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First-Year Engineering Students and Generative AI: Historical Use, Planned Use, and Correlations

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Abstract

This complete research paper reports the extent of prior use (in high school), planned use in first-year (FY) engineering courses, and disclosed use of Generative AI (GenAI) for various tasks in two first-year engineering courses at a single large public institution. Given the rapid evolution of GenAI it is important for instructors of FY engineering courses to understand the previous use history and plans of their students to facilitate appropriate use and discourage uses of GenAI that constitute cheating. It is also important to avoid exacerbating or creating achievement and learning gaps among students from different demographic groups. The research was conducted in the fall 2025 with over 500 students enrolled in a first-year engineering projects (FYEP) course with open-ended team design projects or an engineering tools and analysis course that had learning objectives related to math skills and Matlab. The majority of the students had used GenAI in schoolwork prior to college, with higher use among engineering students compared to students exploring engineering as a major. Disclosed previous GenAI use was higher among male compared to female students. Planned GenAI use varied among types of course activities, with the highest frequency for exploring unfamiliar topics and lowest for help with writing. Planned use of GenAI for some activities was higher among male compared to female students and higher among students who first language was not English. Some differences in planned GenAI use were also found among White, Hispanic, and Asian students. Planned use was weakly correlated with students' reported use at the end of the semester in the FYEP course. On average, reported student use of GenAI during the semester was higher in the engineering problem solving course compared to the FYEP course. Substantial section-level variation in GenAI use and policy perceptions was observed within the first-year engineering projects course, with uneven student understanding of policies even within the same section, highlighting challenges of policy clarity and consistency in multi-section courses. Taken together, these findings show that first-year students enter engineering with prior experience using GenAI, develop intentions for use early in the semester, and adapt their practices in response to course context and instructor policies. As GenAI tools become increasingly embedded in academic and professional contexts, early and explicit guidance in first-year courses will be essential for fostering responsible use while mitigating potential negative impacts on learning and equity.

Introduction

Generative AI (GenAI) and large language models (LLMs) are rapidly evolving tools that have the potential for both positive and deleterious impacts on education [1],[2]. The quality and accessibility of these tools continues to change, including ChatGPT and others which may be free or cost money to use. GenAI queries can give rapid answers to questions, which allows students autonomy to explore topics of interest and receive timely assistance. However, GenAI may also give false information or be used by students to directly answer homework questions without the student learning for themselves. Understanding the previous academic use and expected uses of GenAI by students in first year engineering courses can help educators to plan and communicate their expectations for appropriate and responsible use of AI. It is important to have timely results relevant for first-year engineering courses. Faculty should also consider the extent to which GenAI use might widen achievement gaps among students from different demographic groups.

Students entering college can be expected to have a wide range of experiences with GenAI during their K-12 education, ranging from explicit “AI literacy” education to bans on use due to cheating concerns [3]. As of August 2025, 27 states have issued guidance on AI to public schools [4]. But ultimately, individual school districts adopt policies, and individual teachers can also set their own guidelines.

Previous research has found demographic differences in the use of GenAI, on the basis of gender [5], race/ethnicity [6],[7], and socio-economic status [8]. In Norway, male students used GenAI more frequently and for a wider range of tasks [9]. Male and female university students in Indonesia also differed in their uses and perceived benefits of GenAI [10]. The authors of these studies raised concerns about gender equity and GenAI. Similarly, a white paper from the World Economic Forum explored how AI-driven workplace changes could widen gender gaps in STEM [11] GenAI offers the potential for more personalized learning by neurodivergent students [12],[13]. Overall, GenAI has the potential for both benefits and drawbacks that may be unique for subgroups of students.

Theories can provide insights into why different students might elect to use GenAI tools to support their learning and/or schoolwork. The Technology Acceptance Model (TAM) indicates that use is based on perceived usefulness (improvements in learning quality or speed) and ease of use [14],[15]. This was later expanded to the Unified Theory of Acceptance and Use of Technology (UTAUT) which includes the extent that an individual believes that technology use will help their performance and requires low effort, while also accounting for social influences and facilitating conditions (e.g., access, training) [16]. Social influences likely varied significantly before college (public or private schools, affluence, culture). Facilitating conditions likely included early costs associated with the best GenAI tools, which perhaps more wealthy families purchased. A previous study found that students lacking academic confidence were more likely to use GenAI in their schoolwork [17]. Thus, differences in students’ levels of academic preparation from high school may also affect choices to use GenAI in college.

Research Questions

The following research questions were explored in this study.

RQ1: To what extent do students enrolled in first-year (FY) engineering courses report previously using GenAI for schoolwork? Does this differ between engineering majors and potential engineering majors and/or with other student demographics?

RQ2: To what extent do students enrolled in first-year (FY) engineering courses report they plan to use GenAI for different types of activities in the course? Does this differ among demographic groups? Does planned use correlate with their self-reported previous GenAI use?

RQ3: Does previous or planned GenAI use correlate with student confidence in various content areas and/or skills that will be used in these FY engineering courses? Do correlations differ among demographic groups?

RQ4. What frequency of GenAI use for various activities in the FY engineering courses are disclosed by students at the end of the semester? Did this correlate with planned use frequency? Does disclosed use vary among demographic groups?

Methods

Setting

This research was conducted at a single large public research-intensive institution. The institution does not have a uniform AI use policy for students. The topic is briefly addressed on the student honor code website, which states that policies will vary for each course. The university guidance takes a proactive stance on AI use stating "The goal is to empower students to use the appropriate innovative tools to be successful in their fields." (More information in Appendix A.) Two courses provided data for this study; each is described briefly below.

The first course enrolled incoming students primarily from the Program of Exploratory Studies (PES) who were interested in engineering. The majority of these students had applied to engineering but were not admitted. Often this was because they had applied to particularly competitive majors (e.g., aerospace engineering). Some students were truly uncertain of a major across colleges (e.g., Arts & Sciences, Engineering, Business) and elected to enroll in PES. During the summer PES students were batch enrolled in the FY course "Engineering Tools and Analysis". In this course students apply math concepts from algebra through differential equations to solve engineering problems related to diverse disciplines (e.g., electrical, mechanical, civil engineering). Students generate their own data in hands-on labs. The course also incorporated Matlab. In fall 2025 the course included 3 lecture sections and 6 lab sections, with 3 different course instructors. All 3 course syllabi included explicit generative AI guidance, which varied in specificity and restrictiveness. Two sections drew on similar institutional language describing generative AI capabilities and risks but differed in application: one required prior authorization for any AI use, while the other permitted AI for clearly defined supplementary learning activities such as practice problem generation or writing refinement. The third section adopted a more permissive approach, allowing AI use for assignment checking with appropriate documentation and minimal additional constraints.

The second course was a first-year engineering projects course (FYEP). FYEP introduces the engineering design process through team-based, hands-on projects that span problem scoping, solution development, and communication. Across sections, learning objectives emphasize teamwork, design thinking, ethical awareness, and written and oral communication in an engineering context. The majority of the students in this course were incoming first-year engineering students who were batch enrolled in the course over the summer. This included students who had not yet selected a specific major within engineering (so-called open option). The course included 14 sections taught by 12 different instructors. Each section typically enrolled 30 students (although 6 sections allowed up to 35 students due to instructor discretion to admit students from the waitlist). The course was coordinated by two faculty members who promoted cross-section consistency by providing a Canvas shell and recommended syllabus that included a GenAI statement. Analysis of syllabi from 12 sections showed substantial variation in GenAI policies: three closely followed the recommended statement, while others ranged from complete prohibition to permissive, disclosure-based use; two syllabi did not mention GenAI. This variation suggests that students encountered markedly different expectations regarding GenAI use depending on section enrollment (see Appendix B).

Survey Instrument

Both of these first-year engineering courses participate in ongoing research related to engineering self-efficacy / confidence, identity, and belonging (approved by the institutional IRB for Human Subjects Research). The surveys began with the informed consent statement and allowed students to participate in the research (if they were 18 years of age or more) or take the survey for purely course evaluation purposes. The GenAI questions that were added to the surveys were adapted from [18] (see Appendix C). These questions were located near the middle of each survey. The surveys ended with demographic items. Note that students could choose to skip individual items and some students started but did not complete the survey. The surveys were administered through Qualtrics. Students were invited to participate in the pre-survey within the first week of the semester in August 2025 and in the post-survey during the final week of the semester in December 2025. The PES course allocated time during class to complete the pre-survey but varied among the 3 sections in providing in-class time for the post-survey. The 14 FYEP course sections varied in whether or not time was provided during class for students to complete the surveys.

Data Analysis

Survey responses from Qualtrics were exported to Excel. First the data were cleaned to retain responses from only the students who consented to participate in the research and remove duplicate responses (retaining the most complete or first response). Data analysis computed means and standard deviations, followed by unpaired t-tests comparing pairs of demographic groups and/or courses. While the use frequency data were ordinal, parametric tests were utilized for their established robustness against violations of normality and interval-level assumptions in small-to-moderate samples [19]. A $p < 0.10$ was considered statistically significant. Effect sizes were calculated as Cohen's d, where rules of thumb are 0.2 is small, 0.5 is medium, and 0.8 is large. Differences among sections were explored using non-parametric Kruskal-Wallis (KW) tests in IBM SPSS; post-hoc pairwise comparisons reported significance and adjusted significance based on the Bonferroni correction, and the standard test statistic was used to compute effect size r. Correlations were also computed in Excel followed by p values determined by the online Social Science Statistics calculator [20]. A spreadsheet that aligned the pre and post survey responses from the same students in a single row (based on their name and section) was created to calculate correlations between planned and actual use of GenAI reported on the pre and post surveys, respectively. The different sections of each course were assigned random identifiers (e.g., [S1]) to preserve anonymity.

Respondents

In the PES course ~98% of the students enrolled completed the pre-survey (n=132) and 89% of the pre-survey respondents elected to participate in the research (n=117). In the FYEP course the total number of completed pre-surveys (n=427) represents about 95% of the enrolled students. Among those, 94% participated in the research (n=403). Note that because students could skip survey items, these response numbers may not be represented within all of the data. Based on the fall census date for the university, the FYEP course represents about 57% of the incoming first-year students in engineering majors. For the post-survey the number of students who consented to participate in the research included 58 students in the PES course (8 to 25 per instructor) and 361 students in the FYEP course (ranging from 19 to 31 students per section). The paired data of pre and post responses for individual students in the PES course resulted in 48 pairs and the FYEP course resulted in 308 pairs (with 17 to 30 students per section).

The demographics self-reported by the students at the end of the surveys included: current major / engineering major(s) of interest; gender (male, female, prefer to self describe, prefer not to respond); how they would describe themselves using race/ethnicity categories (allowed to select multiple categories); and whether or not they identified as neurodivergent (yes, maybe, no). The FYEP survey included the additional demographic items of first-generation (FG) college student and whether English was their first language (EFL).

Limitations

Self-reports may not be accurate. The extent to which students feel comfortable disclosing their GenAI use may vary based on their personal ethical beliefs [21], the policies regarding cheating and use in their previous schooling, messages that they received during college orientation or on course syllabi (pre-survey), or instructor policies (post-survey). Instructor policies for GenAI use discussed verbally or explained for particular assignments is unknown; it is unclear to what extent the syllabi fully explain instructor practices or student understanding of their policies. Students may not be fully aware of their GenAI use. For example, do they consider doing a Google search and seeing the AI summary as AI use? Or only if they specifically pull up ChatGPT? There was a large attrition in student consent to participate in the research on the post-survey compared to the pre-survey in the PES course (50%). For the demographic comparisons, some groups had low numbers (e.g., few women among the PES students; racial/ethnic groups other than White, Asian, and Hispanic) which limits the sensitivity of quantitative data analysis.

Results

RQ1. Previous GenAI Use in Schoolwork

The student responses to the question "How often did you use Generative AI / LLM chatbots (e.g., ChatGPT) in your schoolwork last semester?" are summarized in Table 1. Since most incoming students in engineering at this institution matriculate directly from high school, the responses predominantly represent GenAI use as seniors in high school. The majority of the students had previously used GenAI for schoolwork (73% PES, 85% FYEP), with use a few times per month the most prevalent use frequency. The policies for allowable GenAI use or high school courses that required students to use GenAI are unknown and likely were highly variable.

Table 1. Reported previous GenAI use in schoolwork, percentage of students.

Frequency	PES (n = 116)	FYEP (n = 403)	FYEP Male (n = 296)	FYEP Female (n = 96)
1: Never	26.7	15.4	15.5	14.6
2: <1 / month	16.4	27.3	23.6	36.5
3: few times / month	39.7	33.5	34.5	32.3
4: few times / week	14.7	20.3	22.0	15.6
5: daily	2.6	3.5	4.4	1.0

Engineering students reported slightly more frequent GenAI use on average than PES students (mean±stdev FYEP 2.69±1.07; PES 2.50±1.12; p 0.10, d 0.17 very small effect). Comparing male PES and male FYEP students the results were not significantly different (p 0.11, d 0.18; see gender effect discussion below). There were not significant previous use differences among students in different engineering majors in the FYEP course (data not shown).

PES: Among PES students, there were not significant differences in previous GenAI use between male and female students (M 2.56±1.12, F 2.25±0.89; p 0.38), but there were few female student responses (n=8). Hispanic / Latinx students had used GenAI more frequently than White peers (H 3.07±1.27, W 2.50±1.13; p 0.06, d 0.47). There were not significant differences between GenAI use by White students and Asian students. No other race/ethnicity categories had 10 or more responses, so additional comparisons were not made. There were not significant differences between neurotypical and neurodiverse students in their self-reported previous GenAI use.

FYEP: Among FYEP students, male students reported slightly higher prior GenAI use than female students (M = 2.76 ± 1.10 vs. 2.52 ± 0.96; p = 0.04, Cohen's d = 0.23, small effect). No statistically significant differences in previous GenAI use were observed by race/ethnicity, neurodiversity status, first-generation status, or whether English was a student's first language.

RQ2. Planned GenAI Use in FY Engineering Courses

In the first week of the semester students were asked "If and how do you plan to use GenAI / LLM chatbots (e.g., ChatGPT) in this class this semester?" Potential uses relevant for each class were listed on the survey, with 4 items the same and others different. The rating scale was: Never (1), Rarely (2), Sometimes (3), and Often (4). Numerical average results are summarized in Table 2.

Table 2. Planned use of GenAI in FY engineering course, mean ± stdev on 1 to 4 scale.

Use in course this term	PES n = 115	FYEP n = 403	FYEP male	FYEP female	FYEP English FL	FYEP Engl not FL
Explain challenging concepts	2.70±0.96	2.67±0.92	2.67±0.93	2.66±0.87	2.64±0.93	2.89±0.87*
Explore unfamiliar concepts	2.59±0.89	2.52±0.95	2.57±0.96*	2.34±0.89	2.48±0.96	2.77±0.89*
Brainstorming	N/A	2.14±0.88	2.21±0.89*	1.93±0.82	2.11±0.88	2.36±0.92*
Help with coding (Matlab, Arduino)	2.06±0.88*	1.89±0.92	1.95±0.95*	1.69±0.81	1.86±0.92	2.07±0.95
Help solving problems	2.00±0.88	N/A	N/A	N/A	N/A	N/A
Summarize texts	N/A	1.98±0.86	1.99±0.90	1.93±0.74	1.96±0.86	2.11±0.87
Help writing (lab) reports	1.59±0.76*	1.36±0.64	1.39±0.66	1.27±0.59	1.32±0.60	1.64±0.89*
Help writing personal reflections	N/A	1.14±0.45	1.16±0.45	1.09±0.33	1.12±0.39	1.30±0.63*

*N/A = not asked on the survey; * p<0.10 for PES v FYEP, FYEP Male v FYEP Female; FYEP English first-language v not*

The most common expected uses were to explain challenging concepts and explore unfamiliar concepts, with most students planning to sometimes use GenAI for these tasks. These uses might help students learn, particularly those who tend to work alone and/or are uncomfortable asking faculty or teaching assistants for help. Less frequently planned uses of GenAI, on average rarely, were for brainstorming, help with coding, help solving problems, and summarizing texts. These uses may or may not be considered cheating, depending on the specific form of GenAI assistance and instructor policies. The least commonly planned uses of GenAI were for help writing reports and writing personal reflections. Most students indicated they never planned to use GenAI for these tasks. Given that faculty are likely to perceive GenAI assistance for writing personal reflections as cheating, it is encouraging that most students in the FYEP course (89%) rated this as never.

Planned use of GenAI was similar among the PES and FYEP students with the exception of higher use among the PES students for helping writing (lab) reports (p 0.003, d 0.34) and coding (p 0.06, d 0.19); see Figure 1. The PES course required more frequent reports (a weekly lab) and coding compared to the FYEP course, so this difference likely aligns with student perceptions of the frequency of these activities in the course. Limiting the comparison to only male students in both courses, only planned GenAI use to help with writing remained different between the courses (p 0.01, d 0.32).

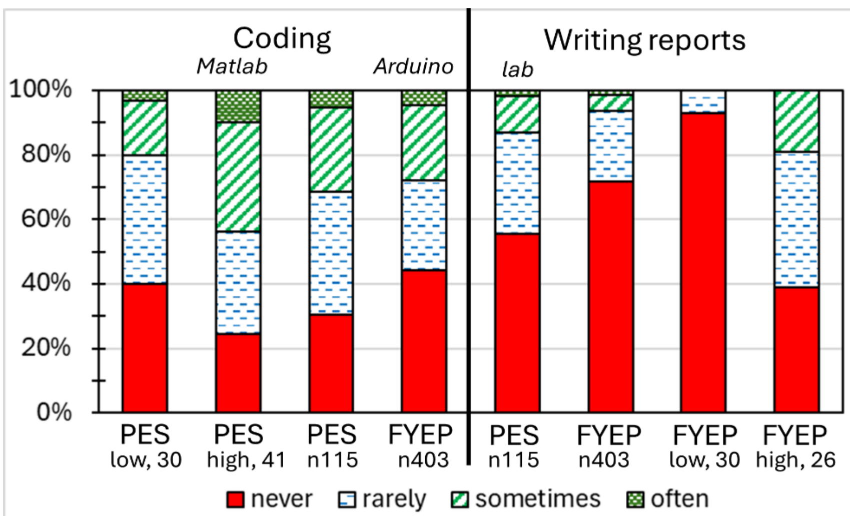

Figure 1. Frequency of planned GenAI use for coding or writing reports by course; aggregate course data and the sections with the lowest and highest use where inter-section differences were statistically significant are shown (sample sizes indicated).

Different GenAI use policies among the three PES instructors appeared to impact students' reported planned use (see Figure 1), with statistically significant differences for coding in the PES class between two sections (one with a very restrictive policy; t-test p 0.03, d 0.51; KW paired post-hoc adj. sig. 0.10, r 0.25). A statistical difference in the planned use of GenAI for writing reports was found among the 14 sections of FYEP (KW p <0.001; max v min paired post-hoc adj. sig. 0.000, r 0.62). Interestingly, the lowest planned use was in the section where the syllabus contained no mention of AI [S9] versus the highest in a section with a specified AI use policy [S13].

Within the FYEP course there were small differences among planned GenAI use among students in different engineering majors. For example, environmental engineering majors planned for higher GenAI use to help with Arduino coding (mean 2.0) than electrical engineering majors (mean 1.6; p 0.08, d 0.48) and lower use of GenAI to summarize texts (mean 1.7) than civil engineering majors (mean 2.2; p 0.09, d 0.63). However, these differences may have been skewed by the representation of women and/or EFL among the students in the majors. In follow-up statistical tests using the data from only male students, fewer differences between engineering majors persisted (e.g., use GenAI to summarize text environmental 1.6, civil 2.3, p 0.06, d 0.84).

PES: Among the PES students comparing Hispanic to White students, the planned use of GenAI was higher for exploring unfamiliar concepts (mean H 2.93, W 2.58, p 0.08, d 0.36) and lower for help with coding (mean H 1.79, W 2.06, p 0.02, d 0.34) and writing lab reports (mean H 1.50, W 1.65, $p < 0.001$, d 0.20). Asian students planned to use GenAI more frequently for help with writing than White students (mean A 1.78, W 1.65, p 0.01, d 0.18). It is unclear if this difference might be due to more non-native English speakers among the Asian students (i.e., international Asian students). There were not significant differences in planned GenAI use between male and female students or between neurodivergent and neurotypical students (data not shown).

FYEP: A number of differences were found among students' planned GenAI use based on different demographic characteristics. As shown in Table 2, male FYEP students planned to use GenAI more frequently than female FYEP students for exploring unfamiliar concepts, brainstorming, and help with coding.

Students whose first language (FL) was not English (n=44) planned to use GenAI more than students who indicated that English was their first language (n=353) for 5 of 7 tasks in the FYEP course (Table 2): help writing reports, help writing personal reflections, exploring unfamiliar concepts, explain challenging concepts, and brainstorming; the effect sizes were small (d 0.28 to 0.42). GenAI use might help this group overcome challenges with language issues such as comprehension and communicating their ideas. This aligns with other findings showing widespread use of GenAI for language translation [22].

Comparing first-generation students (n=42) to those who were not the first generation (FG) in their family to attend college (n=356), higher GenAI use was planned for exploring unfamiliar concepts (FG 2.76 ± 0.76, not FG 2.49 ± 0.97, p 0.04, d 0.31). All of the other planned GenAI uses in the FYEP course did not differ significantly between FG and not FG students.

There were not differences in planned GenAI use frequency among students from different race/ethnic groups, with the exception of higher planned use for help with Arduino coding by Black students (mean 2.2, n=11) compared to Native American / Alaskan native students (mean 1.6, n=9; p 0.08, d 0.82). There were not differences in the planned use of GenAI between neurotypical and neurodiverse students (data not shown).

Not surprisingly, previous use of GenAI for schoolwork were moderately correlated with planned future uses of GenAI in the first-year engineering courses to explore unfamiliar concepts, explain challenging concepts, help solving problems, and brainstorming (Table 3). Previous GenAI use in schoolwork were only weakly correlated with planned use for help with coding, summarizing texts, and help writing reports. It is unclear if students had not previously used GenAI for these tasks, had tried GenAI for these tasks and found it was not helpful, and/or had been taught that GenAI use for these tasks was cheating. It is also interesting that the strength of the correlations varied for different demographic sub-groups. For example, correlations for the PES students were higher than for the engineering majors in the FYEP course. Correlations were also stronger in the FYEP course for male students compared to female students, particularly for summarizing texts and brainstorming.

Table 3. Previous GenAI use correlations with planned use in the FY engineering courses.

Use in course this term	PES (n=115)	FYEP (n=403)	FYEP male (n=296)	FYEP female (n=06)
Explore unfamiliar concepts	0.60 **	0.44 **	0.44 **	0.39 **
Explain challenging concepts	0.57 **	0.50 **	0.52 **	0.43 **
Help solving problems	0.46 **	N/A	N/A	N/A
Help with coding (e.g., Matlab, Arduino)	0.32 **	0.31 **	0.33 **	0.28 *
Brainstorming	N/A	0.40 **	0.43 **	0.26 *
Summarize texts	N/A	0.35 **	0.38 **	0.20 *
Help writing (lab) reports	0.29 *	0.27 **	0.30 **	0.21 *
Help writing personal reflections	N/A	0.16 *	0.21 **	0.11

*N/A = not asked in the survey; ** $p < 0.001$; * $p < 0.10$*

RQ3: GenAI use and student confidence

In the FYEP course, previous use of GenAI did not correlate significantly with other survey items where students rated their confidence or ability in different topics. Among the PES students, a very weak correlation with previous GenAI use was "I am skilled at solving problems with multiple solutions" (1 strongly agree, 7 strongly disagree; correlation 0.19). Thus, students who felt less skilled at this were more likely to report higher previous GenAI use. This confidence impact on GenAI use has been previously reported [17].

Exploring correlations of planned GenAI use in the course with confidence, the only potential relationship was among students within the FYEP course, where higher planned GenAI use for writing reports corresponded with lower confidence in writing skills (correl -0.22, $p < 0.001$). There were not correlations between confidence in coding and plans to use GenAI to help with Arduino (correlation -0.05) or any of the other interactions. Similarly, among PES students there were no correlations between math confidence, or confidence solving problems, writing, etc. and planned GenAI use for different tasks.

RQ4. Disclosed GenAI use in FY engineering courses

At the end of the semester students were asked how often they had used GenAI in the course for different tasks during the semester. Among individual students in the PES course, the average use of GenAI across 5 different tasks ranged from 4.0 (often / weekly; n=4, 7%) to 1.0 (never; n=5, 9%) with a median of 2.00 (rarely / ~3-5 times). The average per student use of GenAI across 7 tasks in the FYEP course ranged from 4.0 (often/weekly; n=2, 0.6%) to 1.0 (never; n=49, 13.6%)

with a median of 1.57 (between rarely and never). Thus, 91% of the PES students and 86.4% of the FYEP students reported some use of GenAI in their respective FY engineering courses.

Students' average reported use of GenAI for different tasks is summarized in Table 4; categorical response data for some uses are shown in Figure 2. The most frequent uses in both courses were explaining challenging concepts and exploring unfamiliar concepts, while few students used GenAI for help writing reflections. Challenging or unfamiliar concepts / tasks might come up at any time in any type of course. But there might not have been many assigned readings during the semester in the FYEP course that required summarizing, thus its lower average use frequency.

Table 4. Students' reported use of GenAI in their FY engineering courses at the end of the semester by demographic groups (scale 1 never to 4 often; mean ± stdev).

GenAI use in the FY course this term	PES (n 58)	FYEP (n 361)	FYEP male	FYEP female	FYEP high section	FYEP low section
Explain challenging concepts	$2.57{\pm}0.96^{*D}$	$2.01{\pm}0.99$	$2.07{\pm}1.00^{*}$	$1.85{\pm}0.94$	$2.60{\pm}1.14$	$1.40{\pm}0.62$
Explore unfamiliar concepts	$2.55{\pm}1.08^{*D}$	$2.05{\pm}0.95$	$2.13{\pm}0.98^{*}$	$1.90{\pm}0.86$	$2.60{\pm}0.88$	$1.53{\pm}0.68$
Brainstorming	N/A	$1.84{\pm}0.84$	$1.89{\pm}0.85^{*}$	$1.72{\pm}0.81$	$2.20{\pm}0.83$	$1.30{\pm}0.47$
Help with coding (Matlab, Arduino)	$2.24{\pm}1.11^{*d}$	$1.92{\pm}1.00$	$1.98{\pm}1.03^{*}$	$1.76{\pm}0.89$	$2.60{\pm}1.05$	$1.40{\pm}0.86$
Help solving problems	$2.17{\pm}1.11$	N/A	N/A	N/A	N/A	N/A
Summarize texts	N/A	$1.30{\pm}0.60$	$1.32{\pm}0.62$	$1.27{\pm}0.53$	$1.55{\pm}0.69$	$1.10{\pm}0.40$
Help writing (lab) reports	$1.47{\pm}0.92$	$1.20{\pm}0.62$	$1.28{\pm}0.63$	$1.32{\pm}0.61$	$1.65{\pm}0.66$	$1.13{\pm}0.34$
Help writing personal reflections	N/A	$1.15{\pm}0.51$	$1.17{\pm}0.56^{*}$	$1.08{\pm}0.34$	$1.54{\pm}0.99$	$1.00{\pm}0.00$

N/A = not asked on the survey; * $p<0.05$ PES v FYEP, Cohen's $^{D} > 0.5$, $^{d} > 0.2$; * $p<0.10$ FYEP Male v Female

Students in the PES course reported more frequent GenAI use to help explain, explore, and code compared to FYEP students. This may reflect the frequency that specific tasks were needed for the course, with more technical content in the engineering tools and analysis course (e.g., problem solving) compared to the FYEP course (e.g., hands-on design projects with teams). Further, individual students may have done less of a task compared to other members of their FYEP team (e.g., one student assigned to do all of the Arduino coding for their team project).

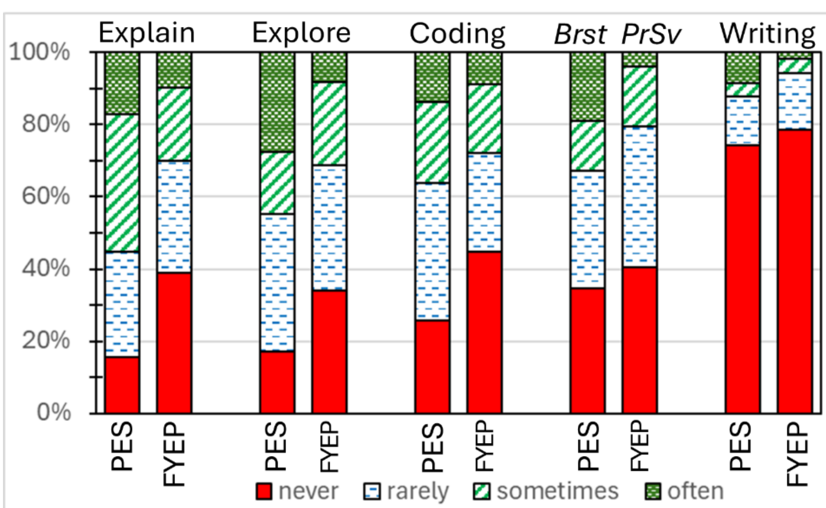

Figure 2. Reported GenAI use frequency in the two courses for various tasks (Brst = brainstorming, PrSv = problem solving); PES n=58, FYEP n=361.

PES: In the PES course there were not significant differences in GenAI use frequency found among students in different sections of the course (data not shown). Demographic comparisons (e.g., gender, race/ethnicity) were not conducted given the small number of post survey respondents.

FYEP: *Demographics.* In the FYEP course, the reported use frequencies of GenAI were compared among demographic groups. Males reported higher use of GenAI than females for explaining challenging concepts, exploring unfamiliar concepts, brainstorming, help with Arduino coding, and help writing personal reflections (see Table 4), but these differences were small (d 0.19 to 0.24). Among students who identified with different racial/ethnic groups, Hispanic/Latinx students (n=38) reported greater use of GenAI compared to White students for brainstorming (mean 2.13 H v 1.81 W, p 0.05, d 0.36), summarizing text (mean 1.53 H v 1.27 W, p 0.07, d 0.37), and help writing personal reflections (mean 1.45 H v 1.14 W, p 0.05, d 0.43). Asian students (n=35) reported higher average use of GenAI to summarize texts than White students (mean 1.49 A v 1.27 W, p 0.09, d 035). No other differences among racial/ethnic groups were statistically significant (but there were fewer than 10 post survey responses from students in other racial/ethnic groups). There were not significant differences in reported GenAI use during the semester between students whose first language was / was not English (n=272 / 56), first-generation / nonFG, and neurodivergent / neurotypical students.

FYEP: *Sections*. Students' self-reported use of GenAI varied significantly across sections of the FYEP course for six of the seven tasks examined (Kruskal–Wallis $p < 0.05$). Sections with the highest and lowest mean use for each task are summarized in Table 4. One section [S7] exhibited the highest average use for five of the seven activities; a syllabus was not available for this section, and the instructor's GenAI policy is therefore unknown. In contrast, another section [S12] showed the lowest average use for the same five activities and was associated with one of the more restrictive GenAI policies identified in the syllabus analysis. Use frequencies for writing reports and personal reflections showed different section-level patterns, with the highest and lowest values occurring in other sections. The extent that different sections required students to write reports and reflections varied. For example, one section of the FYEP course apparently assigned no personal reflection writings.

FYEP: *Policy Perceptions*. Student-reported perceptions of GenAI policies in the FYEP course further illustrates substantial section-level variability and only partial alignment with syllabi. Across sections, required GenAI use was rare (0-4% students) with one outlier section [S10] in which 87% of students reported required use. Perceived encouragement of some GenAI uses ranged from 5% to 45% of the students per section, while reports that at least some uses were discouraged were common across sections but highly variable (27-73%). Reports that ***all*** GenAI use was discouraged ranged from 0% to 48% of the students per section, and the proportion of students indicating that no policy was specified varied widely from 0% to 59%. In many cases, these patterns broadly aligned with syllabus-based assessments of policy restrictiveness; however, several sections showed notable discrepancies between documented policies and student reports. These inconsistencies suggest that GenAI expectations were communicated through multiple channels including verbal guidance or assignment-level instructions and/or evolving expectations during the semester. The uneven uptake among students is notable and likely contributed to both heterogeneous use and uncertainty within the same course.

Correlations. Potential correlations between planned use and reported actual use of GenAI in the FY courses were explored; results are summarized in Table 5. For three of the five ways of using GenAI in the FY engineering tools and analysis course with PES students there were moderately strong positive correlations between planned use on the pre-survey and reported actual use on the post-survey. In the FYEP course all average actual use ratings were lower than planned use, with the exception of help with coding which was similar between reported actual use and planned use. There were weak correlations between the FYEP students' planned use of GenAI at the beginning of the semester with actual use reported at the end of the semester. When aggregated across all students and sections, the strongest correlation was modest (0.32) for brainstorming. Correlation strength varied substantially by section, likely reflecting the influence of individual instructor policies. For six of the seven uses, correlations ranged from 0.51 to 0.69 in the section with the strongest association. Six different sections had the highest correlations. For each use, between 2 to 5 sections showed statistically significant correlations (moderate to weak), and 11 sections of the course had 1 to 4 uses with had statistically significant positive correlations between planned and actual GenAI use.

Table 5. Correlations between planned use on pre-survey and actual use on post-survey; [FYEP section number] and number of the 14 sections with positive correlations.

GenAI Use	PES (n=48)	FYEP All students (n=308)	FYEP Section with highest correlation	FYEP Section with lowest correlation	# FYEP sections with + correlation
Brainstorming	N/A	0.32 **	0.61 * [S11]	-0.01 [S6]	5
Explore unfamiliar concepts	0.44 *	0.28 **	0.51 * [S10]	-0.06 [S6]	3
Summarize texts	N/A	0.27 **	0.40 * [S2]	-0.17 [S1]	2
Explain challenging concepts	0.64 **	0.25 **	0.58 * [S5]	-0.21 [S12]	4
Help writing personal reflections	N/A	0.20 *	0.69 ** [S7]	-0.08 [S12]^	3
Help with coding	0.20	0.17 *	0.69 * [S3]	-0.12 [S6]	2
Help writing reports	0.19	0.16 *	0.63 * [S7]	-0.26 [S6]	3
Help solving problems	0.37 *	N/A	N/A	N/A	N/A

*** p < 0.001; * p < 0.10; N/A = not asked in the survey for the course; ^ in 5 sections the correlation could not be calculated because all of the post ratings were 1 (zero standard deviation and therefore a divide by zero error)*

The correlation findings suggest that many students had reasonably accurate perceptions of their anticipated GenAI use at the start of the semester, potentially shaped by personal ethics and experiences, as well as instructor guidance articulated in syllabi and/or early course meetings. The weakest correlations for all seven uses were negative (though not statistically significant) and clustered in three sections, with [S6] accounting for four of the seven lowest values. This aligns with the absence of a GenAI policy in the syllabus for [S6]. Notably, three sections of the course ([S6], [S8], and [S13]) showed no statistically significant correlations for any use type, implying that instructor policies and practices may meaningfully shape student GenAI use.

FYEP: *Open Responses*. In short write-in responses some students briefly described how their GenAI use was helpful and not helpful in the FYEP course. A number of students seemed generally opposed to GenAI, citing concerns that it weakens student learning and/or negative environmental impacts. In one section of FYEP, [S10], the students were required to use GenAI in their reports, e.g. "We used GenAI in our reports to help give us feedback and what to improve on (part of the assignment.).” Feedback on the usefulness of GenAI for help with their reports was mixed, but more negative than positive. Some examples:

> “It was helpful when we needed to use it for reports, like Coach Clarity. Coach Clarity also was wrong in some aspects of the reports.” [S10]
>
> “I thought using AI to revise our reports and having to respond to the AI feedback was excessive and not really helpful.” [S10]

The most positive student comments related to using GenAI to help with coding and debugging. Some of the responses indicated that the student tried getting help from a person (e.g., teaching assistant, lab worker) but still needed to use GenAI; e.g. “The Arduino wouldn’t work and the people in the electronics center didn’t know how to fix our code so using AI helped us to find the issue and made our final project actually work.” As a counterpoint, a student in the engineering analysis course commented, “I think MATLAB forcing the AI upon you can be annoying, I wish it was helpful and accessible but didn’t immediately show you the answers so you didn’t figure it out yourself.” Other commonly cited uses in the FYEP course were in brainstorming and developing their team name. Some students noted that GenAI was helpful in composing professional email communications with their client (note that a few FYEP sections had project clients but most sections did not).

A number of students referred directly to their instructor’s policy in their response, and this reflected a wide range in acceptable uses. A few examples are provided below:

> “I am glad our instructor allowed us use AI to help write code or generate images, as long as we cited it fairly.” [S7] {section with least restrictive GenAI policy in the syllabus}
>
> “I was impartial to its use as I didn't use it and I agreed with the professor's policy (don't use to generate your work, but ok to help Brainstorm or check work)” [S3]
>
> “I think the policy could be less strict as AI is very useful and now part of our everyday life. Learning how to use it for things like technical reports and coding is such a useful skill.” [S8]
>
> “We were not allowed to use AI to assist.” [S1] *{but other students in this same section described how they had used GenAI e.g., “Helpful to get you started with some ideas or help you trouble shoot issues.”}*

Unfortunately, unclear GenAI policies in certain sections created stress for students navigating team work; for example, one student noted, “It was annoying that the policy was unclear and when my teammates used AI it was a tough spot because I didn't want to get them in trouble but I also didn't want to redo their work.” [S9] This section was one of the two that did not mention GenAI in the course syllabus. (More extensive analysis of the student write-in comments was beyond the scope of this study.)

Discussion

Previous studies have explored GenAI use by engineering students, with use frequencies rapidly increasing over time; e.g. Ovi et al. [18] found significant increases from 2023 to 2024. Although the Ovi study captured engineering students’ GenAI use across all academic contexts while this study focused on use within a single course, a coarse comparison of use frequency is shown in Table 6. In 2024, Ovi et al. reported that approximately 21–25% of engineering students never used LLM-based tools academically, whereas in Fall 2025 only 14% of students in the first-year engineering projects (FYEP) course and 9% of students in the first-year tools and analysis course reported no GenAI use, indicating higher uptake even within a single course. GenAI use frequencies were higher in the engineering tools and analysis course compared to the FYEP course. The difficulty of the assignments and individual nature of the course (math and Matlab heavy) may have led to a greater need for learning support in comparison to the more open-ended design, hands-on, and team-based FYEP course (teammates readily available to help; only some members of the team did particular tasks like coding). In the future the survey should ask students how often they used GenAI when they were doing the particular task (and N/A could be added as an option for those who never did a particular task as part of the course).

Table 6. Comparison of percentage of students reporting different GenAI use frequency.

GenAI / LLM Use	This study FY Eng Course Fall 2025, PES (n = 58)	This study FYEP Course Fall 2025 (n = 361)	Ovi et al. [18], Mech-Civil, FY – grad Sept 2024 (n = 315)
Frequency of use (max any use this study)			
Never (+ only fun in [18])	9	13.6	25.1
Rarely (irregular / once or twice [18])	24	35.7	33.7
Sometimes (regular / once or twice a week [18])	33	33.8	33.7
Often / weekly (Superusers / daily [18])	34	16.9	7.6

Demographic patterns differed between studies. In this work, male students reported slightly higher average GenAI use frequency than female students in the FYEP course, and some differences were observed across racial/ethnic groups, whereas Ovi et al. found no significant gender effects and reported different patterns by race/ethnicity. These contrasts highlight the sensitivity of observed GenAI use patterns to course context, time, and methodological scope.

The practical importance of differential GenAI use among first-year students warrants further exploration. When used ethically, GenAI can help students learn. Thus, differential use may reflect different support needs (based on incoming skills and knowledge of programming, for example), learning preferences (e.g., prefer to ask GenAI because feel uncomfortable asking questions of faculty or teaching assistants), or constraints (e.g., working outside of school to earn money and therefore unable to attend office hours of faculty or teaching assistants, while GenAI can provide assistance at any time of day). If attitudes about GenAI use categorize all uses as unethical or cheating, students may fail to use GenAI as a helpful learning tool which could disadvantage them compared to peers that use GenAI (e.g., if GenAI does in fact make learning or tasks more time efficient). There is also an evolving need for engineers to have GenAI skills in the workplace. Another consideration is whether or not some students are more fearful that they will be accused of inappropriate use, based on stereotypes or other factors [23]. This discussion reflects the potential for GenAI to help redress or exacerbate achievement gaps. There is also the potential that students will misuse GenAI, thereby earning passing grades but in reality degrading their learning. This may have downstream ramifications if pre-requisite material is not learned and other courses assess learning in ways that restrict GenAI use (e.g., an in-class written test without any electronic aids). Over the longer term, erosion of foundational skills could have implications for workforce preparedness and societal outcomes. Understanding this broad range of potential impacts will require qualitative methods and/or longitudinal studies.

Conclusions

As expected, the majority of the students enrolled in first-year engineering courses reported using GenAI in their schoolwork in the previous semester (presumably high school). Female students reported less previous use of GenAI in their schoolwork and less intent to use GenAI for selected tasks in their first-year engineering courses as compared to male students. Some other differences were found in previous and/or planned use based on the demographic characteristics of: major (engineering vs. non-engineering; some specific engineering majors); some racial/ethnic groups; English yes/no first language. The planned uses of GenAI in their first-year engineering courses were most commonly for explaining challenging concepts and exploring unfamiliar concepts. There were moderate correlations between the amount of previous GenAI use and planned use in the first-year engineering courses. Correlations between students' confidence in their knowledge and skills with their planned GenAI use were generally not significant; the sole correlation was within the FYEP course where there was a weak negative correlation between students' confidence in their writing skills and planned use of GenAI to help with writing (weaker confidence, more GenAI use).

The disclosed actual use of GenAI during the semester in the two first-year engineering courses varied significantly among different students ranging from some who used GenAI often (weekly or more) for all 5 or 7 of the use options provided in the survey (7% PES and 0.6% FYEP students), to those who reported never using GenAI for any of the 5 or 7 use options (9% and 13.6% FYEP students). On average, students used GenAI more in the engineering tools and analysis course (PES students) compared to the FYEP course. This may be due to the types and frequency of assignments in these courses and the extent that GenAI could be helpful (e.g., individual homework, lab reports, Matlab coding vs. hands-on team projects). There was significant variation in the extent that GenAI was used in different sections of the FYEP course, which appeared largely due to individual instructor policies for acceptable GenAI use. This was reflected in moderate positive correlations between some of the planned and actual GenAI uses in 11 sections of the course versus no significant correlations in 3 sections. Small differences were found in the frequency that GenAI was used for some tasks in the FYEP course between male and female students and Hispanic and Asian students compared to White students.

Overall, these results provide a snapshot of how students used generative AI in two first-semester, first-year engineering courses. Students identified several uses of GenAI as helpful (e.g., debugging code, generating initial ideas), while also recognizing its limitations. Instructor policies and practices were associated with meaningful differences in student use, and the wide range of policies observed across sections of a single course highlights the variability of student experiences within ostensibly shared curricular contexts. For multi-section courses, these findings suggest the value of intentional discussion among instructors about GenAI expectations; not necessarily to impose uniform policies, but to consider the implications of policy divergence for clarity, equity, and student decision-making. More broadly, faculty are encouraged to engage students in explicit conversations about GenAI use to support the development of informed judgment and ethical reasoning around this powerful and rapidly evolving tool.

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Appendix A – Institution Policy

The University of Colorado Boulder does not have a uniform policy on AI in the curriculum because there is no one-size-fits-all approach to using AI tools on our campus. The goal is to empower students to use the appropriate innovative tools to be successful in their fields.
The guidelines around AI use allow faculty and instructors to determine how and when students can use AI for coursework. However, students are responsible for working with their professors to understand guidelines and clarify questions before using AI for coursework.
All students enrolled in a course at the University of Colorado Boulder are responsible for knowing and adhering to the Honor Code. The unapproved use of artificial intelligence could lead to a student gaining an unfair academic advantage, which is considered academic misconduct and could violate the Honor Code. Another potential violation of the Honor Code is plagiarism, which includes using paper writing services and technology, such as essay bots and other AI, whether paid or unpaid.

Appendix B – Synthetic Generative AI Policy Exemplars

This appendix provides synthetic, illustrative examples of GenAI syllabus policies to represent the range of approaches observed across the multiple sections of the two first-year engineering courses. These examples were not reproduced verbatim from any individual syllabus and do not reflect the views or language of any specific instructor. They were developed to convey aggregate patterns of policy restrictiveness identified through analysis of the 15 syllabi. These exemplars are intentionally written as stand-alone policies; individual syllabus statements in practice were often shorter or embedded within broader course policies. Microsoft 365 Copilot (GPT-based) was used to assist the author in drafting these synthetic exemplar texts and the accompanying feature summary table. The author reviewed, edited, and takes full responsibility for the content, interpretations, and final wording.

Example A. Permissive GenAI Policy

Generative AI Use in This Course

Students may use generative artificial intelligence tools (e.g., text, image, or code generation tools) to support their learning in this course. Appropriate uses may include brainstorming ideas, exploring alternative solution approaches, refining written work, generating practice problems, or checking work for clarity and correctness.

When using AI tools, students remain fully responsible for the accuracy, quality, and integrity of their submitted work. AI tools should not replace engagement with course material or be used to complete assignments on behalf of the student. Students are expected to document and acknowledge how AI tools were used when they contribute to submitted work.

The goal of this course is for students to develop foundational engineering knowledge and skills; AI tools should be used in ways that support, rather than undermine, that learning.

Example B. Representative GenAI Policy

Generative AI Guidance

Generative AI tools are increasingly available and may be useful in limited, clearly defined ways within this course. Students may use AI tools for supplementary purposes such as grammar or style feedback, minor code debugging, or clarification of concepts, unless otherwise specified by the instructor.

AI tools may not be used to generate original content, analysis, or reflections when such work is intended to demonstrate individual understanding. All submitted work must be primarily student-generated. Students are responsible for verifying the accuracy of any AI-assisted content and for avoiding plagiarism or misrepresentation of sources.

Any use of AI tools must be transparently documented following appropriate citation or attribution guidelines. If there is uncertainty about whether AI use is permitted for a particular assignment, students should seek instructor clarification in advance.

Example C. Restrictive GenAI Policy

Generative Artificial Intelligence Policy

The use of generative AI tools is restricted in this course. Assignments are intended to assess students' own thinking, problem-solving, and written communication. As such, AI tools may not be used to generate ideas, text, images, code, or other content for assignments unless explicit prior authorization is granted by the instructor.

If limited AI use is permitted for a specific assignment, students must receive prior approval and must clearly describe how the tool was used and what role it played in the final submission. Students remain fully accountable for the accuracy, originality, and integrity of their work.

Unauthorized use of generative AI may be treated as a violation of academic integrity policies and addressed through established university procedures.

Table A1: Features Represented Across Syllabi

Policy Dimension	Highly Permissive	Conditional	Highly Restrictive
Default stance on AI use	Allowed	Allowed with limits	Prohibited unless approved
Primary framing	Learning support and exploration	Skill development and assessment integrity	Academic integrity and compliance
Permitted uses (examples)	Brainstorming, practice problems, refinement, checking work	Grammar/style feedback, minor debugging, concept clarification	Only case-specific, pre-approved uses
Prohibited uses	Not explicitly enumerated	Generating original content or analysis	Generating any assignment content
Student responsibility emphasized	Accuracy and integrity	Accuracy, originality, and verification	Full accountability and originality
Documentation of AI use	Expected	Required	Required and pre-approved
Instructor discretion	Minimal	Moderate (assignment-level)	High (permission-based)
Enforcement language	Implicit	Conditional	Explicit reference to misconduct procedures

Appendix C - Surveys

PES Pre-Survey GenAI Questions

Q1 How often did you use Generative AI / LLM Chatbots (e.g., ChatGPT) in your schoolwork and academic pursuits last semester?

- o Never (1)
- o Less than once per month (2)
- o A few times per month (3)
- o A few times per week (4)
- o All the time (once or more per day) (5)

Q2a If and how do you plan to use GenAI / LLM chatbots (e.g., ChatGPT) in this *PES* class this semester?

	Never (1)	Rarely (2)	Sometimes (3)	Often (4)
Explore unfamiliar concepts (1)	○	○	○	○
Explain challenging concepts (2)	○	○	○	○
Help with coding (e.g., Matlab) (3)	○	○	○	○
Help solving problems (4)	○	○	○	○
Help writing (e.g., lab reports) (5)	○	○	○	○

Q3 Do you believe that students using GenAI are cheating?

- o No, definitely not (1)
- o Rarely, probably not (2)
- o Sometimes, might or might not (3)
- o Frequently, probably yes (4)
- o Always, definitely yes (5)

FYEP Pre-Survey GenAI Questions

Q1 & Q3 (see PES Pre-Survey GenAI Questions above)

Q2b If and how do you plan to use GenAI / LLM chatbots (e.g., ChatGPT) in this *FYEP* class this semester?

	Never (1)	Rarely (2)	Sometimes (3)	Often (4)
Brainstorming (1)	○	○	○	○
Summarize texts (2)	○	○	○	○
Explore unfamiliar concepts (3)	○	○	○	○
Explain challenging concepts (4)	○	○	○	○
Help with Arduino coding (5)	○	○	○	○
Help writing reports (6)	○	○	○	○
Help writing personal reflections (7)	○	○	○	○

PES Post-Survey GenAI Questions

Q4a. How often did you use GenAI/LLM chatbots (e.g., ChatGPT) for various activities in this GEEN2010 course this semester?

	Never (1)	Rarely / a few times (2)	Sometimes / ~5-10 times (3)	Often / weekly or more (4)
Explore unfamiliar concepts (1)	○	○	○	○
Explain challenging concepts (2)	○	○	○	○
Help with coding (e.g., Matlab) (3)	○	○	○	○
Help solving problems (4)	○	○	○	○
Help writing (e.g., lab reports) (5)	○	○	○	○

Q5. To what extent did you find your GenAI use in the course helpful to your learning when you chose to use it:

- o Not applicable (I never used GenAI in this course) (0)
- o Not at all (1)
- o A little helpful / usually did not help (2)

- o Moderately / sometimes helped (3)
- o Very helpful / usually helped (4)
- o Extremely helpful / helped almost always (5)

Q6. The ethical and appropriate GenAI use policies in this course were clear.

- o Strongly disagree (1)
- o Somewhat disagree (2)
- o Neither agree nor disagree (3)
- o Somewhat agree (4)
- o Strongly agree (5)

Q7. Please provide any comments about GenAI use in this course that you would like to share.

FYEP Post-Survey GenAI Questions

Q4b. How often did you use GenAI/LLM chatbots (e.g., ChatGPT) for different tasks in this class this semester?

	Never (1)	Rarely / a few times (2)	Sometimes / ~5-10 times (3)	Often / weekly or more (4)
Brainstorming (1)	○	○	○	○
Summarize texts (2)	○	○	○	○
Explore unfamiliar concepts (3)	○	○	○	○
Explain challenging concepts (4)	○	○	○	○
Help with Arduino coding (5)	○	○	○	○
Help writing reports (6)	○	○	○	○
Help writing personal reflections (7)	○	○	○	○

Q8. What policies did your instructor have about GenAI use in GEEN1400 this semester? Check all that apply.

- ◻ Required use in 1 or more instances (1)
- ◻ Encouraged use of one of more types (2)
- ◻ Discouraged some uses (3)
- ◻ Discouraged all uses (4)
- ◻ Did not specify a policy (5)

Q9. Briefly describe how your GenAI use or non-use was helpful in GEEN1400 and your suggestion for GenAI integration or course policies in future semesters