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Insights into Faculty's use of Generative Artificial Intelligence systems in Engineering Classrooms.

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Insights into Faculty's Use of Generative Artificial Intelligence Systems in Engineering Classrooms

Introduction

The integration of technology into education has long sparked debate, particularly as emerging tools like generative artificial intelligence (GenAI) challenge traditional teaching practices [1], [2], [3], [4]. This ongoing tension between established pedagogical methods and technological innovation, which offers new affordances, continues to shape contemporary discussions about the adoption of educational technologies, with GenAI being the latest focal point. Many of the concerns surrounding this shift are reflected in the current discourse on GenAI, especially after its rapid, widespread accessibility. While GenAI offers promising benefits, educational systems are struggling to keep up and find appropriate ways to integrate this transformative technology responsibly and prepare students, particularly future engineers, for the evolving demands of the workforce.

The ever-growing and dynamic nature of GenAI, as one of the latest technological advancements, aligns with the rapidly evolving needs of various engineering disciplines, offering enhanced opportunities for student engagement and improved learning outcomes [5], [6]. Johri et al. [7] categorized the impacts of GenAI on research and teaching within engineering. While research activities primarily focus on generative assistance, data analysis, computing efficiency, and research writing, GenAI-enhanced teaching encompasses preparing lessons, generating syllabi, creating assessments, engaging students, and developing lesson plans. Furthermore, the ethical and safe use of GenAI must be considered, particularly in addressing issues such as misinformation, bias, hallucinations, and privacy risks [6], [7], [8].

The emergence of GenAI necessitates a change throughout higher education [9], with faculty playing an integral role in ensuring its success [10]. As key drivers of this transformation, faculty must proactively respond to the rise of GenAI, even before institutions formalize policies and processes to guide its integration. The Chronicle of Higher Education has observed,

> One year after its release, ChatGPT has pushed higher education into a liminal place. Colleges are still hammering out large-scale plans and policies governing how generative AI will be dealt with in operations, research, and academic programming. But professors have been forced more immediately to adapt their classrooms to its presence. Those adaptations vary significantly, depending on whether they see the technology as a tool that can aid learning or as a threat that inhibits it [11].

Faculty perspectives and responses are particularly critical in professional programs such as engineering, medicine, and teacher preparation, where the rapid integration of GenAI presents unique opportunities and challenges. In medicine, faculty must address the use of GenAI to enhance diagnostic accuracy, streamline administrative tasks, and analyze patient data, while also teaching students to navigate ethical concerns such as patient privacy, diagnostic errors, and the balance between human clinical judgment and AI-assisted decision-making. Similarly, in teacher preparation programs, faculty are tasked with guiding future educators to critically assess

GenAI tools for fairness, inclusivity, and their impacts on learning outcomes, ensuring these technologies are applied ethically and effectively in diverse classrooms.

In engineering education, faculty may leverage GenAI to enhance problem-solving skills, automate routine computations, and explore innovative design solutions. However, they must also prepare students to address critical issues like algorithmic bias, safety-critical applications, and sustainable technology practices. Errors in professional fields can have severe consequences, such as GenAI malfunctions in medical diagnoses or engineering failures in design processes. Professional education must teach students to manage risks, take responsibility, and understand the limitations of GenAI systems. These considerations demand rigorous training and critical thinking to ensure graduates can navigate the complexities of GenAI in their respective professions. By proactively engaging with GenAI, faculty across disciplines can influence how the technology is adopted and model responsible and ethical use for their students, ultimately shaping the future of their respective professions.

Regulatory and accreditation standards shape how professional education integrates new technologies. Engineering programs follow ABET standards emphasizing technical expertise and ethical practice. These requirements demand a careful and deliberate integration of any new tools, including GenAI, into professional training. In the initial adoption stages of any technology, innovative faculty often pilot the new technology and create test cases that can serve as precursors to curricular products and policy. Given the foundational importance of workforce readiness in engineering programs, it is critical to prepare students for the effective use, design, and evaluation of GenAI tools. The rapid diffusion of GenAI tools requires much quicker research and development to prepare engineers for the changing workplace. As such, we need to understand engineering faculty perspectives on the use of GenAI tools to gain insights into their awareness of its prevalence among students, the strategies they employ to monitor its usage, and the extent to which they develop and communicate explicit policies addressing its integration.

Literature review

In this section, we will elaborate on the theoretical framework and the adoption of GenAI in both general and engineering education.

Theoretical framework

The Technology Acceptance Model (TAM), developed by Davis [12], provides a framework to understand how users accept and use technology, emphasizing two primary factors: perceived usefulness (the degree to which a user believes the technology enhances performance) and perceived ease of use (the degree to which a user finds the technology free from effort). In the context of GenAI in education, TAM suggests that educators' and students' acceptance of GenAI tools is influenced by their perceived benefits, such as personalized learning, efficiency in administrative tasks, and job preparation, alongside the ease with which these tools can be integrated into educational practices, [13], [14]. The model identifies four primary determinants: performance expectancy (perceived benefits to job performance), effort expectancy (ease of use), social influence (perception of others' views on system use), and facilitating conditions (belief in existing support infrastructure). Research has shown that these factors were moderated by gender, age, experience, and voluntariness of use. The model has shown robust empirical support, accounting for approximately 70% of the variance in the intention to use technology and 50% in actual usage. It incorporates external factors such as social influence and facilitating conditions to explain user behavior in the adoption of GenAI in educational contexts [15], [16].

Venkatesh [17] presented an analysis of GenAI tool adoption challenges and proposed a research agenda grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). Four key concerns emerged from his analysis, including: (1) the inherent opacity of GenAI models and their “blackboxed” nature, which creates barriers to user understanding and trust; (2) the persistent challenge of model errors and learning curves, particularly salient in dynamic operational environments; (3) the complex interplay between human cognitive biases and algorithm aversion, which can impede adoption even when GenAI tools demonstrate superior performance; and (4) the unique challenges posed by operations management contexts, including incomplete data, multiple stakeholder dependencies, and evolving operational parameters. Drawing upon UTAUT's four established predictors, Venkatesh [17] proposed investigating individual characteristics (such as risk tolerance), technology attributes (including transparency), environmental factors (organizational climate), and intervention strategies (training approaches). As a result, our framework emphasizes the importance of data collection that captures the dynamic nature of GenAI tool implementation while acknowledging the need for context-sensitive measurement approaches that can account for the unique complexities of engineering education environments.

Adoption of GenAI in education

The adoption of GenAI in education is rapidly expanding, yet its integration presents a complex landscape of opportunities and challenges. A systematic mapping review conducted by [18] categorized the uses of GenAI in education into five primary groups: improving teaching methods, advanced training, support for writing and increased efficiency, professional development, and interdisciplinary learning. However, the review also highlighted a critical gap in preparedness at institutional levels for applying GenAI effectively, suggesting that while the technology offers substantial potential, its integration is not yet widespread or systematically implemented.

Similarly, Labadze et al. [19] reviewed 67 selected studies to investigate the benefits, opportunities, challenges, limitations, and concerns of using AI chatbots in educational contexts. While acknowledging the educational gains of AI chatbots as a promising solution for offering personalized learning to students, the researchers raised several concerns regarding the significant role of educators in diligent handling of GenAI. As such, educators need professional development training to efficiently integrate GenAI into their teaching practices, learn about the potential capabilities of GenAI, and raise students’ awareness of responsible and ethical adoption of GenAI.

In support of these findings, Deng et al. [20] showed that ChatGPT improved academic affect, motivation, and performance. Concurrently, it was found to reduce mental effort and had no significant effect on self-efficacy. Existing reviews underscored the need for responsible strategies to implement GenAI and for equipping educators with evidence-based guidance on its use to enhance student learning. They also pointed to methodological limitations of their early research, such as the lack of power and concerns regarding measurement. The researchers suggested the use of objective measures by educators to ensure the improvements in students' higher-order thinking skills are not due to the novelty effect of GenAI.

Further reinforcing this need for adaptive teaching practices, Vargas-Murillo et al. [21] explored the impacts of ChatGPT usage in education through a systematic review, emphasizing that educators must continually adapt to technological advancements like GenAI. They emphasized that AI-assisted learning must be carefully managed to foster critical thinking and problem-solving skills in students. Educators should also help students differentiate between using GenAI for text generation versus idea generation, which can enhance the responsible application of the tool while encouraging creativity and deeper cognitive engagement.

Adoption of GenAI in engineering education

Simelane and Kittur [10] conducted a qualitative study to explore engineering instructors' perspectives on the effectiveness of the impacts of ChatGPT on engineering students and faculty members. Their findings indicated that instructors emphasized leveraging ChatGPT as a supplementary learning tool while expressing concerns about the potential of GenAI to hinder authentic learning and foster student over-reliance on technology. The majority of engineering faculty acknowledged the positive impact of integrating GenAI into their teaching, enabling scalable instruction in larger classrooms and offering students more timely and personalized feedback. Other suggestions emphasized the importance of fostering AI literacy among both faculty and students, along with the careful integration of GenAI into teaching and learning to mitigate potential risks, biases, and the risk of students bypassing meaningful learning.

Al Badi et al. [22] explored the impact of ChatGPT in engineering education through conducting a mixed-methods study in the Military Technological College in Oman. The findings of their study revealed that instructors held a very positive view regarding the potential of ChatGPT in engineering education. Instructors believed that it is essential to promote ethical awareness, provide training on GenAI tools, and consider revising assessment methods when incorporating GenAI in education. Additionally, concerns were raised regarding the use of ChatGPT, including the need for precise guidelines, the challenge of detecting AI-generated content, and the possibility of students over-relying on this tool. Therefore, they suggested there is a need for providing engineering instructors with hands-on learning experiences, such as laboratory work and workshops to develop practical skills, redesign assessments, and discovering novel ways of integrating GenAI into engineering education.

Menekse [23] explored the potential of GenAI technologies, such as Large Language Models (LLMs) and diffusion models, to transform engineering education. Considering GenAI as a teaching aid, the author suggested that GenAI can be used to generate instructional resources, such as images, diagrams, and videos, which can improve student learning and engagement. Through incorporating GenAI into their teaching practices, engineering instructors can create personalized learning experiences by offering different at-home and in-class activities and practice problems based on students' prior success and comprehension of concepts. Regarding risks and concerns, the author mentioned that LLMs can generate misleading information due to being trained on uncontrolled data, and they can be biased, leading to discrimination. Additionally, over-reliance on GenAI tools can hinder student learning and reduce student engagement. Therefore, engineering educators should carefully curate GenAI-created content to ensure its suitability for teaching and learning. Moreover, they need to be transparent about how GenAI tools can be used by their students and elaborate on their benefits and drawbacks.

Based on the emerging literature and the UTAUT framework, we formulated the following research questions:

1. To what extent are engineering faculty aware of and monitoring students' use of GenAI tools in their coursework?
2. How frequently do engineering faculty create and communicate explicit policies regarding the use of GenAI tools in their courses?
3. What are the common elements of these AI-related policies in engineering courses (e.g., prohibition, encouragement, or mandatory disclosure)?
4. How do engineering faculty adapt their teaching practices and assignment designs to accommodate or mitigate the use of GenAI in engineering education?

Methods

In this section, we described the setting of the study, participants and the instruments being used. This study utilized an explanatory sequential mixed methods design, first collecting and analyzing quantitative data followed by qualitative data to elaborate on the initial findings. This approach, where one phase builds upon the other, allows for a more in-depth understanding of the research problem [24].

Participants

This study involved 67 faculty members and instructional staff from a College of Engineering at a Midwestern university, representing a range of academic ranks (professors, associate professors, assistant professors, professors of practice, graduate teaching assistants, and adjunct faculty) and professional backgrounds within higher education. Gender distribution analysis revealed 51 males (76.1%), 13 females (19.4%), one non-binary participant (1.5%) with two (3.0%) who did not disclose their gender. Forty-three participants (76.7%) held doctoral degrees, seven participants (12.5%) possessed master's degrees, while qualification data remained unavailable for 8 participants (14.3%). Additionally, the sample included 16 Full Professors (23.9%), 19 Associate Professors (28.4%), 14 Assistant Professors (20.9%), 12 Graduate Teaching Assistants (17.9%), and six participants (9.0%) not specifying their academic rank. Departmental affiliations demonstrated disciplinary diversity across STEM fields, with representation from Biological Systems Engineering (16.66%), Chemical and Biomolecular Engineering (10.60%), Civil and Environmental Engineering (6.06%), Architectural Engineering and Construction (25.75%), Electrical and Computer Engineering (6.06%), Mechanical and Materials Engineering (10.6%), and School of Computing (24.24%). The participants had an average of 12.77 (*SD*=10.95) years of teaching experience. This participant profile established a representative cross-section of academic disciplines and professional hierarchies within the institutional context.

Institutional policy on GenAI

The university studied here recognized that advancements in GenAI require discussions that lead to defining procedural and academic campus policies. Two primary initiatives were underway when the research was conducted. The first is a systemwide AI task force composed of faculty and staff that have collected community perspectives and needs. Until these policies are defined, faculty must rely on guidance and their own perspectives on AI use by their students in their courses. The second was a pilot deployment of ChatGPT for interested faculty.

Professional development

On campus, instructors were afforded multiple opportunities to grow their understanding and skills on the use of GenAI tools for teaching and learning. For example, at the institutional level, through the Center for Transformative Teaching (CTT), faculty are provided with digital resources, recommended readings, and a frequently updated blog. Faculty are also able to take part in a series of workshops addressing various GenAI related topics such as developing course policies, prompting, and using GenAI tools as a student engagement tool. While these opportunities address some of the university's overarching needs, they lack discipline specific examples and discussions. That particular gap is addressed by a specific team, Engineering and Computing Education Core (ECEC), at the College of Engineering. The team has provided workshops on how GenAI tools could be used within the contexts of computing, construction, and engineering. For example, in one workshop instructors in fundamental engineering courses examined how various tools solved fundamental statics questions, construction faculty examined the use of Sora (OpenAI video generation tool) for creating short videos to be used in their instruction, and various departments called upon the team to provide examples on how GenAI tools can be used in engineering education contexts. While opportunities were provided many faculty have not participated in any. In the sample of this study over half of faculty did not participate in any professional development related to GenAI.

Survey

The survey was designed to assess the perspectives and approaches of engineering faculty and instructional staff regarding the integration of GenAI into engineering education. The first part of the survey included 38 items grouped in seven hypothesized domains:

a) Engineering faculty's personal knowledge of GenAI (three items) For example, "How many GenAI-focused professional development sessions have you attended so far?".
b) Engineering faculty's knowledge of GenAI use for pedagogical purposes (six items). For example, "How aware are you of using GenAI for creating exams/quizzes?" (1=Not aware, 2=Aware but have not used, 3=Have tried using GenAI, and 4=Regularly use GenAI for creating exams/quizzes);

c) Engineering faculty's acknowledgment for the potential use of GenAI by undergraduate students (four items). For example, "I believe that my undergraduate students are aware of available GenAI tools." (1=None of my students, 2=Some of my students, 3=Half of my students, 4=Most of my students, and 5=All of my students);

c) Engineering faculty's level of integration of GenAI in their classes (four items). For example, "I know my institution's guidelines (i.e., university, college, or department) on GenAI use for teaching." (1=Definitely false, 2=Probably false, 3=Neither true nor false, 4=Probably true, and 5=Definitely true);

d) Engineering faculty's approaches toward integrating GenAI into students' coursework or assignments (five items). For example, "Proctored exams help prevent the potential use of GenAI." (1=In none of my classes, 2=In some of my classes, and 3=In all of my classes);

e) Engineering faculty's ethical concerns about GenAI (six items). For example, "I am concerned about GenAI's potential biases (for example, cultural, linguistic and racial)." (1=Not concerned, 2=A little concerned, 3=Somewhat concerned, 4=Concerned, and 5=Very concerned);

f) Engineering faculty's actions in their classes about GenAI ethics (six items). For example, "I have assignments/readings/discussions that address copyright infringement issues related to GenAI use." (1=In none of my classes, 2=In some of my classes, and 3=In all of my classes); and

g) Engineering faculty's future perspectives toward GenAI (three items). For example, "GenAI should be used by students in every one of my classes." (1=Strongly agree, 2=Agree, 3=Neither agree nor disagree, 4=Disagree, and 5=Strongly disagree).

Establishing survey validity

To enhance the survey's construct validity, we conducted individual cognitive interviews [25] with three engineering faculty members, using this method to assess how participants interpreted and responded to the survey questions. During these interviews, the first author posed probing questions to explore interviewees' thought processes as they answered each survey item. Based on their feedback and comments, we revised the original questions and finalized the questionnaire.

Semi-structured interviews

To gain deeper insights into participants' perceptions of integrating GenAI tools in engineering education, individual semi-structured interviews were conducted with four volunteers. The interview protocol covered topics such as instructors' views on GenAI, its role in their teaching practices and decision-making, available support and resources, and their outlook on its future use. Following the distribution of the interview invitation across the College of Engineering, four male faculty members agreed to participate. The group included an Assistant Professor of Practice in Biological Systems Engineering (Thomas), an Associate Professor in Mechanical Engineering (Michael), an Assistant Professor of Practice in the School of Computing (Ryan), and an Assistant Professor in the School of Computing (Alex), with an average of 7.5 years of experience teaching engineering courses. To protect their identities, pseudonyms were used throughout this study, and all identifiable details were anonymized.

Results

Engineering faculty's personal engagement and knowledge of GenAI revealed distinct usage patterns. Faculty engagement with GenAI tools varied across levels of awareness and usage. Specifically, 2.98% of respondents reported no awareness of GenAI, while 23.88% were aware but had not used it. An additional 26.8% indicated they were aware and knew how to use GenAI, 26.8% reported using it, and 20.89% actively used GenAI in their teaching. These findings demonstrate a relatively balanced distribution across engagement levels.

Regarding professional development, more than half of the engineering faculty had not attended any GenAI-related training sessions. About a fifth (21%) attended one session, 10.44% attended two sessions, and 14.3% reported attending three or more sessions (two did not report). Although internet-based resources were utilized more frequently than formal training, only 32.2% of faculty reported using such resources with any regularity, indicating limited self-directed learning about GenAI technologies.

Quantitative Analyses of Survey Items

For the quantitative analyses, we included only complete responses to ensure data integrity and consistency across all analyses. Of the 92 participants who initiated the survey, 67 provided complete responses across all items, resulting in a completion rate of approximately 73%. This completion rate is notably high for survey research, which typically experiences substantial attrition, [26], [27]. The strong completion rate suggests that participants found the survey content engaging and relevant, supporting the validity of the resulting data. All subsequent analyses were conducted using this sample of 67 complete responses.

Descriptive statistics

Prior to conducting factor analysis, we examined the descriptive statistics for all items in the final scale. Appendix A includes the descriptive statistics for the 29 items retained in the final solution, including minimum and maximum values, medians, means, standard deviations, and item-total correlations for the subscales retained in the final factor solution. The items' means ranged from 1.709 to 3.38 on the mixed Likert scales (some items used 3-point, 4-point, and 5-point scales), indicating a reasonable distribution of responses across the scale points. Standard deviations ranged from 0.569 to 1.313, suggesting adequate variability in participants' responses. Item-total correlations, which assess the relationship between each item and the total score, excluding item 3, ranged from 0.58 to 0.91, with all values exceeding the recommended threshold of 0.30 [28], indicating that all items contributed meaningfully to the overall scale.

Factor analysis procedure

An exploratory factor analysis (EFA) was conducted to examine the underlying structure of the GenAI survey instrument and establish its construct validity. The initial item pool consisted of 37 Likert-scale items designed to measure various aspects of GenAI perceptions and usage within engineering education. Prior to analysis, the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.87, indicating excellent sampling adequacy, and Bartlett's test of sphericity was significant (2(406) = 1342.345, $p < .001$), confirming that the data were suitable for factor analysis.

To determine the optimal number of factors to retain, we employed multiple criteria including eigenvalues greater than 1.0 [29], examination of the scree plot [30], and theoretical interpretability of the resulting factors. The scree plot analysis revealed a clear “elbow” after the fifth factor, suggesting that a five-factor solution would be most appropriate (see Figure 1). Additionally, the first five factors had eigenvalues greater than 1.0, collectively explaining approximately 59.4% of the total variance in the data.

In addition to examining eigenvalues and the scree plot, we conducted a parallel analysis [31] to determine the optimal number of factors to retain. Parallel analysis compares eigenvalues from the actual data with eigenvalues from randomly generated correlation matrices with the same sample size and number of variables. This approach helps prevent over-extraction of factors that may be due to sampling error. Using the 95th percentile criterion, our parallel analysis results confirmed the five-factor solution, as the eigenvalues from the first five factors in our actual data (5.80, 3.73, 2.11, 1.78, 1.63) exceeded the corresponding eigenvalues from the random data (1.63, 1.25, 1.10, 0.95, 0.82), while the sixth factor eigenvalue (1.21) was smaller than the random data eigenvalue (1.98). This parallel analysis provided further empirical support for our five-factor solution beyond the traditional eigenvalue > 1 criterion and scree plot examination.

Principal axis factoring with varimax rotation was used to extract the factors, as this orthogonal rotation method maximizes the variance of the squared loadings for each factor, thereby simplifying the interpretation of the factor structure by minimizing cross-loadings. Although preliminary correlation analysis showed some moderate correlations between factors (ranging from 0.02 to 0.38), we selected varimax rotation over oblique rotation methods since our theoretical framework suggested relatively independent dimensions of GenAI perceptions, and the orthogonal solution provided clearer interpretability.

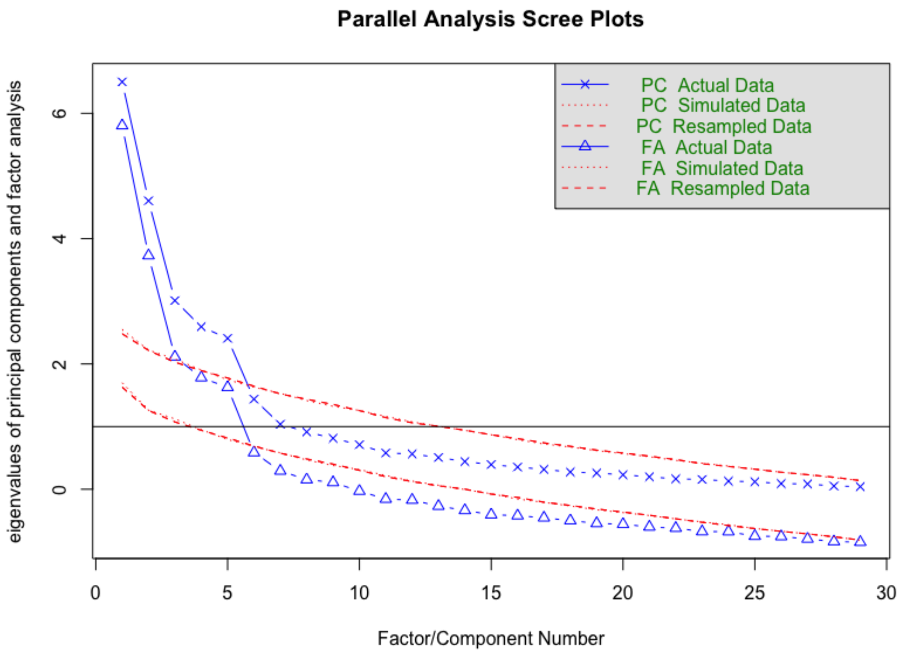

Figure 1. Scree plot for the parallel analysis to determine the number of factors for the GenAI survey

Item reduction and final factor structure

Following best practices in scale development [32], we established a minimum factor loading criterion of 0.40 to retain items, as this threshold indicates a substantive relationship between the item and the factor. The initial EFA of all 37 items revealed that eight items did not meet this criterion, either failing to load substantially on any factor or demonstrating problematic cross-loadings (loading ≥ 0.40 on multiple factors). These items were eliminated from the instrument. In our final 29-item solution, we identified only one item with cross-loadings (loading ≥ 0.40 on more than one factor), which we retained due to its theoretical importance and because its highest loading was substantially greater than its cross-loading.

After removing these problematic items, we conducted a second EFA with the remaining 29 items using the same extraction and rotation methods. The five-factor solution remained stable, with each factor containing between 4 and 8 items with loadings ≥ 0.40, and no significant cross-loadings. Table 1 presents the factor loadings for the final 29-item solution.

Table 1. Factor Loadings for Final 29-Item Solution using Varimax Rotation

Item	Ethical GenAI in Coursework	GenAI in Teaching	GenAI Concerns	Future of GenAI in Engineering Education	Student Awareness of GenAI
Item_1		0.593			
Item_3		0.434			

Item_4		0.707			
Item_5		0.804			
Item_6		0.808			
Item_7		0.656			
Item_8		0.586			
Item_9		0.786			
Item_10					0.723
Item_11					0.898
Item_12				0.532	0.579
Item_13				0.690	0.447
Item_14					0.588
Item_15					0.559
Item_23			0.645		
Item_24			0.764		
Item_25			0.669		
Item_26			0.504		
Item_27			0.743		
Item_28			0.761		
Item_29	0.741				
Item_30	0.871				
Item_31	0.701				
Item_32	0.742				
Item_33	0.876				
Item_34	0.727				
Item_35				0.655	
Item_37				0.778	
Item_38				0.757	

Note. Factor loadings < .40 are omitted from the table to facilitate interpretation of the factor structure. The first factor, Ethical GenAI in Coursework, explains 14.3% of the variance. The second factor, GenAI in Teaching, explains 14.1% of the variance. The third factor, GenAI Concerns, explains 11.5% of the variance. The fourth factor, Future of GenAI in Engineering Education, explains 9.9% of the variance. The last factor, Student Awareness of GenAI, explains 9.5% of the variance.

The five resulting factors and their interpretations were as follows:

- Factor 1 (Ethical GenAI in Coursework) – This factor consists of six items (29-34) with loadings ranging from 0.701 to 0.876. The highest loading items were items #33 (0.876), #30 (0.871), and #32 (0.742). These items primarily address ethical concerns and considerations related to GenAI use, such as issues of transparency, privacy, and responsible implementation.

- Factor 2 (GenAI in Teaching) – Comprising eight items (1, 3-9) with loadings ranging from 0.434 to 0.808, this factor had the largest number of items among all factors. Notable items with the strongest loadings include items #6 (0.808), #5 (0.804), and #9 (0.786). These items focus on the awareness and usage of GenAI in various contexts.
- Factor 3 (GenAI Concerns) – This factor contains six items (23-28) with loadings ranging from 0.504 to 0.764. The items with the highest loadings were items #24 (0.764), #28 (0.761), and #27 (0.743). This factor captures concerns about student usage of GenAI.
- Factor 4 (Future of GenAI in Engineering Education) – The three items in this factor (35, 37, 38) had loadings ranging from 0.655 to 0.778. The strongest indicators include items #37 (0.778), #38 (0.757), and #35 (0.655). These items address perspectives on the future use of GenAI in engineering education.
- Factor 5 (Perception of Student Usage) – This factor includes six items (10-15, with items 12 and 13 cross-loading with Factor 4) with loadings ranging from 0.559 to 0.898. The items with the highest loadings were items #11 (0.898), #10 (0.723), and #14 (0.588). This factor addresses the perception of student usage of GenAI in the classroom.

The five-factor structure aligns well with our theoretical framework, which posited that perceptions of GenAI would encompass multiple dimensions, including awareness and usage, perception of current usage by students, concerns about student usage, ethical considerations for using GenAI, and future perspective of GenAI in the classroom. This multi-dimensional structure supports the complex nature of how educators conceptualize and interact with GenAI technologies across various contexts within the learning environment.

Reliability Analysis

To assess the internal consistency reliability of each factor, we calculated Cronbach's alpha coefficients. Cronbach's alpha [33] is widely regarded as the standard measure of scale reliability, evaluating how closely related a set of items are as a group by measuring the average correlation between items while controlling for the number of items in the scale. As shown in Table 3, all five factors demonstrated satisfactory reliability, with alpha values ranging from 0.78 to 0.91, which exceeds the commonly recommended threshold of 0.70 [34]. These strong reliability coefficients indicate that items within each factor consistently measure the same underlying construct, supporting the internal consistency of our five-factor structure.

Table 2. Reliability Coefficients for the Five Factors

Factors	Number of Items	Cronbach's Alpha	Factor Mean (SD)
Ethical GenAI in Coursework	6	0.91	8.54 (3.32)
GenAI in Teaching	8	0.72	17.7 (3.91)
GenAI Concerns	6	0.85	20.85 (5.7)
Future of GenAI in Engineering Education	6	0.89	9.26 (3.28)
Student Awareness of GenAI	4	0.80	19.36 (4.97)

Note. All factors demonstrated sufficient reliability with Cronbach's alpha values exceeding the commonly recommended threshold of 0.70.

Variance explained

The five factors collectively accounted for approximately 59.4% of the total variance in the data. Factor 1 explained the largest proportion of variance (14.3%, representing 24% of the explained variance), followed by Factor 2 (14.1%, representing 23.7% of the explained variance), Factor 3 (11.5%, representing 19.4% of the explained variance), Factor 4 (9.9 %, representing 16.7% of the explained variance), and Factor 5 (9.5%, representing 16% of the explained variance). This relatively balanced distribution of variance suggests that all five factors contribute meaningfully to the overall construct being measured, with no single factor dominating the measurement.

Discussion of factor structure

The results of the EFA provide strong support for a five-dimensional conceptualization of GenAI Perceptions and Usage. The emergence of five distinct factors with minimal cross-loadings indicates that the instrument effectively distinguishes between different aspects of how engineering educators perceive and interact with GenAI technologies. Moreover, the alignment between the empirically derived factors and our theoretical framework enhances the construct validity of the measure.

Qualitative analysis of semi-structured interviews

In this section, we juxtapose the survey results with interviewee responses to highlight convergences and divergences in perspectives on the integration of GenAI in engineering education.

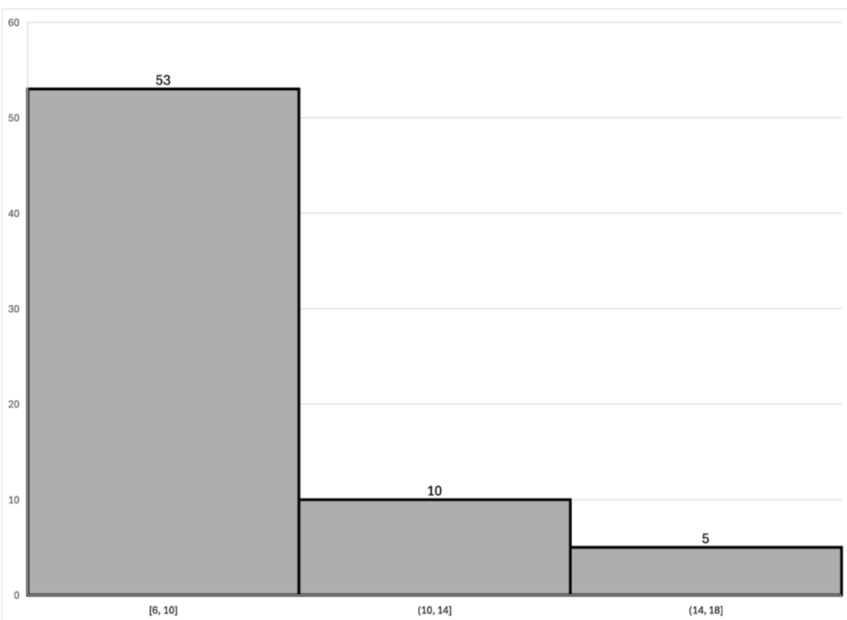

Figure 2. Ethical GenAI in Coursework

More than half of the survey respondents reported having no GenAI policies or guidelines and had not discussed ethical concerns related to GenAI use with their students (see Figure 2). A similar pattern emerged in the interviews, where faculty generally did not include an explicit GenAI policy in their syllabi and instead relied primarily on verbal explanations in the classroom to address its use in coursework.

Thomas, while acknowledging his reluctance for including a specific AI policy in his syllabus, emphasized that “What I've told the students at the start of semester was, you have to just use this appropriately. It's no different than if you ask your neighbor questions. If you just copy it, you're not going to learn”. He also added “I guess the only change has been that I've told them, ‘Ask it, ask it what it says’. The answer is use it to proof check your work, and then what that'll do is reinforce critical thinking. And so that's the only change. Before I would have said, ask your neighbors what they got. See if you all got the same thing. The premise here is AI is just a different neighbor. “

Ryan, who had not considered incorporating GenAI tools in his courses, expressed general support for using GenAI as a learning aid, such as for summarizing content, reviewing topics, or clarifying difficult concepts. However, he opposed relying on GenAI to fully solve problems, emphasizing that it should not replace the learning process. Michael believed that sharing his personal experiences with GenAI tools (specifically ChatGPT) was beneficial for students, as it allowed him to demonstrate misleading results and emphasize the importance of using such tools as aids rather than relying on them to complete assignments. Alex perceived GenAI tools as detrimental to foundational learning in technical domains like web programming. Consequently, they prohibited GenAI use in assignments during the first half of the semester to ensure students grasped fundamental concepts. In the latter half, they permitted and encouraged GenAI to enhance learning after students had established a solid understanding of the course material.

Many survey respondents and interviewed faculty did not establish formal GenAI policies in their courses and relied on verbal communication regarding its appropriate use. Some instructors viewed GenAI as a tool comparable to peer learning or as a helpful aid for tasks like proofreading and concept clarification, cautioning against its use for fully solving problems. Others highlighted the importance of demonstrating GenAI's potential inaccuracies or strategically limiting its early use in technical fields to ensure students first grasp fundamental concepts.

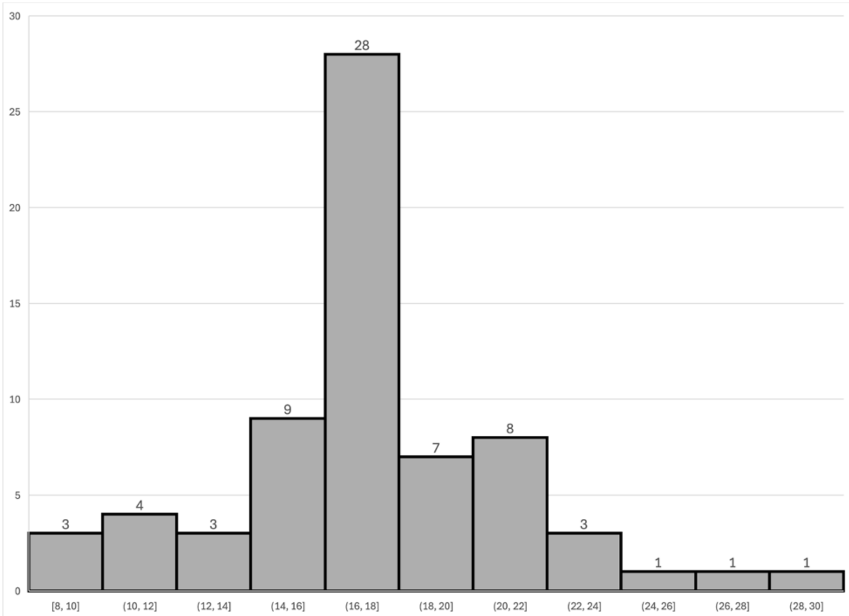

Figure 3. GenAI in Teaching

The largest proportion of survey respondents were at best aware of GenAI tools but did not use them to create instructional materials including quizzes, assignments, rubrics, presentations, etc. (see Figure 3). All interviewees except Ryan had used GenAI to some extent to design their assignments or quizzes; however, Ryan expressed his intention to incorporate GenAI into his class discussions next semester as part of a research project on GenAI use in teaching, “We're working to incorporate some discussion-based AI like in the course. It's not implemented yet, but [it is] something we're working on now”.

Michael stated that after participating in the survey he became interested in trying out ChatGPT for designing rubrics and animations, but he was not satisfied with the GenAI’s outcomes. However, he utilized ChatGPT to design simple quizzes, “I refer to ChatGPT to generate some questions. It is one of the resources. It's not the only one that I use, but it is good for simple questions”. Michael also described using ChatGPT to generate code for algorithms like Horsepool and Merge Sort, though these attempts often resulted in errors requiring correction. Michael also used ChatGPT-generated code to build benchmarks for comparing the performance of different algorithms, such as in string matching, by having it automatically create test data and measure execution times to visually demonstrate their efficiency to students.

Alex encouraged students in web programming to use GenAI tools after they had learned the fundamental concepts (HTML, CSS, etc.). Thomas took an innovative approach and designed a quiz to make students critique GenAI-generated output. He shared,

> I actually had 2 problems. And what I did was I gave them to ChatGPT and asked it to solve them. And then I gave the students the printouts of what ChatGPT said was the answer to each question, and I told them, correct it and fix it. Your test is to tell me what AI did wrong

Thomas incorporated GenAI to provide initial MATLAB code, acting as a catalyst to facilitate students' entry into programming.

The survey indicated that while most respondents were aware of GenAI tools, they rarely used them to develop instructional materials like quizzes, assignments, or rubrics. In contrast, interview participants reported experimenting with GenAI in various ways to support their teaching. These included generating quiz questions, creating coding benchmarks, encouraging student exploration after foundational learning, and designing activities that prompted critical evaluation of GenAI-generated content.

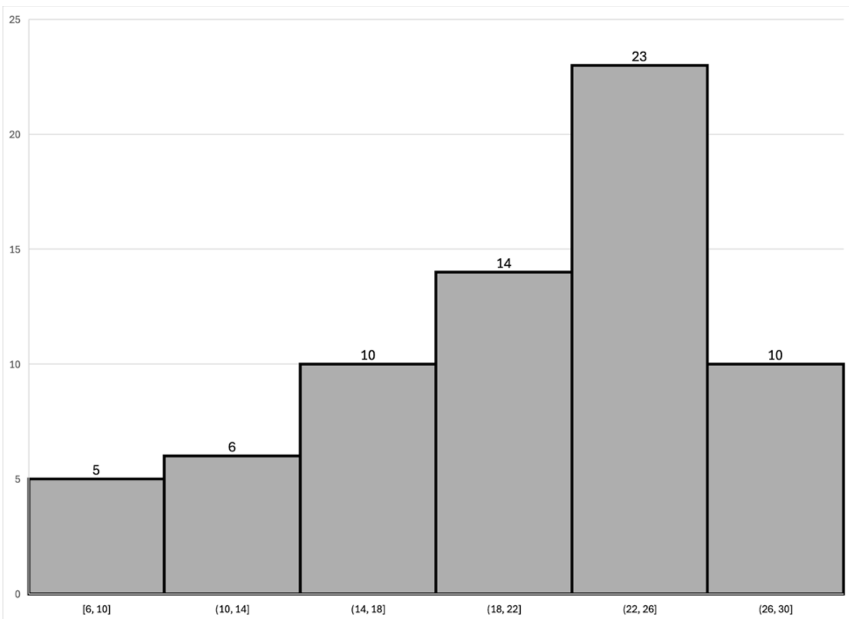

Figure 4. GenAI Concerns

Approximately 70% of survey respondents expressed concern about the use of GenAI, with levels of concern ranging from moderate to high (see Figure 4). All interviewees identified cheating as a major concern related to students' use of GenAI. They also expressed worry that the inappropriate or excessive use of GenAI could undermine student learning. Alex highlighted the challenge of striking a balance: allowing AI to streamline repetitive tasks and avoid unnecessary reinvention while preventing over-reliance that could hinder the grasp of fundamental concepts.

Thomas directly linked copying and pasting AI-generated work to a lack of ethics and equated it to stealing. "Kind of the same way. I would define the ethics that if you are copying and pasting, then you're stealing somebody else's work." He warned students about the ethical implications of not adhering to different faculty policies regarding AI use, suggesting it could hinder their learning outcomes. "I do tell them that not every faculty is going to have the same policy, and you do need to respond appropriately to what the faculty is intended for you. You might ruin your learning outcomes if you use it when you're not supposed to."

Apart from his concerns regarding academic dishonesty, Michael described removing an essay assignment because AI could easily generate it, indicating a concern that students would bypass the intended learning activity. He also shared his experience of explicitly telling students not to “solve the assignment based on ChatGPT”, highlighting a concern about students relying on AI instead of their own understanding.

Many survey respondents expressed concern about the use of GenAI, particularly in relation to academic integrity and its potential impact on student learning. Similar concerns were echoed in the interviews, where participants frequently cited cheating and the risk of students relying too heavily on AI instead of developing their own understanding. Both data sources revealed a shared apprehension about the ethical and learning outcome implications of GenAI use and the challenge of maintaining a balance between leveraging its benefits and preserving core learning objectives.

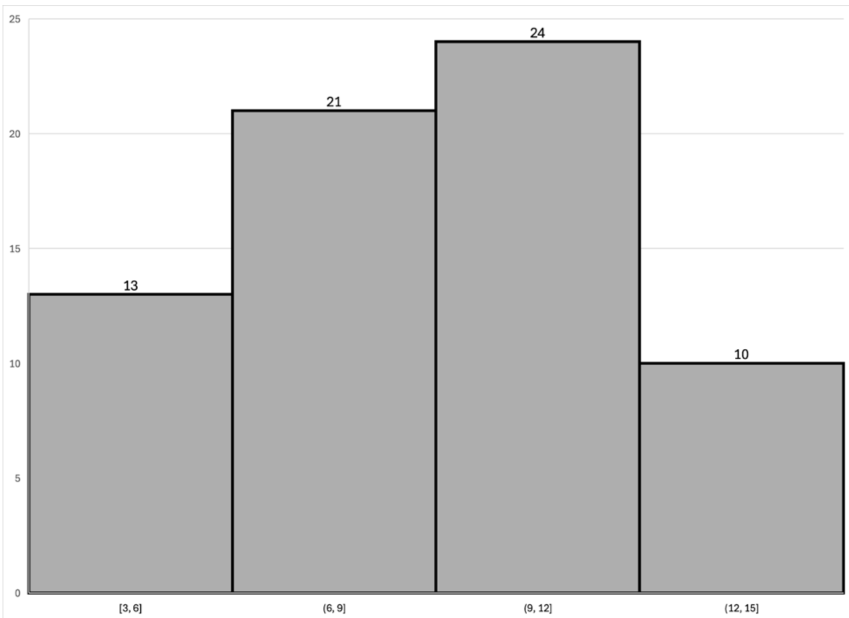

Figure 5. Future of GenAI in Engineering Education

Almost 35% of the respondents believed that GenAI needs to be an integral part of engineering education (see Figure 5). Thomas expected AI to “be around” and emphasized the need to teach students how to use it appropriately rather than trying to fight its emergence. “I expect this to be around. And how do we? Really, the focus went from trying to fight it a little bit to this is just another tool that's available to you. How do you use a tool appropriately.” While expressing his uncertainty about the future impact of GenAI on engineering education, Michael shared,

> Well, it's hard to say, I mean who knows how AI will grow in the next year or 2 years or 3 years. I mean they could grow very fast. And in terms of teaching, I don't know. I mean the teaching, the whole teaching approach of teaching the logic of the teaching could be transformed heavily by the AI. It will make your productivity multiplied.

Alex believed that “AI will eventually evolve. They will go very fast, and you cannot stop them. You cannot just prohibit students from using them. That won't work.” Ryan emphasized the importance of embracing AI in a way that prevents misuse, highlighting its growing significance in the future. To illustrate his point, he used an analogy: “AI will never replace a doctor, but a doctor who knows how to use AI will replace a doctor who doesn't use that yet.” He continued, “I don't think AI will ever replace teaching as a professor. But a professor who uses AI will replace just a typical professor”.

Some survey respondents and interviewees viewed GenAI as an important and inevitable part of engineering education. Rather than resisting its use, participants emphasized the need to guide students in using it responsibly and effectively. While there was some uncertainty about its future impact, there was broad agreement that GenAI is advancing quickly and will likely play a significant role in shaping teaching and learning practices.

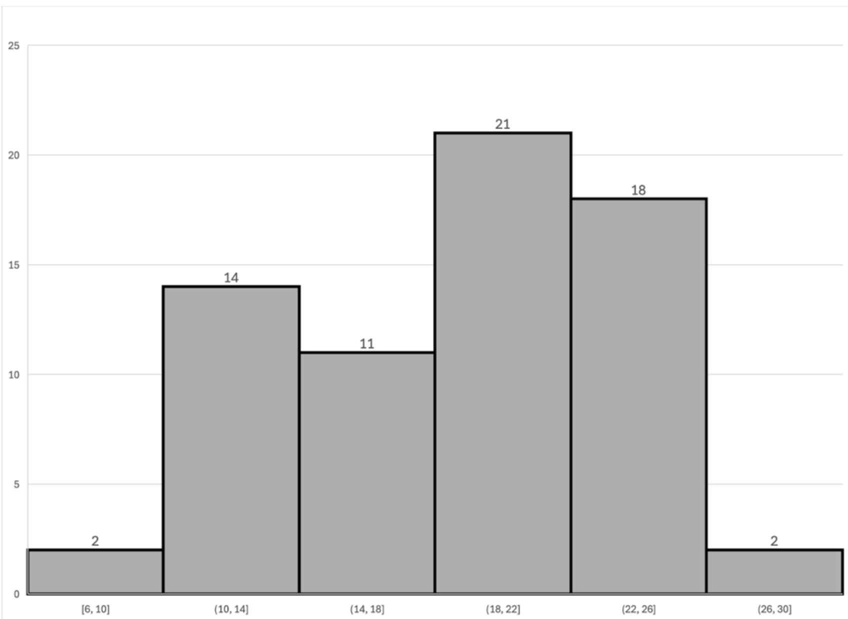

Figure 6. Student Awareness of GenAI

More than 50% of the survey respondents believed that their undergraduate students used GenAI tools in their daily activities and coursework (see Figure 6). Analysis of the participant interviews reinforced the survey findings regarding faculty perceptions of students' use of GenAI in their coursework. One of the interviewees elaborated on the sudden change in students’ writing quality as an indicator of their GenAI use:

> There were some individuals who wrote at a lower level than I would expect of a college student, because they're just writing like it's a journal, since it's a reflection. They are not writing at a deep, high level. And then suddenly, this one person is writing as if they've been writing research papers on transport topics for 20 years. Like. it was obvious you were using AI to do this. I know that you did not write this yourself.

The other interviewee, who had not fully explored GenAI tools in his course, based his beliefs on a workshop in which the instructor showed them how GenAI tools were able to solve Static problems and concluded, “I literally pick up a static problem and show how different AIs can solve that problem. I'm sure students might have utilized solving those problems with those [GenAI tools].” Similar ideas were shared by the other two interviewees who embraced the purposeful use of GenAI tools by their students and encouraged them to explore the affordances of these tools for their learning.

More than half of the survey respondents believed their undergraduate students were using GenAI tools regularly in their coursework. Interview data supported this perception, with one faculty member citing a sudden and uncharacteristic improvement in a student's writing as clear evidence of GenAI use. Other interviewees, while varying in their familiarity with GenAI, acknowledged its presence in students' academic work and, in some cases, encouraged its purposeful use for learning.

Discussion

The findings from the survey instrument supported by individual semi-structured interviews provided valuable insights into engineering faculty's perceptions, attitudes, and practices regarding GenAI in their educational contexts. The relatively balanced distribution of faculty engagement with GenAI from complete unawareness (2.98%) to regular usage (20.89%) suggests that engineering education is currently in a transitional phase regarding GenAI adoption. This distribution pattern aligns with Roger's [35] diffusion of innovation theory. According to [35], there is a distribution of early adopters, the early majority, late majority, and laggards. Our findings show that all groups are represented within the faculty population. The limited participation in formal professional development (More than 50% of respondents reporting no training attendance) indicates a motivational gap leading to a knowledge gap that may put students at a disadvantage as they exit into workplaces that may require the use of GenAI.

The five-factor structure that emerged from our analysis contributes to the theoretical understanding of technology adoption in educational contexts by highlighting the multidimensional nature of faculty engagement with GenAI. This structure extends beyond the traditional binary acceptance-rejection paradigm to encompass ethical considerations, pedagogical applications, concerns, future perspectives, and perceptions of student usage. By offering a more nuanced framework, it may better capture the complexity of faculty decision-making regarding emerging technologies in educational settings.

The survey results showed a discrepancy between awareness and implementation of GenAI in pedagogical contexts. Faculty reported awareness of multiple pedagogical applications of GenAI, but only 37.5% had experimented with at least one application, and only a few (10.7%) reported regular usage. The same trend was evident in individual interviews where faculty stated they use GenAI tools mostly on a regular basis for their academic and personal needs but have not effectively incorporated them into their teaching. This gap may be indicative of the adoption curve and the needs for agents of change that will help individual faculty overcome potential barriers to adoption that may include lack of knowledge of effective implementation strategies, concerns about academic integrity, and concerns about access. The findings regarding classroom and institutional policies reveal a preference for contextual, assignment-specific guidance rather than comprehensive syllabus-based policies. This approach may reflect the rapidly evolving nature of GenAI technologies and the difficulty in establishing universal guidelines for diverse engineering coursework. The neutral mean score on institutional guideline awareness is most likely the absence of formalized policies at the institutions, creating potential inconsistencies in how GenAI is addressed across different courses and departments.

The levels of concern about the use of GenAI were expected since the research has shown generalized concerns about its use [36]. Interviewees were highly aware of the concerns for learning and emphasized the need to focus on critical thinking skills [37]. Faculty expressed lesser concerns about privacy and environmental impacts, suggesting a more nuanced understanding of the multifaceted implications of GenAI beyond immediate educational outcomes.

The ambiguous stance toward GenAI integration into engineering curricula reflects an ongoing tension between traditional pedagogical approaches and technological innovation occurring in professional workplaces. Faculty neither strongly opposed nor enthusiastically endorsed mandatory GenAI integration; rather, their assignment-by-assignment approach suggests a preference for contextual, purpose-driven implementation rather than wholesale adoption. This finding resonates with previous [22] observation that instructors emphasized leveraging GenAI as a supplementary learning tool while expressing concerns about potential over-reliance. The same trend was evident in the individual interviews.

The findings from the interview phase of this study were useful in unpacking the concerns revealed in the survey results. Participants highlighted the ongoing challenges and opportunities in integrating GenAI tools into engineering education. While engineering instructors were significantly aware of GenAI tools and their potential to enhance teaching, the integration remains largely informal and underdeveloped at the institutional level. This lack of formal policies regarding GenAI use in the classroom reflected a gap in institutional preparedness, which aligned with previous research by [18] and [19] that emphasized the need for clear guidelines and structured professional development for educators. While the instructors recognized the benefits of GenAI, their approach to monitoring student use and implementing policies was still evolving. This lack of formalized strategies and institutional policy may be hindering the effective and responsible adoption of GenAI tools in engineering education, potentially leading to over-reliance by students or ethical concerns surrounding the technology's use.

Our findings also suggest that the UTAUT model [17] may require adaptation to fully account for the unique characteristics of GenAI tools, particularly regarding their "blackboxed" nature and the complex interplay between human cognitive biases and algorithm aversion. The concerns expressed by faculty in our study align with [17] identified challenges, reinforcing the need for context-sensitive approaches to technology adoption that account for the specific complexities of engineering education environments.

The pedagogical use identified in this study suggests that some educators are experimenting with GenAI integration. There seems to be a cautious approach to this innovation mixed with lack of knowledge and even the motivation to engage. Instructors have started modifying their assessment strategies, increasing the cognitive complexity of exam questions and enhancing proctoring protocols to address the challenges posed by GenAI. However, the integration of GenAI into teaching practices is still in a transitional phase, with a clear need for structured support and guidance. This result mirrors concerns raised by [22] and [23] about the potential risks of GenAI, such as the generation of misleading information and students bypassing meaningful learning. To move forward, it is crucial for institutions to provide more targeted professional development opportunities and to establish clear, evidence-based policies that will enable instructors to integrate GenAI effectively while addressing the ethical and pedagogical challenges it presents.

Conclusion

This study investigated engineering faculty's perceptions, attitudes, and practices regarding Generative Artificial Intelligence (GenAI) in educational contexts, revealing a complex, multidimensional landscape of adoption and integration. Through factor analysis, we identified five distinct dimensions that characterize faculty engagement with GenAI: Ethical GenAI in Coursework, GenAI in Teaching, GenAI Concerns, Future of GenAI in Engineering Education, and Student Awareness of GenAI. This multifaceted framework extends our theoretical understanding beyond simplistic adoption-resistance models, capturing the nuanced decision-making processes faculty employ when navigating emerging educational technologies.

Our findings demonstrate that engineering education is currently in a transitional phase regarding GenAI adoption, with faculty distributed across Rogers' innovation adoption spectrum. The significant proportion of faculty reporting no formal professional development in GenAI (more than 50%) indicates a critical knowledge gap that institutions must address to prepare engineering students for increasingly AI-integrated professional environments. The discrepancy between awareness and implementation, with only 37.5% of faculty experimenting with GenAI applications and merely 10.7% reporting regular usage, further underscores the need for targeted support mechanisms that facilitate meaningful technological integration.

From a policy perspective, the findings indicate a clear preference among faculty for contextual, assignment-specific guidance rather than comprehensive policy frameworks. This preference, coupled with the generally neutral institutional stance toward GenAI integration, suggests that effective implementation strategies should prioritize flexibility and purpose-driven application rather than mandated adoption. The current policy vacuum at the institutional level represents both a challenge and an opportunity for developing evidence-based guidelines that address the ethical and pedagogical concerns identified in this study.

As engineering education continues to navigate the opportunities and challenges presented by GenAI, this research provides a foundation for developing context-sensitive, evidence-based strategies that prepare both faculty and students for an increasingly AI-integrated professional landscape. By addressing the identified knowledge gaps, supporting purpose-driven implementation, and developing flexible policy frameworks, institutions can facilitate responsible and effective GenAI integration that enhances rather than undermines the core educational mission of engineering programs.

Implications and limitations

The findings of this study have preliminary implications for the integration of GenAI tools in engineering education. They highlight the need for more research as the engineering profession and the technology itself advances. Institutions should support judicious GenAI use to ensure learning and experimentation in classroom practices within specific domains. Further, the study shows that providing professional development opportunities for engineering faculty is not enough and that to effectively integrate GenAI into their teaching methods while addressing potential risks colleges must find ways to motivate faculty to experiment with GenAI use. The results show that engineering educators must be asked to confront the potential use of GenAI by students by becoming more familiar with the potential of the technology. Finally, this study advocates for the establishment of institutional support structures to guide the responsible and effective adoption of GenAI tools, ensuring they are used to enhance, rather than hinder, student learning outcomes.

The study was conducted in one Midwestern university. This makes the sample potentially biased by the specific campus circumstances. First, university policy did not constrain or encourage GenAI use, instead it made recommendations leaving much of the choice (and effort) to the individual faculty member. Second, the university and the college offered multiple learning opportunities. The constraints of one location do not allow us to examine the impact of policy and resource availability on adoption of GenAI tools. In future work, we will add additional institutions and examine change in attitude across institutions with policy and resource differences as well as longitudinal changes as GenAI policies and practices become commonplace in engineering work environments.

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Appendix A. Descriptive Statistics for Scale Items

Item	Min	Max	Median	Mean	SD	Item-Total Correlation
Item_1	1	5	3	3.380	1.124	.62
Item_3	1	4	2	2.392	1.018	-.50
Item_4	1	4	2	2.013	0.759	.74
Item_5	1	4	2	2.000	0.734	.84
Item_6	1	4	2	2.063	0.740	.83
Item_7	1	4	2	2.076	0.712	.66
Item_8	1	4	2	1.709	0.623	.58
Item_9	1	4	2	2.089	0.720	.80
Item_10	1	5	2	2.081	1.156	.67
Item_11	1	5	2	2.568	1.124	.84
Item_12	1	5	3	2.959	1.091	.72
Item_13	1	5	3	2.905	1.100	.61
Item_14	1	5	3	2.901	1.209	.58
Item_15	1	5	3	2.873	1.275	.61
Item_23	1	5	3	2.757	1.313	.66
Item_24	1	5	2	2.586	1.280	.80
Item_25	1	5	2	2.229	1.206	.74
Item_26	1	5	1	1.800	1.098	.58
Item_27	1	5	3	2.857	1.254	.70
Item_28	1	5	3	3.029	1.296	.69
Item_29	1	3	3	2.614	0.644	.75
Item_30	1	3	3	2.657	0.657	.9
Item_31	1	3	3	2.371	0.745	.71
Item_32	1	3	3	2.300	0.823	.75
Item_33	1	3	3	2.643	0.682	.91
Item_34	1	3	3	2.771	0.569	.77
Item_35	1	5	3	3.304	1.180	.88
Item_37	1	5	3	2.797	1.267	.87
Item_38	1	5	2	2.565	1.194	.75