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Generative AI in Higher Education: Demographic Differences in Student Perceived Readiness, Benefits, and Challenges

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Abstract
With the rapid evolution and widespread adoption of Generative AI (GenAI), there has been a recent surge in research on students' perceptions and usage of these tools for learning. However, a critical need remains to understand how students from various demographic groups perceive and utilize GenAI for educational purposes. This research aims to fill this gap by evaluating students' use of GenAI, comfort level, perception of readiness, benefits and challenges, and demographic differences in their perceptions. Through an online survey of 482 students across diverse institutions of higher education primarily within the United States, the findings indicate a significant majority of students feel comfortable using GenAI tools and recognize their potential to enhance productivity and academic success. However, students also reported concerns related to GenAI use, including concerns about academic integrity, overreliance on AI, and data privacy and security. The analysis highlights differences in the subscales of perceived readiness (GenAI Comprehension; GenAI Utilization and Proficiency), benefits (Impact of GenAI; GenAI Empowerment), and challenges (Negative Impact of GenAI; GenAI Limitation) across demographic groups, including student classification, enrollment status, and institution types. Findings suggest a critical need for the integration of AI literacy into curricula to address opportunities and challenges posed by GenAI in higher education, and this study calls for additional research to explore evolving perceptions of GenAI use over time and its long-term impact on higher education.

Keywords Generative AI (GenAI) · Higher Education · Student Perceptions

Introduction

Interest in artificial intelligence (AI) in education is hardly a new concept (Yan et al., 2024), with systematic research into the topic beginning nearly three decades ago with the International AIEd Society's (IAIED) founding in 1997 (Zawacki-Richter et al., 2019). However, a significant increase in attention to AI in higher education emerged recently with the rapid onset of Generative AI (GenAI). GenAI interest exploded in the wake of OpenAI's public release of ChatGPT in November 2022 as questions and concerns abounded about the nature, benefits, and challenges of integrating ChatGPT and other GenAI tools in education (Sier, 2022; Strzelecki & ElArabawy, 2024; Tremblay, 2023). GenAI is a new, highly capable form of AI that leverages complex machine learning algorithms that enable the tool to generate a series of unique, creative responses in diverse formats to satisfy a user-provided prompt (Hardesty, 2017). GenAI is a new innovation in AI technology, leveraging a process known as deep learning to create a system capable of recalling, learning from, and improving future performance over time (Haque et al., 2022; Rahimi & Talebi Bezmin Abadi, 2023; Strzelecki & ElArabawy, 2024).

Early sentiment analyses revealed largely but not exclusively positive feelings amongst early adopters, with nuanced results reported in educational contexts (Tlili et al., 2023), including Haque et al. (2022) noting a 52% positive sentiment regarding GenAI use for education in contrast to 75% and 81% positive sentiments in GenAI-use for business and software development, respectively. When considering GenAI use in the context of education, questions of ethics, academic integrity, and a need for accurate, verifiable results present unique challenges (Haque et al., 2022; Kasneci et al., 2023; Lund et al., 2023; Mollick & Mollick, 2023; Perkins,

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2023; Rahimi & Talebi Bezmin Abadi, 2023; Yan et al. 2024).

Given the novelty of GenAI tools, most initial research remained focused on early adopters' perceptions of GenAI, but as adoption has rapidly expanded, broader concerns regarding its use in education, beyond those of only early adopters, further emphasize the relevance of this study. Additionally, the emerging but scarce empirical research into the acceptance and use of GenAI for higher education students (Strzelecki & ElArabawy, 2024) makes this ongoing research both timely and necessary. Therefore, this study aims to examine higher education students' perceptions and usage of GenAI, mainly focusing on readiness, benefits, and challenges. Furthermore, this study seeks to highlight diverse perspectives and identify unmet student needs by analyzing demographic variables such as academic levels, enrollment and employment status, and institution types within higher education.

Literature Review

Empirical research into the acceptance and use of GenAI for higher education students is emerging but scarce (Strzelecki & ElArabawy, 2024). There are several frameworks for conducting empirical research into technology acceptance, including Expectancy Value Theory (EVT) (Wigfield & Eccles, 2000), the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT/2) (Venkatesh et al., 2003; Venkatesh et al., 2012), and Diffusion of Innovation (DOI) (Rogers, 1962). Previous research yielded nuanced results on student perceptions and integration of GenAI in higher education. EVT posits that individuals who perceive more value in using a specific technology are more likely to use it in the future (Wigfield & Eccles, 2000). Chan and Zhou (2023) reported that student-perceived value of GenAI was a significant determinant of intention to utilize technologies for education.

Student Trust and Perceptions of GenAI

Research indicates students' adoption of GenAI is closely tied to their perceived trustworthiness and confidence with the technology, as students seek to balance optimism of capabilities with skepticism over limitations. Perceived value is one of the many variables that may influence a student's acceptance and use of GenAI in higher education (Chan & Zhou, 2023; Strzelecki, 2024). Students who perceive a system as highly intelligent and capable often develop a positive attitude toward the technology (Rafiq et al., 2022). Research suggests students are aware of GenAI benefits, especially capabilities in the context of education. Multiple studies suggest that students are open to GenAI use in education as they perceive these tools as valuable in the learning process (Chan & Zhou, 2023; Raman et al., 2023) in addition to their potential to improve learning outcomes, increased efficiency in education processes, capacity of GenAI to provide personalized feedback, and rapid idea generation (Bonsu & Baffour-Koduah, 2023; Chan & Zhou, 2023).

Trust is an important consideration as an adoption determinant as, when students perceive that a system can be trusted to protect their data, they are more likely to adopt the technology (Ho et al., 2017). However, challenges in GenAI accuracy and reliability (Joseph, 2023; Imran et al., 2023; Kung et al., 2023) and data security concerns (Zorz, 2023) can influence student concerns and intention to use GenAI. In their study of how student concerns may influence student adoption of GenAI, Jo (2023) and Kaya et al. (2024) suggested intentional faculty integration of AI chatbots in educational contexts can encourage student use of the technologies by demystifying the technology and creating space in academic environments to address concerns while highlighting benefits. Additionally, due to the advanced capabilities of GenAI technologies beyond traditional AI, empirical research into additional adoption determinants like perceived intelligence and trust is needed (Jo, 2023).

Ethical Concerns and Questions of Academic Integrity

Ethical concerns surrounding responsible AI use and academic integrity remain a significant barrier to confident student adoption. Research indicates higher education students are keenly aware of the perceived costs of using GenAI for educational purposes, with multiple studies indicating student concerns around data privacy and security, academic integrity, inaccuracy, overreliance, and financial costs, amongst other potential equity of access issues (Chan & Zhou, 2023; Dahlkemper et al., 2023; Haensch et al., 2023; Yan et al. 2024). Student concerns about academic integrity also relate to anxiety and confusion about accusations of plagiarism and other violations of academic integrity, issues strongly correlated with challenges of using plagiarism-detection software to detect GenAI usage amongst students (Khalil & Er, 2023; Parker et al., 2024; Tlili et al., 2023).

Demographic Differences in Student Perceptions

Researchers have examined the demographic differences in the adoption and perception of GenAI. Empirical studies that analyze the potential nuance of gender differences in GenAI readiness and perceptions are rarer still. Strzelecki and ElArabawy (2024) found gender to be an insignificant moderating factor in their Polish sample but partially significant in their Egyptian sample, prompting a call for additional research into ChatGPT usage by gender. Furthermore, Stöhr et al. (2024) found statistically significant differences between gender groups consistent with UTAUT predictions (Venkatesh et al., 2003), and recent research (Nouraldeen, 2023) indicates males have more positive attitudes and higher usage of GenAI than females. Kaya et al. (2024), however, did not find a gender correlation in predicting AI attitudes, contradicting studies that suggest males are more likely to form positive attitudes (European Commission & Directorate-General for Communications Networks, Content & Technology, 2017; Martin et al., 2020; Nouraldeen 2023; Stöhr et al., 2024).

The findings of Kaya et al. (2024) led to their suggestion that gender may be overshadowed by other factors influencing AI perceptions. However, research into additional moderating factors, including age, academic discipline, educational level, and social influence, have produced nuanced results in empirical research into AI perception and use. Kaya et al. (2024) reported that age did not relate to attitudes toward AI, consistent with prior research from Chocarro et al. (2021).

Kaya et al. (2024) also found education level was not a significant predictor of AI perceptions, although previous research indicates a higher education level may influence more positive AI perceptions (Gnambs & Appel, 2019; Zhang & Dafoe, 2019). Haque et al. (2022) and Stöhr et al. (2024) also indicate potential differences in GenAI perceptions amongst those from different academic disciplines, finding engineering students more optimistic in GenAI perceptions than those in arts, humanities, medicine, and health care, contradicting the findings of Santomartino and Yi (2022).

Poonpanich and Buranasiri (2022) and Sobaih et al. (2024) identified social influence as a potential AI adoption determinant, defined by Venkatesh et al. (2003) as "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451). Kelly et al. (2023) also identified a lower level of GenAI awareness amongst international students, potentially due to the reported difficulty of those students in building a social network (Khanal & Gaulee, 2019). However, the potential impact of social influence as an adoption determinant was not observed by Alshammari and Alshammari (2024).

Research examining the demographic influences on GenAI perceptions amongst higher education students reveal a nuanced, sometimes contradictory, landscape where factors like gender, age, academic discipline, education level, and social influence show inconsistent effects across studies. These nuanced findings highlight the need for broader, context-sensitive investigations into how student backgrounds may influence perceptions of their readiness, benefits, and concerns regarding GenAI use.

Purpose

This study answers the call for additional quantitative research into larger sample sizes (Alshammari & Alshammari, 2024) across diverse institutional contexts (Kelly et al., 2023) to improve the generalizability of findings regarding student perceptions of GenAI in higher education. Furthermore, this study includes a preliminary investigation into additional demographic factors that have not been thoroughly explored in prior research, like the potential relationship between institution type or employment status. Although the findings of Stöhr et al. (2024) and Kelly et al. (2023) indicated differences in perceptions across academic disciplines, research has not yet investigated if these differences persist in different institution types. Additionally, to the best of our knowledge, this will be the first study to specifically investigate the relationship between employment status of higher education students and GenAI perceptions, which, given research indicating GenAI can improve efficiency in academic processes (Bonsu & Baffour-Koduah, 2023; Chan & Zhou, 2023), may be an important topic for consideration in addition to other variables like gender, age, academic level, and discipline, which have revealed nuanced perspectives of GenAI amongst higher education students (Kaya et al., 2024; Kelly et al., 2023; Stöhr et al., 2024). The following research questions guided this study:

1. How do students use generative AI tools in their learning practices within higher education settings?
2. What are the comfort levels of students regarding the use of generative AI for learning in higher education settings?
3. What are the students' perceived readiness (GenAI comprehension; ethical awareness of GenAI, GenAI utilization and proficiency), benefits (GenAI effectiveness; GenAI empowerment) and challenges (Ethics and privacy concerns; negative educational impact; GenAI limitations regarding accuracy and sensitivity) of using generative AI tools for learning in higher education settings?
4. How do students from different demographic backgrounds (e.g., gender, age, classification, enrollment status, employment status, online courses taken, and institution type) differ in the subscales of perceived readiness, benefits, and challenges?

Methodology

Procedures

This survey research was conducted from March to May 2024, during the Spring academic semester. An electronic survey was distributed to several listservs of professional organizations, including the Association for Educational Communications and Technology (AECT) and the American Educational Research Association (AERA) Online Teaching and Learning Special Interest Group (SIG). Institutional Review Board (IRB) approval was obtained from the researchers' institution. Informed consent was collected from all participants, who were required to select the "Yes, I am a student, and I agree to participate in this study" option in the online survey invitation to partake in the survey.

Measures

The electronic survey included items regarding the use of GenAI and the comfort level in using GenAI. These items were adapted from Amani et al. (2023), Jo (2023), and Strzelecki (2024). Specifically, it had two questions about the frequency of using such tools (6-point Likert scale, 1 = never to 6 = always), two questions to gauge participants' comfort level with using GenAI for general and learning purposes (4-point Likert scale, 1 = not at all to 4 = very comfortable), and one question asking the specific purposes of using GenAI. Additionally, participants answered five additional questions regarding their perceptions of GenAI as a safe and supportive learning tool (e.g., "GenAI is useful for student support services due to anonymity").

Following the descriptive items, the survey further assessed participants' perceived readiness, benefits, and challenges of integrating GenAI tools into learning practices. Specifically, the survey had 12 questions for readiness, 14 for benefits, and 19 for challenges. A team of researchers carefully developed three scales by adapting items from several existing measures (Amani et al., 2023; Chan & Zhou, 2023; Foroughi et al., 2023; Lemke et al., 2023; Wang, et al., 2023) and leveraging their content expertise. These new scales were designed to assess students' perceptions of GenAI in learning. The three measures underwent scale validation through content alignment and a confirmatory factor analysis (authors, under review).

The Readiness scale has three factors: 1) GenAI Comprehension, 2) Ethical Awareness of GenAI, and 3) GenAI Utilization and Proficiency. The Benefit scale has two factors:1) Effectiveness and 2) Empowerment. Finally, the Challenge scale includes three factors: 1) Ethics and Privacy Concerns, 2) Negative Educational Impact, and 3) Accuracy and Sensitivity. Their reliability was satisfactory, with Cronbach's alpha coefficients of 0.85, 0.86, and 0.91, respectively. Each question required participants to indicate their level of agreement on a five-point Likert scale, from 1 = Strongly Disagree to 5 = Strongly Agree.

In addition, the survey included a demographic questionnaire to gather participant information, including gender, age, location, number of online courses taken, institutional type, education level, employment status, and enrollment status (part-time or full-time).

Participants

The survey targeted enrolled students actively taking online, in-person, and/or hybrid coursework through higher education institutions. A total of 482 students participated in the survey. 22 cases from the survey were excluded from the analysis due to the incompleteness of the responses (< 70% missing) leaving a total of 460 participants. The demographic information of the participants is provided in Table 1.

The participants were from diverse backgrounds. In terms of their location, the sample group consisted of students from 41 states in the United States and one student from outside of the United States. Nearly half of the participants identified themselves as female (n = 253; 55.0%), were at a public or state college or university (n = 228; 49.6%), and did not currently work (n = 216, 47.0%). Their age range was predominantly between 18–24 years (n = 268; 58.3%) or 25–34 years (n = 162; 35.2%). A significant portion of the students were either Juniors (n = 105; 22.8%), Seniors (n = 103; 22.4%), or pursuing master's degrees (n = 119; 25.9%). Additionally, the majority were full-time students (n = 326; 70.9%).

Data Analysis

To address the first research question, we examined frequency distributions to explore how participants used GenAI. Descriptive statistics, including the mean and standard deviation, were used for the second and third research questions. The fourth question was tackled using ANOVA tests across major categorical demographic variables. After rejecting the ANOVA tests, Tukey's test was applied to examine significant mean differences between specific groups.

Results

Research Question 1: Use of GenAI

Table 2 displays the frequency of students' use of GenAI for (1) any reason and (2) learning. The majority of students use GenAI for any reason very frequently (n = 207, 45.0%) or occasionally (n = 155, 33.7%). Similarly, for learning purposes, most students use GenAI very frequently (n = 185, 40.2%) or occasionally (n = 179, 38.9%).

Table 3 shows the frequency of students' purposes for using GenAI. Notably, many students used GenAI to (a) ask general knowledge questions (n = 240, 52.2%), (b)

Table 1 Student participants demographics

Gender	N	%	Employment Status	N	%
Female	253	55.0	Not currently working	216	47.0
Male	196	42.6	Working part-time	189	41.1
Missing	11	2.4	Working full-time	44	9.6
Age			Missing	11	2.4
18–24 years old	268	58.3	Number of online courses taken		
25–34 years old	162	35.2	Under 5	57	12.4
35–44 years old	15	3.3	5–10	187	40.7
45–54 years old	3	0.7	11–20	147	32.0
55–64 years old	1	0.2	21–30	27	5.9
65–74 years old	0	0.0	31 +	31	6.7
Missing	11	2.4	Missing	11	2.4
Classification			Institution Type		
Undergrad, Freshman	35	7.8	Two-year technical or community college	5	1.1
Undergrad, Sophomore	73	15.9			
Undergrad, Junior	105	22.8	Technical or community college	55	12.0
Undergrad, Senior	103	22.4			
Graduate, Master	119	25.9	For-profit college or university	31	6.7
Graduate, Doctorate	14	3.0			
Missing	11	2.4	Private college or university	98	21.3
Enrollment Status					
Part-time	123	26.7	State or public college or university	228	49.6
Full time	326	70.9			
	11	2.4	Postgraduate-only institution	25	5.4
Missing					
			Missing	18	3.9

Table 2 Frequency of use of generative AI

Frequency	Never	Very Rarely	Rarely	Occasionally	Very Frequently	Always
For any reason	4 (0.9%)	23 (5.0%)	29 (6.3%)	155 (33.7%)	207 (45.0%)	42 (9.1%)
For learning	5 (1.1%)	20 (4.3%)	37 (8.0%)	179 (38.9%)	185 (40.2%)	33 (7.2%)

Table 3 Purpose of generative AI use

Purpose of Use	Students ($n = 460$)
Asking general knowledge questions	240 (52.2%)
Writing technical documents	175 (38.0%)
Carrying on a conversation out of curiosity	175 (38.0%)
Asking technical questions	170 (37.0%)
Receiving feedback	133 (28.9%)
Checking for solutions capability of generative AI for the coursework	133 (28.9%)
Completing online discussion assignments	86 (18.7%)
Querying generative AI for research-related activities	81 (17.6%)
Have not used generative AI	3 (0.7%)

write technical documents ($n = 175$, 38.0%), and (b) carry on a conversation out of curiosity ($n = 175$, 38.0%). Also, over one-third of students used GenAI to ask technical questions ($n = 170$, 37.0%).

Research Question 2: Comfort Level and Perceptions of GenAI as a Safe and Supportive Learning Tool

Table 4 shows the participants' perceived comfort level in using GenAI for general purposes and learning purposes. Most participants indicated they felt either fairly ($n = 272$, 59.1%) or very ($n = 100$, 21.7%) comfortable. No notable difference was found between their comfort level for general purposes and learning purposes.

Table 5 highlights some survey items measuring students' perceptions of GenAI as a safe and supportive learning tool. Generally, students tended to find GenAI to be a safe and supportive learning tool, as indicated by high ratings. On the 5-point Likert scale, the mean closer to 4.00 means that many students, on average, endorsed "Somewhat Agree" on the questions. Particularly noteworthy is that students perceived GenAI as useful because they are not judged by it (M = 3.97) and because of its anonymity (M = 3.85).

Research Question 3: Student Perception of Readiness, Benefits, and Challenges of Using GenAI for Learning in Higher Education

Descriptive statistics of the perceived readiness, benefits, and challenges associated with using GenAI among students in higher education are shown in Table 6. Results indicate a moderate to high level of readiness, with participants perceiving comprehension (M = 3.71), ethical awareness (M = 3.72), and proficiency in GenAI (M = 3.74). Regarding the perceived benefits, participants also perceived a positive impact of GenAI (M = 3.80) and felt empowered by its capabilities (M = 3.78). While students generally reported feeling comfortable using GenAI tools and recognized their benefits, results indicate moderate concerns (M = 3.40), some perceived negative educational impacts (M = 3.18), and acknowledgment of specific limitations regarding accuracy and sensitivity in GenAI (M = 3.38). Although the overall mean ratings for challenges were lower than readiness and benefits, the ratings still indicate that most students perceive potential negative effects associated with GenAI.

Research Question 4: Differences Across Demographic Groups

Student perceptions regarding using GenAI for their learning were analyzed across different demographic variables, including gender, age, class, enrollment status, employment status, online courses taken, and institution type. First, significant differences in Readiness, Benefits, and Challenges subscales were observed across student classifications (Table 7). Specifically, doctoral students

Table 4 Comfort level of using GenAI

Frequency	Not at all	A little comfortable	Fairly comfortable	Very comfortable
GenAI for general use	4 (0.9%)	84 (18.3%)	272 (59.1%)	100 (21.7%)
GenAI for learning activities or assignments	6 (1.3%)	87 (18.9%)	249 (54.1%)	118 (25.7%)

Table 5 Student perceptions of GenAI as a safe and supportive learning tool

GenAI as a Safe and Supportive Learning Tool	Mean (SD)
GenAI will not judge me, so I feel comfortable with it	3.97 (0.909)
GenAI is useful for student support services due to anonymity	3.85 (0.864)
I can ask questions to GenAI that I would otherwise not ask an instructor	3.82 (0.885)
I am more comfortable receiving feedback from GenAI than an instructor	3.71 (0.891)
Students will need to use GenAI for future careers	3.69 (0.845)

Table 6 Overall readiness, benefits, and challenges for generative AI Use

	N	# of Items	Min	Max	M	SD
Readiness Subscale 1	460	6	1.17	5.00	3.71	0.59
Readiness Subscale 2		3	1.00	5.00	3.72	0.63
Readiness Subscale 3		3	1.00	5.00	3.74	0.66
Benefit Subscale 1	454	8	1.63	5.00	3.80	0.53
Benefit Subscale 2		6	2.00	5.00	3.78	0.55
Challenge Subscale 1	450	5	1.00	5.00	3.40	0.64
Challenge Subscale 2		9	1.11	5.00	3.18	0.74
Challenge Subscale 3		5	1.00	5.00	3.38	0.70

The Readiness scale has three subscale factors: 1) GenAI Comprehension, 2) Ethical Awareness of GenAI, and 3) GenAI Utilization and Proficiency. The Benefit scale has two subscale factors of 1) GenAI Effectiveness and 2) GenAI Empowerment. The Challenge scale includes three subscale factors: 1) GenAI Concerns, 2) Negative Educational Impact of GenAI, and 3) GenAI Limitations (Accuracy and Sensitivity)

Table 7 Significant differences in readiness, benefits, and challenges by class

Scale	Factor	ANOVA/Effect Size (η^2)	Post hoc Tukey Test		
			Group 1 (M)	Group 2 (M)	*P*-value/Effect Size (d)
Readiness	GenAI Comprehension	F(5,443) = 2.826* (0.031)	Freshman (3.57)	Doctorate (4.12)	0.026 (0.843)
	GenAI Utilization & Proficiency	F(5,443) = 2.571* (0.028)	Senior (3.60)	Sophomore (3.93)	0.009 (0.525)
Benefits	Effectiveness	F(5,443) = 2.644* (0.029)	Senior (3.70)	Doctorate (4.09)	0.081 (0.788)
	Empowerment	F(5,443) = 3.667** (0.040)	Senior (3.70)	Sophomore (3.97)	0.013 (0.522)
			Master (3.69)	Sophomore (3.97)	0.008 (0.526)
Challenges	Accuracy and Sensitivity	F(5,443) = 3.780** (0.041)	Master (3.54)	Junior (3.18)	0.002 (0.524)

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

(M = 4.12) tended to perceive themselves as having better GenAI Comprehension than freshmen students (M = 3.57). However, due to the small sample size for doctoral students (n = 14), this finding should be interpreted with caution and replicated in future research to support more valid conclusions. Similarly, sophomore students (M = 3.93) felt more proficient in GenAI Utilization and Proficiency compared to senior students (M = 3.60). Also, Sophomore students (M = 3.97) perceived GenAI as a more promising tool for their education than Senior (M = 3.70) or Master students (M = 3.69). By contrast, Masters (M = 3.54) perceived the Limitations of GenAI to be significantly higher than Junior (M = 3.18) due to its possible inaccuracy and insensitivity.

In addition, employment status showed significant differences in perceived benefits (Table 8). Full-time working students had a lower mean than part-time working students and non-working students on both subscales of the Benefit scale.

Students exhibited differences across different institution types. Specifically, (two-year) technical/community college or university students generally reported a higher level of readiness, perceived GenAI as more beneficial, and expressed fewer concerns than other types of institutions. Similarly, perceived benefits were significantly higher for technical or community colleges or universities. Note that due to the limited sample size for two-year technical or community colleges (N = 5), this group was combined with technical college or university (N = 55). The results reported in Table 9 are based on this merged group.

The results of this study indicate students are actively using GenAI tools in their learning, with a majority indicating occasional to very frequent use. Students generally feel comfortable using GenAI for either general or learning purposes, perceiving these tools as beneficial especially with regard to their anonymity and non-judgmental nature. Analysis of student perceptions of GenAI readiness, benefits, and challenges revealed moderate to high levels of readiness and perceived benefit, but students also expressed moderate concerns, acknowledging potential negative impacts and limitations of GenAI use. Additionally, significant differences were observed across student classifications and employment status. Most notably, doctoral students reported higher levels of GenAI comprehension than undergraduate Freshmen, while Sophomore students indicated feeling more proficient in GenAI utilization in addition to perceiving greater empowerment than their Senior counterparts. Full-time working students reported a lower perceived benefit when compared to part-time and non-working students.

Discussion

This study investigated higher education student use and perceptions of GenAI in education. The findings reveal key insights into whether GenAI use and perceptions amongst higher education students differ across gender, age, class, enrollment status, employment status, the number of online courses taken, and higher education institution type.

Table 8 Significant differences in readiness, benefits, challenges by student status

Scale	Factor	ANOVA/Effect Size (η^2)	Post hoc Tukey Test		
			Group 1 (M)	Group 2 (M)	*p*-value/Effect Size (d)
Benefits	Effectiveness	F(2,446) = 7.840*** (0.034)	Part-time (3.85)	Full-time (3.52)	< 0.001 (0.635)
			Not working (3.84)	Full-time (3.52)	< 0.001 (0.590)
Benefits	Empowerment	F(2,446) = 7.246*** (0.031)	Part-time (3.78)	Full-time (3.52)	0.008 (0.485)
			Not working (3.85)	Full-time (3.52)	< 0.001 (0.635)

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

Table 9 Significant differences in readiness, benefits, challenges by institution type

Scale	Factor	ANOVA/Effect Size (η^2)	Post hoc Tukey Test		
			Group 1 (M)	Group 2 (M)	*p*-value/Effect Size (d)
Readiness	GenAI Comprehension	F(4,437) = 6.232*** (0.054)	Technical (3.95)	For-profit (3.40)	< 0.001 (0.902)
			Technical (3.95)	Private (3.63)	0.006 (0.531)
			For-profit (3.40)	State or public (3.74)	0.012 (0.634)
			For-profit (3.40)	Postgraduate (3.89)	0.011 (0.952)
	Ethical Awareness	F(4,437) = 3.187* (0.028)	Technical (3.94)	For-profit (3.53)	0.033 (0.691)
			Technical (3.95)	Private (3.62)	0.017 (0.513)
	GenAI Utilization & Proficiency	F(4,437) = 5.994*** (0.052)	Technical (4.08)	For-profit (3.53)	0.004 (1.055)
			Technical (4.08)	Private (3.64)	0.003 (0.749)
			Technical (4.08)	State or public (3.74)	0.024 (0.534)
Benefits	Effectiveness	F(4,437) = 4.484*** (0.039)	Technical (3.97)	For-profit (3.59)	0.007 (0.785)
			Technical (3.97)	Private (3.70)	0.013 (0.570)
	Empowerment	F(4,437) = 4.237** (0.037)	Technical (4.04)	Private (3.69)	< 0.001 (0.696)
			Technical (4.04)	State or public (3.78)	0.006 (0.481)
Challenges	Negative Educational Impact	F(4,437) = 4.693*** (0.041)	Technical (2.84)	For-profit (3.32)	0.027 (0.636)
			Technical (2.84)	Private (3.26)	0.005 (0.585)
			Technical (2.84)	State or public (3.23)	0.002 (0.515)

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

Results for our first research question indicate that higher education students in diverse institutional contexts frequently use GenAI for diverse purposes. More than half of the students surveyed reported asking general knowledge questions to GenAI tools. More than 30% of respondents indicated they utilize GenAI to ask technical questions, write technical documents, and carry on a conversation out of curiosity, representing an increase from prior research (Amani et al., 2023) in the use of GenAI tools for general knowledge and technical questions, as well as writing technical documents and carrying on questions out of curiosity. A minuscule percentage of students surveyed (0.7%) indicated that they had not used GenAI for any reason, representing another increase from previous research into the usage and frequency of usage of GenAI amongst students (Lobet et al., 2023; Stöhr et al., 2024; Vogels, 2023; Welding, 2023).

Our second research question investigated students'comfort levels with regard to using GenAI in higher education settings. Greater than 80% of survey respondents felt fairly to very comfortable using GenAI for general purposes, with more than 79% indicating they feel fairly to very comfortable using GenAI in education-specific contexts. Students comfortability in using GenAI tools in both general and education-specific contexts supports the Technology Acceptance Model's concept of perceived ease of use as an adoption determinant, as the natural language processing, conversational nature of these tools facilitate their use (Davis, 1989; Haque et al., 2022).

A closer analysis of our findings revealed that student perceptions of GenAI as a safe and supportive learning tool include preparation for potential future use cases, tightly aligned to the findings of Chan and Zhou (2023), who found attainment value, or the belief that participating in a specific behavior will help the student reach an important outcome, was significantly correlated with student desire to use GenAI for educational purposes. Further echoing the findings of Chan and Zhou (2023), our participants also indicated a strong level of comfort in using GenAI tools because they are not judged by the tool and appreciate the anonymity of use. This judgment free nature may increase their enjoyment in using the tool, a finding that indicates a potential relationship between student use of GenAI in educational settings and the expectancy-value theory of intrinsic value, defined by the enjoyment a student may feel as they perform a task (Chan & Zhou, 2023; Wigfield & Eccles, 2000).

Our results related to the third research question also indicate students generally feel prepared to use GenAI in educational contexts, reflecting findings that GenAI knowledge may also influence intention to use (Chan & Zhou, 2023). Participants also acknowledged GenAI's benefits, which include performance expectancy-related benefits like accomplishing tasks quickly, increasing productivity, and improving learning effectiveness, reflecting similar findings to prior research indicating performance expectancy to be a significant determinant in student use of GenAI tools (Al-Emran et al., 2023; Bonsu & Baffour-Koduah, 2023; Foroughi et al., 2023; Rahim et al., 2022; Raman et al., 2023).

Participants were also aware of the potential challenges of GenAI's integration into higher education, indicating their awareness of the limitations of this technology for educational purposes. These findings are similar to Jo's (2023), who found trust to be a significant determinant in student intention to use GenAI. With diverse factors from data security to perceived intelligence influencing an individual's trust in GenAI tools, reducing trust-related perceived costs might increase student acceptance and use of GenAI, leading multiple researchers to claim that embedding AI literacy within curricula may shape student perceptions of GenAI in a more positive way (Chan & Zhou, 2023; Stöhr et al., 2024).

Our findings relative to our fourth research question revealed differences in student readiness and perceptions of GenAI for education across demographic groups. Results show freshman and sophomore students were more likely to acknowledge GenAI's perceived benefits than senior students, indicating that lower-class students tend to perceive GenAI more positively than senior students. These findings contrast with that of Stöhr et al. (2024), who found that advanced-level students reported greater familiarity and usage than other groups of students.

Employment status also showed significant differences in perceived benefits. Full-time working students had a lower perceived benefit mean than part-time and non-working students. In the context of prior research that indicates the time saving benefits of GenAI as an advantage (Bonsu & Baffour-Koduah, 2023), one might assume full-time students may perceive greater benefit in using GenAI to balance the time demands of employment and student status. However, our research indicates this is not the case, as part-time or non-working students had a greater perceived benefit. This finding may relate to the expectancy-value theory of cost (Wigfield & Eccles, 2000), as students who are employed full-time may not be able to commit the time to gain familiarity with GenAI tools as their part-time or non-employed peers. In essence, full-time working students may prioritize immediate task completion over exploration of new technologies, resulting in a lower perceived usefulness as described by the TAM (Davis, 1989).

Our findings also reveal students from technical colleges generally reported a higher level of readiness, perceived GenAI as more beneficial, and expressed fewer concerns compared to other institution types. Higher positive perceptions amongst technical college students may stem from a tighter alignment of GenAI's use purposes reported in Table 3 (e.g., technical questions, immediate feedback) to the greater career-focused, skills-oriented curricula of technical colleges. From an EVT perspective, students who perceive a higher utility value in GenAI use for their future career may report greater readiness and perceived benefits (Wigfield & Eccles, 2000). Additionally, students enrolled at a technical college may have a stronger baseline of technology familiarity, which may also enhance their acceptance and use (Chocarro et al., 2021; Venkatesh et al., 2003). While perceived benefits were significantly higher for students at two-year technical or community colleges, the small number of participants in that group illustrates a need for caution in making this generalization.

In contradiction to prior research (Martin et al., 2020; Nouraldeen, 2020; Stöhr et al., 2024), no statistically significant difference was found in terms of gender with regard to GenAI readiness or perceptions of benefits and concerns to education in our survey responses. This finding is similar to Strzelecki and ElArabawy's (2024) Polish sample finding but different from their Egyptian sample.

Conclusion and Implications

Our findings revealed that, as of May 2024, GenAI tools are widely used by students across higher education institutional settings, and the number of students who are familiar with and actively using GenAI tools for diverse purposes is growing. Our findings indicate that students recognize several benefits of GenAI in educational settings, including its potential to prepare them for future careers and the judgment-free anonymity these tools provide. However, our findings also reveal significant variation in perceptions of readiness, benefits, and challenges based on higher education students' classification, employment status, and institution type.

These findings yield several implications for practice and research in higher education. First, these results reinforce the claims of prior studies that there is a clear and imminent need to integrate AI literacy into curricula (Chan & Zhou, 2023; Jo, 2023; Stöhr et al., 2024), ensuring students develop the technical, ethical, and critical skills necessary for responsible AI use. As the use of GenAI tools is becoming increasingly prevalent amongst higher education students, it is critical that students not only have knowledge of how these tools operate and the skills to operate them effectively and safely but also that students are capable of critical consideration of the ever-changing practical and ethical implications of the use of these tools in education and other spaces. Educators at all levels will play a pivotal role in developing this knowledge and skills amongst students by designing learning activities that leverage GenAI responsibly.

Second, higher education instructors should recognize that student demographic differences, including employment status, academic level, and institution type, shape their perceptions of GenAI. Tailored supports like workshops, learning modules, or advising interventions can be developed by meet the specific needs that shape the unique perspectives of different students and student groups. For example, part-time or non-traditional students may benefit from targeted resources that scaffold GenAI integration into their learning routines. Higher education faculty members can also integrate assessments and learning activities that not only enable student use of GenAI, but that also require critical reflection on its outputs, limitations, and ethical implications. By seeking to foster a culture of critical consideration rather than blind reliance, faculty can empower students to maximize GenAI's benefits while mitigating risks and concerns.

Furthermore, institutional policies must also evolve to address the ethical concerns present in our findings, from data privacy issues to concerns surrounding academy integrity and potential overreliance on GenAI tools in the future. Institutions must develop clear guidelines for using GenAI in academic settings to enable students to leverage the benefits of these tools while mitigating risks. Still, these policy guidelines must also be responsive to the rapidly evolving nature and capability of GenAI tools, creating a significant and evolving problem of practice facing institutions of higher education daily. In addition to developing clear but responsive policies to address the use of GenAI in education, it is prudent for institutions to offer AI literacy-related training sessions to support faculty and students in navigating the evolving opportunities and challenges GenAI presents.

Our study highlights several opportunities for future research. Given our limitations in diversity amongst our participant groups, specifically the small representation of two-year technical college students as well as doctoral students, future research should aim to include more diverse and larger sample sizes to enhance the generalizability of the findings and provide a more comprehensive understanding of GenAI readiness and perceptions across educational contexts.

Additionally, there is a significant need for longitudinal studies to examine how perceptions of GenAI evolve over time as these tools continue to also evolve and advance in their capabilities. While this study provides a clear picture of student perceptions at a specific moment in time, additional studies, especially those of a longitudinal nature, can build on these findings to further investigate the deeper and evolving meanings behind student use decisions. Furthermore, exploring additional demographic variables, such as socioeconomic status and cultural background, may further illuminate the factors influencing the adoption and use of GenAI for educational purposes. Due to the novelty of these tools at present, future research must also critically evaluate the long-term impact of GenAI tools on learning outcomes, academic performance, and student success to provide insights into how these tools can be effectively and responsibly integrated into educational practices.

Limitations

This study contains several limitations that influence the generalizability of these results. These results feature a small sample size of two-year technical and community college students ($n = 5$), representing 1% of the sampled population, and a small sample size of graduate-level doctoral students ($n = 14$). Additionally, although this study featured participants from 41 states across the United States, only one individual from outside of the United States participated. Future research using this study method or instrument should aim to reach a wider participant population across geographic and institutional settings to increase opportunities for comparison between and across population groups within the sample.

This study also features time limitations that, when considered in the context of a rapidly developing landscape of GenAI technologies, may influence the generalizability and usability of these results over time. The survey for this study was open from March through May of 2024, so the results of this study show a particular snapshot in time of participant experiences and the GenAI technologies at their disposal.

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Data Availability The data for this study are not publicly available. Access to deidentified data may be considered upon direct request to the corresponding author.

Declarations

Ethics Statement Institutional Review Board (IRB) approval was obtained from the researchers' institution. Informed consent was collected from all participants, who were required to select the "Yes, I am a student, and I agree to participate in this study" option in the online survey invitation to partake in the survey.

Conflict of interest The authors declare they have no known financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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