college, where 'access to professors... was so much better'. He perceived that university researchers were often 'busier' and 'in their lab', creating a distance that he felt compelled to bridge with AI. Thus, GenAI acted as a support scaffold that filled a void for him in human connection to maintain his academic momentum.

Theme 2 - Perceived Risks: Dependency and Inaccuracy

The second theme that emerged was **'*Perceived Risks of GenAI Dependency and Inaccuracy*'** **(**Theme 2) which demonstrated that the students' strategies were a direct response to the risks they identified. The primary concern was *GenAI Dependency*. All three students articulated this fear. Alpha stated it most clearly:

> *"One drawback that it has is it doesn't really make you know it. So, if you rely too much on ChatGPT, right? You will be able to do it, but you won't know as much as you should... I wouldn't say dependent per se... It would just reduce the speed of performance."*

Beta, the non-traditional student, was concerned about '*younger students*' who '*are so focused on... getting the grade*' that they '*overuse it'* in a way that is *"detrimental to overall understanding later."* This highlights another sub-theme, which is the **Competence-Dependency**

Paradox. Both participants recognized that while GenAI simulates competence in the short term (performance), it threatens actual competence in the long term (mastery). Beta observed that younger students often struggle to 'put off that immediate gratification' for longer-term understanding, prioritizing 'getting the grade' over acquiring the knowledge."

Finally, students were concerned with Inaccuracy and Academic Integrity. Gamma, the most cautious user, expressed a clear fear of the *system* rather than the tool itself: *"I get really nervous because some of those things If Turnitin catches… flags you for AI, I could lose my scholarship or, I could be expelled."* This fear, combined with their experience of GenAI giving 'bad answers' in math, led them to use it as a last resort. Furthermore, Gamma's anxiety reveals the sub-theme of **systemic fear of algorithmic surveillance**. They worried about 'false positives,' noting that even if they wrote an essay authentically, *'if I have [a] uniform enough style that sounds like a computer, I can get flagged'*. This suggests that the 'risk' of GenAI is not just about receiving wrong answers, but about the psychological burden of navigating a punitive academic system.

Theme 3 - Enacting Self-Regulated Learning Strategies (SRL)

The third theme, which answers RQ2, directly addresses faculty concerns about over-reliance which is ***'Enacting Self-Regulated Learning Strategies'*** (Theme 3). The data shows these students were not passive users; they were active, self-regulating learners who understood the tool's limitations and developed strategies to manage them.

Alpha, the "power user" described this as an active, directive process:

> *"What I would do is try to direct it to what I want by writing lines of code... I then ask it to follow the direction of what I want. So, I've kind of changed its course... to focus on, 'This is the solution I'm trying to provide.'"*

This is a high-level SRL strategy. Alpha actively "teaches" the GenAI to get the result he needs, forcing him to engage critically with the content. We categorize this sub-theme as **Directive Prompting**. Alpha does not treat the GenAI as an oracle but as a junior developer requiring supervision. By writing *'10, 20 lines of code'* himself first to establish the logic, he retains cognitive ownership of the problem, using the GenAI only to accelerate the syntax generation rather than to conceive the solution. Beta (the junior) was similarly reflective, stating: *"Whenever I get feedback from ChatGPT, I'm a lot more critical of that information... I have to verify on top of getting that information."* We categorize this sub-theme as **Skeptical Integration**. Alpha directs GenAI's actions. Whereas, Beta simply adds GenAI to his work process. However, Beta remains suspicious and constantly verifies the results.

Gamma (the sophomore) had the most explicit step-by-step routine. They learned from experience that GenAI was unreliable for math and physics, so they developed a clear help-seeking process:

> *"I would usually start with internet. I'd text my friends and then I would do ChatGPT if all else fails... usually I find it's a lot of cross-checking, just to make sure that the information is accurate."*

Gamma described this as the sub-theme of a **Verification Stack** that prioritizes human sources. Their workflow (i.e., Internet → Friends → AI) ensures that GenAI is never the sole source of truth. This 'last resort' strategy allows them to filter GenAI hallucinations through a layer of previously acquired human knowledge. This counters the 'easy button' narrative, demonstrating that effective GenAI use requires intense critical engagement. Ultimately, these strategies serve as the bridge between the students' psychological needs and the tool's limitations, a dynamic we formalize in the following section.

Implications for Practice:
This study directly addresses the "necessary curriculum adjustments" mentioned in RQ3. The data shows that faculty "abstinence" policies (as Beta called them) are misaligned with student reality. (1) *Teaching SRL to move past GenAI Abstinence:* Instructors should focus on teaching the SRL strategies that Alpha, Beta, and Gamma discovered on their own instead of just banning tools overall. This means explicitly teaching students *how* to cross-check GenAI output and *how* to write effective prompts without violating academic integrity. For example, a task could be created where students are given intentionally flawed, AI-generated code and are graded on the quality of their *Verification Stack* process to solve it. It also involves teaching them how to cite to maintain the academic policies and *how* to reflect on the tool's limitations. (2) *Acknowledge and address the 'Support Gap':* Students like Beta are using GenAI to fill a gap left by unavailable instructors. This points to a larger institutional issue. We must consider how to make human support more accessible, especially with GenAI being so easily accessible and around us all the time. Such that GenAI is a *complement* (as the students intended), not a *replacement*. (3) *Use GenAI for Competence:* The students who felt most successful (Alpha and Gamma in programming) used GenAI to get *immediate* feedback on their own work. This indicates a pedagogical use-case in engineering education. For example, instructors should encourage students to use GenAI as a real-time tutor to debug their code or check their problem-solving steps to ensure that the students are developing competence.

5. Discussion

The findings from this exploratory study, while not generalizable, provide a nuanced model for understanding *how* and *why* engineering students are using GenAI. The data suggests that GenAI's primary value is not as a simple *answer-getter* but as a psychological support tool that helps students manage their own learning.
Participant Gamma's avoidance of office hours supports the argument that GenAI reduces the social anxiety associated with help-seeking, fostering greater learner **autonomy** [3]**.** Similarly, Alpha's use of GenAI to bridge skill gaps illustrates how GenAI serves as a scaffold for **competence**, allowing students to attempt complex tasks within their Zone of Proximal Development [21]. Lastly, the dependence on GenAI by Beta in the absence of instructors underscores the use of the tool in mitigating resource challenges in large institutions of higher learning.

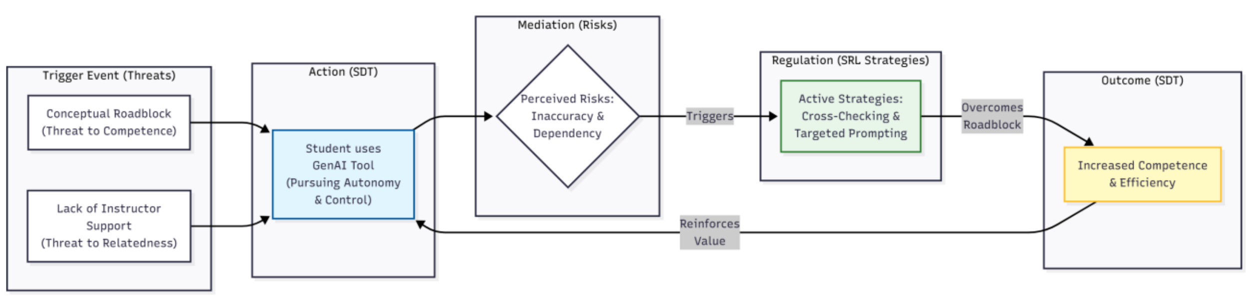

Figure 3. Conceptual model of the GenAI student experience.

By integrating our findings, we propose a conceptual model (Figure 3) of this process. The student experience with GenAI is considered as a cyclical loop. It is not just a simple input-output process. (1) A student encounters a conceptual roadblock in their learning process (which is a threat to *competence*) and a lack of immediate support from the institution (which is a threat to *Relatedness*). (2) They turn to GenAI, which gives them a sense of *autonomy* (a sense of control over pace and privacy of their learning). (3) This use of GenAI is mediated by *Perceived Risks* (i.e., inaccuracy, dependency) which in turn (4) triggers their *SRL Strategies* (e.g., cross-checking, prompting). (5) The successful application of these strategies to overcome the roadblock results in a feeling of *competence* by having a better outcome on their requirement from GenAI. Thus, it reinforces the value of GenAI for future use and a new cycle begins creating an increase in the usage.

The participants' behaviors illustrate sophisticated Self-Regulated Learning adaptations in response to GenAI. Beta and Gamma's insistence on verification exemplifies **metacognitive monitoring**, where learners actively calibrate their trust in the tool to mitigate the risk of hallucinations [22]. Gamma's multi-step validation routine further demonstrates effective **resource management**, triangulating GenAI outputs against social and static sources to ensure accuracy. Meanwhile, Alpha's approach of "teaching" the GenAI mirrors **generative processing** strategies; by explicitly defining the code structure before requesting GenAI assistance, he retains **active control** over the problem-solving process, effectively utilizing prompt engineering as a form of cognitive engagement rather than passive consumption [23].

Building on these adaptations, the 'Verification Stack' strategies employed by Alpha and Gamma (e.g., cross-checking, Internet → Friends → AI) represent an emerging form of GenAI literacy. This approach exemplifies the distinction made by Bearman and Ajjawi [24] between 'learning from AI' (passive reception) and 'learning to work with the black box' (active negotiation). Our participants demonstrate the latter. Alpha's strategy of 'teaching' GenAI by providing initial code mirrors the 'AI as Student' pedagogical model, which has been shown to deepen conceptual understanding by forcing the student to articulate logic clearly [25]. This suggests that the 'hallucination' problem paradoxically serves a pedagogical function: it forces students to remain in the 'monitoring' phase of Self-Regulated Learning, preventing the 'cognitive offloading' that educators fear.

This model reframes the discussion from *'cheating'* to *'coping'*. Beta's comment about GenAI *'filling that gap'* is a powerful indictment of a learning environment where students feel unsupported. Beta's use of GenAI to 'fill the gap' complicates the narrative of the 'democratization of personalized tutoring' [25]. While proponents argue that GenAI can serve as a universal tutor, Beta's experience suggests that students are using it less as a *supplement* to abundant resources, and more as a *survival mechanism* in resource-constrained environments. This echoes concerns raised by Bozkurt et al. [26], who warn that GenAI might become a 'crutch' for under-resourced institutions, potentially widening the digital divide where students at large universities rely on algorithms while elite students retain access to human mentorship. Gamma's *'fear of offending a professor'* suggests that GenAI is perceived as a psychologically *'safer'* tool for learning than the human instructors themselves. This alignment with 'psychological safety' corroborates recent findings on student help-seeking behaviors in digital environments. Merikko and Silvola [27] highlight that artificial agents can facilitate help-seeking by offering a **'non-judgmental space,'** thereby reducing the **fear of judgment** often associated with asking for assistance. For Gamma, the fear of 'offending a professor' reflects a classic help-seeking barrier in engineering education, the fear of appearing incompetent. GenAI effectively mitigates this by acting as a low stake 'transitional space' where students can formulate their thoughts before engaging with faculty, a phenomenon similarly noted by Chan [28], who found that students value GenAI as a **'non-judgmental'** resource where they feel **comfortable asking questions they would otherwise not voice to their teachers**. This distinction highlights how students prioritize different needs to solve the 'Support Gap': Logistical Relatedness versus Protective Autonomy. Beta's experience represents the logistical dimension (Relatedness), where GenAI acts as a proxy when human support is physically unavailable. In contrast, Gamma's experience reflects the autonomous dimension (Autonomy), where GenAI provides a buffer against social anxiety to preserve agency. This suggests that for vulnerable or introverted students, the 'Support Gap' is not just about office hour availability, but about the emotional safety required to reveal one's own confusion.

While the data aligned with proposed theoretical framework, there are subtle contradictions and nuances that complicate a simple narrative of GenAI as a universal motivator. (1) *SRL vs. Increased Engagement:* SRL framework implies that students' active strategies increase critical engagement. However, when directly asked, two out of the three students did not feel GenAI increased their engagement in learning overall. *Beta* stated he didn't think it '*increased or decreased*' his engagement judging it was *'about the same'*. *Gamma* was neutral by stating they were *'not really'* more engaged aside from the specific programming class. (2) *Competence vs. Over-Reliance:* The competence need is satisfied by doing tasks efficiently but this is immediately contradicted by the risk of GenAI Dependency. *Alpha* noted that over-reliance *'doesn't really make you know it'*. Also, *Beta* was worried about younger students overusing it in a way *'detrimental to overall understanding later'*. This hints at a tension where GenAI supports Competence in doing *(efficiency)* but threatens Competence in knowing *(deep understanding).* (3) *Competence vs Accessibility:* The free versions of GenAI (e.g., GPT 3.5 at the time of the interview) are accessible, but *Gamma* explicitly stopped using the free models for math and physics because the answers were '*bad'* and *'not accurate'*. This suggests that while access to a tool is free but access to a competent tool (one that can accurately solve complex problems) may be restricted by a paywall (e.g., GPT-4 or fine-tuned models at the time of the interview). While our data does not confirm financial barriers, Gamma's experience with 'bad' free models hypothesizes a tiered system where learning quality is dictated by access to premium tools.

6. Limitations and Future Research

This study offers nuanced insights but is subject to limitations. Primarily regarding sample size and generalizability. The small sample (n=3) allowed for detailed within-case analysis but precludes statistical generalization to the wider engineering population. Specifically, the distinct academic contexts of the participants may not represent students across different disciplines or developmental stages. Additionally, the reliance on volunteer recruitment introduces potential self-selection bias. This likely skewed the sample toward students who are already comfortable, reflective, or "high achieving" users of GenAI. Consequently, the sample likely excludes the "silent majority" of struggling students and the students who may use it to cheat. Similarly, relying on self-reported data subjects the study to social desirability bias. Data was collected exclusively through interviews. As the researcher is an "insider" (a PhD student in Engineering

Education), participants may have subconsciously sanitized their responses to appear more ethical or competent (social desirability bias). While we found evidence of "Skeptical Integration" and active checking strategies, it is possible that students under-reported instances where they accepted GenAI outputs passively. Fourth, institutional context. The study was conducted at a single large, public R1 university. As noted by Participant Beta, who contrasted this environment with his previous community college experience, the "Support Gap" identified here may be unique to large research institutions where faculty accessibility is a challenge. Students at smaller, teaching-focused colleges might perceive the role of GenAI differently. Finally, technological volatility. This study captures a snapshot of student usage during Fall 2024. Given the rapid evolution of Large Language Models (e.g., the shift from GPT-3.5 to GPT-4 and beyond), the specific "hallucinations" and limitations students described may become less relevant as technology improves, potentially altering the "Verification Stack" strategies required in the future. To address these limitations, future research should expand in three key directions. Firstly, to address the issue of small sample sizes, there is a requirement for quantitative approaches such as surveys to assess how common the strategies of the "Verification Stack" are on a larger scale. Secondly, it may be possible to confirm through comparison between research universities and teaching colleges whether the "Support Gap" theme (Theme 1) is a concern driven by institution sizes or if it is a commonality for all students. Finally, to mitigate social desirability bias, researchers should move beyond self-reports to observational methods (i.e., screen-recording or think-aloud protocols) to capture the real-time cognitive processes of students as they debug code or solve problems with GenAI.

7. Conclusion

This exploratory study reveals that for engineering students, Generative AI is much more than just a *faster search engine* or a *shortcut for homework*. Instead, it functions as a vital psychological support system that satisfies three deep-seated needs: Autonomy, Competence, and Relatedness. We found that students value the tool because it gives them control over the pace of their learning. Furthermore, it provides a non-judgmental safe space to ask questions they might be too intimidated to ask a professor. For some, GenAI even serves as a necessary bridge, filling the *support gap* when human instructors are unavailable or difficult to reach.

Crucially, our findings challenge the common fear that GenAI makes students passive or lazy. The students in this study were not blindly trusting the magic button; they were active, skeptical learners. They developed their own sophisticated strategies that we identified as *Skeptical Integration* and *Verification Stack* to constantly cross-check GenAI answers against friends, textbooks, and the internet. They understood that the tool could *hallucinate* and they took responsibility for catching those errors.

Therefore, the path forward for engineering education is clear. The focus should be shifted from prohibition to pedagogy. It is unlikely to work if institutions ban these tools. Particularly when students are already using them to fill gaps in their education. Instead, universities should formally teach the skills that these students are currently figuring out by themselves. Students are learning to verify information and write effective prompts by treating GenAI as a tutor instead of a replacement for reasoning. Thereby securing the critical GenAI literacy needed for future engineering roles.

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Appendix A

Interview Questionnaire

1. What Generative AI tools have you used during your studies?
2. For what purposes do you use Generative AI tools in your engineering coursework? (e.g., homework assistance, project guidance, conceptual understanding, among others)
3. What is your opinion on whether Generative AI tools have influenced your approach to studying or solving engineering problems?
4. In your opinion, did Generative AI tools provide feedback on your learning? (For example, have they offered personalized explanations or problem-solving steps?)
5. How does the feedback that you received from Generative AI tools compare to the feedback from your instructors?
6. Can you provide an example of when feedback from Generative AI might have helped you better understand an engineering concept?
7. In your opinion, what are the strengths of feedback generated by Generative AI in meeting your individual learning needs?
8. Have you encountered any limitations or inaccuracies with feedback generated by Generative AI and how did you handle them?
9. Does using Generative AI increase your engagement in learning?
10. In what ways do you find Generative AI tools helpful (or not) in enhancing your understanding of complex engineering topics?
11. Do you feel more confident in your engineering skills after using Generative AI tools for feedback?
12. What are your thoughts on integrating Generative AI tools into the engineering curriculum?
13. Do you think incorporating AI-driven features within a Learning Management System (LMS) like Canvas or Moodle (such as, real-time feedback, personalized problem-solving assistance, or AI tutoring) would enhance learning? Why or why not?
14. What challenges or barriers do you see in using Generative AI tools effectively in your learning process?
15. How could engineering programs better support students in the use of Generative AI for learning?
16. What kind of training or guidance would help students use Generative AI tools more effectively for personalized feedback?
17. Do you think accessibility could be an issue for Generative AI as it has different options depending on subscription (for example, free feature use old GPT models, paid feature use better model, limited free prompts for everyone per day, etc.)
18. Reflecting on your experience with Generative AI, do you see yourself continuing to use these tools in the future for your studies or career?
19. What improvements or additional features would you like to see in Generative AI tools to enhance their usefulness in your engineering education?
20. Is there anything else you would like to share about your experiences with Generative AI in learning?

Appendix B

#	Code	Description	Excerpt
Theme 1: Supporting Student Needs (SDT)			
1	Autonomy (Control)	The ability to control the pace, privacy, and source of help without social friction or scheduling barriers.	'It's really nice because I'm able to say that I have this line of code and It's not working for me... and I don't have to be afraid of offending a professor or I don't have to plan to go to office hours.' (Gamma/P3)
2	Autonomy (Social Safety)	Using GenAI as a non-judgmental 'safe space' to ask questions one fears might appear incompetent to a human.	'It's kind of nice to just have ChatGPT right at your fingertips... and not having to plan around the professor's schedule.' (Gamma/P3)
3	Competence (Efficiency)	Using GenAI to overcome immediate hurdles, debug code, or speed up execution to build a sense of efficacy.	'Something that was taking you one hour of debugging, you'll probably have an accurate code in like 20 minutes.' (Alpha/P1)
4	Relatedness (Logistical)	Using GenAI as a proxy for human support when instructors are physically unavailable or difficult to reach.	'It is harder to get ahold of professors... I do feel chats have helped with kind of filling that gap when I can't get a hold of somebody.' (Beta/P2)
Theme 2: Perceived Risks of AI Dependency and Inaccuracy			
1	Competence-Dependency Paradox	The tension between being able to *do* a task (performance) versus *knowing* the underlying concept (mastery).	'One drawback that it has is it doesn't really make you know it... It helps you to do it; it doesn't really help you to know.' (Alpha/P1)
2	Institutional/Systemic Fear	Anxiety regarding academic integrity policies, false positives, and the 'policing' of student work by algorithms.	'If Turnitin catches... flags you for GenAI... I could lose my scholarship... even if I don't use GenAI in my writing at all.' (Gamma/P3)
3	Delayed Gratification Deficit	Concern that reliance on GenAI prevents students from struggling through problems, affecting long-term retention.	'Younger students haven't really lived enough life... to understand the benefit of putting off that reward versus the instant reward.' (Beta/P2)
Theme 3: Enacting Self-Regulated Learning Strategies (SRL)			
1	Directive Prompting	Actively guiding GenAI by providing initial code or context to force a specific output (Active Control).	'I then ask it to follow the direction of what I want. So, it is like, I've kind of changed its course... to focus on, like, 'This is the solution I'm trying to provide'.' (Alpha/P1)
2	Skeptical Integration	Using GenAI output but treating it as inherently suspicious; requiring external validation before acceptance.	'Whenever I get feedback from GPTs... I'm a lot more critical of that information... I have to verify on top of getting that information.' (Beta/P2)
3	Verification Stack	A specific workflow of prioritizing human sources (Internet → Friends) before resorting to GenAI to filter hallucinations.	'I'd start with internet. I'd text my friends and then I would do chat GPT if all else fails... usually it's a lot of cross-checking.' (Gamma/P3)