Paper ID #53282

University Students' Engagement with Generative AI: Attitudes, Beliefs, and Academic Practices

Zepei Li, University of Illinois at Urbana - Champaign

Zepei Li is a Ph.D. student in Computer Science at the University of Illinois Urbana-Champaign (UIUC). He holds an M.S. and B.S. in Computer Science from UIUC. His research interests span AI in education, computer science education, and human-computer interaction. His previous work includes assessing student learning in database query languages and examining students' behaviors, attitudes, and beliefs toward generative AI in educational settings. He aims to enhance AI tools to better support educational applications.

Dr. Sotiria Koloutsou-Vakakis, University of Illinois at Urbana - Champaign

Dr. Sotiria Koloutsou-Vakakis holds a Diploma in Surveying Engineering (National Technical University of Athens, Greece), a M.A. in Geography (University of California, Los Angeles), and M.S. and Ph.D. degrees in Environmental Engineering (University of Illinois Urbana-Champaign). Her interests include air quality, environmental policy, and supporting student learning and professional development.

Prof. Tomasz Kozlowski, University of Illinois at Urbana - Champaign

Dr. Tomasz Kozlowski is a Professor and Associate Head for the Undergraduate Programs in the Department of Nuclear, Plasma, and Radiological Engineering at the University of Illinois Urbana-Champaign. He received a Ph.D. in Nuclear Engineering from Purdue University in 2005, where he worked on spatial homogenization methods for neutron transport calculations, multi-physics coupling, and PARCS code development. Dr. Kozlowski has been an instructor in professional workforce development courses and summer schools, including MeV, FJOH, SUNCOP, and NRS-HOT (since 2006). He has been an active member of the American Nuclear Society (since 1997) and the American Society for Engineering Education (since 2016). He is a member of the OECD/NEA Nuclear Science Committee Working Party on Reactor Systems (NSC/WPRS) (since 2010) and is serving on the Scientific Board and Technical Committee of the OECD/NEA Benchmark for Uncertainty Analysis in Best-Estimate Modelling for Design, Operation and Safety Analysis of Light Water Reactors (LWR-UAM) (since 2008). He is an Associate Editor of Nuclear Technology (since 2021) and has been a reviewer for several journals in the fields of nuclear engineering, fluid flow and heat transfer, and uncertainty quantification (since 2006).

Ms. Meredith Blumthal, University of Illinois at Urbana - Champaign

Meredith Blumthal has been in the field of international education for 15 years. As the Director for International Programs in Engineering (IPENG) at the University of Illinois, she leads the study abroad initiatives and programming for the college. Ms. Blumthal's team includes three study abroad advisors, a receptionist and peer advisors. Together the IPENG office provides study abroad advising, expertise, international exchanges, and cultural experiences in over 60 programs throughout 20 countries, with the goal of providing transformative learning experiences that empower students to develop global competency skills. Through partnerships with partner universities abroad, alumni, faculty, staff and student groups, Ms. Blumthal leads the IPENG team to provide study abroad advising, informational events, and class presentations. She works with the 12 engineering departments to develop and grow studying abroad programming with overseas partners to grow connections with universities, and facilitates the study abroad fair. Meredith is responsible for developing faculty-led programing an engagement within the College of Engineering. Her areas of expertise include ideation, program development, partner collaboration, faculty training and development, comprehensive program management, marketing and promotion, co-curricular development, study abroad advising, and student development.

Dr. Volodymyr Kindratenko, University of Illinois at Urbana - Champaign

Volodymyr Kindratenko is the Director for the Center for Artificial Intelligence Innovation (CAII) at the National Center for Supercomputing Applications (NCSA). He is also an Adjunct Associate Professor in

©American Society for Engineering Education, 2026

the Departments of Electrical and Computer Engineering and a Research Associate Professor in the Siebel School of Computing and Data Science. His research interests lie at the intersection of AI systems and applications, with a focus on generative AI solutions for science and education. His team is developing the uiuc.chat chatbot platform, which facilitates rapid knowledge distillation.

Dr. Abdussalam Alawini, University of Illinois Urbana-Champaign

Dr. Alawini is a Teaching Associate Professor in the School of Computing and Data Science at the University of Illinois at Urbana-Champaign. He holds a bachelor's degree from the University of Tripoli and master's and doctoral degrees in Computer Science from Portland State University. His research focuses on data management systems and computing education. Dr. Alawini is passionate about building data-driven, AI-based systems for improving teaching and learning.

©American Society for Engineering Education, 2026

University Students' Engagement with Generative AI: Attitudes, Beliefs, and Academic Practices

Abstract

Since the emergence of generative artificial intelligence (GenAI) tools, students have increasingly integrated them into their academic work, prompting growing research on their educational benefits, risks, and responsible use. Building on this body of work, our study examines the current landscape of GenAI use in engineering education and explores whether students' learning experiences, attitudes, and ethical views differ across disciplinary and background factors. We administered a comprehensive survey probing students' GenAI behaviors, attitudes, and beliefs at the University of Illinois Urbana-Champaign in the United States across two consecutive semesters, collecting over 800 responses from students in multiple engineering disciplines. Using descriptive statistics and quantitative analyses, we examine relationships among students' majors, year of schooling, prior computing experience, GenAI usage frequency, purposes of use, and self-reported impacts. The results show that while overall usage patterns align with prior studies, meaningful differences emerge across majors and experience levels, with students expressing varying degrees of enthusiasm, reliance, and concern about GenAI. These findings provide an updated snapshot of student perceptions in 2025 and offer insights to help educators and institutions design more equitable, ethical, and effective approaches to integrating GenAI in engineering education.

1 Introduction

Generative Artificial Intelligence (GenAI), which refers to a type of artificial intelligence that can generate text, images, videos, or audio content upon users' request [8], has received increasing attention in both academic research [2] and real-world applications [17]. Education is one of the fields that has received significant attention in GenAI research, as GenAI has the potential to introduce new opportunities, benefits, and challenges for educational practice and learning processes [4, 5, 7]. A 2024 review study indicates that prior research has primarily focused on "application, impact and potential" (59.5%), "ethical implication and risks" (20.9%), "perspectives and experiences" (17.2%), and five other different areas [32]. Although a growing body of work has examined students' perspectives on the use of GenAI in educational contexts [14, 24, 27], to the best of our knowledge, there remains limited research investigating the experiences and perspectives of engineering students at universities regarding GenAI in their everyday academic lives.

Existing research indicates that GenAI may impact engineering education across multiple dimensions and domains, including, but not limited to, task-specific assistance (e.g., coding support, data analysis, and paper drafting or editing), assessment practices, and instructional support [11]. Such impacts have been validated through analyses of students' interaction log data with chatbots [1, 15]. While these analyses provide an objective view of how GenAI may influence engineering education, they offer limited insight into how engineering students themselves perceive GenAI and how their perspectives have evolved in the current educational context. To develop a more comprehensive understanding of students' perspectives and the current state of GenAI use in engineering education, we propose the following research questions:

RQ1: What is the current landscape of GenAI usage in university engineering education in 2025?

RQ2: Will students with different backgrounds (e.g., major, year of school, prior computer science experience) hold distinct opinions about using GenAI?

We developed a survey to address both research questions, aiming to understand university students' attitudes, beliefs, and academic practices (see Section 3 for survey details). After collecting responses from engineering students across two consecutive semesters in 2025, we conducted a series of analyses to answer our research questions. The results indicate that GenAI usage has become predominant in engineering students' academic practices, although students with different backgrounds exhibit significant differences in usage frequency. Furthermore, students' perceptions of GenAI and self-reflections vary partially across some background factors, while remain similar across others. These variations might suggest that educators should be cautious about treating students as a homogeneous group when designing instruction or providing guidance, as students' perspectives can differ substantially based on their backgrounds.

This study presents perspectives of engineering students on GenAI and examines how students from different backgrounds may have differing opinions about GenAI across multiple domains. Our paper contributes to the existing body of research on AI in education, providing insights to inform the design of future AI tools and instructional practices.

2 Related Work

AI in education is a complex and relatively new research area that encompasses multiple branches of inquiry. Prior research indicates that the majority of AI-in-education studies have focused on the applications, impacts, and potential of GenAI in educational contexts [32]. Within this research theme, representative studies include those that identify educational needs, develop or enhance GenAI tools or systems, and evaluate their performance [12, 18], as well as studies that examine the potential of GenAI to support various aspects of education, such as personalized learning and timely feedback [16, 21]. Researchers have also investigated the ethical implications and risks associated with AI use in education. Common ethical concerns include privacy and data security, bias and fairness, user autonomy and dependence, and AI accountability [26]. Additionally, some studies have explored the potential risks of AI use in educational settings, such as learning loss or overreliance on AI tools [5, 22]. Another research theme centers on perspectives and experiences. Within this line of work, researchers seek to understand both instructors' [13, 31] and students' [6, 10] perspectives and experiences on the use of AI in education across different domains and contexts.

Surveys are a widely used method for understanding individuals' perspectives and have been extensively employed to examine students' perspectives on AI in education. For example, one study developed and validated a survey instrument to measure undergraduates' attitudes toward GenAI tools, identifying key attitudinal dimensions through factor analysis based on responses from 297 students at a U.S. university [30]. Another survey study of 1,041 undergraduates reported a surge in GenAI usage alongside emerging benefits, widening digital divides, and gaps in institutional guidance and AI literacy [9]. Furthermore, one study analyzed responses from 194 university students and identified distinct user groups, novice, cautious, and enthusiastic, highlighting disparities in knowledge, confidence, and intended use of GenAI tools [3]. Studies also conducted outside the U.S., for instance, a large-scale online survey was conducted on 1,963 students in Hong Kong with follow-up qualitative interviews to examine students' perceptions, usage patterns, and satisfaction with ChatGPT in learning [20]. Similarly, a survey of 1,157 students at an Indonesian university and found that GenAI technologies are already deeply embedded in students' everyday learning practices [29]. Together, these studies build a comprehensive picture of how, why, and to what extent students use GenAI in education.

Although prior studies have explored students' perspectives on AI in education, several important limitations and gaps remain. First, as GenAI technologies and associated tools continue to evolve rapidly, students' perspectives may change substantially over time. Second, there is limited research specifically focused on understanding the perspectives of engineering students from diverse backgrounds. Addressing these gaps is therefore essential, and the present study contributes by examining both aspects to provide a more comprehensive understanding of engineering students' perspectives on GenAI in the current educational context.

3 Methodology

3.1 Study Design

We designed a survey to better understand engineering students' attitudes, beliefs, and behaviors toward GenAI tools. Prior to conducting the survey, we found that no existing, ready-to-use instrument adequately addressed the two research questions examined in this study. Therefore, the authors designed a new survey to cover these research questions, following established survey design principles from survey research in HCI [19]. The survey was reviewed by experts in computing education and human–computer interaction. We targeted engineering students and widely distributed our survey across courses in various engineering departments, including, but not limited to, Electrical and Computer Engineering, Computer Science, Civil and Environmental Engineering, and Nuclear, Plasma & Radiological Engineering The survey was created and distributed via Qualtrics, an online survey platform [23]. The survey was first launched in the Spring 2025 semester and received 320 distinct student responses across different majors and years of schooling. To further strengthen the findings and gain a comprehensive understanding of the GenAI landscape in engineering education in 2025, we distributed the same survey again in the Fall 2025 semester, targeting the same population. In total, we gathered 842 survey responses from the University of Illinois Urbana-Champaign in the United States. We plan to continue this study in subsequent years to conduct a longitudinal analysis in the future.

Although we focused on an engineering education students, it is reasonable to assume that non-engineering students also enroll in engineering courses (for example, a statistics major may take a database course in the Computer Science department). Therefore, the target population consisted of students from multiple majors, with most being engineering majors. The survey was distributed across both introductory and senior-level courses, resulting in participation from a mix of undergraduate and graduate students.To better understand variations in students' attitudes, beliefs, and behaviors across backgrounds, we collected relevant variables including major, academic year, prior computing experience, gender, and other demographic information, as voluntarily provided by participants. We announced the survey via course communication platforms such as Canvas and Campuswire. Participation was entirely voluntary, and all study procedures adhered to the approved IRB protocol.

3.2 Survey Instrument

The survey contains 5 sections - Usage and Interaction (5 questions), Computing-related Questions (3 questions), Attitude and Impact (9 questions), Scenario Questions (4 questions), Background and Demographics (4 questions) - 25 questions in total. It contains Likert-scale items, multiple-choice questions, scenario-based ethical questions, and open-ended responses. The survey was designed to be completed in 20 minutes. The median completion time among student participants was 7 minutes and 30 seconds. After excluding outliers, defined as responses in the top and bottom 1st percentiles based on survey completion duration, the average completion time was 10 minutes and 38 seconds.

3.3 Data Cleaning and Preparation

The survey was designed and administered on a voluntary basis, and we anticipated that not all respondents would answer every question fully or consistently. We filtered out responses in the lowest 1st percentile based on survey completion time (i.e., respondents who completed the survey in 71 seconds or less). We observed that some participants (17.5%) spent more than 20 minutes completing the survey. This may be because they spent additional time on open-ended questions or did not complete the survey in a single sitting, possibly saving their progress and returning to it later. After examining these responses, we chose to retain them, as they reflected relatively high-quality answers. We also removed missing responses for each question before conducting the analysis.

3.4 Data Analysis

We used a mixed-methods approach that included both descriptive statistics and quantitative analysis to examine survey responses and address our research questions. Built-in functions in Qualtrics [23] were used to analyze the results, and the data were also exported for additional statistical testing. To answer RQ1, which explores the current landscape of GenAI use in engineering education, we relied on descriptive statistics to characterize overall usage, including frequency, motivations, and students' attitudes and self-reflections. To address RQ2, which examines differences in students' opinions across backgrounds, we conducted cross-tabulation analyses to compare responses across variables. Specifically, we examined potential differences in AI perceptions, self-reflections, and confidence across background factors, including major, year of study, and prior experience.

4 Results

In this section, we address each research question in sequence and present the corresponding findings to provide a comprehensive picture of students' attitudes, beliefs, and behaviors toward GenAI in engineering education.

4.1 RQ1: Current landscape of GenAI usage in engineering education

In this section, we present our findings indicating the current landscape of GenAI usage in engineering education, including, but not limited to, the frequency of usage, reasons for use, students' attitudes toward these tools, and their self-reflections on usage.

4.1.1 The frequency of usage

To examine the current landscape, this study first investigates students' reported frequency of GenAI use in their academic lives during the 2025 academic year. As shown in Figure 1, on average, 56.1% of students reported using GenAI tools multiple times a day, and 91.9% reported using them more than once a week. We also found that only a small number of students (7) reported never using GenAI, representing less than 1% of the sample population. Based on these results, it seems that GenAI tool usage in engineering education is highly frequent and has become an integral part of students' academic lives.

We also compared the results for the Spring 2025 semester and Fall 2025 semester to see if there is a significant difference between the two semesters. Although for some of the categories, such as students who use multiple times a day and several times a week, showed an increasing trend in percentage, a chi-square test of independence conducted on the full distribution of response categories indicated that the overall distributions were not significantly different between two semesters ($\chi^2(6) = 11.59, p = .072$). As shown in Table 1, both groups reported very high levels of frequent use, with a majority of respondents in each group indicating usage multiple times a day. These results suggest that students in the Spring 2025 and Fall 2025 semesters exhibit largely similar patterns of generative AI use. Combining them together, it might provide a view of the current landscape of GenAI usage frequency in engineering education.

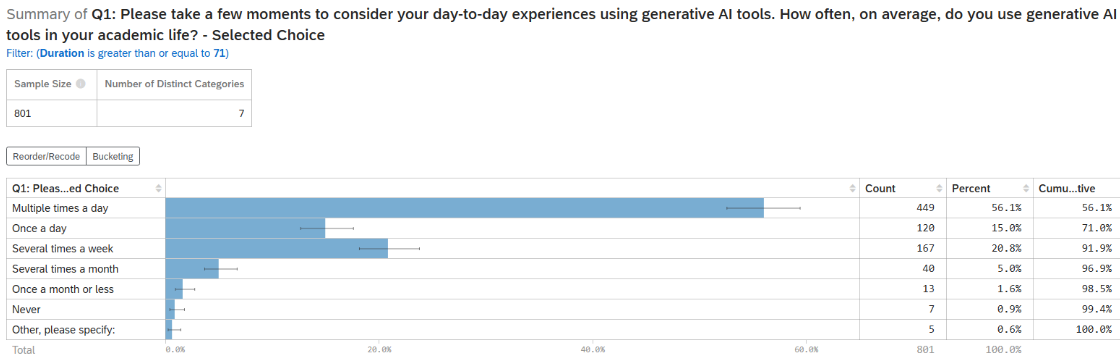

Figure 1: The valid responses after filtering for the question: How often, on average, do you use generative AI tools in your academic life?

Table 1: Frequency of GenAI Tool Usage by Semester

Semester	Multiple times a day	Once a day	Several times a week	Several times a month	Once a month or less	Never	Other
Spring 2025	150 (51.9%)	47 (16.3%)	58 (20.1%)	21 (7.3%)	6 (2.1%)	3 (1.0%)	4 (1.4%)
Fall 2025	299 (58.4%)	73 (14.3%)	109 (21.3%)	19 (3.7%)	7 (1.4%)	4 (0.8%)	1 (0.2%)

Although there is no significant difference in overall usage when students are considered as a group, a closer examination across background factors reveals meaningful differences. Specifically, students with different years of schooling, majors, and levels of programming experience reported significantly different usage frequencies. In general, students with more years of experience or those majoring in computing–related fields reported more frequent GenAI use. We also identified additional potential differences across other background factors, which we report in subsection 4.2.

4.1.2 Students' motivations behind the use of generative AI

We also aimed to understand, from the students' perspective, what motivates them to use generative AI. Previous studies have found that concept-related questions are the dominant category when analyzing students' interactions with GenAI via their conversation prompts [1, 15]. To facilitate the analysis and validate these findings, we collected and analyzed student responses using a broader set of categories, based both on reasons observed during academic life and those suggested by students during survey design. The results are presented in Figure 2. We observed that nearly all students (93.1%) reported using GenAI to understand concepts. The next three most common reasons were debugging code (63.8%), revising or editing writing (59.7%), and receiving feedback (48.1%). Although these reasons did not dominate usage as strongly as concept understanding, they still represent frequent motivations for GenAI use. In the survey prompt, we emphasized the anonymous nature of responses, allowing us to also include categories that could represent potential academic integrity concerns, such as using GenAI to help with difficult assignments or to meet looming deadlines. Both of these categories were reported at relatively high rates, 41.9% and 23.6% respectively, indicating that the noticeable challenges related to academic integrity brought by GenAI should not be ignored.

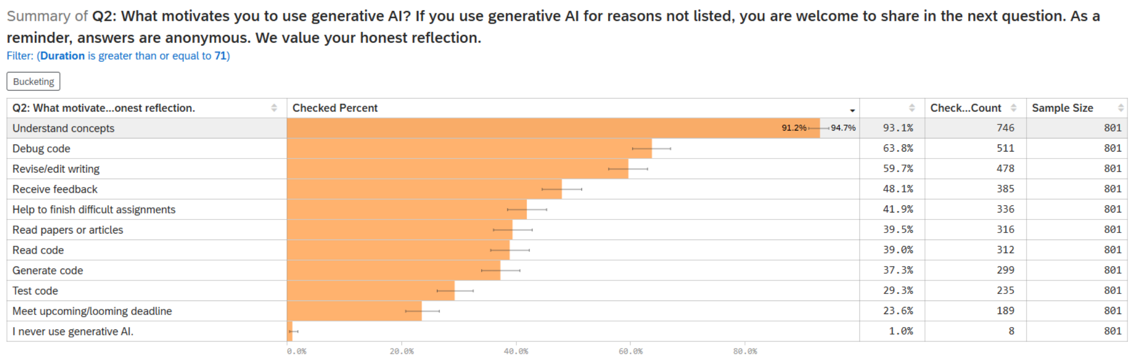

Figure 2: Motivation for Students to Use Generative AI

4.1.3 General attitudes and beliefs

In this part, we will present students' responses related to their attitude toward GenAI tools and their self-reflections on GenAI usage. We first examine students' perceptions of GenAI across five domains: ease of use, accuracy, effectiveness, support for learning, and creativity. As shown in Table 2, a relatively high proportion of students reported positive perceptions of the ease of use, effectiveness, and support for learning (88%, 72%, and 83.2%, respectively). In contrast, a smaller proportion of students expressed positive views regarding the accuracy and creativity of GenAI tools (44.6% and 35.3%, respectively). While most students held generally positive opinions of GenAI when considering it as a tool, they also expressed concerns about its potential negative implications. In response to the question, "How concerned are you about the potential negative implications of generative AI?", only 3.8% of students reported no concern. Among the remaining respondents, 25.0% reported being a little concerned, 38.8% moderately concerned, 21.2% very concerned, and 11.2% extremely concerned.

In addition to students' attitudes toward different aspects of GenAI tools, we also asked their opinions on the usefulness of various academic activities in the era of GenAI. As shown in Figure 3, overall, students rated lectures, collaborative learning activities,

Table 2: Students' Perceptions of Generative AI on Different Dimensions

Response	**Ease of use**	**Accuracy**	**Effectiveness**	**Support for learning**	**Creativity**
Extremely negative	1 (0.1%)	12 (1.6%)	6 (0.8%)	4 (0.5%)	54 (7.0%)
Somewhat negative	4 (0.5%)	106 (13.8%)	26 (3.4%)	24 (3.1%)	156 (20.3%)
Neutral	87 (11.3%)	308 (40.1%)	181 (23.6%)	101 (13.2%)	286 (37.3%)
Somewhat positive	359 (46.7%)	300 (39.1%)	425 (55.5%)	374 (48.8%)	197 (25.7%)
Extremely positive	317 (41.3%)	42 (5.5%)	128 (16.7%)	264 (34.4%)	74 (9.6%)

Table 3: Students' Agreement with Statements Regarding the Use of Generative AI in Educational Settings

Response	**Generative AI can enhance my learning experience**	**Generative AI helps me better understand concepts and knowledge**	**In the future, I will be able to perform tasks independently that generative AI currently assists me with**	**Involving generative AI in education will improve the overall educational experience**
Strongly disagree	2 (0.3%)	2 (0.3%)	3 (0.4%)	18 (2.3%)
Somewhat disagree	14 (1.8%)	4 (0.5%)	43 (5.6%)	49 (6.4%)
Neutral	70 (9.1%)	79 (10.3%)	144 (18.8%)	179 (23.4%)
Somewhat agree	392 (51.2%)	324 (42.4%)	322 (42.0%)	315 (41.1%)
Strongly agree	288 (37.6%)	356 (46.5%)	254 (33.2%)	205 (26.8%)

course projects, and homework assignments as the most useful. In contrast, office hours and quizzes/exams were rated as less useful. Notably, a substantial proportion of students (31.4%) believe that office hours are not quite useful, which may indicate a need to reconsider the arrangement or format of office hours in the era of GenAI.

Q15: How helpful do you find the following subjects with the emergence of generative AI?

	Lectures	Office hours	Collaborative learn...	Course projects	Homework assign...	Quizzes and exams	Total
Not at all useful	8.7%	14.9%	5.8%	2.6%	2.1%	9.9%	
Slightly useful	12.4%	16.5%	15.4%	11.8%	10.8%	15.6%	
Moderately useful	24.5%	25.2%	28.0%	28.6%	29.3%	28.8%	
Very useful	34.9%	24.4%	31.8%	35.3%	37.7%	27.2%	
Extremely useful	19.6%	19.1%	19.1%	21.6%	20.1%	18.5%	
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	

Figure 3: Students' Perceived Usefulness of Different Course Components in the Context of Generative AI.

We also examined students' self-reflections on GenAI use by asking questions about learning-related experiences and applications. In the general educational context, as indicated by Table 3, the majority of students believe that GenAI can enhance their learning experience and lead to better educational outcomes. Many students also expressed confidence that tasks currently supported by GenAI can be performed independently in the future without AI assistance. We further examine these patterns through cross-tabulation analyses in RQ2.

Before asking programming-related questions, we included a screening question (*"Have you ever used AI to help with understanding, debugging, or writing code?"*) to identify students who had used generative AI to assist with programming tasks. Based on the responses, 90.9% of students reported having used GenAI in at least one programming-related way. Students who indicated that they had never used GenAI for programming tasks were automatically skipped from the programming-related section of the survey. Among the 728 students who answered "Yes" to the question, most reported feeling at least somewhat comfortable using generative AI for programming tasks. 61.1% of respondents reported being either somewhat comfortable (42.4%) or extremely comfortable (18.7%) using GenAI for programming. In contrast, 18.4% reported feeling somewhat or extremely uncomfortable, while 20.6% selected a neutral response.

When asked about their confidence in programming-related skills (Table 4), most students reported moderate to high confidence. Specifically, 36.0–42.3% of students indicated being "very confident" across the four domains, and 21.8–35.1% indicated being "extremely confident." Fewer students reported low confidence, with only 1.1–1.9% selecting "not confident at all" and 3.0–9.0% selecting "not very confident." Overall, students felt most confident in understanding AI-generated code and using GenAI to support their learning, while slightly fewer reported the highest confidence in writing programs independently or evaluating AI-generated code. We further discuss and interpret these results in Section 5.

Table 4: Students' Confidence in Programming-related Skills Across Four Domains

Response	I can write programs without AI	I can understand AI-generated code	I can evaluate AI-generated code	Generative AI supports my learning
Not confident at all	12 (1.7%)	8 (1.1%)	14 (1.9%)	4 (0.6%)
Not very confident	65 (9.0%)	35 (4.8%)	50 (6.9%)	22 (3.0%)
Moderately confident	228 (31.5%)	178 (24.6%)	195 (27.0%)	154 (21.3%)
Very confident	261 (36.0%)	306 (42.3%)	279 (38.6%)	289 (40.0%)
Extremely confident	158 (21.8%)	196 (27.1%)	185 (25.6%)	254 (35.1%)

4.2 RQ2: Differences in students' opinions across backgrounds

So far, we presented the overall perspectives of students on various topics related to GenAI. To further examine potential differences within the student population, we conducted cross-tabulation analyses focusing on major, year of study, and prior experience in relation to attitudes, self-reflections, and confidence.

Specifically, we ran cross-tabulations for students' perceptions of GenAI on different dimensions (see Table 2) against students' major, year of school, and prior programming experience. We used the Chi-Squared Test to compare two variables and report our findings in Table 5. Among all categories, creativity was the only perception that showed statistically significant results across all three background factors. Taking years of programming experience as an example, the results indicate that students with more years of experience held more negative views on the creativity of GenAI tools (this was also true for year of school). We also observed that a student's major appears to influence their perception of the effectiveness of GenAI tools, while their programming experience influences their perception of the tools' ability to support learning. Although there were statistically significant relationships between major and both effectiveness and creativity, a closer examination of the data revealed no consistent or convincing trends.

Table 5: Statistical Significance of Relationships between AI Perceptions and Student Backgrounds

AI Perception Dimension	Major	Year of School	Programming Experience
Ease of use	NS	NS	NS
Accuracy	NS	NS	NS
Effectiveness	*	NS	NS
Support for learning	NS	NS	*
Creativity	*	*	*

Note: * = statistically significant; NS = not statistically significant

The second group of analyses was conducted on students' self-reported agreement with statements regarding the use of generative AI in educational settings (see Table 3) and the three background variables. According to the data in Table 6, students with different backgrounds hold significant different point of view on wheather GenAI can enhance either personal or overall educational experience. Generally, the more senior in school and the more programming experience, the more optimistic about GenAI's ability in enhancing learning experience. Regarding the question *"In the future, I will be able to perform tasks independently that generative AI currently assists me with"* (abbreviated as *Perform tasks independently*), programming experience showed a statistically significant relationship. The data reveal a clear positive trend: students with more programming experience expressed stronger agreement with this statement. Among students with less than 1 year of experience, 78.6% agreed or strongly agreed (51.8% somewhat agree, 26.8% strongly agree), while this proportion increased steadily with experience, reaching 89.6% among students with more than 5 years of experience (43.2% strongly agree, 46.4% somewhat agree).

The final group of analyses examined students' self-reported confidence in programming-related skills across four domains (see Table 4) and the three background

Table 6: Statistical Significance of Relationships between AI Impact on Learning and Student Backgrounds

Perceived AI Impact on Learning	Major	Year of School	Programming Experience
Enhance learning experience	*	*	*
Better understand concepts	*	NS	NS
Perform tasks independently	NS	NS	*
Overall educational experience	*	*	*

Note: * = statistically significant; NS = not statistically significant; Full question wording in Table 3

factors. In this group, as indicated in Table 7, all factors showed statistically significant relationships with confidence in programming-related skills. We observed that the trends for year of school and programming experience still hold for this group. For majors, Computing-related majors (Computer Science, Computer Engineering, Electrical Engineering) generally felt more confident across all four statements.

Table 7: Statistical Significance of Relationships between Confidence in Programming-related Skills and Student Backgrounds

Confidence Statement	Major	Year of School	Programming Experience
Write programs without AI	*	*	*
Understand AI-generated code	*	*	*
Evaluate AI-generated code	*	*	*
Supports learning	*	*	*

Note: * = statistically significant; Full question wording in Table 4

5 Discussion

In this section, we recap our key findings, discuss potential explanations, and offer suggestions where applicable. We begin by discussing the current landscape of GenAI usage. First, in 2025, we found that the majority of students use GenAI on a daily basis. By comparison, when GenAI tools first emerged (2022–2023), students primarily experimented with these tools and used them only occasionally [25]. Studies conducted in 2023–2024 further indicate that most students used GenAI on a weekly basis [28]. Although the survey populations differ across studies, a clear trend of increasing frequency of use can be observed compared to earlier stages of adoption. This trend is also evident within our data when comparing two consecutive semesters: a larger percentage of students in the fall semester reported using GenAI tools multiple times per day. Taken together, these findings might suggest that GenAI usage frequency increases over time. Second, consistent with previous studies that identified conceptual questions as the predominant type of query in GenAI conversation histories [1, 15], we find that students primarily use GenAI tools to support their conceptual understanding. Beyond understanding concepts, students also use GenAI tools for various purposes, including *programming support* (debug code, read code, generate code, test code), *writing support* (revise/edit writing and read paper or articles), *receiving feedback*, and *assignment help* (help to finish difficult assignments and meet upcoming/looming deadlines). Notably, based on students' self-reflections, a relatively high proportion of students report using GenAI tools for assignment-related help, which may lead to potential learning loss and academic integrity concerns. Given the prevalence of this usage and its importance to students' learning, it is crucial to consider approaches that encourage more beneficial and responsible use of GenAI tools. Lastly, among traditional course activities, office hours were identified as the least useful component. One possible explanation is that students may use GenAI tools to replace some of the support functions that office hours have traditionally provided. In the era of AI, it may therefore be necessary to reconsider the purpose and relative emphasis of traditional course components to better meet students' evolving needs.

We conducted cross-tabulation analyses on three aspect (attitude, self-reflection, and confidence) against three students' background factors (major, year of school, and prior experience) to determine whether students with different backgrounds hold different opinions about GenAI tools and reflect differently on their use. Regarding AI perceptions, there were generally no significant differences across background factors for aspects such as ease of use and accuracy - students with different majors, years of study, or programming experience tended to hold similar opinions. However, when considering creativity, all background factors showed significant differences in students' opinions. This may be because students with more experience or higher seniority hold higher standards for identifying something as creative. Moving to students' self-reflection, we found that students with different backgrounds hold markedly different views on whether GenAI tools can enhance their personal or overall educational experience. This might suggests that educators need to carefully consider what aspects of GenAI to integrate and how to embed these tools into educational practices, particularly when supporting students with relatively less prior experience or seniority. Turning to students' confidence related to programming activities, we find that, in general, students with more years of experience tend to report higher levels of confidence. In addition, years of experience, year of study, and major all have a significant influence on students' confidence levels. Therefore, it appears necessary to focus on students with little or no prior experience and provide targeted support to help build their confidence.

6 Limitations and Future Work

We acknowledge that, due to the voluntary nature of the survey, the number of responses differed substantially between the two semesters. Although we distributed the survey across multiple engineering majors, response rates also varied by major and year of study, which may introduce bias into our analysis. Our goal in this study was to provide an overall view of the current landscape of GenAI use and to examine potential differences in attitudes, perceptions, and behaviors among engineering students with different backgrounds. Due to page limitations, although the survey included scenario-based questions to examine students' opinions on potential academic integrity violations, we do not present those findings in this paper. Future work should extend this study across multiple years and institutions to gain a more comprehensive understanding of students' perspectives. In addition, we plan to conduct a complementary survey of instructors to examine whether they hold similar or differing views regarding the capabilities, usefulness, and concerns associated with GenAI tools, as well as scenario-based questions related to academic integrity violations.

7 Conclusions

In this work, we analyzed survey data from over 800 students at the University of Illinois Urbana-Champaign in the United States across two consecutive semesters in 2025. Our goal is to understand students' engagement with generative AI, with a particular focus on the current landscape of engineering students' attitudes, beliefs, and academic practices related to GenAI. We found that most students use GenAI tools on a daily basis, and that the frequency of use is substantially higher than what has been reported in studies from earlier years. We further examined students' perceptions of GenAI and found that they generally hold positive views regarding ease of use, effectiveness, and the tools' ability to support learning, while expressing comparatively lower satisfaction with accuracy and creativity. Across attitude and self-reflection measures, we observed that students with different backgrounds shared similar opinions in some categories, while exhibiting notable differences in others. In general, students with more years of experience or higher academic seniority reported greater confidence and were more likely to agree that GenAI can support their learning. Taken together, this study provides a clearer understanding of the current landscape of GenAI use in engineering education from students' perspectives and identifies key needs for the future development of instructional GenAI tools, as well as critical pain points that warrant attention.

References

[1] Abdulrahman AlRabah, Zepei Li, Meredith Blumthal, Sotiria Koloutsou-Vakakis, Volodymyr Kindratenko, Tomasz Kozlowski, and Abdussalam Alawini. Data-driven insights into ai-powered learning: Analyzing student interactions with ai-bot in engineering education. In *2025 ASEE Annual Conference & Exposition*, number 10.18260/1-2–56204, Montreal, Quebec, Canada, June 2025. ASEE Conferences. https://peer.asee.org/56204.

[2] João Batista, Anabela Mesquita, and Gonçalo Carnaz. Generative ai and higher education: Trends, challenges, and future directions from a systematic literature review. *Information*, 15(11):676, 2024.

[3] Karley Beckman, Tiffani Apps, Sarah Katherine Howard, Claire Rogerson, Ann Rogerson, and Jo Tondeur. The genai divide among university students: A call for action. *The Internet and Higher Education*, page 101036, 2025.

[4] Cecilia Ka Yuk Chan and Wenjie Hu. Students' voices on generative ai: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1):43, 2023.

[5] Binglin Chen, Colleen M. Lewis, Matthew West, and Craig Zilles. Plagiarism in the Age of Generative AI: Cheating Method Change and Learning Loss in an Intro to CS Course. In *Proceedings of the Eleventh ACM Conference on Learning @ Scale*, L@S '24, pages 75–85, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3657604.3662046`.

[6] Jennifer Chung, Michael Henderson, Nicole Pepperell, Christine Slade, and Yifei Liang. Student perspectives on ai in higher education: Student survey, 2024.

[7] Amanda S. Fernandez and Kimberly A. Cornell. CS1 with a Side of AI: Teaching Software Verification for Secure Code in the Era of Generative AI. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, SIGCSE 2024, pages 345–351, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3626252.3630817`.

[8] Stefan Feuerriegel, Jochen Hartmann, Christian Janiesch, and Patrick Zschech. Generative ai. *Business & Information Systems Engineering*, 66(1):111–126, 2024.

[9] Josh Freeman. Student generative ai survey 2025. 2025.

[10] Ghazi Mauer Idroes, Teuku Rizky Noviandy, Aga Maulana, Irvanizam Irvanizam, Zulkarnain Jalil, Lensoni Lensoni, Andi Lala, Abdul Hawil Abas, Trina Ekawati Tallei, and Rinaldi Idroes. Student perspectives on the role of artificial intelligence in education: A survey-based analysis. *Journal of Educational Management and Learning*, 1(1):8–15, 2023.

[11] Aditya Johri, Andrew S. Katz, Junaid Qadir, and Ashish Hingle. Generative artificial intelligence and engineering education. *Journal of Engineering Education*, 112(3):572–577, 2023. doi: https://doi.org/10.1002/jee.20537. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/jee.20537`.

[12] Breanna Jury, Angela Lorusso, Juho Leinonen, Paul Denny, and Andrew Luxton-Reilly. Evaluating

LLM-Generated Worked Examples in an Introductory Programming Course. In *Proceedings of the 26th Australasian Computing Education Conference*, ACE '24, pages 77–86, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3636243.3636252`.

[13] Jinhee Kim. Leading teachers' perspective on teacher-ai collaboration in education. *Education and information technologies*, 29(7):8693–8724, 2024.

[14] Anna E Korchak, Yevgeny D Patarakin, and Jamie Costley. Exploring the use of generative artificial intelligence by university students: a systematic literature review. *. :* , 22(1):37–57, 2025.

[15] Zepei Li, Sotiria Koloutsou-Vakakis, Tomasz Kozlowski, Volodymyr Kindratenko, and Abdussalam Alawini. How students use generative ai: Insights from conversation log analysis. In *2025 IEEE Frontiers in Education Conference (FIE)*, pages 1–7, 2025. doi: 10.1109/FIE63693.2025.11328645.

[16] Rongxin Liu, Carter Zenke, Charlie Liu, Andrew Holmes, Patrick Thornton, and David J. Malan. Teaching CS50 with AI: Leveraging Generative Artificial Intelligence in Computer Science Education. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, SIGCSE 2024, pages 750–756, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3626252.3630938`.

[17] Yan Liu and He Wang. Who on earth is using generative ai? *World Development*, 199:107260, 2026.

[18] Wenhan Lyu, Yimeng Wang, Tingting (Rachel) Chung, Yifan Sun, and Yixuan Zhang. Evaluating the Effectiveness of LLMs in Introductory Computer Science Education: A Semester-Long Field Study. In *Proceedings of the Eleventh ACM Conference on Learning @ Scale*, L@S '24, pages 63–74, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3657604.3662036`.

[19] Hendrik Müller, Aaron Sedley, and Elizabeth Ferrall-Nunge. Survey research in hci. *Ways of Knowing in HCI*, pages 229–266, 2014.

[20] Joey Ng, Mavis Tong, Eva YM Tsang, Kevin Chu, and William Tsang. Exploring students' perceptions and satisfaction of using genai-chatgpt tools for learning in higher education: A mixed methods study. *SN Computer Science*, 6(5):476, 2025.

[21] Ha Nguyen and Vicki Allan. Using GPT-4 to Provide Tiered, Formative Code Feedback. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, SIGCSE 2024, pages 958–964, New York, NY, USA, 2024. Association for Computing Machinery. URL `https://doi.org/10.1145/3626252.3630960`.

[22] Griffin Pitts, Neha Rani, Weedguet Mildort, and Eva-Marie Cook. Students' reliance on ai in higher education: identifying contributing factors. In *International Conference on Human-Computer Interaction*, pages 86–97. Springer, 2025.

[23] Qualtrics. Qualtrics XM Platform [computer software], 2025. URL `https://www.qualtrics.com`.

[24] Nicole B Reinke, Ann L Parkinson, and Georgia R Kafer. A tutorial activity for students to experience generative artificial intelligence: students' perceptions and actions. *Advances in Physiology Education*, 49(2):461–470, 2025.

[25] Mika Saari, Petri Rantanen, Mikko Nurminen, Terhi Kilamo, Kari Systä, and Pekka Abrahamsson. Survey of ai tool usage in programming course: Early observations. In *International Conference on Agile Software Development*, pages 182–191. Springer Nature Switzerland Cham, 2022.

[26] Said A Salloum. Ai perils in education: Exploring ethical concerns. *Artificial intelligence in education: The power and dangers of ChatGPT in the classroom*, pages 669–675, 2024.

[27] Sandra Saúde, João Paulo Barros, and Inês Almeida. Impacts of generative artificial intelligence in higher education: research trends and students' perceptions. *Social Sciences*, 13(8):410, 2024.

[28] Sigrid Schefer-Wenzl, Christoph Vogl, Sahani Peiris, and Igor Miladinovic. Exploring the adoption of generative ai tools in computer science education: A student survey. In *Proceedings of the 2024 16th International Conference on Education Technology and Computers*, ICETC '24, page 173–178, New York, NY, USA, 2025. Association for Computing Machinery. ISBN 9798400717819. doi: 10.1145/3702163.3702188. URL `https://doi.org/10.1145/3702163.3702188`.

[29] Mario ES Simaremare, Chandro Pardede, Irma NI Tampubolon, Daniel A Simangunsong, and Putri E Manurung. The penetration of generative ai in higher education: A survey. In *2024 IEEE Integrated STEM Education Conference (ISEC)*, pages 1–5. IEEE, 2024.

[30] Xiuxiu Tang, Si Chen, Ying Cheng, Nitesh V Chawla, Ronald Metoyer, and G Alex Ambrose. Understanding student attitudes and acceptability of genai tools in higher ed: Scale development and evaluation. *arXiv preprint arXiv:2508.01926*, 2025.

[31] Derya Uygun. Teachers' perspectives on artificial intelligence in education. *Advances in Mobile Learning Educational Research*, 4(1):931–939, 2024.

[32] Abdullahi Yusuf, Nasrin Pervin, Marcos Román-González, and Norah Md Noor. Generative AI in Education and Research: A Systematic Mapping Review. *Review of Education*, 12(2):e3489, 2024.