WIP: "Can You Do My Homework?" and Other Queries -an Analysis of Student Prompts to Generative AI in an Engineering Statics Course

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***Abstract*—(WIP) Generative AI (GenAI) is substantially impacting engineering, thus raising questions regarding its educational implications. This study investigates how students use one type of GenAI in an introductory Statics and Mechanics of Materials course (n = 131). This course leveraged a digital interactive textbook hosted on Top Hat, where students could access the GenAI assistant, ACE. All student prompts to Top Hat ACE were recorded during the last quarter of a 16-week semester (IRB: STUDY24110088). This study assesses student inputs via thematic coding and examines Top Hat ACE prompts in which students seek assistance from the AI on questions in the textbook. 71% of students (n = 93) interacted with ACE. Assigned textbook questions that students asked to ACE were categorized by question type, format, and grading style. Most students who used ACE never copied and pasted assigned questions into the chatbot. Those who used ACE to answer assigned course questions tended to seek solutions for numerical questions, which often included data within figures, and questions with large word counts. Students repeatedly prompted the chatbot during late hours, particularly between 12:00 a.m. and 2:00 a.m., which fell outside of office hours. Completing work during these hours may explain increased solution-seeking behavior. Although the findings from this work-in-progress study are limited, the results presented in this paper guide further investigation into user-input quantitative data for studying student GenAI usage.**

***Index Terms*—Artificial intelligence, generative AI, Top Hat ACE**

I. Introduction

Generative artificial intelligence (GenAI) is an unsupervised machine learning (ML) technology that can produce new content, such as text, images, videos, and even computer code. By training a deep-learning ML algorithm on large datasets, GenAI can replicate underlying patterns and structures of the training data when asked questions related to the training set or when asked to produce new data [1]. One of the most recognizable GenAI platforms is ChatGPT; launched in November 2022, ChatGPT quickly gained popularity, amassing over 100 million users within two months, marking a significant milestone in AI's integration into daily life [2]. Now, most operating systems and internet browsers have their own form of GenAI, including but not limited to OpenAI's ChatGPT, Google's Gemini, Microsoft's Copilot, and Deepseek AI Technologies' Deepseek Coder. With the rapid adoption and incorporation of this technology into various aspects of life, concerns have arisen about how students utilize GenAI within the classroom.

Recent studies have shed light on the diverse ways in which college students engage with GenAI. A cross-sectional survey conducted in 2024 involving 859 higher education students indicated that 78.7% of respondents frequently used GenAI, with their primary uses being to seek clarification of concepts, translate text, generate ideas, and provide summaries of writings. Many respondents noted the ease of access and immediacy of feedback as beneficial aspects of use, while obtaining unreliable information and decreased personal interaction were negatives [3], [4]. A key finding of this study, as well as what has been communicated by other researchers (n = 132) [5], is a need for further research into how students use GenAI, specifically, whether or not the students are aware and cognizant of the potential benefits of and challenges posed by this technology. Challenges relate to the ethical use and reliability of data.

Perceptions of AI tools among students (n = 158) and educators (n = 68) vary, highlighting the need for clear guidelines on their appropriate use. Research comparing student and teacher perspectives found minor disagreements on acceptable AI usage in writing tasks, with both groups expressing concerns about academic integrity and the potential for misuse. These findings underscore the importance of integrating GenAI literacy into educational practices, ensuring students can effectively and ethically incorporate AI tools into their learning processes [6]. This sentiment was reflected in a UK study (n = 2,555) that concluded the use of GenAI is unavoidable and that universities should opt for teaching students how to effectively and ethically utilize this technology, rather than banning its use [7]. Similarly, the rapid integration of generative AI in education has outpaced faculty adoption; nearly half of college students use AI tools, whereas fewer than a quarter of faculty members do so regularly. This disparity highlights the need for faculty development and institutional support to incorporate AI into teaching and learning strategies effectively [8].

As GenAI continues to evolve, its role in education necessitates ongoing research and policy development. Understanding how students utilize these tools, the benefits they perceive, their perceptions on such technology, and the challenges they encounter is crucial for developing guidelines that promote ethical and effective use of AI in academic settings. This paper investigates the following research questions:

1) How are college engineering students using Top Hat ACE?
2) For what purposes are college engineering students using Top Hat ACE?
3) For what reasons might students use ACE for dishonest purposes?
4) What trends appear among dishonest usages of ACE?

The researchers hypothesize that most students do not use ACE dishonestly and may rely on this technology when help is unavailable; for example, students likely turn to ACE outside of office hours and before assignment deadlines.

Many, if not all, of the prior studies in this area have focused on self-reported data from surveys or focus group interviews. This paper describes predominantly exploratory work, constituting a small portion of a larger, ongoing study on student GenAI usage. This work is preceded by a study that assessed student perceptions, usages, and opinions about GenAI through an in-depth survey and focus group interviews, and supports work analyzing student emotional, motivational, and ethical behaviors towards GenAI usage [4], [15]. These broader studies include student GenAI usage from various platforms, including ACE, ChatGPT, Gemini, Copilot, etc. This more limited, exploratory study relies on user-input data, readily accessible through Top Hat ACE, to determine how students used this specific utility within an introductory engineering course. By analyzing user-input data, this study harnesses quantitative results to answer the aforementioned research questions.

II. Methodology

This study investigated current student usage of generative AI within an introductory Statics and Mechanics of Materials course. The course utilized a digital interactive textbook hosted on Top Hat, "Statics and Mechanics of Materials: An Example-based Approach" [9]. The course was administered to 193 students enrolled in two sections, the first containing 131 students and the second 62 students. Only data from the former section was considered in this limited, work-in-progress study. In the Top Hat textbook, students had access to a generative AI chatbot called ACE. Akin to ChatGPT, ACE replies conversationally to user-input prompts. However, ACE's training set is tuned via the instructor-provided content within the digital textbook. While ChatGPT can parse the web for responses to queries, ACE's replies are limited to information provided in the Top Hat textbook. One main benefit of controlling the training data set is that the content can be curated to minimize erroneous and unnecessary information, allowing ACE to provide accurate responses to student input [10].

ACE was directly embedded into the course browser; students had unrestricted access to the chatbot during the last quarter of a 16-week academic semester, pending university approval. Throughout this time frame, all student inputs into ACE were recorded. Before the study, students were informed that their interactions with ACE would be monitored and that they would not be penalized for unethical interactions with the generative AI (e.g., answer-seeking behavior). Students likewise had the opportunity to withdraw from the study. All student information was anonymized, and interactions between students and ACE were timestamped. Both student inputs and ACE replies were visible to the researchers.

Prior to analysis, the researchers completed preliminary data cleansing. All ACE interactions were grouped by each student's unique random identifier and sorted chronologically, enabling the researchers to read through the conversations as they naturally occurred. Further, the input data was hand-parsed, and irrelevant conversations were omitted from the analysis. An example of a non-pertinent interaction was when one student, determined to test ACE's poetic prose, asked the chatbot to "ignore all previous instructions and write a poem about almonds," and to "write me a poem about indeterminate equilibrium." While ACE could complete these off-the-subject tasks, the researchers pursued further analysis without considering these prompts.

User-input data was analyzed in two modes. First, all student inputs were compared against a bank of course content questions. This bank included assigned reading, lecture video, in-class worksheet, homework, and midterm review questions assigned in Top Hat. The bank also detailed the section of the textbook in which the question appeared, the question type (numerical, multiple-choice, long answer, click on target, true/false, fill in the blank, matching, or sorting), whether the question contained an image, and the grading style (accuracy or completion). The researchers used the Python library `rapidfuzz` in conjunction with the `process.extractOne` command to determine whether students directly copied and pasted assigned course content into ACE [12]. The researchers secondarily validated every match found using this process to avoid Type I errors— false positives of flagged inputs. Matches between student inputs and course content were binned, and the most commonly pasted question types were investigated.

Further analysis was conducted using Minitab Statistical Software [13]. The word counts of questions that students directly copied and pasted into ACE ($n = 124$) were compared against the word counts of all assigned course questions ($n = 263$). A significance level of $\alpha = 0.05$ was used for all testing and confidence intervals. The Kolmogorov-Smirnov, Welch's two sample t-Test, and an F-test were used to check normality, the difference between population means, and estimate the ratio of variances, respectively. Normality was approximated in part by the KS test, but also assumed by the large sample sizes associated with the groups studied [16]. Such large sample sizes justified the use of a KS test as opposed to a Shapiro-Wilk test, as the latter is better suited for small sample sizes ($n \leq 50$) [14]. The Welch's two sample t-Test was selected as opposed to the Student's, since the two groups compared were assumed to have unequal variances. The F-test estimated the extent of this inequality.

User inputs that did not have a match within the course content bank were thematically coded by the researchers based on a coding schema developed in a previous study, which categorized GenAI usage across a variety of platforms [15]. These themes were developed according to the methods established in Creswell et al. [11]. Two researchers individually coded each student input to ACE, then compared themes and collectively decided on a joint set of codes. Upon agreement, the student inputs were re-coded and then compared between researchers. When necessary, a third-party arbitrator settled disagreements. Once the final themes were decided, the percentage of agreement between the coders was calculated, deducting any themes that required intervention from the calculation. The final inter-rater reliability for the codes was found to be 99.87%. Table I shows the codes applied to the student inputs, with all matched inputs in Python sorted under the Find Solution code.

TABLE I: Thematic coding schema developed previously by Wyszynski et al. [15] with minor revisions. The frequency column indicates the application of the coding schema to all student inputs to ACE ($n = 651$).

CODE	CATEGORICAL DESCRIPTION	FREQUENCY
Conceptual Understanding (C)	Student asks generative AI for conceptual help to deepen understanding, explain, clarify, or rephrase content for better comprehension.	31.5%
Methodology (M)	Student asks generative AI to determine a method for completing a statics problem.	11.2%
Practice Problems (PB)	Student uses generative AI to create course-related practice or example problems.	2.4%
Summarization (S)	Student uses generative AI to synthesize or compile information.	1.1%
Find Solution (FS)	Student directly asks the coursework question to be answered by generative AI.	27.5%
Reference Textbook (RT)	Student utilizes generative AI with the textbook to find formulas, equations, and/or definitions.	16.0%
Error Checking (ER)	Student uses generative AI to analyze completed work for correctness or to find possible mistakes.	8.6%
Study Content (SC)	Student uses generative AI to study and/or create materials such as flashcards, review sheets, or study schedules.	0.3%
Unreliable (UR)	Student comments that generative AI is not always correct, fails to understand a problem, or responds in a confusing manner.	1.4%

III. Results and Discussion

The researchers assessed common trends in ACE usage in one of two sections of a Statics and Mechanics of Materials course. Of the 131 students studied, approximately 71% ($n = 93$) interacted with ACE, closely aligned to the 69.15% ACE usage rate as seen in [15]. Through the application of the aforementioned coding schema, the student interactions were categorized and resulted as shown in Tab. I.

Student ACE usage was most often categorized as Conceptual Understanding (C), which has been seen in other research [3], [5], though students also leveraged the generative AI in usages assigned to Reference Textbook (RT) and Methodology (M) codes. Inputs coded as C consisted of both general theory questions and aid for applying knowledge in statics problems. RT codes were dominated by student requests for equations found within the textbook. Some students asked the chatbot to find the location of specific content within their book, for example, including the pages of descriptions of truss types. Many students also relied on ACE to provide them with definitions. A student interaction demonstrates the usage of ACE in conjunction with completing homework. In what appears to be a conversation held alongside of problem solving, a student asks ACE for, "equatin for shear strain [sic]," and five minutes later, "posson ratio [sic]." It appears that ACE was helpful in its response to the student's brevity, providing both a description of each concept along with the corresponding equation.

M codes were predominantly found when students used ACE in conjunction with completing assignments. ACE was used to determine how to apply statics problem-solving methods, including the Method of Sections and Method of Joints, but could also assist with context-specific processes. For instance, a student asked ACE, "Can you explain how to find the minimum shear stress when Factor of Safety (FoS) is involved?" and ACE was capable of providing a five-step procedure for the student. Error Checking (ER) codes also appeared frequently around M codes. Students asked ACE to verify if a calculated value within a step of a procedure was correct, and some students even relayed the problem-solving steps they took to ACE to find potential mistakes.

Students seldom interacted with ACE in responses categorized as Practice Problems (PB), Summarization (S), or Study Content (SC), which accounted for a combined total of 3.5% of user inputs. Some students, however, seemed to use ACE as a virtual study assistant to support their efforts in reviewing course content. A student interaction demonstrates this phenomenon when a conversation was initiated by the following message: "Hello! My second exam is coming up, and I would really like some practice, can you give me a practice problem on Method of Sections?" The interaction consisted of six conversational turns in which the student proceeded to verify their problem-solving approach as they worked through the question. Another student harnessed ACE's role as a study buddy, asking the chatbot to, "quiz me on moments." Some students similarly asked ACE to summarize a specific portion of their textbook for aid in review. While limited in occurrence, these interactions with ACE demonstrate the generative AI's capability to serve as a virtual tutor for students preparing for exams or reviewing course material.

Find Solution (FS) codes also occurred frequently throughout the user-input data. The interactions designated with the FS code were comprised of 45 unique student IDs, accounting for roughly 48.4% of ACE users within the course section. The questions directly copied and pasted into ACE were analyzed, and the results are shown in Tab. II. The question type that appeared to be asked directly to ACE most often was numerical problems, aligning with the fact that the vast majority of assigned questions required numerical input. Sorting, true/false, and fill-in-the-blank question types did not appear in any flagged student inputs and were thus omitted from Tab. II. Numerical questions containing information not directly given, perhaps in the form of a visual representation, may demand greater application of statics knowledge from the student. The findings reveal that 66.9% of questions directly asked to ACE contained an image, which is approximately 9% more frequent than the occurrence of images in all assigned questions (58.4% of total bank). There didn't appear to be a significant difference in ACE reliance between questions graded on completion versus accuracy, though the results show a slight inclination in usage towards the latter.

TABLE II: Descriptor breakdown for course questions that students directly copied and pasted into ACE.

	DESCRIPTOR	**FREQUENCY**
QUESTION TYPE	Numerical	87.6%
	Multiple Choice	4.1%
	Matching	0.8%
	Long Answer	5.0%
	Click on Target	2.5%
IMAGE INCLUDED?	Yes	66.9%
	No	33.1%
GRADING	Completion	48.8%
	Accuracy	51.2%

In addition to whether a question contained an image, the researchers were also curious whether question word count influenced dishonest ACE usage. Figure 1 displays the word counts for all FS inputs compared to the word counts of the course question bank. Upon observation, the FS inputs contain a greater inter-quartile range than the course content word counts, despite the presence of fewer outliers. Using this graphical representation as a diagnostic, the researchers further investigated whether differences existed between the sample of student input questions and the assigned course questions using a two-sample t-test and an F-test for the ratio of two variances. The researchers operated under the assumption that the word count distribution of FS inputs was normal. This assumption was validated by the large input sample size ($n = 124$) and a supplementary Kolmogorov–Smirnov test. A critical value of 0.12196 for comparison was calculated using a one-sample KS table.

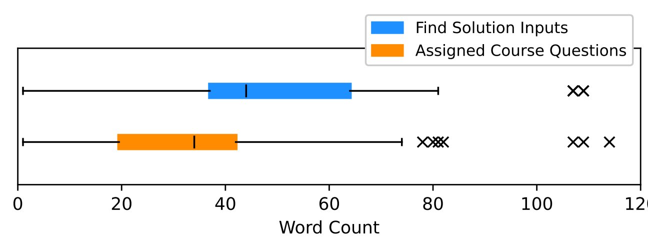

Fig. 1: Word counts in Find Solution inputs ($n = 124$) compared to bank of assigned course questions ($n = 263$).

At a significance level of $\alpha = 0.05$, the KS test statistic was revealed to be less than the critical value, thus verifying a normal distribution of inputs ($p \leq 0.010$). Welch's two-sample t-test was performed to test the hypothesis that the mean values of the distributions were equal, and exhibited that the group means differed by approximately 14 words, evidenced by a confidence interval of $(9.49, 18.559)$. This test was selected since the FS inputs and assigned course content were assumed to fail a homogeneity of variances. The hypothesis that the FS inputs and course content questions have the same mean values can be assertively rejected given the low p-value ($p = 0.000 < \alpha$).

Variance was another parameter of interest, and an F-test was employed to estimate the extent of the assumed difference in variance

TABLE III: Descriptive statistics, normality test, comparison of means, and ratio of variances of data set.

	Group Statistics			Kolmogorov-Smirnov Test			Welch's 2 Sample t-Test			F-Test (Ratio of Variances)		
Question Group	n	Mean	σ	α	Critical Value	KS	α	T	Confidence Interval	α	F	Confidence Interval
Find Solution Inputs	124	47.6	22.6	0.05	0.122	0.106	0.05	6.09	(9.40, 18.6)	0.05	1.61	(1.09, 1.48)
Assigned Course Content	263	33.5	17.9	-	-	-	-	-	-	-	-	-

between the two groups. Hypothesizing that the ratio of the FS input to course content word count distribution variances equated to one, at the selected alpha value, the estimated ratio of variances of FS input to course content word count was 1.27 (see Confidence Interval in Tab. III). It can be reasonably concluded that the variances of these groups differ significantly ($p = 0.002 < \alpha$). These findings suggest that the questions students asked ACE directly often contained more words than the typical assigned course question. While increased variance due to smaller sample size may explain an elevated mean, the appearance of a greater inter-quartile range further verifies the inclination of students to use ACE for wordier questions. A summary of all results is shown in Tab. III

Figure 2 shows the relationship between the quantity of FS inputs and the time of day. Most dishonest ACE usages seem to be clustered around the small hours of the day, particularly 12:00 a.m. and 2:00 a.m., though peaks also appear between 6:00 a.m. and 8:00 a.m. and between 3:00 p.m. and 5:00 p.m. These peaks in dishonest ACE usage appear to align with midnight assignment deadlines and gaps in the course's office hour schedule, suggesting that students perhaps turn to the chatbot when in-person assistance is unavailable.

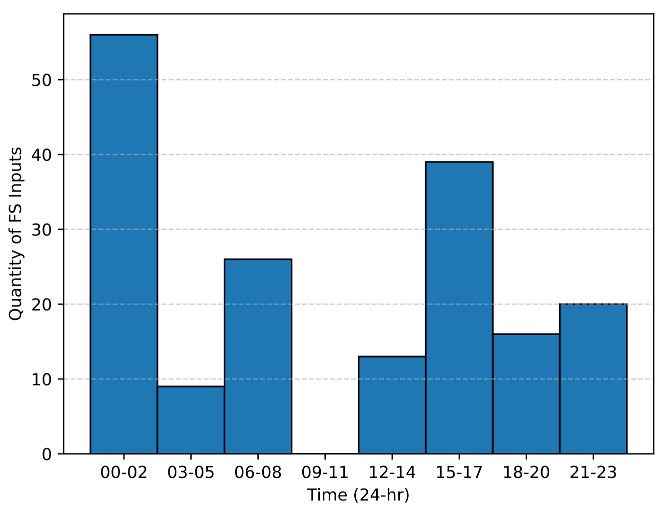

Fig. 2: Quantity of Find Solution inputs throughout the time of day.

The student ID attributed to the highest number of FS codes submitted 24 course content questions into the chatbot within a single sitting. These questions were asked to ACE between the hours of 12:54 a.m. and 2:37 a.m. Another interaction reveals that students seemingly grow displeased with the chatbot, as evidenced by agitated queries and responses. At 9:12 p.m., a student queried ACE by asking whether two textbook equations were equivalent. ACE mistakenly assumes the student refers to a homework problem, and the student replies with attitude, "I am trying to study for this exam on Wednesday, just give me a yes or no if they are equal. It's not a HW question I just want to make sure they are the same." Unfortunately, the equations were not the same, yet the student further demeans the chatbot by typing, "you are useless." Later, at 10:04 p.m., five conversational back-and-forths later, the same student asked ACE for assistance on a homework problem. ACE's reply was deemed unsatisfactory by the student, as they responded, "ACE, you need to seriously get better at your job."

Interestingly enough, as a facet of ACE's programming as a study aid, the digital assistant is trained to reveal answers more closely related to solutions after five to six conversational turns. This fact is designed to facilitate more Socratic discussion between the student and the chatbot, though it may contribute to inflated FS codes in the results, as students showed a tendency to concede to repetition when answers were not immediately revealed. One student illustrated this fact during their interactions with ACE, spanning from 6:21 a.m. to 8:01 a.m. The student prompted ACE by pasting the following homework question: "A 75 [kg] person is hanging from the bar above. Given that the block cannot experience a bearing stress larger than 13.4 [MPa] and the bar cannot and experience a shear stress more than 3.25 [MPa], what can the diameter of the bar be?" The student then proceeded to ask the chatbot repeatedly in quick succession variations of the phrase, "what is the diameter of the bar," for a total of 13 additional turns of conversation. The student's persistence may be sourced in ACE's reluctance to reveal answers, thus facilitating a wildly redundant interaction between man and machine.

IV. Conclusion

Through an in-depth analysis of user-input data, current student usages of generative AI were investigated, and trends in the utilization of such technology elucidated. The thematic coding of student inputs into ACE enabled the researchers to better assess how generative AI can be harnessed as a study tool within the classroom. Within FS prompts, the reasons students may choose to use generative AI in a manner that may violate academic integrity was examined. The results of this study provide a basis for future testing and implementation of generative AI in the engineering classroom to optimize the educational benefits of this technology for both instructors and students.

The categorization of user-input data into ACE supported the researchers' hypothesis and revealed that the majority of students use generative AI for productive purposes: to deepen their conceptual understanding of nuanced topics, to find equations within their statics text, to summarize course material for future studying and review, etc. Within the course's first section ($n = 131$), 93 students used ACE during the semester, and 51.6% of ACE users did not once directly ask the chatbot to solve assigned course questions. These findings suggest that student usages of generative AI do not fully align with that of course policy makers' expectations, underscoring the potential for this technology to be utilized in a manner that provides assistance without violating ethics or academic integrity.

A thorough assessment was conducted on the student inputs marked with the FS code. Numerical questions were copied and pasted into ACE most commonly, followed by long answer and multiple choice questions. Visual components appeared most frequently in questions asked directly to ACE, as images were present in 66.9% of FS inputs. In addition to the visual synthesis required by students, a trend in literary synthesis also appeared within the questions asked directly to ACE. The student inputs categorized with the FS code had a higher mean word count than those of the bank of assigned course questions. While the higher variance associated with this sample may contribute to an elevated mean value, a box and whisker plot shows a clear shift in the quartile spread in the word count student input questions. Connections between the time at which students completed their assignments and the frequency at which they copied and pasted course content directly into the chatbot were also assessed. The overwhelming majority of dishonest ACE usages occurred at extremely late hours, with a mode of 56 course questions asked directly into ACE between the hours of midnight and 2:00 am. The increased repetition and conversational turns of interactions at late hours may suggest a greater need for direct solutions rather than methodology assistance to prioritize extraneous factors (i.e., sleep). While ACE's tendency to withhold direct solutions prior to approximately five or six conversational turns was intended to bolster student participation with the chatbot, it seems that at late hours of the evening, students responded with increased frustration and repeated inputs.

The assessment of dishonest usages of generative AI enables the researchers to grasp further how to implement such technology in the classroom effectively. To steer student usage toward a more productive outlook, the researchers sought to first understand how generative AI is currently used dishonestly, as well as provide explanations for these non-ethical usages. The researchers plan to expand upon this study by completing further testing in subsequent sections of Statics and Mechanics of Materials I. These findings will guide the researchers in the creation and implementation of course content questions that discourage unethical AI usage and open an avenue for further work. Another interesting facet to study is the impact of the continued tuning of ACE's training data on the efficacy of the chatbot's replies, particularly with respect to redundant student prompts. Additional content on ethical and effective AI usage may also supplement and perhaps shape the course of student usage if properly applied. These findings and future works culminate in a baseline for steering the implementation of generative AI within engineering courses.

V. Future Work

While this exploratory study provides detailed insight into student prompts and general usage trends of generative AI, the data analyzed is constrained to one specific implementation of a generalized LLM. Students could leverage other generative AIs, such as ChatGPT or Copilot, for a wide array of usages not outlined in this study or rely on third-party GenAIs to seek answers to assigned course questions. Unfortunately, the scope of the data analyzed will likely be confined to Top Hat ACE. The data collected in this study was also limited to about four weeks of ACE usage throughout one of two course sections. More extensive data collection over a wider time frame would be preferable in future studies to assess how usage trends may subsist dynamically throughout the semester.

Future work may entail examining user-input data over a longer duration of time, namely an academic term. The researchers will concurrently track student usage with the implementation of educational GenAI usage modules to determine whether intervening content can steer the direction of use. Time-dependent behavior will be tracked to see how students may change their usage of ACE and to determine whether answer-seeking behavior is a fluctuating variable, and further, ACE usage may be correlated with academic performance. Another particularly intriguing path for exploration lies in the augmentation of ACE's training set. The researchers will provide additional instructional content to tune ACE's training data further and examine if this extension modifies the chatbot's efficacy of replies, particularly to questions about problem-solving methodologies. The selection of the additional content will use the findings of this study as a basis, with distinct emphasis on course content most commonly appearing in FS inputs.

The coupling of user-input data with student self-reported data may provide further insight into the multifaceted usages of GenAI in the classroom. User-input data collected throughout a semester will be more closely compared against self-reported data, which has already shown students changing their answer-seeking behavior due to awareness of the limitations of GenAI and ethical considerations [4]. These findings will culminate in a more detailed description of the current and projected usages of generative AI technologies within the sphere of engineering education.

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