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Examining Faculty and Student Perceptions of Generative AI in University Courses

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Abstract
As generative artificial intelligence (GenAI) tools such as ChatGPT become more capable and accessible, their use in educational settings is likely to grow. However, the academic community lacks a comprehensive understanding of the perceptions and attitudes of students and instructors toward these new tools. In the Fall 2023 semester, we surveyed 982 students and 76 faculty at a large public university in the United States, focusing on topics such as perceived ease of use, ethical concerns, the impact of GenAI on learning, and differences in responses by role, gender, and discipline. We found that students and faculty did not differ significantly in their attitudes toward GenAI in higher education, except regarding ease of use, hedonic motivation, habit, and interest in exploring new technologies. Students and instructors also used GenAI for coursework or teaching at similar rates, although regular use of these tools was still low across both groups. Among students, we found significant differences in attitudes between males in STEM majors and females in non-STEM majors. These findings underscore the importance of considering demographic and disciplinary diversity when developing policies and practices for integrating GenAI in educational contexts, as GenAI may influence learning outcomes differently across various groups of students. This study contributes to the broader understanding of how GenAI can be leveraged in higher education while highlighting potential areas of inequality that need to be addressed as these tools become more widely used.

Keywords ChatGPT · Generative AI · Higher Education · Perception · Technology Acceptance

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Introduction

Technology in Education

Integrating technology into higher education has historically been marked by both innovation and disagreement (Waits & Demana, 2000; Foer, 2012). As new technologies emerge and become incorporated into educational practice, they often lead to shifts in pedagogical approaches and a resulting re-evaluation of traditional teaching and learning. While these transitions can lead to improvements in educational practices, they are not without challenges. Often, the introduction of new technological tools has sparked adversarial interactions between students and educators during the critical phase of adoption and adaptation in educational communities. The incorporation of new technologies into education has been met with resistance. An illustrative example can be found in the reaction of the ancient Greek philosopher Socrates to written text; he feared that the written word would undermine the foundational educational practice of memorization, which he deemed essential for true learning (Foer, 2012).

The incorporation of calculators into the educational framework for math and science courses further demonstrates the pattern of resistance followed by integration. The use of calculating tools, from simple slide rules to advanced graphing calculators, was initially viewed as a form of cheating in schools (Waits & Demana, 2000). However, educators' perceptions of calculators transformed as the tool's effectiveness in enhancing the learning process was recognized. Within just six years, the percentage of high school students in the United States having access to calculators in the classroom increased from 26% in 1986 to 92% in 1992 (Waits & Demana, 2000), reflecting the rapid acceptance of calculators as educational tools. The development of the internet introduced further complexities into education, initially prompting concerns about academic integrity due to the ease of plagiarism. This challenge led to the development of plagiarism-detection software, a step toward using the internet's potential for educational purposes (Warn, 2006). Over time, educators began to explore the social and creative capabilities of the internet, incorporating these features into pedagogical practices (Grosseck, 2009). Educators' perspective on the use of social media in education, for example, has evolved from a problematic distraction to a valued component of the educational experience (Cooke, 2017). Now, web-based course-management software and online courses (Dumford & Miller, 2018) are ubiquitous in higher education.

These examples – from books to calculators to the internet – demonstrate the recurring pattern of initial resistance followed by acceptance of novel technologies in educational settings. Each technological advancement, originally contentious, has been assimilated into educational practices and has become a crucial tool for teaching and learning.

Generative AI in Education

This historical perspective provides a valuable context for understanding the current attitudes toward the use of generative AI in higher education. The advent of generative AI, particularly following the launch of ChatGPT in 2022, has generated substantial interest and concern within the educational community. Generative AI refers to a class of artificial intelligence that is good at generating content in various formats—text, images, code, and more—in response to user prompts (Dwivedi et al., 2023). ChatGPT, for instance, can produce human-like text, solve problems, summarize content, and even assist in coding tasks. These capabilities have opened new possibilities for enhancing education but have also prompted significant debate about their appropriate use in academic settings.

Generative AI is unique compared to earlier technological tools in education because of its versatility and accessibility. Unlike calculators, which were introduced primarily as aids in mathematics and science, or the internet, which revolutionized access to information, generative AI has the potential to impact a broad range of academic activities. It can assist students in drafting essays, developing research ideas, improving writing fluency, debugging code, and offering personalized learning experiences by providing instant feedback and guidance. This potential makes generative AI a powerful tool for fostering student autonomy, creativity, and engagement in learning (Farrelly & Baker, 2023).

However, with this potential comes considerable challenges. One of the most pressing concerns in the integration of generative AI into education is its impact on assessment and academic integrity. AI-generated content raises questions about the fairness and validity of traditional assessments, which often rely on students' ability to produce original work. As generative AI tools become more capable of completing tasks such as writing essays, developing code, solving equations, or generating creative work, educators are faced with the dilemma of how to differentiate between a student's authentic learning and AI-generated assistance. This has led to concerns about the potential for AI tools to result in academic dishonesty, particularly in environments that rely heavily on written assessments or problem-solving tasks that can be completed by AI (Smolansky et al., 2023).

Beyond concerns about cheating, generative AI also poses challenges related to the learning process itself. There is apprehension that students may become overly reliant on AI tools, thereby undermining the development of critical-thinking skills, problem-solving skills, and creative skills that are central to higher education (Michel-Villarreal et al., 2023). For example, while generative AI can help students quickly produce a written response or code solution, there is a risk that students may bypass the deeper cognitive processes involved in learning and instead rely on the generative AI to perform tasks that they should be mastering themselves. This raises questions about the long-term educational outcomes of integrating such powerful tools into the learning environment. In addition, recent studies highlight that while generative AI can assist with tasks such as content creation and feedback, human teachers possess irreplaceable qualities like critical thinking, emotional intelligence, and the ability to foster social-emotional competencies in students (Chan & Tsi, 2024).

In response to these challenges, universities are beginning to establish guidelines and policies that regulate the use of generative AI in academic contexts. Some institutions have embraced generative AI tools as valuable educational resources, encouraging their use in teaching and learning while providing training on how to use generative AI ethically and responsibly (Chan, 2023). These institutions recognize that generative AI can be a beneficial supplement to traditional educational practices, particularly in providing personalized support to students and enhancing their learning experiences. For example, international students who face language barriers may use generative AI tools to improve their comprehension and communication skills, thereby leveling the playing field in multilingual classrooms (Farrelly & Baker, 2023).

Conversely, some universities have taken a more restrictive approach, viewing generative AI as a potential threat to academic integrity and the core values of education. In these cases, policies have been implemented that limit or even ban the use of generative AI in certain types of assessments or coursework. This reflects an ongoing debate within higher education about the proper role of generative AI in learning, teaching, and evaluation.

Recent developments have further complicated the landscape. For instance, as generative AI continues to evolve, it is increasingly being integrated into widely used educational software, such as learning management systems (LMS) and online course platforms. Generative AI-powered tools are now capable of automating aspects of teaching, such as grading, generating feedback, and even creating lesson plans (Moorhouse et al., 2023). This has led to discussions about the role of educators in the age of generative AI, where tasks traditionally performed by human instructors could potentially be automated by AI systems. While this has the potential to reduce workload and improve efficiency, it also raises ethical concerns about the dehumanization of education and the diminishing role of instructors in fostering deep, meaningful learning experiences (Chan & Tsi, 2024).

Moreover, the use of generative AI is not limited to formal academic contexts. Students are increasingly experimenting with generative AI tools outside of the classroom, using them to explore topics of interest, create personal projects, or prepare for future careers. This highlights the dual nature of generative AI in education: while it presents challenges within the traditional structures of teaching and assessment, it also offers opportunities for innovation and creativity in self-directed learning. Universities will need to account for these informal uses of generative AI when developing policies and guidelines, as students' experiences with generative AI outside of the classroom will inevitably shape their expectations and behaviors within it.

In sum, generative AI represents both a frontier of educational innovation and a significant challenge to existing pedagogical frameworks. As institutions of higher education grapple with how to best incorporate generative AI tools into their curricula, they must balance the potential benefits of enhanced learning, efficiency, and personalization with the need to maintain academic integrity and foster critical thinking and creativity. The current state of generative AI in education is thus one of rapid development, marked by both enthusiasm for its possibilities and concern over its implications. However, relatively little empirical work has explored the landscape of students' and educators' attitudes toward generative AI in education.

The Current Study

Previous studies have emphasized the need for a more comprehensive exploration of the attitudes and perceptions of students and faculty regarding the integration of generative AI into higher education. For instance, a study by Hmoud et al. (2024) focused on a small cohort of students and explored the relationship between student motivation and ChatGPT use, finding that generative AI use enhanced motivation. Smolansky et al. (2023) expanded the scope of their study to include both students and faculty in an exploration of AI's perceived effects on assessment practices; both groups were interested in including AI in assessment, but they were apprehensive about how ChatGPT could negatively affect creativity and academic integrity. Although faculty generally acknowledge the potential of AI tools in educational contexts, their willingness to integrate them into coursework often depends on their level of understanding and confidence with the technology (Harper, 2024).

Most crucially, there is a need for investigation into how these attitudes differ across disciplines and demographic groups. In response to this need, our study aims to fill this gap by investigating the attitudes and behaviors of students and faculty toward generative AI in higher education. Our survey examined key topics such as perceived ease of use, ethical concerns, the impact of generative AI on learning, and intentions to use generative AI tools in coursework or teaching. Additionally, this study focused on differences by role (student vs. faculty), gender, and discipline (STEM vs. non-STEM). By exploring these differences, this study offers new insights into how generative AI is being integrated into higher education and highlights potential areas of disparity that require further attention.

The significance of this study lies in its potential to inform university administrators, policymakers, and educators as they develop policies and guidelines for the use of generative AI in educational settings. As generative AI becomes increasingly prevalent, it is crucial to ensure that its adoption does not exacerbate existing inequalities in education. For example, some student populations may face greater challenges or ethical dilemmas when using generative AI tools, which could affect their learning outcomes. Understanding these nuances will help universities develop more inclusive policies that address the diverse needs of their student body while promoting the responsible use of generative AI. Furthermore, this study contributes to the broader field of educational technology by identifying the conditions under which generative AI can enhance learning and by drawing attention to the ethical considerations that must be navigated to ensure its beneficial integration into the classroom. Our research questions are designed to explore:

- How do students and faculty differ in their attitudes toward the use of generative AI (e.g., ease of use, ethical concerns, intention to use, and impacts of AI) in coursework and teaching?
- What roles do gender and academic discipline (STEM vs. non-STEM) play in shaping attitudes and behaviors related to generative AI in educational settings?
- How do perceptions of generative AI's impact on learning vary across different student populations, particularly with respect to academic performance and ethical considerations?

This study makes three key contributions to the emerging research on generative AI in higher education. First, it offers a novel investigation into how demographic and disciplinary differences shape attitudes and behaviors toward generative AI tools, focusing on gender and STEM versus non-STEM fields. This approach provides unique insights that have not been explored in prior research. Second, the study examines both student and faculty perspectives, enabling a comprehensive understanding of how generative AI is perceived across roles in higher education. Finally, the findings inform the development of inclusive policies and educational practices that address the diverse needs of university communities as they navigate the integration of generative AI into teaching and learning.

Conceptual Framework

To aid our understanding of the attitudes toward generative AI and its use in higher education, this study is framed in the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh and colleagues (2012, 2016). The UTAUT model provides a robust theoretical foundation for exploring the factors affecting technology use. The model identifies seven factors that explain an individual's intention to use technology: **Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value**, and **Habit**. These factors have been widely applied in numerous studies examining the acceptance of various technologies in educational settings, providing empirical support for their relevance and utility.

Applications of UTAUT in Educational Contexts

The UTAUT model has been validated in several empirical studies focused on educational technology adoption. For instance, Strzelecki (2023) used the UTAUT model to examine students' acceptance of ChatGPT in higher education. Strzelecki (2023) demonstrated that **Performance Expectancy** (i.e., students' belief that ChatGPT would improve their productivity and academic performance) was a strong predictor of intention to use the tool. Khlaif et al. (2024) found that performance expectancy and other factors also affected educators' behavioral intentions to integrate generative AI into their teaching practices. Similarly, **Effort Expectancy** (the perceived ease of use) significantly influenced students' willingness to integrate ChatGPT into their learning practices, which was consistent with the model's predictions.

Another study by Abbad (2021) applied the UTAUT model to explore student use of e-learning systems in higher education. Their research found that **Facilitating Conditions**—such as access to resources, training, and institutional support—played a crucial role in shaping students' patterns of technology usage. This aligns with the UTAUT framework's emphasis on the importance of environmental factors in facilitating technology use.

In the context of mobile learning, Alyoussef (2021) employed the UTAUT model to assess student engagement with mobile learning technologies. They found that

Social Influence—the effect of peers and instructors encouraging the use of technology—was an important factor influencing students' use of mobile learning. This illustrates how the UTAUT model can capture the social dynamics involved in technology acceptance in educational environments.

The **Hedonic Motivation** factor has also been shown to play a significant role in technology adoption in education. For example, a study by Nikolopoulou et al. (2021) explored the use of mobile internet in education through tablets and phones. Their research indicated that students' enjoyment and satisfaction with these technologies (i.e., Hedonic Motivation) positively influenced their sustained engagement and use. This empirical evidence suggests that motivation derived from the entertainment and enjoyment of technology can be a powerful driver of acceptance in educational settings.

These studies collectively demonstrate the applicability of the UTAUT model to educational technologies, highlighting its relevance in contexts like the present study on generative AI. The consistent finding across studies is that UTAUT factors strongly explain individuals' technology acceptance. These insights provide validation for the use of UTAUT in examining attitudes toward generative AI in higher education.

Adaptation of UTAUT for Generative AI

This study adopts a modified version of the UTAUT, developed by Strzelecki (2023, 2024) and Strzelecki et al. (2024). Strzelecki's modification replaces the **Price Value** factor with **Personal Innovativeness**, based on Agarwal and Prasad's (1998) conceptualization of an individual's willingness to adopt and experiment with new technologies. This modification is particularly relevant to the study of generative AI, as many AI tools are free to use or carry minimal costs (e.g., ChatGPT's premium subscription is around $20 per month), making Price Value less pertinent in predicting technology adoption in this context. Instead, Personal Innovativeness captures the propensity of individuals to be early adopters of new technologies.

Relevance of UTAUT Factors in This Study

In applying the UTAUT model to this study, we focus on six key factors: Performance Expectancy, Effort Expectancy, Social Influence, Habit, Hedonic Motivation, and Personal Innovativeness. These factors have been shown to influence technology acceptance in educational settings and are likely to shape attitudes toward generative AI in higher education. By examining these factors, this study seeks to provide a comprehensive understanding of the drivers behind the adoption of generative AI among students and faculty. Moreover, the inclusion of Personal Innovativeness offers insights into how early adopters of technology may drive the integration of generative AI into academic work. Understanding the interplay of these factors is crucial as universities develop policies to encourage the responsible use of generative AI while also fostering innovation and enhancing educational outcomes.

Although UTAUT provides a solid framework for understanding technology acceptance and use, the specific context of generative AI in higher education involves additional complexities (Fig. 1). Education is not simply a straightforward progression toward degree completion, and educational technologies must also support learning competencies (e.g., critical thinking, problem solving, and teamwork) and learning-related attitudinal constructs (e.g., self-efficacy, intrinsic motivation, engagement, and test anxiety). Therefore, this study also considers the perceived benefits of generative AI to learning and academic performance, areas only partially addressed by the Performance Expectancy factor. These factors were adopted from the survey instrument developed by Amani et al. (2023) and White et al. (2024).

Furthermore, the emerging nature of generative AI as an educational tool brings ethical issues to the forefront of discussions (e.g., Kim et al., 2024a, 2024b). The moral acceptability of using generative AI in coursework and how such usage aligns with university policies could influence student and faculty behavioral intentions. These considerations include both individual ethical views and university guidelines dictating permissible use in educational settings, which will be investigated by survey instruments that were adopted and modified from those developed by Amani et al. (2023) and White et al. (2024). The integration of generative AI tools into higher education requires a nuanced analysis of student and faculty views on this complex issue. By using a modified UTAUT framework and including additional factors related to learning and ethics, this study aims to provide a comprehensive understanding of how students and faculty perceive the potential role of generative AI in higher education, providing valuable insights into stakeholder views as generative AI in education moves from initial resistance to, potentially, acceptance and integration. Figure 1 illustrates the conceptual framework of our study.

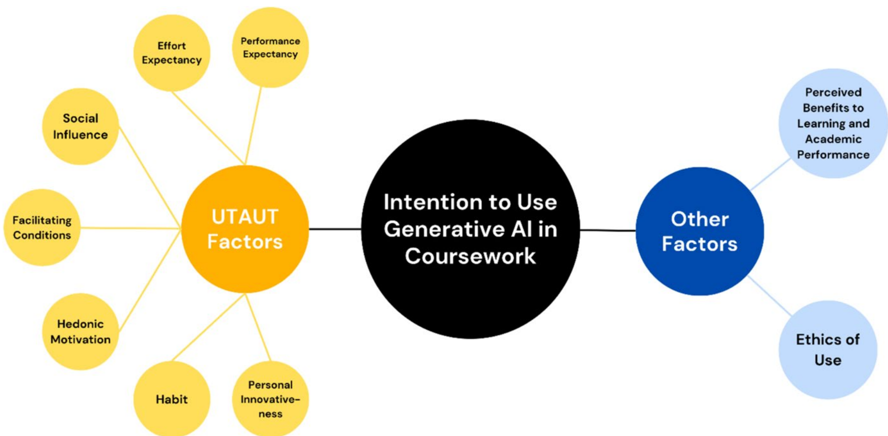

Fig. 1 Conceptual framework, combining Unified Theory of Acceptance and Use of Technology (UTAUT) with additional factors that may affect respondents' intention to use generative AI in university coursework

Methodology

Study Population

This study was conducted within a large land-grant institution in the southeastern United States; the university offers a diverse array of academic programs from broad disciplines, including both STEM (Science, Technology, Engineering, and Math) and non-STEM degree programs. The population for this study was selected from individuals who were actively engaged (e.g., enrolled in or taught at least one regular class, excluding colloquium, field study, and internship courses) in the university's academic environment during the 2023 fall semester. This timeframe was chosen to ensure the relevance and timeliness of the data, given the rapidly evolving landscape of AI use since the launch of ChatGPT in November 2022. The study population was composed of two groups: students and faculty. By examining both student and faculty perspectives, we aim to provide a comprehensive overview of the perceptions of generative AI use in higher education. Student participants were enrolled in at least one regular course at the university during fall 2023 to ensure that the participants had recent experience with the institution's educational offerings and potentially with generative AI tools as part of their experience. Similarly, the faculty participants taught at least one course at the university during fall 2023. This group included professors and lecturers from all colleges at the university.

Survey Instrument and Data Collection

The survey instrument used in this study was developed based on existing studies (e.g., Amani et al., 2023; Strzelecki, 2023, 2024; Strzelecki et al., 2024; White et al., 2024) that investigated individuals' perceptions of the use of generative AI tools in learning environments. We first adopted the model proposed by Strzelecki (2023, 2024), which identifies seven factors to explain behavioral intention and use of a generative AI tool. Strzelecki's (2023) model is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) theoretical framework, and the survey was designed to explore the attitudes toward generative AI use in higher education. The survey used Likert-scale categories for responses, allowing participants to express their level of agreement or disagreement with statements related to predictors identified by Strzelecki (2023) and Strzelecki et al. (2024). The specific survey items are listed in the Appendix of this article for reference. Furthermore, we adopted a survey instrument developed by Amani et al. (2023) that was used to examine university students' and instructors' perceptions of generative AI tools, particularly focusing on individuals' perceived impacts of generative AI on the overall learning environments and eight specific learning goals: critical thinking, problem-solving, teamwork, self-efficacy, test anxiety, academic performance, intrinsic motivation, and student engagement (Amani et al., 2023; White et al., 2024). Although the survey includes questions regarding how students and faculty utilize generative AI tools for individual classes, a course-level analysis was outside the research scope of this manuscript.

Data were collected through an anonymous online survey that was distributed to faculty and students at the university through multiple outlets, such as the university's online learning platform pop-up message, the research team's personal e-mail list, and flyers. Survey participation was voluntary, and approval for the study was granted by the researchers' Institutional Review Board (IRB). To encourage participation, the study included an incentive in the form of a drawing for a gift card. The survey was disseminated between December 2023 and January 2024. This timeframe was purposefully selected because it was near the end of the fall 2023 semester so that participants would be most able to recall how they utilized generative AI tools for their learning and teaching. A total of 982 student responses and 76 faculty responses met the study's criteria after excluding responses that did not pass the qualifying questions (Table 1).

Analyses

Data Pre-processing

We categorized the majors of student respondents as either STEM (e.g., Biological Sciences, Physical Sciences, Engineering, Math and Statistics, and Computer Science) or non-STEM based on each student's listed major. This categorization is important for understanding the disciplinary context of attitudes toward generative AI. Preliminary analysis revealed significant differences in the gender ratio between STEM and non-STEM majors, which could potentially bias the outcomes. To address this, we conducted an analysis that accounted for differences across all four gender-STEM groups. This approach allowed for a more comprehensive and equitable examination of the data that better reflected the diversity of the student population.

Following the methodology of Strzelecki (2023), we conducted the confirmatory factor analysis (CFA) and calculated factor scores for seven constructs: Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Personal Innovativeness, and Behavioral Intention, while Facilitating Conditions factor was excluded from the final results due to relatively weak

Table 1 Demographic characteristics of the survey participants

		Student ($n=982$)	Faculty ($n=76$)
Gender	Female	48%	51%
Race/Ethnicity	Non-Hispanic White	51%	68%
Teaching Experience	Longer than 10 years	-	57%
Academic Level	Undergraduate	72%	-
Major	STEM	50%	-

STEM majors include Biological Sciences, Physical Sciences, Engineering, Math and Statistics, and Computer Science performance, as indicated by its low Cronbach's alpha and inadequate CFA results. These factors were derived from survey items designed to measure the theoretical constructs in the UTAUT framework, and the specific survey items associated with each factor construct are listed in the Appendix. Calculating these scores allowed for a structured analysis of the attitudes toward generative AI.

Statistical Analyses

A confirmatory factor analysis (CFA) was employed to obtain the factor score of the seven constructs. Cronbach's alpha scores of the seven constructs were obtained to check the internal validity, and CFI, TLI, and RMSEA were obtained to investigate the CFA model fitness (Tables 5 and 6 in Appendix). Welch's two-sample t-tests were used to compare factor scores between students and faculty for the seven attitudinal constructs. ANOVA and Tukey's HSD post-hoc tests were used to compare attitudinal factor scores among the four student groups regarding gender (i.e., females vs. males) and majors (i.e., STEM vs. Non-STEM). This approach allowed us to identify significant differences across groups within the student population. Lastly, the Wilcoxon rank sum test allowed us to compare Likert-scale items between students and faculty. Since the data did not follow a normal distribution, this non-parametric test was useful in providing insights into survey questions on student competencies, overall learning, ethics, and frequency of AI use. Eight hundred fifty observations were used for the student subgroup analysis because of missing values regarding gender. For analysis regarding views on learning, student competencies, and the use of generative AI tools, five observations from the faculty sample were excluded because of missing values. All analyses were conducted using R Statistical Software (R Core Team, 2021). Specifically, we used the *likert* package (Bryer & Speerschneider, 2016), *lavaan* package (Rosseel, 2012), *ltm* package (Rizopoulos, 2006), and *psych* package (Revelle, 2023) to facilitate our analyses.

Several limitations should be acknowledged regarding the statistical analyses. First, the faculty sample size ($n = 76$) is relatively small compared to the student sample ($n = 982$), which may introduce a potential imbalance in the data and limit the robustness of comparisons between these groups. To mitigate this, we employed statistical techniques such as Welch's t-tests and non-parametric tests to account for differences in sample sizes, ensuring more reliable comparisons. However, the smaller faculty sample may still affect the generalizability of the findings related to instructor attitudes toward generative AI. Second, the study was conducted at a single large public university in the southeastern United States, which may limit the broader applicability of the results to other institutions with different student populations, educational environments, or technological policies. While the findings provide valuable insights into generative AI use in higher education, caution should be exercised when extending these conclusions to different institutional contexts, such as smaller colleges, private universities, or international settings.

Results

In the following sections, we present our findings on (1) attitudes related to generative AI tools in learning and teaching, (2) perceived impacts of generative AI tools on students' learning, (3) views on the ethics and policy need for generative AI use in higher education, and (4) the frequency of generative AI use in learning and teaching. For these four topics, we will present (a) comparisons between faculty and students and (b) comparisons among student groups based on majors (i.e., STEM vs. Non-STEM) and gender (i.e., females vs. males).

Comparing Attitudes about the Use of Generative AI Tools in Courses

Table 2 illustrates the results of the two-sample t-test on the factor scores of the seven constructs between students and faculty. For three of the seven attitudes related to the use of generative AI tools in higher education, students and faculty did not differ significantly. However, students thought that generative AI tools were easier to learn (Effort Expectancy; $p < 0.01$) and more fun to use (Hedonic Motivation;

Table 2 Comparison of factor scores of students and faculty attitudes related to generative AI tools for learning and teaching in university

Attitudinal Construct	Comparison between faculty and students	Comparison between four student subgroups (STEM Male, STEM Female, Non-STEM Male, Non-STEM Female)	
	t(*df*)	*F*	Tukey's Post-hoc Test
Performance Expectancy	1.322 (85.395)	12.37	STEM Male vs. STEM Female ** STEM Male vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female *
Effort Expectancy	2.758 (88.784) **	24.23	STEM Male vs. STEM Female *** STEM Male vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female ***
Social Influence	1.127 (86.59)	10.15	STEM Male vs. STEM Female ** STEM Male vs. Non-STEM Female ***
Hedonic Motivation	2.580 (86.787) *	15.64	STEM Male vs. STEM Female *** STEM Male vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female *
Habit	-2.032 (85.02) *	15.14	STEM Male vs. STEM Female *** STEM Male vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female **
Personal Innovativeness	2.943 (85.75) **	51.64	STEM Male vs. STEM Female *** STEM Male vs. Non-STEM Male * STEM Male vs. Non-STEM Female *** STEM Female vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female ***
Behavioral Intention	-0.874 (86.82)	11.93	STEM Male vs. STEM Female ** STEM Male vs. Non-STEM Female *** Non-STEM Male vs. Non-STEM Female *

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

$p < 0.05$) than did faculty respondents, as seen in Fig. 2. Students were also significantly more interested in exploring new technologies (Personal Innovativeness; $p < 0.01$) compared to faculty. Conversely, generative AI use is more habitual for faculty than students (Habit; $p < 0.05$). However, these attitudinal differences toward generative AI did not translate into significant differences between the two groups in their intentions to use generative AI tools (Behavioral Intention).

When comparing the four major/gender groups of students, we found significant differences for each of the attitudinal constructs (Table 2). In many of the constructs, we observed similar patterns, where males in STEM fields were the most positive about generative AI tools, followed by STEM females and non-STEM males, with non-STEM females being the least positive about generative AI tools (Fig. 3). This

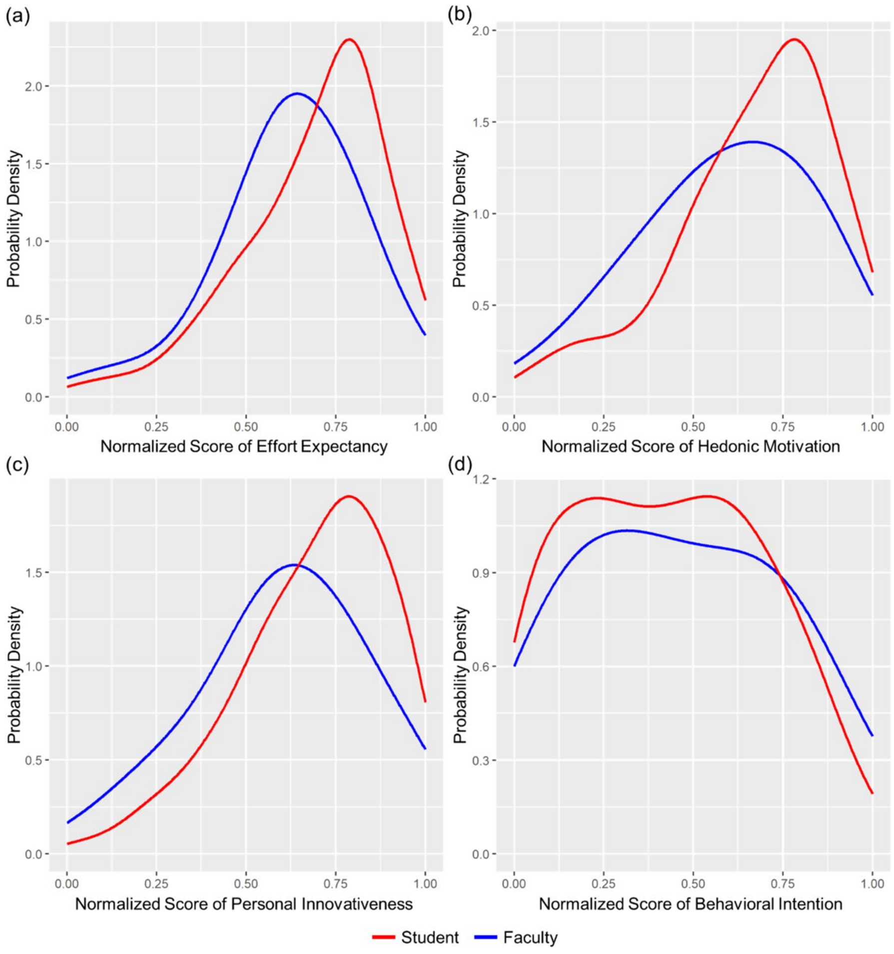

Fig. 2 Comparison of student and faculty attitudes (factor scores) about (**a**) Effort Expectancy, (**b**) Hedonic Motivation, (**c**) Personal Innovativeness, and (**d**) Behavioral Intention as related to using generative AI tools

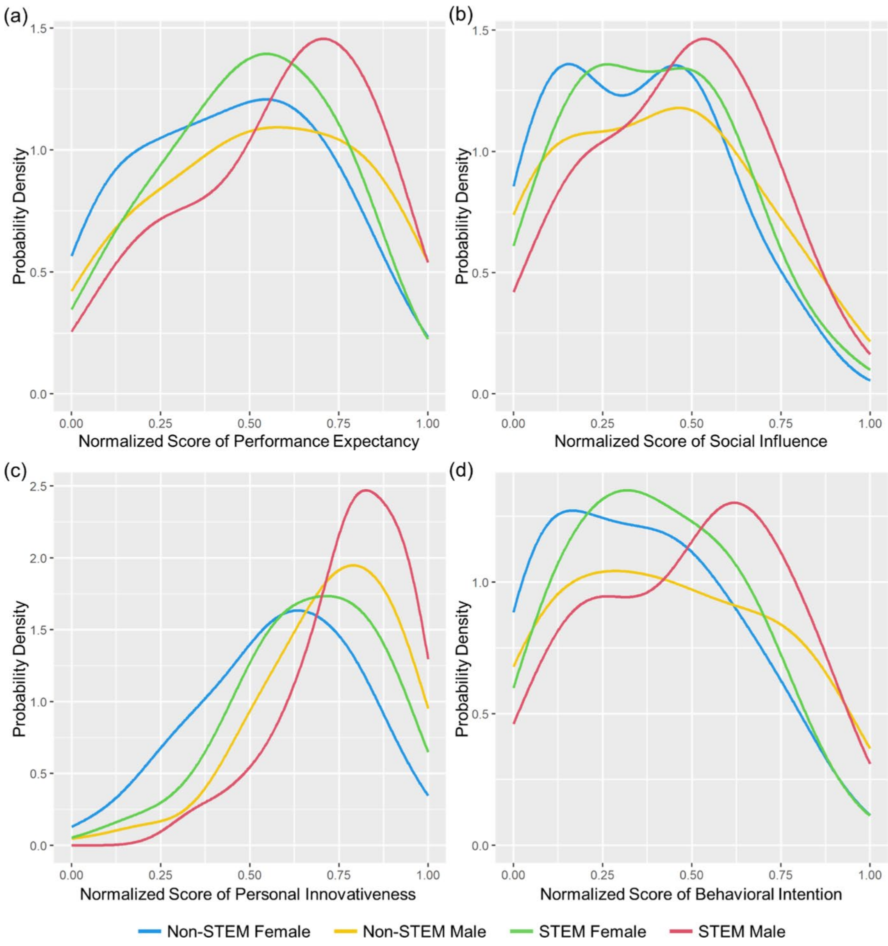

Fig. 3 Comparison of STEM and non-STEM students, by gender, for attitudes (factor scores) about (**a**) Performance Expectancy, (**b**) Social Influence, (**c**) Personal Innovativeness, and (**d**) Behavioral Intention

pattern was also evident in students' plans to use generative AI tools (Behavioral Intention) in future university courses (Fig. 3).

Comparing Views on Learning, Student Competencies, and Use of Generative AI Tools

Students and faculty did not differ significantly in most of their views on how generative AI tools could affect specific student learning competencies or overall learning, as illustrated in Table 3. The sole exception was Academic Performance (Fig. 4), where students were significantly more positive than faculty about the potential benefits of generative AI tools ($W = 39{,}673$, $p < 0.001$). Given the other agreements between the students and faculty, we interpret this discrepancy to

Table 3 Comparison of student and faculty perceptions of generative AI's potential impacts on student learning competencies

Learning Competencies	Comparison between faculty and students		Comparison between four student subgroups (STEM Male, STEM Female, Non-STEM Male, Non-STEM Female)
	W	*p*-value	
Critical Thinking	32,719	0.227	Not Significant
Problem-Solving	33,598	0.107	Not Significant
Teamwork	29,058	0.595	STEM Male vs. Non-STEM Female *
Self-efficacy	30,843	0.754	STEM Male vs. STEM Female *
Test Anxiety	34,284	0.051	Not Significant
Intrinsic Motivation	32,841	0.209	Not Significant
Engagement	30,927	0.723	Not Significant
Academic Performance	39,673	0.000***	STEM Male vs. STEM Female *
Overall Learning	32,556	0.260	STEM Male vs. Non-STEM Female **

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

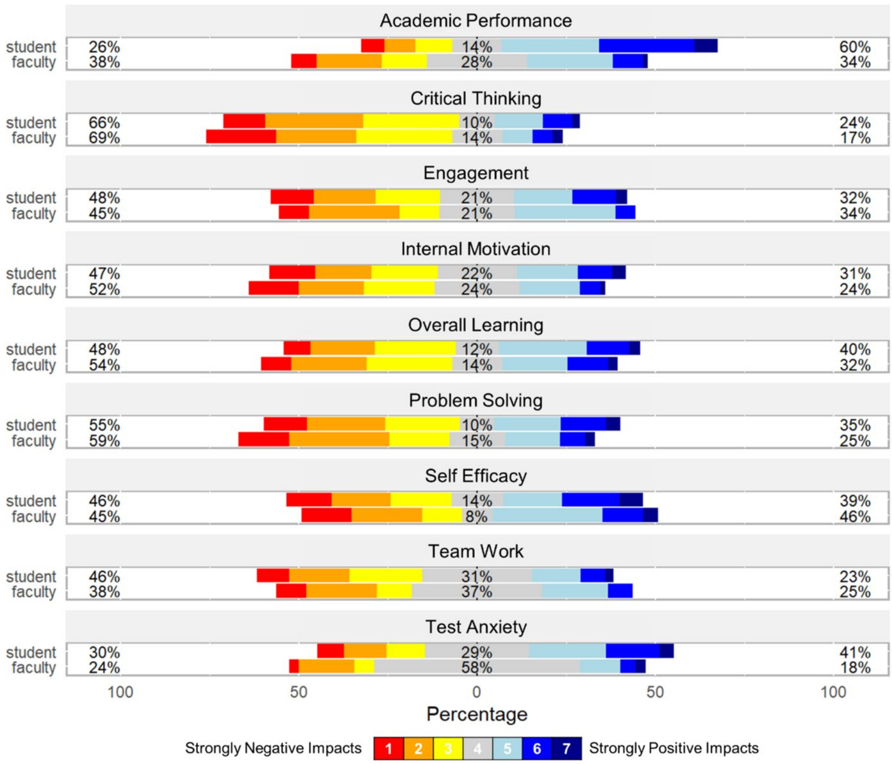

Fig. 4 Comparison of student and faculty views of the impacts of generative AI tools on student learning

reflect different interpretations of the phrase “Academic Performance” – students may be thinking of course grades, while faculty may be thinking of learning. Overall, both groups tended to agree that generative AI will have more negative effects than positive effects on most aspects of student learning, such as Problem Solving, Teamwork, Self-efficacy, Test Anxiety, Intrinsic Motivation, and Engagement.

When comparing the four major/gender groups of students (Fig. 5), there were no significant differences in Critical Thinking, Problem Solving, Test Anxiety, Intrinsic Motivation, and Engagement. However, there were significant differences

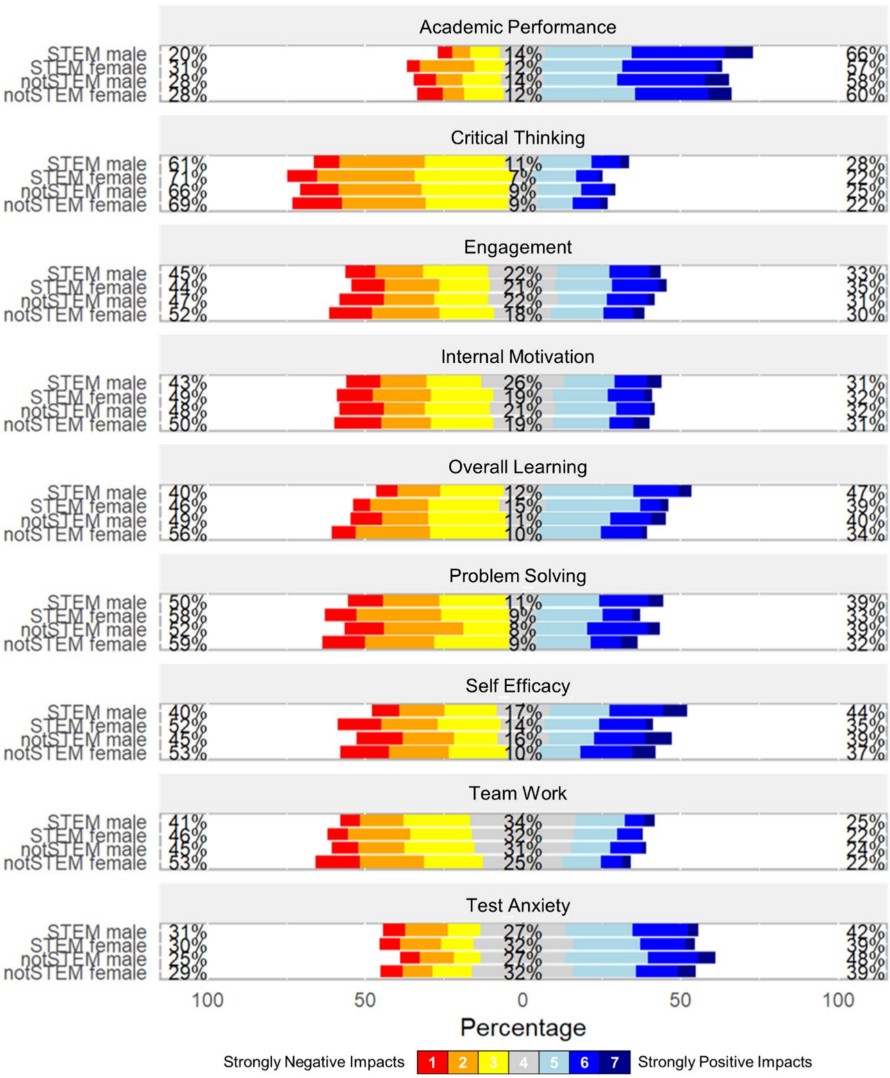

Fig. 5 Comparison of views of STEM and non-STEM students, by gender, about generative AI's impact on student learning

regarding Teamwork, Self-efficacy, Academic Performance, and Overall Learning. For instance, STEM male students think generative AI would have more positive impacts on academic performance than STEM female students ($p < 0.05$). Additionally, STEM male students report generative AI would have more positive impacts on overall learning than non-STEM female students ($p < 0.01$).

Comparing Attitudes on Ethics of Using Generative AI Tools in Courses

Overall, there were no substantial differences between students and faculty regarding their views on the ethics of and need for policy relating to generative AI tools (Table 4 and Fig. 6). For instance, students and faculty agreed that generative AI tools can exacerbate academic dishonesty and cheating (W = 33,283; $p = 0.140$) but should still be used in courses (W = 34,005; $p = 0.071$). Approximately 80% of respondents agreed with the statement, "The university should develop formal policies that guide students' usage of generative AI tools in their classes." The two groups may disagree on the content of such policies, however, as students were significantly more likely than faculty to find the use of generative AI for coursework to be inappropriate (W = 35,334; $p = 0.015$) or unethical (W = 34,934; $p = 0.025$). Student groups agreed on the ethical issues associated with generative AI use in courses regardless of their gender and major, except for the need to develop a university policy (Fig. 7). Non-STEM male students agree that such a need exists more than non-STEM female students ($p < 0.05$). More than two-thirds of students noted that generative AI can promote dishonesty, but half of students still felt that it is ethical and appropriate to use generative AI in coursework.

Comparing the Frequency of Use of Generative AI Tools in Courses

Students and faculty use generative AI tools at similar rates (W = 33,630; $p = 0.542$). Approximately 70% of students and faculty used generative AI tools less than once per week (Fig. 8); only 6% of students and 9% of faculty used generative AI tools daily in Fall 2023. Generative AI use for university coursework and teaching preparation is still relatively rare, with approximately two-thirds of students and faculty using generative AI tools less than once per week. Reflecting their overall comfort with AI, STEM male students use generative AI tools at significantly higher rates than non-STEM female students ($p < 0.001$). Moreover, non-STEM male students use generative AI tools at significantly higher rates than non-STEM female students ($p < 0.05$). The overall results highlight the important role of gender and academic majors in students' use of generative AI tools, which corroborates the findings reported above.

Table 4 Comparison of student and faculty attitudes on ethics of using generative AI tools in courses

Statements	Comparison between faculty and students		Comparison between four student subgroups (STEM Male, STEM Female, Non-STEM Male, Non-STEM Female)
	W	*p*-value	
Generative AI tools will promote students' academically dishonest behaviors	33,283	0.140	Not Significant
Using generative AI tools for coursework is an unethical behavior	34,934	0.025*	Not Significant
Using generative AI tools for coursework is inappropriate	35,334	0.015*	Not Significant
Students should not utilize generative AI tools for their classes	34,005	0.071	Not Significant
The university should develop formal policies that guide students' usage of generative AI tools	28,527	0.428	Non-STEM Male vs. Non-STEM Female *

*$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

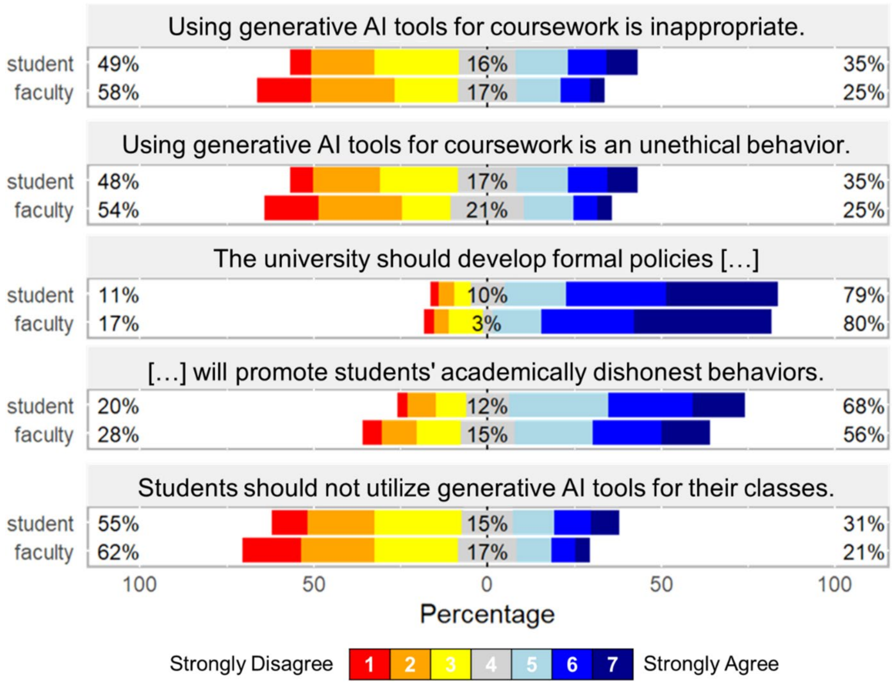

Fig. 6 Comparison of views of faculty and students on ethics and policies of using generative AI tools in courses

Discussion

Summary of Results

This study highlights key perspectives on the adoption of generative AI in higher education, revealing differences and similarities among students and faculty. Students reported greater enjoyment and ease of learning with generative AI tools and were more comfortable exploring new technologies than faculty. However, there was no significant difference in the usage of generative AI tools between students and faculty. Significant differences were evident among student sub-populations, particularly between STEM and non-STEM majors and across gender lines, with males in STEM showing the strongest positive attitudes toward generative AI. Despite recognizing the potential benefits to academic performance, students and faculty were concerned about negative impacts on student learning competencies and about ethical considerations. Both groups agreed that policies or guidelines are needed to navigate the inclusion of generative AI tools in educational settings.

The specific differences observed in performance expectancy and personal innovativeness might result from a combination of contextual factors, such as the different academic environments and disciplinary cultures in STEM and non-STEM fields. For example, performance expectancy might be higher among STEM students due to their more frequent interaction with generative AI tools in technical disciplines,

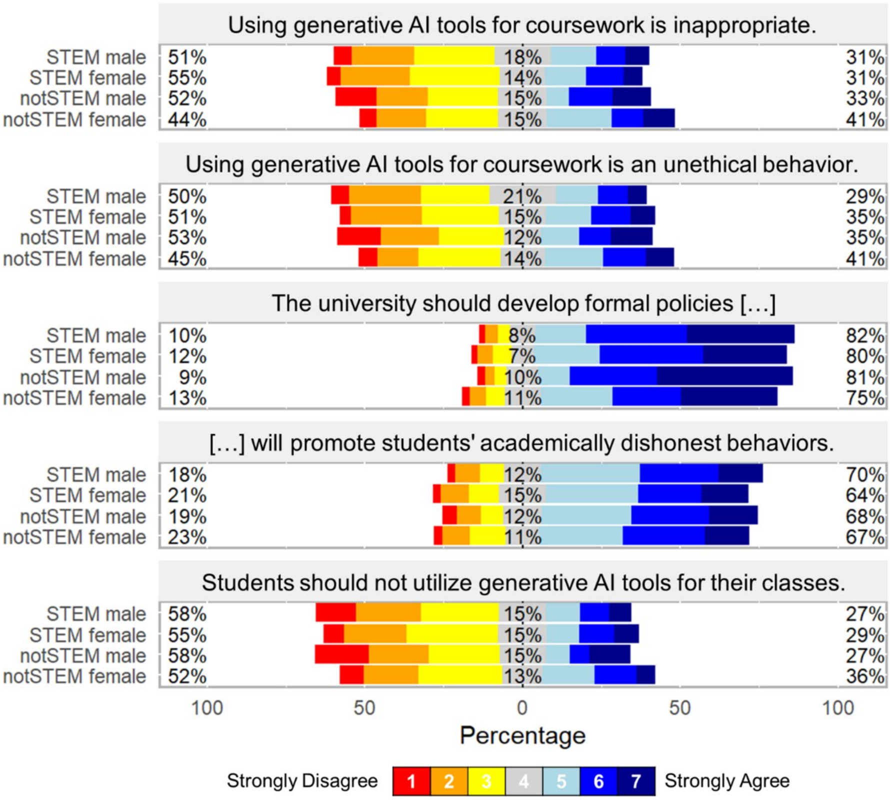

Fig. 7 Comparison of views of STEM and non-STEM students, by gender, about ethics of and policies for using generative AI tools in courses

where these technologies are often integrated into coursework and professional practice. Similarly, personal innovativeness might be influenced by the greater emphasis on experimentation and technology adoption in STEM fields, where students are encouraged to explore new tools for problem-solving and research. These group disparities reflect not only the nature of the disciplines but also differing levels of exposure to and familiarity with emerging technologies, which shape students' and faculty's perceptions of generative AI's utility and their willingness to adopt it.

Alignment with Past Research

Our investigation aligns with the Unified Theory of Acceptance and Use of Technology (Venkatesh & Xu, 2012; Venkatesh et al., 2016), revealing an overarching positive attitude toward generative AI in education, highlighted by its perceived ease of use, potential benefits, and the enjoyment of engaging with new technology. However, the study also uncovered significant apprehension about generative AI's impact on foundational learning competencies (Amani et al., 2023; White et al.,

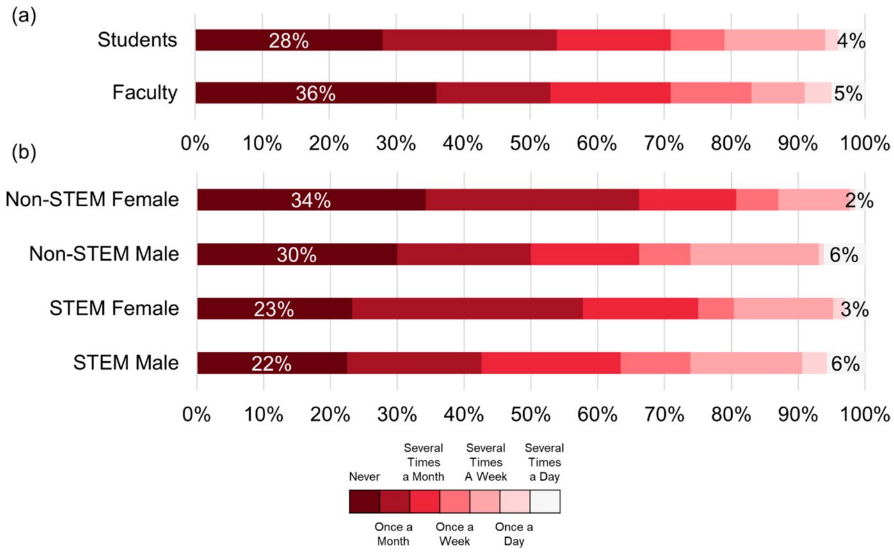

Fig. 8 **a** Comparison of frequency of generative AI use by students and faculty. **b** Comparison of frequency of generative AI use among STEM and non-STEM majors, by gender

2024), including critical thinking and problem solving. Respondents' views on the ethical issues are somewhat contradictory; while recognizing that generative AI use may promote academic dishonesty, both students and faculty generally feel its use in courses is appropriate and ethical and should not be banned. Interestingly, the apprehension surrounding generative AI's inappropriateness in an academic setting is stronger among students than faculty. This finding aligns with the theory of ontological security, which focuses on the importance of having a stable identity in a predictable world (Browning & Joenniemi, 2017; Lupovici, 2023). The disruptive nature of new technologies, like generative AI, may pose a greater threat to the identity and stability of students, who are at formative stages of personal and professional development.

Despite the recognized potential of generative AI in education (Alasadi & Baiz, 2023; Atkins et al., 2024; Chan & Hu, 2023; Lo, 2023; Wang et al., 2023), its actual use is low, with more than half of respondents reporting infrequent or no use of generative AI tools. The low usage rate also corroborates a nationwide study that reports only 14% of adults used ChatGPT (Vogels, 2023). According to the UTAUT framework, this low usage reflects the interaction of multiple factors that we observed. The ethics associated with this technology are still contentious, and any guidelines for use are vague. This pattern demonstrates a resistance common in the historical introduction of new technology (Waits & Demana, 2000; Foer, 2012), suggesting that generative AI is in its early stages of integration into education. Students majoring in STEM fields, however, are further toward acceptance, with more positive attitudes and fewer ethical qualms about generative AI. This leads to greater use of generative AI among STEM students compared to non-STEM majors. This implies that, when formulating university policies about generative AI, administrators may want to consider the differences in acceptable use for STEM versus non-STEM classroom settings. We also identified the importance of gender in students' attitudes and behaviors of generative AI use in higher education settings, which aligns with results from the nationwide survey (Vogels, 2023). Perceptions of female non-STEM students were significantly different from those of male STEM students. This suggests more nuanced approaches in terms of gender and academic majors are needed when discussing generative AI adoption in higher education.

Policy Recommendations

This study highlights a critical juncture for universities in deciding how to navigate the future of generative AI in education (Chan, 2023). The choice between restricting generative AI's use through policy or facilitating its integration through guidance and instruction will significantly influence the role of generative AI in educational settings. Students and faculty note the need for university policies for generative AI; these guidelines must be clear, principle-based, and able to adapt to the changing landscape of generative AI while also conforming to the university's values.

To support the ethical and effective integration of generative AI into higher education, universities should consider adopting clear and adaptable guidelines that reflect the diversity of their student and faculty populations. Research indicates that educators are more likely to adopt generative AI tools when supported by systematic strategies for assignment design and institutional guidance on ethical use (Khlaif et al., 2024). When developing these guidelines, our results suggest that it is important to include a variety of stakeholders—including faculty, university administrators, and students representing diverse majors and genders—because of the diversity of perceptions about generative AI. Although many universities have actively engaged in formulating guidelines (e.g., Harvard University, 2024; The Ohio State University, 2024; University of Michigan, 2023; University of Pittsburgh, 2023) student and faculty perspectives could be incorporated more. One example of an AI policy developed with substantial stakeholder input is the *ChatGPT, Generative Artificial Intelligence, and Natural Large Language Models for Accountable Reporting and Use Guidelines* (CANGARU) initiative (Cacciamani et al., 2023). Although this initiative focuses on the research protocol, the approaches used for this initiative—a Delphi consensus process—can guide future policy development.

Ideally, institutions can establish task forces or working groups that include representatives from various departments, including STEM and non-STEM disciplines, as well as students and faculty from different demographic backgrounds. These groups can work together to draft generative AI policies that address academic integrity, student learning outcomes, and the ethical use of tools in coursework. For instance, policies can clarify when and how generative AI tools may be used for assignments, provide guidance on distinguishing between legitimate AI assistance and academic dishonesty, and ensure that AI-generated work is appropriately acknowledged.

One practical step toward implementing generative AI guidelines is to incorporate training and workshops on AI literacy into the curriculum for both students and faculty. The ability to effectively use generative AI will become a critical skill that will be needed by industry, as well as in the academic domain (Edelman & Abraham, 2023; Edwards, 2023). Recent research recommends a balanced approach, emphasizing that universities should support educators in leveraging AI's strengths while maintaining the unique qualities of human teaching, such as fostering critical thinking and social-emotional skills (Chan & Tsi, 2024). Faculty with limited experience using generative AI tools often lack the confidence to implement these technologies and express a need for additional training and education (Harper, 2024). Generative AI training sessions can help users understand the capabilities of generative AI tools like ChatGPT, ensuring that they are used effectively and ethically. Universities can also create online resources, such as tutorials and best practice guides, that offer ongoing support for generative AI use. These resources should be updated regularly to reflect the evolving capabilities of generative AI technologies and their potential impacts on academic work.

Perhaps as important as teaching the effective use of generative AI tools (e.g., Dubey et al., 2024; Jang & Kim, 2024; Jang et al., 2024), courses and workshops can also instruct on generative AI's weaknesses, such as hallucinations, inaccuracies, and biases (e.g., Atkins et al., 2024; Kim & Lee, 2023; Kim et al., 2024b), as well as the ethical issues associated with the use of tools (e.g., Kim et al., 2024a, 2024b). In this light, it is imperative that non-STEM students be prepared to use generative AI tools responsibly. However, to our best knowledge, there are limited formal education opportunities (e.g., semester-long classes) on generative AI tools for non-STEM students provided by higher education schools in the United States. Thus, we recommend universities make efforts to fill this critical gap.

Educational Practices

In addition to policy development, universities should promote best practices for generative AI use in the classroom that enhance learning outcomes and minimize the risks of misuse. One recommendation is to encourage instructors to design generative AI-inclusive assessments that focus on higher-order thinking skills, such as critical analysis, problem solving, and creativity, rather than rote memorization or formulaic responses that generative AI tools can easily generate. For instance, assessments could require students to explain their reasoning processes, reflect on their use of generative AI, or demonstrate their understanding by applying AI-generated insights to novel contexts. Faculty-development programs should also be expanded to include training on how to effectively integrate generative AI into teaching. This could involve workshops on designing AI-augmented assignments, leveraging generative AI for personalized feedback, and understanding the ethical implications of generative AI in education. Ultimately, the goal of these policies and practices is to foster an educational environment where generative AI can be used to support and enhance rather than undermine student learning. By providing clear guidelines, offering training, and promoting thoughtful integration, universities can ensure that generative AI is adopted in ways that enhance equity, uphold academic integrity, and prepare students for future careers in an increasingly AI-driven world.

Limitations and Future Research

There are several limitations that future studies can address. First, as a cross-sectional study, we did not explore how students' and faculty's perceptions of generative AI may evolve over time. Given the rapidly changing landscape of generative AI tools, a valuable direction for future research is to conduct longitudinal studies that track shifts in attitudes and behaviors over multiple semesters or academic years. These studies can examine how continued exposure to generative AI tools impacts students' learning strategies and faculty's teaching practices, particularly as generative AI becomes more integrated into educational platforms and resources.

Second, our study's limited faculty sample size suggests that future research should aim to include larger, more diverse faculty populations. Increasing the faculty sample size and diversity would allow for more nuanced comparisons across different academic departments and roles within the university, such as comparing tenured professors, adjunct faculty, and teaching assistants. Additionally, future studies should explore differences between faculty who are early adopters of generative AI technologies and those who are more hesitant to integrate these tools into their teaching, identifying factors that influence these adoption patterns.

Third, expanding the geographic and institutional scope of future research could significantly enhance the generalizability of findings. Our study focused on one large land-grant institution in the southeastern United States, which limits the ability to generalize the results to other settings. Future research should include multiple universities with varying characteristics, such as private universities, community colleges, liberal arts colleges, and institutions outside the United States. Comparative studies across different educational systems and institutional types would provide deeper insights into how institutional culture, resources, and policies influence the adoption and impact of generative AI.

Finally, future research should investigate the role of generative AI at the course level, particularly in how generative AI use may vary across different academic disciplines and course types. For instance, generative AI tools may be more appropriate for advanced courses in computer science, where students are tasked with complex programming projects, than for introductory courses that focus on foundational skills like computational thinking. Course-level analyses could explore which types of courses benefit most from generative AI integration and how generative AI might be tailored to support discipline-specific learning objectives, which will be a focus of a subsequent study of our research team.

Conclusion

In conclusion, this study presents a nuanced understanding of the current perceptions of generative AI among students and faculty by conducting an online survey of 982 students and 76 faculty from a large land-grant university in the southeastern United States. The results demonstrate the complexities that universities must address as they attempt to integrate generative AI into educational practices.

Appendix

Table 5 Results of the confirmatory factor analysis (CFA)

Survey Item	Student ($n=982$)		Faculty ($n=76$)	
	Cronbach's Alpha	Loading	Cronbach's Alpha	Loading
Performance Expectancy				
I believe that generative AI tools are helpful in my university studies. (Faculty: […] in preparing me for teaching.)	0.935	0.879	0.965	0.948
Using generative AI tools increases the likelihood of achieving important things (e.g., productivity, efficiency) in my university studies. (Faculty: […] when preparing for my teaching.)	-	0.876	-	0.901
Using generative AI tools helps me get tasks and projects done faster in my university studies. (Faculty: […] in my teaching preparation.)	-	0.874	-	0.927
Using generative AI tools increases my productivity for university studies. (Faculty: […] in my teaching preparation.)	-	0.909	-	0.952
Effort Expectancy				
Learning how to use generative AI tools is easy for me	0.889	0.874	0.896	0.887
Generative AI tools are clear to use	-	0.757	-	0.779
I find generative AI tools easy to use	-	0.855	-	0.712
It is easy for me to become skillful at using generative AI tools	-	0.792	-	0.905
Social Influence				
People who are important to me think I should use generative AI tools	0.896	0.861	0.924	0.943
People who influence my behavior believe that I should use generative AI tools	-	0.841	-	0.941
People whose opinions I value prefer me to use generative AI tools	-	0.880	-	0.813
Hedonic Motivation				
Using generative AI tools is fun	0.911	0.925	0.922	0.930
Using generative AI tools is enjoyable	-	0.881	-	0.849
Using generative AI tools is very entertaining	-	0.834	-	0.909

Table 5 (continued)

Survey Item	Student ($n=982$)		Faculty ($n=76$)	
	Cronbach's Alpha	Loading	Cronbach's Alpha	Loading
Habit				
Using generative AI tools has become a habit for me	0.858	0.885	0.840	0.877
I am addicted to using generative AI tools	-	0.695	-	0.728
I must use generative AI tools	-	0.731	-	0.618
Using generative AI tools has become natural for me	-	0.810	-	0.838
Behavioral Intention				
I intend to continue using generative AI tools for my university studies in the future. (Faculty: […] for my teaching preparation in the future.)	0.911	0.898	0.941	0.925
I will always try to use generative AI tools in my university studies. (Faculty: […] in my teaching preparation.)	-	0.831	-	0.889
I plan to use generative AI tools frequently for my university studies. (Faculty: […] for my teaching preparation.)	-	0.918	-	0.947
Personal Innovativeness				
I like experimenting with new technologies	0.873	0.849	0.891	0.890
If I heard about new technologies, I would look for ways to experiment with them	-	0.848	-	0.853
Among my family and friends, I am usually the first to try out new technologies	-	0.690	-	0.771
In general, I do not hesitate to try out new technologies	-	0.833	-	0.797
Model fit indices				
CFI	-	0.959	-	0.919
TLI	-	0.951	-	0.904
RMSEA	-	0.053	-	0.089
SRMR	-	0.044	-	0.075

Table 6 Survey instruments for the student competencies, impacts on learning, ethical consideration, and demographic and academic characteristics

Category	Survey Questions
Frequency of Use	Please choose your overall usage frequency of generative AI tools for your university studies
Student Competencies	Overall, how do you think generative AI tools will impact the following specific competencies of students?
	Critical thinking
	Problem-solving
	Teamwork
	Self-efficacy
	Test anxiety
	Academic performance
	Intrinsic motivation
	Student engagement
Learning	Overall, how do you think generative AI tools will impact students' learning?
Ethical Considerations	Generative AI tools will promote students' academically dishonest behaviors (e.g., cheating)
	Students should not utilize generative AI tools for their classes
	The university should develop formal policies that guide students' usage of generative AI tools in their classes
	Using generative AI tools for coursework is an unethical behavior
	Using generative AI tools for coursework is inappropriate
Demographic and Academic Characteristics	Please indicate your gender
	Which year are you in the current semester?
	Are you Hispanic or Latino?
	Please check one or more of the following groups in which you consider yourself to be. (American Indian or Alaska Native; Asian; Black or African American; Native Hawaiian or Other Pacific Islander; White; Prefer Not to Say)
	Please check your primary major (or your home department). If you have two or more majors, check all of your majors

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Data Availability Data cannot be shared openly to protect the privacy of human subjects.

Declarations

Consent to Participate Informed consent was obtained from participants included in the study (IRB 23-1243).

Competing Interests The authors declare they have no competing interests.

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