Preprints.org

Article

Not peer-reviewed version

Technology Readiness, Social Influence, and Anxiety as Predictors of University Educators' Perceptions of Generative AI Usefulness and Effectiveness

Malik Sallam *, Ahmad Samed Al-Adwan , Maad M. Mijwil , Doaa H. Abdelaziz , Asmaa Al-Qaisi , Osama Mohamed Ibrahim , Mohammed Sallam

Posted Date: 7 May 2025

doi: 10.20944/preprints202505.0338.v1

Keywords: generative AI; higher education; educational technology; artificial intelligence in education; educational innovation; educational policy

doi:10.20944/preprints202505.0338.v1

Article

Technology Readiness, Social Influence, and Anxiety as Predictors of University Educators' Perceptions of Generative AI Usefulness and Effectiveness

Malik Sallam [1,2,*], Ahmad Samed Al-Adwan [3], Maad M. Mijwil [4,5], Doaa H. Abdelaziz [6,7], Asmaa Al-Qaisi [8], Osama Mohamed Ibrahim [9] and Mohammed Sallam [10,11,12,13]

[1] Department of Pathology, Microbiology and Forensic Medicine, School of Medicine, The University of Jordan, Amman 11942, Jordan
[2] Department of Clinical Laboratories and Forensic Medicine, Jordan University Hospital, Amman 11942, Jordan
[3] Department of Business Technology, Al-Ahliyya Amman University, Amman 19111, Jordan
[4] College of Administration and Economics, Al-Iraqia University, Baghdad 10081, Iraq
[5] Computer Techniques Engineering Department, Baghdad College of Economic Sciences University, Baghdad 10, Iraq
[6] Department of Clinical Pharmacy, Faculty of Pharmacy, Al-Baha University, Al Baha 65779, Saudi Arabia
[7] Department of Clinical Pharmacy, National Hepatology and Tropical Medicine Research Institute, Cairo 11638, Egypt
[8] Department of Dentistry, Jordan University Hospital, Amman 11942, Jordan
[9] Clinical Pharmacy Department, School of Pharmacy, Newgiza University, Giza 12577, Egypt
[10] Department of Pharmacy, Mediclinic Parkview Hospital, Mediclinic Middle East, Dubai P.O. Box 505004, United Arab Emirates
[11] Department of Management, Mediclinic Parkview Hospital, Mediclinic Middle East, Dubai P.O. Box 505004, UAE
[12] Department of Management, School of Business, International American University, Los Angeles, CA 90010, USA
[13] College of Medicine, Mohammed Bin Rashid University of Medicine and Health Sciences (MBRU), Dubai P.O. Box 505055, United Arab Emirates
* Correspondence: malik.sallam@ju.edu.jo; Tel.: +962-79-184-5186

Abstract: Generative Artificial Intelligence (genAI) tools, such as ChatGPT, hold promise for higher education but also raise valid concerns. Critical questions arise regarding university educators' attitudes toward the growing use of genAI in education. This multinational study aimed to examine the determinants of genAI Perceived Usefulness and Effectiveness among educators in Arab universities. The study applied the validated Technology Acceptance Model (TAM)-based theoretical framework using the Ed-TAME-ChatGPT survey instrument. Data were collected using a self-administered structured online questionnaire distributed in November–December 2024 via SurveyMonkey platform. The final sample comprised 685 academics across the Gulf Cooperation Council countries, Levant/Iraq, Egypt/Sudan, and the Maghreb countries. In multivariate analyses, Social Influence ($\beta = 0.445$ and 0.531, $p < 0.001$) and Technology Readiness ($\beta = 0.325$ and 0.314, $p < 0.001$) positively predicted Perceived Usefulness and Effectiveness, respectively, while Anxiety was a negative predictor ($\beta = -0.154$ and -0.088, $p < 0.001$ and $p = 0.007$, respectively). Across demographic and academic factors, Perceived Effectiveness varied by nationality and university location, whereas Perceived Usefulness was associated with academic qualification. This study showed the ubiquitous use of genAI tools especially ChatGPT among university educators in Arab universities and confirmed the validity of the Ed-TAME-ChatGPT instrument. The findings highlighted that effective genAI integration in higher education requires specific policies that enhance technology readiness, promote a culture of peer and institutional support, and address genAI concerns. To compete in the

 doi:10.20944/preprints202505.0338.v1

new AI era, higher education institutions should prioritize faculty-focused strategies that build competence, trust, and ethical, value-based adoption of genAI.

Keywords: generative AI; higher education; educational technology; artificial intelligence in education; educational innovation; educational policy

1. Introduction

In a rapidly evolving era of digital transformation, generative Artificial Intelligence (genAI) tools, exemplified by ChatGPT, are expected to reshape education [1,2]. Universities, which are the longstanding pillars of human intellect are now at a critical juncture, grappling with the dualities of genAI innovation and disruption [3–5]. For university educators, the shift brought about by genAI evokes both the allure of unprecedented opportunities and the disquieting specter of obsolescence [6,7]. Recent reports highlighted the growing uncertainty among university educators regarding genAI adoption, which may carry significant implications for higher education [8,9]. This uncertainty is rooted not merely in technological unfamiliarity and perceived risks but in the very identity and purpose of education itself [10–12].

A primary concern among educators is the perceived threat that genAI poses to their professional roles [13,14]. In higher education, genAI models have the ability to generate coherent course plans, automate students' assessments, and simulate dialogues and feedback [2,8,15,16]. However, these advantages of genAI raise unsettling concerns. There is growing apprehension that the university educator—traditionally seen as the cornerstone of intellectual inquiry—may be rendered superfluous. Budget-conscious institutions might increasingly view genAI as a cost-effective substitute for human expertise. While these fears are understandable, they risk reducing genAI to a narrative of displacement, overlooking its potential for collaborative synergy alongside human educators [17,18].

The second issue represents a deeper existential challenge to university educators, namely the preservation of originality and intellectual integrity in the genAI era [19–21]. The core of academia, built upon the pillars of critical thinking and innovation, faces a new test. GenAI tools with their remarkable ability to generate text, images, and videos, challenge the traditional notions of authorship and creativity [22–24]. In this context, critical concerns emerge. The presence of genAI in classrooms may erode the authenticity of student work, while growing reliance on these tools could diminish the intellectual contributions of educators themselves. These issues strike at the core of academic purpose, demanding a redefinition of how originality is cultivated in an era of ubiquitous genAI [3,17,25].

In higher education, resistance to genAI adoption is often reinforced by tradition—a defining trait of institutions that value historical continuity [26,27]. Thus, university educators —particularly those deeply embedded in established practices— find the leap to integrating novel technologies including genAI in their routine practice a daunting and even threatening task [28–31]. Technological readiness among university educators, though critical, remains far from universal [32–34]. Yet, history demonstrates that resistance to innovation seldom delays its ultimate course [35,36]. From personal computers and internet search engines to smartphones and digital classrooms, higher education has consistently, albeit reluctantly adapted to technological change [37–39]. For educators and institutions ready to embrace the genAI transformation, the opportunities would be both significant and far-reaching as recently highlighted by Kurtz et al. and Dempere et al. [40,41].

Building on the aforementioned points, genAI would inevitably present higher education with transformative tools that challenges traditional pedagogical boundaries and motivate the students to engage in the learning process [42–45]. Far beyond novelty, genAI has the potential to revolutionize teaching, learning, and assessment by automating routine tasks, personalizing education, and enabling innovative instructional methods [7,46,47]. Yet, genAI adoption in higher education remains controversial [48,49]. Concerns about academic integrity, faculty readiness, and equitable access highlight the complexity of this transition [50,51]. Considering the current evidence pointing to widespread adoption of genAI in higher education, particularly among university students, the key question is not whether genAI will reshape the educational landscape, but how effectively universities can successfully integrate it into its policies [52–55]. By drawing on established frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), stakeholders in higher education can anticipate barriers and develop strategies to ensure genAI complements—rather than replaces—the essential role of human educators [56,57].

The rapid rise of genAI tools in higher education, particularly ChatGPT, has been well-documented across multiple studies. By mid-2023, approximately one-quarter of surveyed Arab students in a multinational study reported actively engaging with ChatGPT [58]. This adoption was driven by determinants such as perceived ease of use, perceived usefulness, positive attitudes toward technology, social influence, and minimal anxiety or perceived risks [58]. In the United Arab Emirates (UAE), similar patterns of genAI adoption have emerged, reflecting an emerging norm among university students in Arab countries [59]. Globally, this trend has been corroborated by a multinational study conducted across Brazil, India, Japan, the United Kingdom, and the United States [60]. The widespread use of ChatGPT for university assignments, as reported in several recent studies, indicates a global shift in student behavior that transcends cultural and geographic boundaries [52,61,62].

The growing adoption of genAI by students and educators in higher education calls for rigorous research to assess its impact and inform responsible, ethical, and effective integration [63–65]. GenAI implications extend beyond technological novelty, challenging the very foundations of higher education—learning outcomes, academic integrity, and pedagogical frameworks [8,66]. Thus, the current study aimed to evaluate university educators' attitudes toward genAI. This study employed a TAM-based approach recognizing that genAI adoption is shaped by Perceived Usefulness and Effectiveness [67–69]. This study also sought to confirm the validity of the Ed-TAME-ChatGPT tool, which was specifically developed to assess educators' perspectives on ChatGPT [70]. Conducted in a multinational context, the study aimed to generate broad, generalizable insights to inform higher education policy in both the Arab region and globally.

2. Materials and Methods

2.1. Study Design and Theoretical Framework

This cross-sectional study was conducted from November to December 2024 using the previously validated Ed-TAME-ChatGPT tool [70]. A self-administered questionnaire was distributed through convenience sampling to facilitate rapid data collection. The survey targeted academics in Arab countries, specifically those residing in Egypt, Iraq, Jordan, Kuwait, Saudi Arabia, and the UAE.

The study was theoretically grounded in the Ed-TAME-ChatGPT framework, an education-adapted extension of the TAM, which categorizes predictors of genAI attitude into three interrelated domains: positive enablers, perceived barriers, and contextual traits, with attitudinal outcomes measured as Perceived Usefulness and Perceived Effectiveness [70]. The framework posits that educators' attitudes—specifically Perceived Usefulness and Perceived Effectiveness of genAI—are influenced by four key factors: Technology Readiness, Social Influence, Anxiety, and Perceived Risks.

Guided by Ed-TAME-ChatGPT instrument, the following hypotheses were tested (**Figure 1**):

H1: Technology Readiness positively predicts Perceived Usefulness and Perceived Effectiveness.

H2: Social Influence positively predicts Perceived Usefulness and Perceived Effectiveness.

H3: Anxiety negatively predict Perceived Usefulness and Perceived Effectiveness.

H4: Perceived Risks negatively predict Perceived Usefulness and Perceived Effectiveness.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

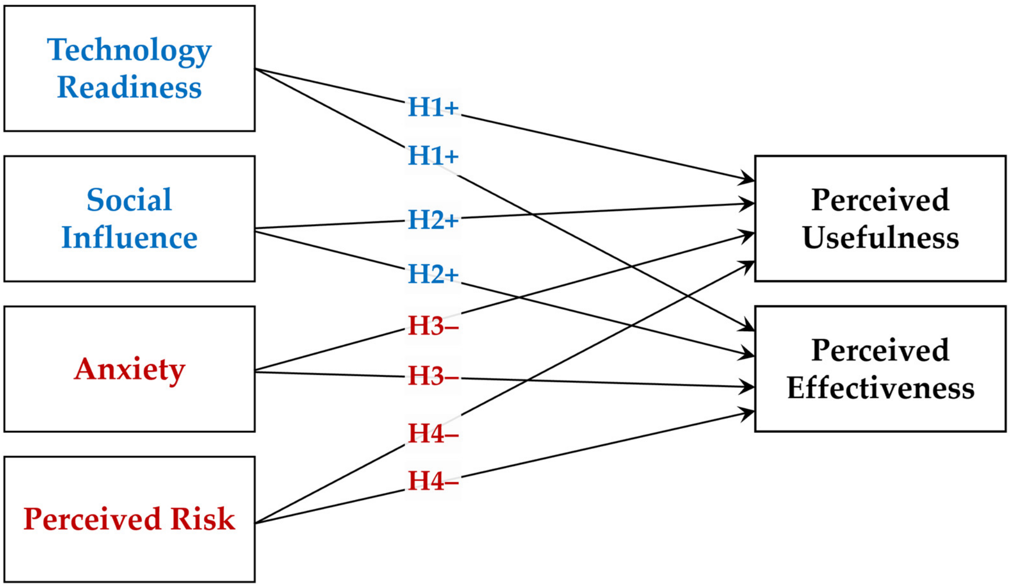

Figure 1. Conceptual Framework of the Study Based on the Ed-TAME-ChatGPT Constructs with Hypothesized Paths. H1+: Technology Readiness positively predicts Perceived Usefulness and Perceived Effectiveness; H2+: Social Influence positively predicts Perceived Usefulness and Perceived Effectiveness; H3–: Anxiety negatively predicts Perceived Usefulness and Perceived Effectiveness; and H4–: Perceived Risk negatively predicts Perceived Usefulness and Perceived Effectiveness. Positive paths are denoted in blue, negative paths in red, with arrows indicating the direction of hypothesized influence.

2.2. Recruitment of Participants, Sample Size Determination, and Ethical Approval

To maximize outreach, we utilized our professional networks and social media platforms, including LinkedIn, WhatsApp, Facebook Messenger, and Telegram for survey link distribution. A snowball sampling approach was employed, encouraging initial participants to distribute the survey link further within their networks, thereby expanding the respondent pool [71]. The survey was hosted on SurveyMonkey (SurveyMonkey Inc., San Mateo, California, USA), with no incentives provided for participation and it was provided concurrently in Arabic and English. For quality control (QC) purposes, the survey access was limited to a single response per IP address, and the duration of survey completion was noted.

Our study design adhered to confirmatory factor analysis (CFA) guidelines which suggest a minimum of 200 participants for sufficient statistical power [72,73]. Given the multinational scope of the study and the variability in educational contexts, a larger target sample of over 500 educators was pursued to enhance the generalizability of the findings.

The survey began with an electronic informed consent form, ensuring participants' understanding of the study objectives and explicit agreement to participate. Ethical approval for the study was obtained from the Institutional Review Board (IRB) of the Deanship of Scientific Research at Al-Ahliyya Amman University, Amman, Jordan, granted on 12 November 2024. IP addresses were removed from the dataset following data collection to maintain participant confidentiality during analysis.

2.3. Introductory Section of the Survey and Demographic Variables' Assessment

The survey began with an introductory section outlining the study objectives and the following eligibility criteria: (1) respondents understood that their answers would remain confidential and their identities anonymous, (2) participants confirmed they were faculty members currently employed at an Arab university, and (3) they voluntarily agreed to participate in the research by completing the questionnaire. Following this introduction, participants were presented with a mandatory electronic informed consent form, which was required before proceeding to the demographic assessment.

Demographic questions assessed participants' characteristics, starting with their age group (25–34, 35–44, 45–54, or 55+ years) and sex (male or female). Nationality was selected from a comprehensive list, including Algerian, Bahraini, Egyptian, Emirati, Iraqi, Jordanian, Kuwaiti, Lebanese, Libyan, Moroccan, Omani, Palestinian, Qatari, Saudi, Sudanese, Tunisian, Yemeni, or "Others" for unlisted nationalities. Participants also identified the country where their university is located, using the same list of options provided for nationality. The countries were later grouped into five categories: Gulf Cooperation Council (GCC) countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE); Levant and Iraq (Iraq, Jordan, Lebanon, and Palestine); Egypt and Sudan; the Maghreb (Algeria, Libya, Morocco, and Tunisia); and Others (Yemen and Others).

Further questions categorized faculty members by discipline (Humanities, Health Sciences, or Scientific disciplines) and university type (Public or Private). Participants indicated their highest academic qualification (Bachelor's degree, Master's or specialization degree, or PhD/doctoral/fellowship degree) and specified whether it was obtained from an Arab or non-Arab country. Lastly, participants were asked to report their current academic rank (Teaching Assistant, Lecturer, Assistant Professor, Associate Professor, or Professor).

2.4. Assessment of genAI Use, Frequency of Use, and Self-Rated Competency

Participants' experiences with genAI were assessed through a structured sequence of questions. Initially, respondents were asked whether they had ever used any genAI tool (Yes/No). If they indicated previous genAI use, they were further asked to specify whether they had used ChatGPT, Microsoft Copilot, Gemini, Llama, My AI on Snapchat, or other genAI tools (Yes/No for each). A composite genAI use score was calculated by summing affirmative responses across these tools, with each "Yes" response contributing 1 point and each "No" contributing 0.

Frequency of genAI use was measured by asking, "How often do you use generative AI tools?" with response options categorized as daily, a few times a week, weekly, or less than weekly. To assess self-rated genAI competency, the participants were asked to rate their proficiency with genAI tools on a four-point scale: very competent, competent, somewhat competent, or not competent. Self-rated genAI competency was dichotomized into competent/very competent versus somewhat competent/not competent, while frequency of genAI use was categorized as daily versus less than daily.

2.5. Ed-TAME-ChatGPT Constructs and Items

The Ed-TAME-ChatGPT tool assessed faculty perspectives across six theoretical constructs using a series of statements rated on a five-point Likert scale (1 = Disagree, 2 = Somewhat Disagree, 3 = Neutral/No Opinion, 4 = Somewhat Agree, 5 = Agree) as outlined by Barakat et al. in [70]. The exact items for each construct were as follows: Perceived Usefulness with five items: (1) I think that ChatGPT is helpful to improve the quality of my academic duties; (2) I think that ChatGPT use would be helpful to increase my research output; (3) I think that ChatGPT would be helpful to find research information more quickly and accurately; (4) I believe that using ChatGPT would enhance the quality of research output; and (5) I think that using ChatGPT would provide me with new insights on my research. Perceived Effectiveness with five items: (1) ChatGPT would be helpful in increasing student engagement with academic tasks; (2) ChatGPT would be helpful in improving the overall quality of education and students' performance; (3) ChatGPT would be helpful in enhancing the creativity in my academic duties; (4) I feel comfortable with the idea of incorporating ChatGPT into my academic duties; and (5) Adopting ChatGPT would efficiently enhance my performance in academic duties.

The Technology Readiness construct comprised five items: (1) I regularly incorporate technology into my research and teaching; (2) I have the habit of staying up to date with the latest technological advancements; (3) I feel comfortable using technology to assist in my academic duties; (4) I am confident in my ability to learn new technologies quickly; and (5) I regularly seek training and resources to improve my technological skills. The Social Influence construct comprised four items: (1) I would adopt ChatGPT if it is recommended by a reputable colleague in my academic field; (2) I

 doi:10.20944/preprints202505.0338.v1

believe that using ChatGPT in research and teaching is an acceptable practice among my academic colleagues; (3) I would be more likely to use ChatGPT if my students express a positive attitude toward it; and (4) I would be more likely to use ChatGPT if it was recommended by my university or college.

The Anxiety construct comprised five items: (1) I fear that ChatGPT would disrupt the traditional methods of research and teaching; (2) I am concerned about the reliability of ChatGPT in research and education; (3) I fear that the use of ChatGPT would lead to errors in my research and academic duties; (4) I am concerned about the potential impact of ChatGPT on the originality of my work; and (5) I am concerned about new ethical issues created by ChatGPT in research and teaching. Finally, the Perceived Risk comprised three items: (1) Adopting ChatGPT could lead to loss of academic jobs or reduced job security for academics; (2) I feel concerned that using ChatGPT would negatively impact the quality of my research and teaching; and (3) I feel concerned about the privacy and security of my data when using ChatGPT.

2.6. Statistical and Data Analysis

Data analysis was conducted using IBM SPSS Statistics for Windows, Version 27.0 (Armonk, NY: IBM Corp.) and JASP software (Version 0.19.0, accessed 9 November 2024) [74]. To validate the structure of the Ed-TAME-ChatGPT scale, an exploratory factor analysis (EFA) was performed using maximum likelihood estimation with Oblimin rotation. Sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) measure, while factorability was confirmed with Bartlett's test of sphericity. A subsequent CFA was conducted to validate the latent factor structure of the scale. Model fit was evaluated using multiple fit indices, including the root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), goodness of fit index (GFI), and the Tucker-Lewis index (TLI). Internal consistency for each Ed-TAME-ChatGPT construct was measured using Cronbach's α, with a threshold of ≥0.60 considered acceptable for reliability [75,76].

Ed-TAME-ChatGPT construct scores were calculated as the average of item scores within each construct, with Agree = 5, Somewhat Agree = 4, Neutral/No Opinion = 3, Somewhat Disagree = 2, and Disagree = 1. Data normality for scale variables was assessed using the Kolmogorov-Smirnov test, which indicated non-normality across all constructs ($p < 0.001$). Consequently, non-parametric tests were applied for univariate analysis, including the Mann-Whitney U test (M-W) and Kruskal-Wallis test (K-W). Categorical variables were compared using the Chi-squared test for associations. To examine the bivariate association between Ed-TAME-ChatGPT constructs, Spearman's rank-order correlation coefficient (ρ) was used [77]. This non-parametric test was selected because the constructs showed non-normal distribution as stated earlier.

To explore the determinants of educators' attitudes toward genAI, specifically Perceived Usefulness and Perceived Effectiveness, univariate analyses were initially conducted to identify candidate predictors based on a significance threshold of $p \leq 0.100$. Multivariate linear regression models were then applied, with the validity of each model confirmed through analysis of variance (ANOVA). Multicollinearity diagnostics were performed using the variance inflation factor (VIF), with a threshold of VIF > 5 indicating potential multicollinearity issues [78]. Statistical significance for all analyses was set at $p < 0.050$.

3. Results

3.1. Description of the Final Study Sample

A total of 887 responses were received, with 881 participants consenting to participate (99.3%). Of these, 772 participants fully completed the survey (87.0%). To ensure data quality, responses from participants who completed the survey in less than 99 seconds (10th percentile, $n = 76$) were excluded, leaving 696 responses deemed fully engaged. Further exclusions were made for inconsistencies in reporting genAI use, resulting in a final sample of 685 participants (77.2% of total responses) as highlighted in (**Figure 2**).

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

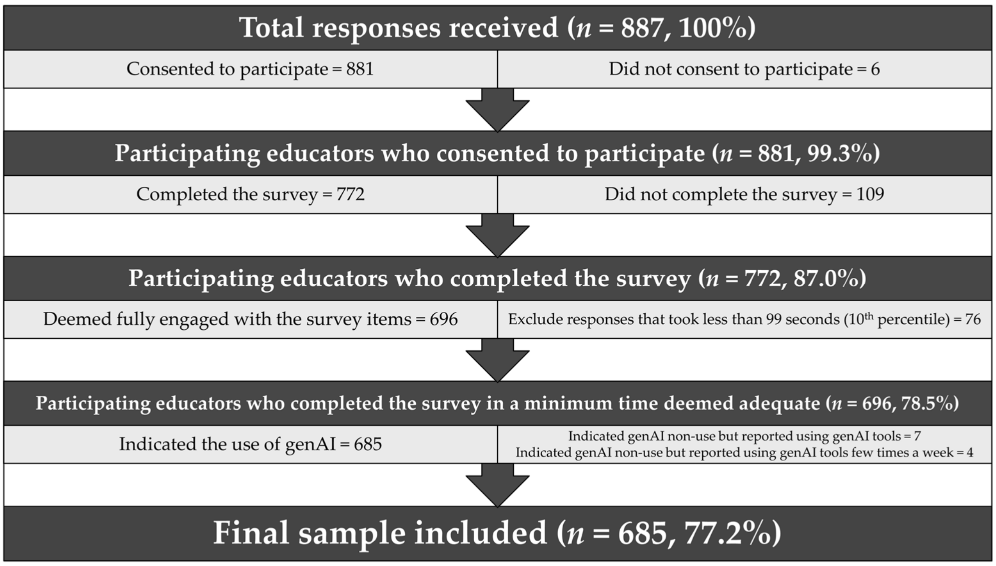

Figure 2. Participant recruitment and quality control (QC) measures implemented. genAI: generative artificial intelligence.

The final study sample consisted of 685 participants with diverse demographic and professional backgrounds. The majority of participants were aged between 35–44 years (30.5%), followed by the 25–34 age group (29.2%), while the 45–54 and 55+ age groups represented 25.8% and 14.5%, respectively. Male participants comprised 58.8% of the sample, while 41.2% were female. Regarding nationality, the largest group represented was from the Levant/Iraq region (43.5%), followed by Egypt/Sudan (25.3%), GCC countries (15.6%), the Maghreb countries (8.8%), and others (6.9%). When asked about the country of their university, 35.9% were affiliated with institutions in the GCC countries, 34.3% in the Levant/Iraq, 19.4% in Egypt/Sudan, 8.6% in Maghreb, and 1.8% in other regions (**Figure 3**).

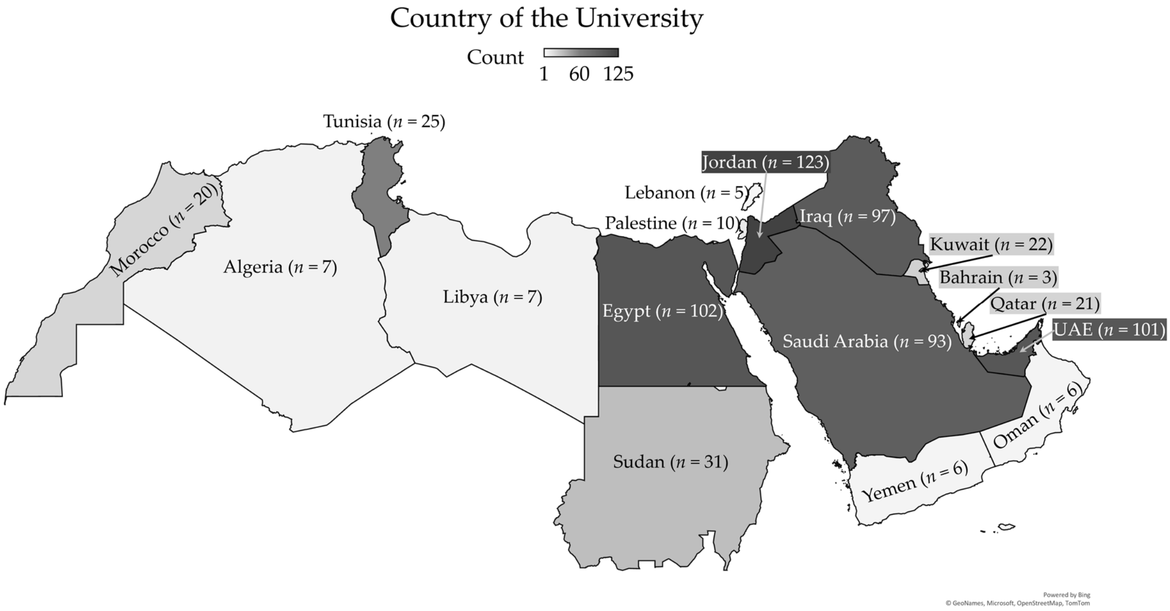

Figure 3. Distribution of study participants based on the country of their university affiliation. UAE: United Arab Emirates. The map was generated in Microsoft Excel, powered by Bing, © GeoNames, Microsoft, OpenStreetMap, TomTom, Wikipedia. We are neutral with regard to jurisdictional claims in this map. The symbols were generated in Microsoft PowerPoint.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

Faculty distribution was skewed towards health sciences, with 65.5% of participants belonging to this category, while scientific disciplines accounted for 17.7% and humanities for 16.8%. Public university educators made up 58.7% of the sample, while 41.3% were from private institutions. The highest academic qualification held by participants was a PhD, doctorate, or fellowship degree (55.3%), followed by a master's or specialization degree (26.7%) and a bachelor's degree (18.0%). Just over half (53.9%) received their highest qualification from an Arab country, while 46.1% obtained it from a non-Arab country. In terms of academic rank, lecturers represented the largest group (25.7%), followed by teaching assistants (23.1%), assistant professors (18.8%), associate professors (18.7%), and professors (13.7%, **Table 1**).

Table 1. Demographic and professional characteristics of the final study sample (*N* = 685).

Variable	Category	Count (%)
Age	25–34 years	200 (29.2)
	35–44 years	209 (30.5)
	45–54 years	177 (25.8)
	55+ years	99 (14.5)
Sex	Male	403 (58.8)
	Female	282 (41.2)
Nationality	GCC [1]	107 (15.6)
	Levant and Iraq	298 (43.5)
	Egypt and Sudan	173 (25.3)
	Maghreb	60 (8.8)
	Others	47 (6.9)
In which country is your university?	GCC	246 (35.9)
	Levant and Iraq	235 (34.3)
	Egypt and Sudan	133 (19.4)
	Maghreb	59 (8.6)
	Others	12 (1.8)
Faculty	Humanities	115 (16.8)
	Health	449 (65.5)
	Scientific	121 (17.7)
Your university is	Public	402 (58.7)
	Private	283 (41.3)
The highest academic qualification	Bachelor's degree	123 (18.0)
	Master's or a specialization degree	183 (26.7)
	PhD, any doctorate, or fellowship degree	379 (55.3)
The country in which you received your highest qualification	Arab country	369 (53.9)
	non-Arab country	316 (46.1)
Current rank	Teaching assistant	158 (23.1)
	Lecturer	176 (25.7)
	Assistant Professor	129 (18.8)
	Associate Professor	128 (18.7)
	Professor	94 (13.7)

[1] GCC: Gulf Cooperation Council countries.

3.2. Frequency of GenAI Use, Self-Rated GenAI Competency and its Associated Factors

The majority of participants (94.9%, *n* = 650) reported prior use of genAI tools, with varying degrees of engagement across different tools. ChatGPT was the most frequently used genAI tool, followed by Microsoft Copilot and Gemini, while lower usage rates were observed for My AI on Snapchat and Llama. The distribution of genAI tools used by participants is illustrated in (**Figure 4**).

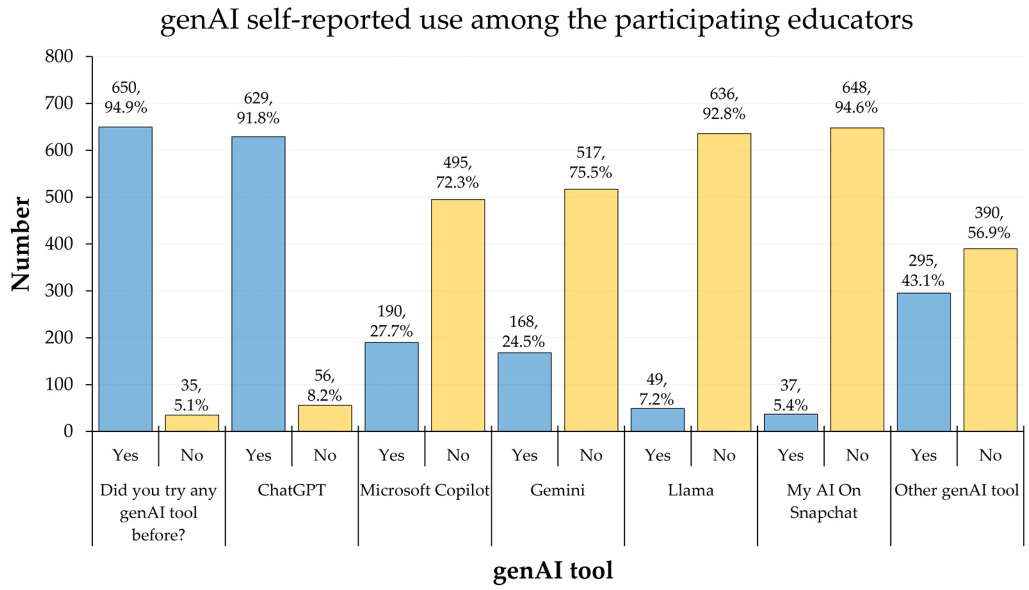

Figure 4. Distribution of generative AI (genAI) tools' used by the participating educators.

The mean genAI use score among participants was 2.00±1.23. Nearly half of the participants (46.0%) reported using genAI tools daily, while 28.2% used them a few times a week, 7.2% weekly, and 18.7% less than weekly. Regarding self-rated competency, 14.0% of participants described themselves as very competent, 28.0% as competent, 52.6% as somewhat competent, and 5.4% as not competent. The frequency of genAI use and the genAI use score varied significantly across multiple demographic and professional categories as shown in (**Table 2**).

Table 2. Factors associated with the frequency of generative AI (genAI) use and genAI use score.

Variable	Category	Frequency of genAI use		*p* value	genAI use score	*p* value
		Daily	Less than daily			
		Count (%)	Count (%)		Mean±SD [2]	
Age	25–34 years	112 (56.0)	88 (44.0)	<0.001	2.17±1.22	0.028
	35–44 years	98 (46.9)	111 (53.1)		1.89±1.07	
	45–54 years	76 (42.9)	101 (57.1)		2.03±1.34	
	55+ years	29 (29.3)	70 (70.7)		1.83±1.33	
Sex	Male	202 (50.1)	201 (49.9)	0.009	2.03±1.27	0.516
	Female	113 (40.1)	169 (59.9)		1.95±1.18	
Nationality	GCC [1]	75 (70.1)	32 (29.9)	<0.001	2.64±1.42	<0.001
	Levant and Iraq	100 (33.6)	198 (66.4)		1.85±1.25	
	Egypt and Sudan	76 (43.9)	97 (56.1)		1.99±1.06	
	Maghreb	42 (70.0)	18 (30.0)		1.90±0.99	
	Others	22 (46.8)	25 (53.2)		1.60±1.06	

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

In which country is your university?	GCC	149 (60.6)	97 (39.4)	<0.001	2.37±1.36	<0.001
	Levant and Iraq	59 (25.1)	176 (74.9)		1.63±1.14	
	Egypt and Sudan	63 (47.4)	70 (52.6)		2.07±1.05	
	Maghreb	41 (69.5)	18 (30.5)		1.85±0.98	
	Others	3 (25.0)	9 (75.0)		1.50±0.90	
Faculty	Humanities	40 (34.8)	75 (65.2)	<0.001	1.69±1.13	0.009
	Health	234 (52.1)	215 (47.9)		2.08±1.23	
	Scientific	41 (33.9)	80 (66.1)		2.00±1.29	
Your university is	Public	167 (41.5)	235 (58.5)	0.005	1.93±1.26	0.029
	Private	148 (52.3)	135 (47.7)		2.10±1.18	
The highest academic qualification	Bachelor's degree	72 (58.5)	51 (41.5)	0.001	2.11±1.26	0.560
	Master's or a specialization degree	90 (49.2)	93 (50.8)		1.90±1.05	
	PhD, any doctorate, or fellowship degree	153 (40.4)	226 (59.6)		2.01±1.30	
The country of the highest qualification	Arab country	176 (47.7)	193 (52.3)	0.332	1.93±1.17	0.203
	non-Arab country	139 (44.0)	177 (56.0)		2.08±1.29	
Current rank	Teaching assistant	82 (51.9)	76 (48.1)	0.007	2.04±1.21	0.193
	Lecturer	79 (44.9)	97 (55.1)		1.93±1.05	
	Assistant Professor	67 (51.9)	62 (48.1)		2.09±1.31	
	Associate Professor	59 (46.1)	69 (53.9)		2.09±1.34	
	Professor	28 (29.8)	66 (70.2)		1.80±1.31	

[1] GCC: Gulf Cooperation Council countries; [2] SD: Standard deviation.

Younger participants, particularly those aged 25–34, reported more frequent daily use (56.0%) and higher genAI use scores (mean = 2.17±1.22) compared to older age groups. Males reported significantly higher daily use compared to females (50.1% vs. 40.1%, $p = 0.009$), though no significant difference was noted in genAI use scores between the sexes ($p = 0.516$). Nationality and university location were significant factors, with participants from GCC countries showing the highest daily use (70.1%) and the highest genAI use score (mean = 2.64±1.42), while the lowest usage was observed among participants from Levant/Iraq ($p < 0.001$ for both).

Faculty-wise, health sciences faculty had the highest daily use (52.1%) and genAI use score (2.08±1.23), while humanities and scientific faculty reported lower usage ($p < 0.001$ for frequency and $p = 0.009$ for genAI score). Participants from private universities showed significantly higher daily use (52.3%) and genAI use scores (2.10±1.18) compared to those from public universities ($p = 0.005$ and $p = 0.029$, respectively). Regarding academic qualifications, participants with a bachelor's degree reported the highest daily use (58.5%) and use score (2.11±1.26), though differences in genAI use scores among qualification groups were not statistically significant ($p = 0.560$). Academic rank was associated with frequency of genAI use, with teaching assistants and assistant professors reporting higher daily use than full professors ($p = 0.007$).

Self-rated genAI competency varied significantly across several demographic and professional factors as shown in (**Table 3**). Younger participants, particularly those aged 25–34 and 35–44, reported higher competency levels compared to older age groups ($p = 0.003$). Nationality significantly influenced competency, with GCC participants reporting higher rates of competency compared to the Maghreb region, where lower rates were observed ($p < 0.001$). Similarly, university location was associated with genAI competency, with GCC-based educators reporting greater proficiency compared to those from Egypt, Sudan, and Maghreb countries ($p < 0.001$). Educators in private universities reported significantly higher competency compared to those in public institutions ($p < 0.001$). Regarding academic qualifications, participants with a master's degree reported the highest competency, while those with a bachelor's degree or PhD reported lower rates ($p = 0.001$). Academic rank also influenced competency, with lecturers and assistant professors reporting the highest self-rated competency, while teaching assistants, associate professors, and full professors reported lower levels of competency ($p = 0.004$, **Table 3**).

Table 3. Factors associated with self-rated generative AI (genAI) competency.

Variable	Category	Self-rated genAI competence		*p* value
		Competent or very competent	Somewhat competent or not competent	
		Count (%)	Count (%)	
Age	25–34 years	91 (45.5)	109 (54.5)	0.003
	35–44 years	104 (49.8)	105 (50.2)	
	45–54 years	61 (34.5)	116 (65.5)	
	55+ years	32 (32.3)	67 (67.7)	
Sex	Male	163 (40.4)	240 (59.6)	0.311
	Female	125 (44.3)	157 (55.7)	
Nationality	GCC [1]	50 (46.7)	57 (53.3)	<0.001
	Levant and Iraq	147 (49.3)	151 (50.7)	
	Egypt and Sudan	63 (36.4)	110 (63.6)	
	Maghreb	7 (11.7)	53 (88.3)	
	Others	21 (44.7)	26 (55.3)	
In which country is your university?	GCC	119 (48.4)	127 (51.6)	<0.001
	Levant and Iraq	119 (50.6)	116 (49.4)	
	Egypt and Sudan	39 (29.3)	94 (70.7)	
	Maghreb	7 (11.9)	52 (88.1)	
	Others	4 (33.3)	8 (66.7)	
Faculty	Humanities	43 (37.4)	72 (62.6)	0.446
	Health	190 (42.3)	259 (57.7)	
	Scientific	55 (45.5)	66 (54.5)	
Your university is	Public	142 (35.3)	260 (64.7)	<0.001
	Private	146 (51.6)	137 (48.4)	
The highest academic qualification	Bachelor's degree	44 (35.8)	79 (64.2)	0.001
	Master's or a specialization degree	99 (54.1)	84 (45.9)	
	PhD, any doctorate, or fellowship degree	145 (38.3)	234 (61.7)	
The country of the highest qualification	Arab country	165 (44.7)	204 (55.3)	0.126
	non-Arab country	123 (38.9)	193 (61.1)	
Current rank	Teaching assistant	59 (37.3)	99 (62.7)	0.004
	Lecturer	93 (52.8)	83 (47.2)	
	Assistant Professor	59 (45.7)	70 (54.3)	
	Associate Professor	44 (34.4)	84 (65.6)	
	Professor	33 (35.1)	61 (64.9)	

[1] GCC: Gulf Cooperation Council countries.

3.3. Confirmation of the Ed-TAME-ChatGPT Scale Reliability

The CFA demonstrated an acceptable fit for the hypothesized six-factor structure of the Ed-TAME-ChatGPT scale. The χ^2 test for the factor model was statistically significant ($\chi^2 = 1195.896$, df =

309, $p < 0.001$), with substantial improvement over the baseline model ($\chi^2 = 11686.246$, df = 351). Fit indices confirmed a good model fit, including a CFI of 0.922, TLI of 0.911, and a RMSEA of 0.065 (90% confidence interval (CI): 0.061–0.069). The SRMR of 0.046 further indicated a good model fit as shown in (**Table 4**).

Table 4. Confirmatory factor analysis results and reliability metrics for the Ed-TAME-ChatGPT scale.

Category	Metric	Value
Chi-Square Test	Baseline model	11686.246 (df = 351)
Chi-Square Test	Factor model	1195.896 (df=309, $p < 0.001$)
Fit Indices	Comparative Fit Index (CFI)	0.922
Fit Indices	Tucker-Lewis Index (TLI)	0.911
Fit Measures	Root Mean Square Error of Approximation (RMSEA) 90% CI [1]	0.065 (0.061 – 0.069)
Fit Measures	Standardized Root Mean Square Residual (SRMR)	0.046
Measures	Goodness of Fit Index (GFI)	0.986
Reliability	Perceived Usefulness	α=0.877
Reliability	Perceived Effectiveness	α=0.892
Reliability	Technology Readiness	α=0.851
Reliability	Social Influence	α=0.817
Reliability	Anxiety	α=0.899
Reliability	Perceived Risk	α=0.695

[1] CI: Confidence interval; df: Degree of freedom.

Sampling adequacy was excellent, as reflected by the KMO measure (0.936), with individual item measures of sampling adequacy (MSA) exceeding 0.85. Bartlett's test of sphericity was significant ($\chi^2 = 11501.427$, df = 351, $p < 0.001$), supporting the suitability of the data for factor analysis. The factor covariances revealed meaningful relationships among constructs. Perceived Usefulness was positively correlated with Perceived Effectiveness (r = 0.828, $p < 0.001$) and Social Influence (r = 0.775, $p < 0.001$) but inversely correlated with Anxiety (r = −0.435, $p < 0.001$) and Perceived Risk (r = −0.402, $p < 0.001$). Technology Readiness showed positive correlations with Perceived Usefulness (r = 0.652, $p < 0.001$) and Perceived Effectiveness (r = 0.676, $p < 0.001$), while negatively correlating with Anxiety (r = −0.293, $p < 0.001$) and Perceived Risk (r = −0.305, $p < 0.001$). Reliability estimates indicated strong internal consistency across the subscales, with Cronbach's α values ranging from 0.695 (Perceived Risk) to 0.899 (Anxiety), supporting the scale's reliability and construct validity as shown in (**Table 4**).

3.4. Predictors of GenAI Perceived Usefulness and Effectiveness in Univariate Analysis

In univariate analyses assessing the role of demographic and academic characteristics in shaping attitudes toward genAI, significant variation was observed in both Perceived Usefulness and Perceived Effectiveness scores. Higher scores on both scales indicated more favorable attitudes. Educators aged 25–44 reported higher Perceived Usefulness (mean: 4.07±0.75 and 4.08±0.66, respectively) and Effectiveness (3.78±0.82 and 3.85±0.76) compared to older age groups ($p < 0.001$). No significant differences were found by sex. Participants from GCC countries and those working at GCC-based universities reported significantly higher scores for both outcomes than peers in other regions. Faculty in health-related fields and those affiliated with private universities showed more favorable attitudes than their counterparts in humanities or public institutions ($p < 0.001$). Educators with a master's or specialization degree and those who obtained their highest qualification from an Arab country reported significantly higher scores than those with doctoral degrees or non-Arab academic credentials ($p < 0.001$). Lastly, junior academic ranks (teaching assistants and lecturers) were associated with more favorable perceptions compared to senior ranks ($p < 0.001$, **Table 5**).

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

Table 5. Univariate analysis of Perceived Usefulness and Effectiveness of generative AI (genAI) among university educators by demographic and academic characteristics.

Variable	Category	Perceived Usefulness		Perceived Effectiveness	
		Mean±SD [2]	*p* value [3]	Mean±SD	*p* value
Age	25–34 years	4.07±0.75	<0.001	3.78±0.82	<0.001
	35–44 years	4.08±0.66		3.85±0.76	
	45–54 years	3.75±0.70		3.48±0.73	
	55+ years	3.76±0.71		3.52±0.77	
Sex	Male	3.95±0.68	0.859	3.68±0.73	0.322
	Female	3.94±0.78		3.70±0.86	
Nationality	GCC [1]	4.06±0.64	0.003	3.76±0.71	0.001
	Levant and Iraq	3.85±0.76		3.63±0.86	
	Egypt and Sudan	4.03±0.74		3.75±0.78	
	Maghreb	3.86±0.48		3.43±0.41	
	Others	4.08±0.77		3.99±0.75	
In which country is your university?	GCC	4.09±0.64	0.003	3.85±0.71	0.003
	Levant and Iraq	3.82±0.78		3.60±0.90	
	Egypt and Sudan	3.96±0.77		3.66±0.77	
	Maghreb	3.85±0.60		3.42±0.53	
	Others	3.77±0.73		3.80±0.57	
Faculty	Humanities	3.67±0.73	<0.001	3.48±0.80	<0.001
	Health	4.04±0.71		3.80±0.78	
	Scientific	3.85±0.70		3.50±0.73	
Your university is	Public	3.83±0.73	<0.001	3.54±0.80	<0.001
	Private	4.11±0.67		3.90±0.72	
The highest academic qualification	Bachelor's degree	4.08±0.67	<0.001	3.71±0.68	<0.001
	Master's or a specialization degree	4.12±0.76		3.95±0.82	
	PhD, any doctorate, or fellowship degree	3.82±0.70		3.56±0.77	
The country of the highest qualification	Arab country	4.03±0.76	<0.001	3.79±0.81	<0.001
	non-Arab country	3.84±0.66		3.57±0.74	
Current rank	Teaching assistant	4.03±0.63	<0.001	3.71±0.68	<0.001
	Lecturer	4.06±0.77		3.89±0.82	
	Assistant Professor	3.93±0.72		3.62±0.85	
	Associate Professor	3.82±0.68		3.57±0.71	
	Professor	3.78±0.78		3.53±0.84	

[1] GCC: Gulf Cooperation Council countries; [2] SD: Standard deviation; [3] *p* value: Calculated using Mann-Whitney and Kruskal-Wallis tests.

Spearman's rank-order correlations revealed significant associations between the Ed-TAME-ChatGPT constructs and both Perceived Usefulness and Perceived Effectiveness of genAI. Technology Readiness was positively correlated with Perceived Usefulness ($\rho = 0.561$, $p < 0.001$) and Effectiveness ($\rho = 0.573$, $p < 0.001$). Similarly, Social Influence showed strong positive correlations with both outcomes ($\rho = 0.605$ and 0.706, respectively; $p < 0.001$). In contrast, Anxiety was negatively correlated with Perceived Usefulness ($\rho = -0.406$, $p < 0.001$) and Perceived Effectiveness ($\rho = -0.345$, $p < 0.001$). Perceived Risk also showed negative associations with both outcomes ($\rho = -0.309$ and -0.280, respectively; $p < 0.001$, **Figure 5**).

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

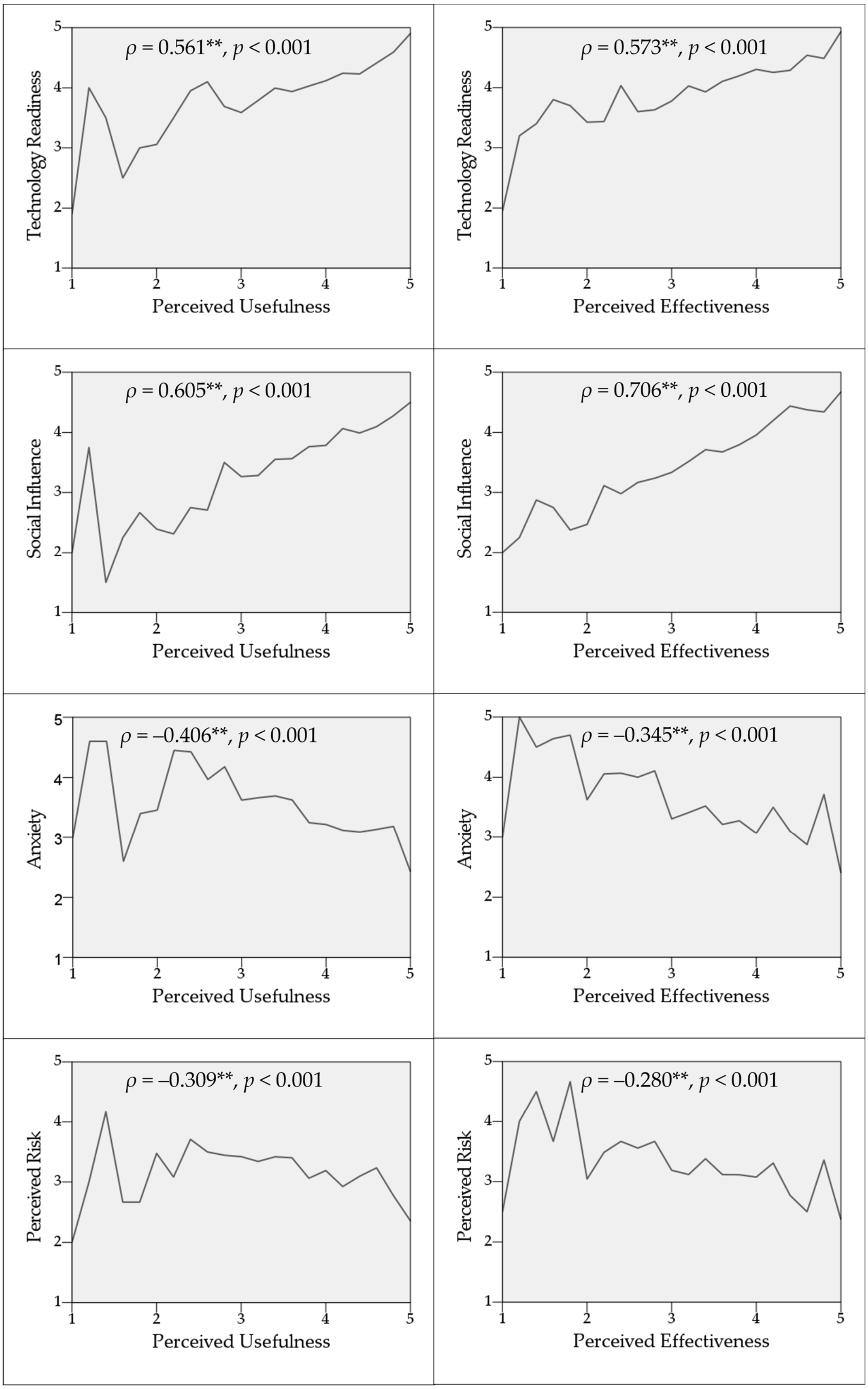

Figure 5. Univariate correlations between Ed-TAME-ChatGPT constructs and Perceived Usefulness and Effectiveness of Generative AI. **Correlation is significant at the 0.01 level (2-tailed).

3.5. Predictors of GenAI Perceived Usefulness and Effectiveness in Multivariate Analysis

In multivariate regression analyses, predictors from the Ed-TAME-ChatGPT framework accounted for substantial variance in educators' attitudes toward genAI, with an R^2 of 0.562 for

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

Perceived Usefulness and 0.647 for Perceived Effectiveness. Social Influence emerged as the strongest positive predictor for both Perceived Usefulness (β = 0.445, $p < 0.001$) and Effectiveness (β = 0.531, $p < 0.001$, **Table 6**). Technology Readiness was also significantly associated with more favorable attitudes (β = 0.325 for Usefulness, β = 0.314 for Effectiveness; $p < 0.001$ for both). Anxiety negatively predicted both outcomes (β = −0.154 and −0.088; $p < 0.001$ and $p = 0.007$, respectively). While Perceived Risk was not a significant predictor of Perceived Usefulness ($p = 0.872$), it approached significance for Perceived Effectiveness ($p = 0.052$, **Table 6**). Among demographic variables, receiving the highest qualification from a non-Arab country predicted lower Perceived Usefulness (β = −0.098, $p = 0.019$), and nationality and university country were significantly associated with Perceived Effectiveness ($p = 0.005$ and $p = 0.013$, respectively, **Table 6**) with higher Perceived Effectiveness in the GCC region and lower scores in the Maghreb. VIFs for all predictors were < 5, indicating no multicollinearity concerns (**Table 6**).

Table 6. Multivariate linear regression analyses predicting Perceived Usefulness and Perceived Effectiveness of generative AI (genAI) among university educators.

Model $R^2 = 0.562$	Unstandardized Coefficients	Standardized Coefficients	*p* value	VIF [2]
Dependent Variable: Perceived Usefulness	**B (95.0% CI [1] for B)**	**β**		
Age	0.008 (−0.044 to 0.061)	0.012	0.753	2.242
Nationality	0.040 (−0.002 to 0.082)	0.059	0.061	1.534
In which country is your university?	−0.037 (−0.080 to 0.007)	−0.052	0.096	1.518
Faculty	0.031 (−0.032 to 0.095)	0.026	0.334	1.071
Your university is	0.027 (−0.055 to 0.109)	0.018	0.516	1.230
The highest academic qualification	−0.091 (−0.168 to −0.015)	−0.098	**0.019**	2.625
The country of the highest qualification	−0.010 (−0.099 to 0.080)	−0.007	0.833	1.528
Current rank	0.009 (−0.039 to 0.058)	0.017	0.709	3.320
Technology Readiness	0.365 (0.300 to 0.430)	0.325	**<0.001**	1.336
Anxiety	−0.124 (−0.181 to −0.067)	−0.154	**<0.001**	2.030
Perceived Risk	−0.005 (−0.065 to 0.055)	−0.006	0.872	1.926
Social Influence	0.469 (0.407 to 0.531)	0.445	**<0.001**	1.364
Model $R^2 = 0.647$	**Unstandardized Coefficients**	**Standardized Coefficients**	***p* value**	**VIF**
Dependent Variable: Perceived Effectiveness	**B (95.0% CI for B)**	**β**		
Age	0.027 (−0.024 to 0.079)	0.035	0.302	2.242
Nationality	0.059 (0.018 to 0.100)	0.081	**0.005**	1.534
In which country is your university?	−0.054 (−0.097 to −0.011)	−0.070	**0.013**	1.518
Faculty	−0.049 (−0.111 to 0.014)	−0.036	0.127	1.071
Your university is	0.074 (−0.006 to 0.154)	0.046	0.068	1.230
The highest academic qualification	−0.024 (−0.099 to 0.050)	−0.024	0.521	2.625
The country of the highest qualification	−0.065 (−0.153 to 0.022)	−0.041	0.144	1.528
Current rank	0.001 (−0.047 to 0.048)	0.001	0.983	3.320
Technology Readiness	0.384 (0.320 to 0.448)	0.314	**<0.001**	1.336
Anxiety	−0.077 (−0.133 to −0.021)	−0.088	**0.007**	2.030
Perceived Risk	−0.058 (−0.116 to 0.001)	−0.062	0.052	1.926
Social Influence	0.611 (0.550 to 0.671)	0.531	**<0.001**	1.364

[1] CI: Confidence interval; [2] VIF: Variance inflation factor. Statistically significant *p* values are highlighted in bold style.

4. Discussion

In this large multinational study of university educators in Arab countries, the Ed-TAME-ChatGPT instrument demonstrated strong construct validity and internal consistency, supporting its use as a theory-driven tool for assessing attitudes toward genAI in higher education. The multivariate

 doi:10.20944/preprints202505.0338.v1

analyses affirmed the theoretical model: Technology Readiness and Social Influence emerged as strong positive predictors of Perceived genAI Usefulness and Effectiveness, while Anxiety was consistently associated with more negative perceptions. These findings reinforce the Ed-TAME-ChatGPT explanatory utility and its consistency with broader TAM-based research on digital innovation in education. The results suggests that Ed-TAME-ChatGPT represents a coherent framework that aligns with established evidence obtained via TAM-based studies for technology acceptance (e.g., using online platform, metaverse, etc.) in education [79–82]. The validated Ed-TAME-ChatGPT framework provides educational institutions with a practical means to benchmark faculty readiness for genAI adoption and to guide targeted interventions that address both enabling factors and barriers. This is especially critical in a context where faculty attitudes, while broadly supportive of genAI tools like ChatGPT, remain shaped by underlying concerns about academic integrity, pedagogical impact, and institutional preparedness [83,84]. These concerns revolve around the absence of clear policies, particularly regarding academic integrity, learning effectiveness, and teaching efficiency, as demonstrated by Jiang et al. analysis of X (formerly Twitter) data [85].

The findings of this study highlighted the ubiquitous adoption of genAI among university faculty in Arab countries. Notably, 95% of the participants in this study reported previous use of genAI tools, with an overwhelming 92% specifically using ChatGPT. This near-universal engagement with genAI tools among university educators marks a profound departure from earlier phases of digital adoption in academia, suggesting not merely a passing interest but an accelerating transformation in the way educators interface with technology. This trend aligns with the growing evidence from diverse educational settings across the globe among the students and educators alike [86–89]. For example, Ogurlu and Mossholder reported that while 67% of educators were aware of ChatGPT in a qualitative study, its use was more limited, reflecting the rapid escalation in both awareness and functional engagement observed in the current study [90]. Similarly, Kiryakova et al. documented widespread ChatGPT adoption among Bulgarian university professors, especially for tasks integral to academic duties, such as grammar correction, translation, transcription, and educational content creation [88]. In Malaysia, Au observed that approximately half of surveyed faculty reported using ChatGPT for academic purposes, further reinforcing the notion that this technological shift is neither isolated nor region-specific [91].

This body of evidence collectively contradicts the prevailing notion that novel technologies such as genAI tools are primarily the domain of students which was shown in various studies in different contexts through the notable work of Strzelecki [52,61,92,93]. While previous studies, including a systematic review by Deng et al. [94], and research from the UAE [59], Jordan [95], Indonesia [96], Nigeria [97], Slovakia, Portugal, and Spain [98], have predominantly documented the adoption of genAI among students for tasks such as academic writing assistance and information synthesis, the present study findings revealed a parallel evolution among faculty. This result highlighted that educators are not merely passive observers of technological shifts but active participants, integrating these tools into their professional routines in line with findings by Al-kfairy and Bhat et al. [99,100].

Perceived Usefulness and Perceived Effectiveness which were the central attitudinal outcomes in this study, both strongly predicted by core constructs of the Ed-TAME-ChatGPT framework. The results of hypothesis testing further affirmed the theoretical model as follows. Technology Readiness (H1) and Social Influence (H2) were consistently and positively associated with both Perceived Usefulness and Effectiveness, while Anxiety (H3) demonstrated significant negative associations. Perceived Risk (H4), while theoretically important, showed weaker and inconsistent effects, emerging as non-significant in the model predicting usefulness and only approaching significance in the effectiveness model.

Consistent with H1, Technology Readiness emerged as a significant positive predictor of both Perceived Usefulness and Perceived Effectiveness. Faculty who reported feeling confident, comfortable, and proactive in using new technologies were more likely to view genAI favorably. This finding aligns with existing literature identifying technology readiness as a key enabler of innovation adoption in academic settings and highlights the importance of institutional investment in digital literacy development [101–103]. Importantly, H1 reinforces the principle that access to technology, when paired with familiarity and self-efficacy, fosters engagement and skill development [104,105]. This is an aspect that should be considered in order to decrease any genAI-related digital divide and improve educational equity as shown by Afzal et al. [106]. Thus, the positive association between Technology Readiness and genAI attitudes emphasizes the crucial role of institutional investment in digital literacy and continuous faculty development [107]. However, it is important to highlight that technology readiness alone does not guarantee advanced technology use but rather basic operational comfort—a distinction that policymakers must consider when designing faculty genAI training programs [108].

Hypothesis 2 was also supported, with Social Influence emerging as the strongest positive predictor of both Perceived Usefulness and Perceived Effectiveness of genAI. These findings underline the important role of perceived normative support in shaping faculty attitudes toward educational innovation and suggest that social context may exert a notable influence on genAI adoption in higher education [109–111]. The prominence of Social Influence in the predictive models highlights the importance of cultivating an institutional culture that visibly supports genAI integration. Strategies such as peer-led professional development, recognition of early adopters, and student engagement initiatives may serve to reinforce the positive view of genAI use as a social norm [112–114].

The findings also supported H3, with Anxiety demonstrating a significant negative association with both Perceived Usefulness and Perceived Effectiveness of genAI. Educators who reported discomfort, uncertainty, or ethical concerns regarding genAI were less likely to perceive it as beneficial. This finding highlights the role of psychological and moral apprehensions as substantive barriers to genAI adoption in academic settings as recently reported among health students in Arab countries [55]. Notably, Anxiety reflects more than technological unfamiliarity; it encompasses deeper concerns related to academic integrity, intellectual displacement, and the erosion of scholarly originality [115,116]. In contrast, H4 in this study, which posited that Perceived Risk such as job displacement, data privacy, and academic quality concerns would negatively influence attitudes toward genAI, was not supported. Perceived Risk did not emerge as a significant predictor of educators' attitudes in the multivariate analysis of Perceived Usefulness or Perceived Effectiveness. These findings suggest that although risk-related concerns are present among educators, they exert limited influence on core attitudinal outcomes once factors such as Social Influence, Anxiety, and Technology Readiness are accounted for. This may indicate that risk perceptions are either normalized within the broader discourse on digital transformation or are outweighed by the perceived benefits of genAI in academic practice.

Interestingly, while nationality and university location significantly predicted Perceived Effectiveness in this study, they did not emerge as significant predictors of Perceived Usefulness. This distinction may reflect the contextual nature of what "Effectiveness" means in practice. While Perceived Usefulness is likely driven by individual-level assessments of productivity and utility—relatively stable across academic cultures—Perceived Effectiveness may be more sensitive to the institutional environment, pedagogical norms, and broader educational infrastructure. For example, faculty working in universities with greater digital integration or institutional endorsement of AI may feel that genAI tools are more effectively implemented, regardless of their personal views on usefulness [117]. Similarly, cultural factors tied to nationality—such as openness to pedagogical innovation, attitudes toward automation, or institutional trust—may influence how educators evaluate genAI's capacity to deliver meaningful educational outcomes [118]. These findings suggest that effectiveness perceptions are not merely individual judgments but are shaped by the academic settings in which educators operate [119]. For example, The GCC region investment in digital transformation strategies, paired with sustained professional development and integration of emerging technologies into educational policy, likely accounts for this higher genAI competency [120–122]. Conversely, regions with lower reported genAI competence may reflect resource limitations, restricted access to training, or a cultural hesitancy toward disruptive technologies

[106,123,124]. These findings highlight the need for regionally customized educational policies, where disparities in technological equity are addressed not through uniform policies but through context-sensitive strategies that prioritize both capacity-building and resource allocation [125].

A noteworthy and somewhat counterintuitive finding in this study was the inverse association between academic qualification level and Perceived Usefulness of genAI. Educators holding a PhD or equivalent consistently rated genAI as less useful than those with a master's or even a bachelor's degree, a trend confirmed in both univariate and multivariate analyses. This pattern may reflect deeper epistemological reservations among doctoral-trained faculty, who often emphasize originality, methodological rigor, and theoretical depth—qualities they may perceive as compromised by AI-generated outputs. Moreover, seasoned academics may be more entrenched in established workflows and less receptive to altering scholarly habits with emerging technologies. In contrast, educators with lower academic ranks may prioritize efficiency, accessibility, and practical enhancement of academic tasks—leading to more favorable appraisals of genAI's usefulness. This distinction suggests that Perceived Usefulness is not merely a function of exposure or competence, but also of disciplinary culture, academic identity, and professional expectations [126].

4.1. Policy Implications and Recommendations

The findings of this study highlight the importance of developing evidence-informed, context-sensitive policies for integrating genAI into higher education. Rather than relying on generalized technology access strategies, institutional responses should prioritize individual faculty readiness, address psychological and ethical barriers, and reduce regional disparities. The significant roles of Technology Readiness, Social Influence, and Anxiety in shaping faculty attitudes toward genAI suggest multiple actionable insights for intervention.

Given that Social Influence emerged as the most powerful predictor of both perceived usefulness and effectiveness of genAI, institutional strategies should prioritize the cultivation of normative support and peer-led momentum. Social Influence in the context of educational technology adoption encompasses perceived endorsement from colleagues, students, and leadership, which can significantly shape individual attitudes and behaviors. This finding aligns with broader theoretical perspectives, including the UTAUT, which positions Social Influence as a key determinant of behavioral intention which should be taken into consideration in educational policies that aim to integrate genAI use as a routine useful practice [111,114,127].

The consistent predictive power of Technology Readiness across both attitudinal outcomes highlights the need to move beyond tool provision and toward structured capacity-building. Institutions should develop targeted, discipline-specific professional development programs that emphasize applied genAI use in teaching, research, and administration. Importantly, these programs should accommodate differing levels of technological fluency. Intergenerational mentorship—pairing digitally fluent early-career academics with senior faculty—could help bridge confidence gaps and normalize genAI use across career stages. Such inclusive strategies are essential for fostering equitable genAI readiness across academic ranks and disciplines [128].

The negative association between Anxiety and both Perceived Usefulness and Effectiveness in this study reinforces the need for clear ethical and pedagogical boundaries around genAI use [129]. Faculty unease—whether tied to intellectual displacement, originality concerns, or fear of losing academic integrity—is not merely reactionary but rooted in legitimate academic concerns [130]. Institutions must therefore craft transparent, enforceable guidelines on acceptable genAI applications in both instruction and scholarship [131]. These guidelines should be co-developed with faculty to ensure they are grounded in academic reality and uphold principles of academic integrity. Topics such as data privacy, authorship, plagiarism detection, and acceptable assistance in assessments should form the core of these frameworks [131].

The finding that nationality and university location predicted Perceived Effectiveness—but not Usefulness—highlights the influence of institutional and regional disparities in infrastructure, genAI integration, and digital culture. Faculty in GCC countries and private universities reported more

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 7 May 2025 doi:10.20944/preprints202505.0338.v1

favorable attitudes, likely due to greater institutional support. To address these structural inequities, policymakers should invest in under-resourced institutions and establish national digital literacy standards that respect local educational systems. Regional collaboration through faculty exchanges, joint training, and academic consortia can further bridge gaps in genAI preparedness and foster equitable adoption across higher education contexts.

4.2. Study Strengths and Limitations

While the current study offered valuable insights into the adoption of genAI among university educators in the Arab region, several limitations must be acknowledged. First, the use of convenience and snowball sampling may have introduced selection bias, as participants were drawn primarily from the authors' professional networks and social media platforms, potentially limiting the representativeness of the broader academic population in Arab universities. Second, the reliance on self-reported data for both genAI frequency of use and genAI competency raises concerns about social desirability bias, where participants may have either overestimated or underestimated their technological proficiency. Third, the cross-sectional design, while useful to get a snapshot of educators attitude to genAI, constrained the ability to assess how attitudes and practices evolve over time with continued exposure to genAI tools. Finally, while the study spanned multiple Arab countries, variations in national education policies, technological infrastructure, and institutional culture may limit the generalizability of the findings beyond the sampled regions.

Despite the aforementioned limitations, the study possesses several notable strengths that reinforce the validity and relevance of its findings. First, the inclusion of a large and diverse sample of university educators across multiple academic disciplines and geographical regions provided a comprehensive snapshot of genAI adoption patterns in Arab universities. Second, the study employed rigorous QC measures, including minimum completion time thresholds and the verification of unique IP addresses, which helped to ensure the integrity of data and participant engagement which addressed caveats in survey studies as reported by Nur et al. [132]. Third, the use of the validated Ed-TAME-ChatGPT scale, a psychometrically valid instrument, ensured strong construct validity and internal consistency, enhancing the methodological robustness of our study. Finally, the exploration of multiple demographic, professional, and institutional predictors helped to provide actionable insights for policy development and faculty support strategies. These strengths ensured that the findings remain highly relevant for policymakers, academic leaders, and institutional decision-makers in the attempt to address the challenges of genAI successful integration in higher education.

5. Conclusions

This multinational study among university educators in Arab countries provides strong empirical support for the Ed-TAME-ChatGPT framework in understanding attitudes toward genAI. Technology Readiness and Social Influence significantly and positively predicted both Perceived Usefulness and Perceived Effectiveness, while Anxiety demonstrated significant negative associations. The findings highlight that the adoption of genAI in higher education is shaped not by passive exposure to new technologies, but by a rational evaluation of their academic utility, embedded within a social and institutional context. Faculty perceptions are strongly influenced by peer norms and institutional culture—making Social Influence the most powerful driver—as well as by their own digital readiness and psychological comfort with emerging tools. These insights underline the need for higher education institutions to move beyond access-based policies and instead implement targeted, evidence-based strategies that build digital competence, foster inclusive dialogues around ethical use, and cultivate supportive academic environments. The integration of genAI must be guided by policies that reflect both empirical realities and academic values—ensuring that innovation enhances, rather than disrupts, the integrity and equity of higher education systems.

 doi:10.20944/preprints202505.0338.v1

Author Contributions: Conceptualization, Malik Sallam; methodology, Malik Sallam, Ahmad Samed Al-Adwan, Maad M. Mijwil, Doaa H. Abdelaziz, Asmaa Al-Qaisi, Osama Mohamed Ibrahim, Mohammed Sallam; software, Malik Sallam; validation, Malik Sallam, Ahmad Samed Al-Adwan and Mohammed Sallam; formal analysis, Malik Sallam; investigation, Malik Sallam, Ahmad Samed Al-Adwan, Maad M. Mijwil, Doaa H. Abdelaziz, Asmaa Al-Qaisi, Osama Mohamed Ibrahim, Mohammed Sallam; resources, Malik Sallam; data curation, Malik Sallam, Ahmad Samed Al-Adwan, Maad M. Mijwil, Doaa H. Abdelaziz, Asmaa Al-Qaisi, Osama Mohamed Ibrahim, Mohammed Sallam; writing—original draft preparation, Malik Sallam; writing—review and editing, Malik Sallam, Ahmad Samed Al-Adwan, Maad M. Mijwil, Doaa H. Abdelaziz, Asmaa Al-Qaisi, Osama Mohamed Ibrahim, Mohammed Sallam; visualization, Malik Sallam; supervision, Malik Sallam; project administration, Malik Sallam. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (IRB) of the Deanship of Scientific Research at Al-Ahliyya Amman University, Amman, Jordan, granted on 12 November 2024.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original data presented in the study are openly available in public data tool Open Science Framework (OSF) at https://osf.io/jm9ap/; DOI: 10.17605/OSF.IO/JM9AP.

Acknowledgments: We are deeply thankful for Kholoud Al-Mahzoum, Haya Alaraji, and Noor Alhaider for their help in survey distribution. This study used ChatGPT-4o for language refinement (improving grammar, sentence structure, and readability of the manuscript). We confirm that all AI-assisted processes were critically reviewed by the authors to ensure the integrity and reliability of the results. The final decisions and interpretations presented in this article were solely made by the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ANOVA	Analysis of variance
CFA	Confirmatory factor analysis
CI	Confidence interval
Ed-TAME-ChatGPT	Educators attitude to ChatGPT through Edited Technology Acceptance Model
EFA	Exploratory factor analysis
GCC	Gulf Cooperation Council
GFI	Goodness of fit index
genAI	Generative artificial intelligence
KMO	Kaiser-Meyer-Olkin
K-W	Kruskal-Wallis test
MSA	Measure of sampling adequacy
M-W	Mann-Whitney *U* test
QC	Quality Control
RMSEA	Root mean square error of approximation
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TLI	Tucker-Lewis index
UAE	United Arab Emirates
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance inflation factor

References

1. Bhullar, P.S.; Joshi, M.; Chugh, R. ChatGPT in higher education - a synthesis of the literature and a future research agenda. *Education and Information Technologies* **2024**, *29*, 21501-21522, doi:10.1007/s10639-024-12723-x.
2. Alfirević, N.; Rendulić, D.; Fošner, M.; Fošner, A. Educational Roles and Scenarios for Large Language Models: An Ethnographic Research Study of Artificial Intelligence. *Informatics* **2024**, *11*, 78, doi:10.3390/informatics11040078.
3. Luo, J. A critical review of GenAI policies in higher education assessment: a call to reconsider the "originality" of students' work. *Assessment & Evaluation in Higher Education* **2024**, *49*, 651-664, doi:10.1080/02602938.2024.2309963.
4. Farrokhnia, M.; Banihashem, S.K.; Noroozi, O.; Wals, A. A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International* **2024**, *61*, 460-474, doi:10.1080/14703297.2023.2195846.
5. Sallam, M.; Al-Mahzoum, K.; Sallam, M.; Mijwil, M.M. DeepSeek: Is it the End of Generative AI Monopoly or the Mark of the Impending Doomsday? *Mesopotamian Journal of Big Data* **2025**, *2025*, 26-34, doi:10.58496/MJBD/2025/002.
6. Strzelecki, A.; Cicha, K.; Rizun, M.; Rutecka, P. Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies* **2024**, *29*, 22943-22968, doi:10.1007/s10639-024-12765-1.
7. Sallam, M. ChatGPT Utility in Healthcare Education, Research, and Practice: Systematic Review on the Promising Perspectives and Valid Concerns. *Healthcare (Basel)* **2023**, *11*, 887, doi:10.3390/healthcare11060887.
8. Yusuf, A.; Pervin, N.; Román-González, M. Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education* **2024**, *21*, 21, doi:10.1186/s41239-024-00453-6.
9. Yilmaz, R.; Karaoglan Yilmaz, F.G. The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence* **2023**, *4*, 100147, doi:10.1016/j.caeai.2023.100147.
10. Bouchard, J. ChatGPT and the separation between knowledge and knower. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-13249-y.
11. Wang, H.; Dang, A.; Wu, Z.; Mac, S. Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence* **2024**, *7*, 100326, doi:10.1016/j.caeai.2024.100326.
12. Menon, D.; Shilpa, K. "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. *Heliyon* **2023**, *9*, e20962, doi:10.1016/j.heliyon.2023.e20962.
13. Bearman, M.; Ryan, J.; Ajjawi, R. Discourses of artificial intelligence in higher education: a critical literature review. *Higher Education* **2023**, *86*, 369-385, doi:10.1007/s10734-022-00937-2.
14. Şimşek, N. Integration of ChatGPT in mathematical story-focused 5E lesson planning: Teachers and pre-service teachers' interactions with ChatGPT. *Education and Information Technologies* **2025**, doi:10.1007/s10639-024-13258-x.
15. Davis, R.O.; Lee, Y.J. Prompt: ChatGPT, Create My Course, Please! *Education Sciences* **2024**, *14*, 24, doi:10.3390/educsci14010024.
16. Law, L. Application of generative artificial intelligence (GenAI) in language teaching and learning: A scoping literature review. *Computers and Education Open* **2024**, *6*, 100174, doi:10.1016/j.caeo.2024.100174.
17. Bozkurt, A.; Xiao, J.; Farrow, R.; Bai, J.Y.H.; Nerantzi, C.; Moore, S.; Dron, J.; Stracke, C.M.; Singh, L.; Crompton, H.; et al. The Manifesto for Teaching and Learning in a Time of Generative AI: A Critical Collective Stance to Better Navigate the Future. *Open Praxis* **2024**, *16*, 487–513, doi:10.55982/openpraxis.16.4.777.
18. Capraro, V.; Lentsch, A.; Acemoglu, D.; Akgun, S.; Akhmedova, A.; Bilancini, E.; Bonnefon, J.-F.; Brañas-Garza, P.; Butera, L.; Douglas, K.M.; et al. The impact of generative artificial intelligence on socioeconomic inequalities and policy making. *PNAS Nexus* **2024**, *3*, pgae191, doi:10.1093/pnasnexus/pgae191.
19. Preiksaitis, C.; Rose, C. Opportunities, Challenges, and Future Directions of Generative Artificial Intelligence in Medical Education: Scoping Review. *JMIR Med Educ* **2023**, *9*, e48785, doi:10.2196/48785.

20. Lane, S.H.; Haley, T.; Brackney, D.E. Tool or Tyrant: Guiding and Guarding Generative Artificial Intelligence Use in Nursing Education. *Creat Nurs* **2024**, *30*, 125-132, doi:10.1177/10784535241247094.
21. Tan, M.J.T.; Maravilla, N. Shaping integrity: why generative artificial intelligence does not have to undermine education. *Front Artif Intell* **2024**, *7*, 1471224, doi:10.3389/frai.2024.1471224.
22. Creely, E.; Blannin, J. Creative partnerships with generative AI. Possibilities for education and beyond. *Thinking Skills and Creativity* **2025**, *56*, 101727, doi:10.1016/j.tsc.2024.101727.
23. Haase, J.; Hanel, P.H.P. Artificial muses: Generative artificial intelligence chatbots have risen to human-level creativity. *Journal of Creativity* **2023**, *33*, 100066, doi:10.1016/j.yjoc.2023.100066.
24. Caldwell, M. What Is an" Author"?-Copyright Authorship of AI Art through a Philosophical Lens. *Hous. L. Rev.* **2023**, *61*, 411, doi:N.A. Available from: https://houstonlawreview.org/article/92132-what-is-an-author-copyright-authorship-of-ai-art-through-a-philosophical-lens.
25. Kostanek, E.; Nagaraju, R.A.; Michalska, A. The British Battle for Authenticity: Defending Academic Integrity in the Age of AI. In *Academic Integrity in the Age of Artificial Intelligence*, Mahmud, S., Ed.; IGI Global: Hershey, PA, USA, 2024; pp. 21-40, doi:10.4018/979-8-3693-0240-8.ch002.
26. Martin, M.; Moriuchi, E.; Smith, R.; Moeder, J.D.; Nichols, C. The importance of university traditions and rituals in building alumni brand communities and loyalty. *Academy of Marketing Studies Journal* **2015**, *19*, 107-118, doi:NA. Available from: https://scholars.fhsu.edu/appliedbusiness_facpubs/2/.
27. Watermeyer, R.; Lanclos, D.; Phipps, L.; Shapiro, H.; Guizzo, D.; Knight, C. Academics' Weak(ening) Resistance to Generative AI: The Cause and Cost of Prestige? *Postdigital Science and Education* **2024**, doi:10.1007/s42438-024-00524-x.
28. Yu, H. Reflection on whether Chat GPT should be banned by academia from the perspective of education and teaching. *Front Psychol* **2023**, *14*, 1181712, doi:10.3389/fpsyg.2023.1181712.
29. Moerschell, L. Resistance to Technological Change in Academia. *Current Issues in Education* **2009**, *11*, doi:NA. Available from: http://cie.asu.edu/volume11/number6.
30. Gratz, E.; Looney, L. Faculty Resistance to Change: An Examination of Motivators and Barriers to Teaching Online in Higher Education. *International Journal of Online Pedagogy and Course Design* **2020**, *10*, 1-14, doi:10.4018/IJOPCD.2020010101.
31. Singh, H.; Singh, P.; Sharma, D. Faculty acceptance of virtual teaching platforms for online teaching: Moderating role of resistance to change. *Australasian Journal of Educational Technology* **2023**, *39*, 33-50, doi:10.14742/ajet.7529.
32. Bayaga, A.; Bossé, M.J.; Sevier, J.; Fountain, C.; Williams, D.; Bosire, S.; Blignaut, S. University Faculty Opinions of Preservice Teachers' Technological Readiness. *Canadian Journal of Science, Mathematics and Technology Education* **2021**, *21*, 44-64, doi:10.1007/s42330-021-00138-6.
33. El Alfy, S.; Gómez, J.M.; Ivanov, D. Exploring instructors' technology readiness, attitudes and behavioral intentions towards e-learning technologies in Egypt and United Arab Emirates. *Education and Information Technologies* **2017**, *22*, 2605-2627, doi:10.1007/s10639-016-9562-1.
34. Lloyd, S.; McCoy, T.; Byrne, M. Faculty perceived barriers to online education. *MERLOT Journal of Online Learning and Teaching* **2012**, *8*, 1-12, doi:NA. Available from: https://jolt.merlot.org/vol8no1/lloyd_0312.pdf.
35. Trouche, L. Calculators in Mathematics Education: A Rapid Evolution of Tools, with Differential Effects. In *The Didactical Challenge of Symbolic Calculators: Turning a Computational Device into a Mathematical Instrument*, Guin, D., Ruthven, K., Trouche, L., Eds.; Springer US: Boston, MA, 2005; pp. 9-39, doi:10.1007/0-387-23435-7_2.
36. Shehata, B.; Tlili, A.; Huang, R.; Hodges, C.B.; Kanwar, A. Implications and Challenges of Technology Adoption in Education: A 20-Year Analysis of Horizon Reports. *TechTrends* **2024**, doi:10.1007/s11528-024-01027-z.
37. Marshall, S.; Blaj-Ward, L.; Dreamson, N.; Nyanjom, J.; Bertuol, M.T. The reshaping of higher education: technological impacts, pedagogical change, and future projections. *Higher Education Research & Development* **2024**, *43*, 521-541, doi:10.1080/07294360.2024.2329393.
38. Sitar-Tăut, D.-A.; Mican, D.; Moisescu, O.-I. To be (online) or not to be? The antecedents of online study propensity and e-learning-dependent dropout intention in higher education. *Technological Forecasting and Social Change* **2024**, *207*, 123566, doi:10.1016/j.techfore.2024.123566.

39. Westberry, N.; McNaughton, S.; Billot, J.; Gaeta, H. Resituation or resistance? Higher education teachers' adaptations to technological change. *Technology, Pedagogy and Education* **2015**, *24*, 101-116, doi:10.1080/1475939X.2013.869509.
40. Kurtz, G.; Amzalag, M.; Shaked, N.; Zaguri, Y.; Kohen-Vacs, D.; Gal, E.; Zailer, G.; Barak-Medina, E. Strategies for Integrating Generative AI into Higher Education: Navigating Challenges and Leveraging Opportunities. *Education Sciences* **2024**, *14*, 503, doi:10.3390/educsci14050503.
41. Dempere, J.; Modugu, K.; Hesham, A.; Ramasamy, L.K. The impact of ChatGPT on higher education. *Frontiers in Education* **2023**, *8*, 1206936, doi:10.3389/feduc.2023.1206936.
42. Giannakos, M.; Azevedo, R.; Brusilovsky, P.; Cukurova, M.; Dimitriadis, Y.; Hernandez-Leo, D.; Järvelä, S.; Mavrikis, M.; Rienties, B. The promise and challenges of generative AI in education. *Behaviour & Information Technology* **2024**, 1-27, doi:10.1080/0144929X.2024.2394886.
43. Granić, A. Educational Technology Adoption: A systematic review. *Education and Information Technologies* **2022**, *27*, 9725-9744, doi:10.1007/s10639-022-10951-7.
44. Mohamed, A.M.; Shaaban, T.S.; Bakry, S.H.; Guillén-Gámez, F.D.; Strzelecki, A. Empowering the Faculty of Education Students: Applying AI's Potential for Motivating and Enhancing Learning. *Innovative Higher Education* **2024**, doi:10.1007/s10755-024-09747-z.
45. Jose, E.M.K.; Prasanna, A.; Kushwaha, B.P.; Das, M. Can generative AI motivate management students? The role of perceived value and information literacy. *The International Journal of Management Education* **2024**, *22*, 101082, doi:10.1016/j.ijme.2024.101082.
46. Sallam, M.; Salim, N.A.; Barakat, M.; Al-Tammemi, A.B. ChatGPT applications in medical, dental, pharmacy, and public health education: A descriptive study highlighting the advantages and limitations. *Narra J* **2023**, *3*, e103, doi:10.52225/narra.v3i1.103.
47. Omran Zailuddin, M.F.N.; Nik Harun, N.A.; Abdul Rahim, H.A.; Kamaruzaman, A.F.; Berahim, M.H.; Harun, M.H.; Ibrahim, Y. Redefining creative education: a case study analysis of AI in design courses. *Journal of Research in Innovative Teaching & Learning* **2024**, *17*, 282-296, doi:10.1108/JRIT-01-2024-0019.
48. Khlaif, Z.N.; Ayyoub, A.; Hamamra, B.; Bensalem, E.; Mitwally, M.A.A.; Ayyoub, A.; Hattab, M.K.; Shadid, F. University Teachers' Views on the Adoption and Integration of Generative AI Tools for Student Assessment in Higher Education. *Education Sciences* **2024**, *14*, 1090, doi:10.3390/educsci14101090.
49. Hasanein, A.M.; Sobaih, A.E.E. Drivers and Consequences of ChatGPT Use in Higher Education: Key Stakeholder Perspectives. *Eur J Investig Health Psychol Educ* **2023**, *13*, 2599-2614, doi:10.3390/ejihpe13110181.
50. Chan, C.K.Y. A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education* **2023**, *20*, 38, doi:10.1186/s41239-023-00408-3.
51. Currie, G.M. Academic integrity and artificial intelligence: is ChatGPT hype, hero or heresy? *Seminars in Nuclear Medicine* **2023**, *53*, 719-730, doi:10.1053/j.semnuclmed.2023.04.008.
52. Strzelecki, A. To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments* **2024**, *32*, 5142-5155, doi:10.1080/10494820.2023.2209881.
53. Sallam, M.; Al-Mahzoum, K.; Almutairi, Y.M.; Alaqeel, O.; Abu Salami, A.; Almutairi, Z.E.; Alsarraf, A.N.; Barakat, M. Anxiety among Medical Students Regarding Generative Artificial Intelligence Models: A Pilot Descriptive Study. *International Medical Education* **2024**, *3*, 406-425, doi:10.3390/ime3040031.
54. Alotaibi, N.S. The Impact of AI and LMS Integration on the Future of Higher Education: Opportunities, Challenges, and Strategies for Transformation. *Sustainability* **2024**, *16*, 10357, doi:10.3390/su162310357.
55. Sallam, M.; Al-Mahzoum, K.; Alaraji, H.; Albayati, N.; Alenzei, S.; AlFarhan, F.; Alkandari, A.; Alkhaldi, S.; Alhaider, N.; Al-Zubaidi, D.; et al. Apprehension toward generative artificial intelligence in healthcare: a multinational study among health sciences students. *Frontiers in Education* **2025**, *10*, 1542769, doi:10.3389/feduc.2025.1542769.
56. Wang, K.; Ruan, Q.; Zhang, X.; Fu, C.; Duan, B. Pre-Service Teachers' GenAI Anxiety, Technology Self-Efficacy, and TPACK: Their Structural Relations with Behavioral Intention to Design GenAI-Assisted Teaching. *Behavioral Sciences* **2024**, *14*, 373, doi:10.3390/bs14050373.

57. Kong, S.C.; Yang, Y.; Hou, C. Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model. *Computers and Education: Artificial Intelligence* **2024**, *7*, 100328, doi:10.1016/j.caeai.2024.100328.
58. Abdaljaleel, M.; Barakat, M.; Alsanafi, M.; Salim, N.A.; Abazid, H.; Malaeb, D.; Mohammed, A.H.; Hassan, B.A.R.; Wayyes, A.M.; Farhan, S.S.; et al. A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. *Scientific Reports* **2024**, *14*, 1983, doi:10.1038/s41598-024-52549-8.
59. Sallam, M.; Elsayed, W.; Al-Shorbagy, M.; Barakat, M.; El Khatib, S.; Ghach, W.; Alwan, N.; Hallit, S.; Malaeb, D. ChatGPT usage and attitudes are driven by perceptions of usefulness, ease of use, risks, and psycho-social impact: a study among university students in the UAE. *Frontiers in Education* **2024**, *9*, 1414758, doi:10.3389/feduc.2024.1414758.
60. Ibrahim, H.; Liu, F.; Asim, R.; Battu, B.; Benabderrahmane, S.; Alhafni, B.; Adnan, W.; Alhanai, T.; AlShebli, B.; Baghdadi, R.; et al. Perception, performance, and detectability of conversational artificial intelligence across 32 university courses. *Sci Rep* **2023**, *13*, 12187, doi:10.1038/s41598-023-38964-3.
61. Strzelecki, A. Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education* **2024**, *49*, 223-245, doi:10.1007/s10755-023-09686-1.
62. Mansour, T.; Wong, J. Enhancing fieldwork readiness in occupational therapy students with generative AI. *Front Med (Lausanne)* **2024**, *11*, 1485325, doi:10.3389/fmed.2024.1485325.
63. Abrahams, D.A. Technology adoption in higher education: a framework for identifying and prioritising issues and barriers to adoption of instructional technology. *Journal of Applied Research in Higher Education* **2010**, *2*, 34-49, doi:10.1108/17581184201000012.
64. Gammoh, L.A. ChatGPT risks in academia: Examining university educators' challenges in Jordan. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-13009-y.
65. Monib, W.K.; Qazi, A.; Mahmud, M.M. Exploring learners' experiences and perceptions of ChatGPT as a learning tool in higher education. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-13065-4.
66. Van Wyk, M.M.; Adarkwah, M.A.; Amponsah, S. Why All the Hype about ChatGPT? Academics' Views of a Chat-based Conversational Learning Strategy at an Open Distance e-Learning Institution. *Open Praxis* **2023**, *15*, 214-255, doi:10.55982/openpraxis.15.3.563.
67. Liu, Q.; Geertshuis, S.; Grainger, R. Understanding academics' adoption of learning technologies: A systematic review. *Computers & Education* **2020**, *151*, 103857, doi:10.1016/j.compedu.2020.103857.
68. Creswell, J.; Guetterman, T. *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research, 6th Edition*; 2018.
69. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly* **1989**, *13*, 319-340, doi:10.2307/249008.
70. Barakat, M.; Salim, N.A.; Sallam, M. University Educators Perspectives on ChatGPT: A Technology Acceptance Model-Based Study. *Open Praxis* **2025**, *17*, 129–144, doi:10.55982/openpraxis.17.1.718.
71. Johnson, T.P. Snowball Sampling: Introduction. In *Wiley StatsRef: Statistics Reference Online*; 2014, doi:10.1002/9781118445112.stat05720.
72. Mundfrom, D.J.; Shaw, D.G.; Ke, T.L. Minimum Sample Size Recommendations for Conducting Factor Analyses. *International Journal of Testing* **2005**, *5*, 159-168, doi:10.1207/s15327574ijt0502_4.
73. Koran, J. Preliminary Proactive Sample Size Determination for Confirmatory Factor Analysis Models. *Measurement and Evaluation in Counseling and Development* **2016**, *49*, 296-308, doi:10.1177/0748175616664012.
74. Jasp Team. JASP (Version 0.19.0) [Computer Software]. Available online: https://jasp-stats.org/ (accessed on 9 November 2024).
75. Taber, K.S. The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education* **2018**, *48*, 1273-1296, doi:10.1007/s11165-016-9602-2.
76. Tavakol, M.; Dennick, R. Making sense of Cronbach's alpha. *Int J Med Educ* **2011**, *2*, 53-55, doi:10.5116/ijme.4dfb.8dfd.
77. Schober, P.; Boer, C.; Schwarte, L.A. Correlation Coefficients: Appropriate Use and Interpretation. *Anesth Analg* **2018**, *126*, 1763-1768, doi:10.1213/ane.0000000000002864.

78. Kim, J.H. Multicollinearity and misleading statistical results. *Korean J Anesthesiol* **2019**, *72*, 558-569, doi:10.4097/kja.19087.
79. Suliman, M.A.E.; Zhang, W.; Suluman, R.A.I.; Sleiman, K.A.A. Medical student's acceptance of mobile learning: Integrating TAM model with perceived reusability. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-12917-3.
80. Adouani, Y.; Khenissi, M.A. Investigating computer science students' intentions towards the use of an online educational platform using an extended technology acceptance model (e-TAM): An empirical study at a public university in Tunisia. *Education and Information Technologies* **2024**, *29*, 14621-14645, doi:10.1007/s10639-023-12437-6.
81. Al-Adwan, A.S.; Li, N.; Al-Adwan, A.; Abbasi, G.A.; Albelbisi, N.A.; Habibi, A. "Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms". *Education and Information Technologies* **2023**, *28*, 15381-15413, doi:10.1007/s10639-023-11816-3.
82. Al-Hattami, H.M. Understanding perceptions of academics toward technology acceptance in accounting education. *Heliyon* **2023**, *9*, e13141, doi:10.1016/j.heliyon.2023.e13141.
83. Eke, D.O. ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology* **2023**, *13*, 100060, doi:10.1016/j.jrt.2023.100060.
84. Mamo, Y.; Crompton, H.; Burke, D.; Nickel, C. Higher Education Faculty Perceptions of ChatGPT and the Influencing Factors: A Sentiment Analysis of X. *TechTrends* **2024**, *68*, 520-534, doi:10.1007/s11528-024-00954-1.
85. Jiang, Y.; Xie, L.; Lin, G.; Mo, F. Widen the debate: What is the academic community's perception on ChatGPT? *Education and Information Technologies* **2024**, *29*, 20181-20200, doi:10.1007/s10639-024-12677-0.
86. Arowosegbe, A.; Alqahtani, J.S.; Oyelade, T. Perception of generative AI use in UK higher education. *Frontiers in Education* **2024**, *9*, 1463208, doi:10.3389/feduc.2024.1463208.
87. Livberber, T.; Ayvaz, S. The impact of Artificial Intelligence in academia: Views of Turkish academics on ChatGPT. *Heliyon* **2023**, *9*, e19688, doi:10.1016/j.heliyon.2023.e19688.
88. Kiryakova, G.; Angelova, N. ChatGPT—A Challenging Tool for the University Professors in Their Teaching Practice. *Education Sciences* **2023**, *13*, 1056, doi:10.3390/educsci13101056.
89. Adarkwah, M.A.; Amponsah, S.; van Wyk, M.M.; Huang, R.; Tlili, A.; Shehata, B.; Metwally, A.H.S.; Wang, H. Awareness and acceptance of ChatGPT as a generative conversational AI for transforming education by Ghanaian academics: A two-phase study. *Journal of Applied Learning and Teaching* **2023**, *6*, doi:10.37074/jalt.2023.6.2.26.
90. Ogurlu, U.; Mossholder, J. The Perception of ChatGPT among Educators: Preliminary Findings. *Research in Social Sciences and Technology* **2023**, *8*, 196-215, doi:10.46303/ressat.2023.39.
91. Au, W.C. Examining the adoption of chatgpt technology among academics in higher education institutions in malaysia. UTAR, 2023.
92. Strzelecki, A. ChatGPT in higher education: Investigating bachelor and master students' expectations towards AI tool. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-13222-9.
93. Strzelecki, A.; ElArabawy, S. Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology* **2024**, *55*, 1209-1230, doi:10.1111/bjet.13425.
94. Deng, R.; Jiang, M.; Yu, X.; Lu, Y.; Liu, S. Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education* **2025**, *227*, 105224, doi:10.1016/j.compedu.2024.105224.
95. Sallam, M.; Salim, N.A.; Barakat, M.; Al-Mahzoum, K.; Al-Tammemi, A.B.; Malaeb, D.; Hallit, R.; Hallit, S. Assessing Health Students' Attitudes and Usage of ChatGPT in Jordan: Validation Study. *JMIR Med Educ* **2023**, *9*, e48254, doi:10.2196/48254.
96. Nagy, A.S.; Tumiwa, J.R.; Arie, F.V.; Erdey, L. An exploratory study of artificial intelligence adoption in higher education. *Cogent Education* **2024**, *11*, 2386892, doi:10.1080/2331186X.2024.2386892.
97. Ofem, U.J.; Owan, V.J.; Iyam, M.A.; Udeh, M.I.; Anake, P.M.; Ovat, S.V. Students' perceptions, attitudes and utilisation of ChatGPT for academic dishonesty: Multigroup analyses via PLS–SEM. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-12850-5.

98. Žáková, K.; Urbano, D.; Cruz-Correia, R.; Guzmán, J.L.; Matišák, J. Exploring student and teacher perspectives on ChatGPT's impact in higher education. *Education and Information Technologies* **2024**, doi:10.1007/s10639-024-13184-y.
99. Bhat, M.A.; Tiwari, C.K.; Bhaskar, P.; Khan, S.T. Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. *Journal of Information, Communication and Ethics in Society* **2024**, *22*, 331-353, doi:10.1108/JICES-03-2024-0033.
100. Al-kfairy, M. Factors Impacting the Adoption and Acceptance of ChatGPT in Educational Settings: A Narrative Review of Empirical Studies. *Applied System Innovation* **2024**, *7*, 110, doi:10.3390/asi7060110.
101. Uren, V.; Edwards, J.S. Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management* **2023**, *68*, 102588, doi:10.1016/j.ijinfomgt.2022.102588.
102. Godoe, P.; Johansen, T.S. Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students* **2012**, *3*, 38-52, doi:10.5334/jeps.aq.
103. Bruno, I.; Lobo, G.; Covino, B.; Donarelli, A.; Marchetti, V.; Panni, A.; Molinari, F. *Technology readiness revisited: a proposal for extending the scope of impact assessment of European public services*; 2020; pp. 369-380.
104. Ng, D.T.K.; Leung, J.K.L.; Su, J.; Ng, R.C.W.; Chu, S.K.W. Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational technology research and development* **2023**, *71*, 137-161, doi:10.1007/s11423-023-10203-6.
105. Timotheou, S.; Miliou, O.; Dimitriadis, Y.; Sobrino, S.V.; Giannoutsou, N.; Cachia, R.; Monés, A.M.; Ioannou, A. Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review. *Educ Inf Technol (Dordr)* **2023**, *28*, 6695-6726, doi:10.1007/s10639-022-11431-8.
106. Afzal, A.; Khan, S.; Daud, S.; Ahmad, Z.; Butt, A. Addressing the Digital Divide: Access and Use of Technology in Education. *Journal of Social Sciences Review* **2023**, *3*, 883-895, doi:10.54183/jssr.v3i2.326.
107. Gicheru, W.; Mwangi, N. Identifying the need to institutionalize digital equity among faculty: the experience of the Kenya Medical Training College. *Frontiers in Education* **2023**, *8*, 1252842, doi:10.3389/feduc.2023.1252842.
108. Yfanti, S.; Sakkas, N. Technology Readiness Levels (TRLs) in the Era of Co-Creation. *Applied System Innovation* **2024**, *7*, 32, doi:10.3390/asi7020032.
109. Shata, A.; Hartley, K. Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI. *International Journal of Educational Technology in Higher Education* **2025**, *22*, 14, doi:10.1186/s41239-025-00511-7.
110. Nevárez Montes, J.; Elizondo-Garcia, J. Faculty acceptance and use of generative artificial intelligence in their practice. *Frontiers in Education* **2025**, *10*, 1427450, doi:10.3389/feduc.2025.1427450.
111. Jang, M. AI Literacy and Intention to Use Text-Based GenAI for Learning: The Case of Business Students in Korea. *Informatics* **2024**, *11*, 54, doi:10.3390/informatics11030054.
112. Straub, E.T. Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research* **2009**, *79*, 625-649, doi:10.3102/0034654308325896.
113. Acosta-Enriquez, B.G.; Arbulu Ballesteros, M.; Vilcapoma Pérez, C.R.; Huamaní Jordan, O.; Martin Vergara, J.A.; Martel Acosta, R.; Arbulu Perez Vargas, C.G.; Arbulú Castillo, J.C. AI in academia: How do social influence, self-efficacy, and integrity influence researchers' use of AI models? *Social Sciences & Humanities Open* **2025**, *11*, 101274, doi:10.1016/j.ssaho.2025.101274.
114. Amer jid Almahri, F.A.; Bell, D.; Gulzar, Z. Chatbot Technology Use and Acceptance Using Educational Personas. *Informatics* **2024**, *11*, 38, doi:10.3390/informatics11020038.
115. Kim, J.J.H.; Soh, J.; Kadkol, S.; Solomon, I.; Yeh, H.; Srivatsa, A.V.; Nahass, G.R.; Choi, J.Y.; Lee, S.; Nyugen, T.; et al. AI Anxiety: a comprehensive analysis of psychological factors and interventions. *AI and Ethics* **2025**, doi:10.1007/s43681-025-00686-9.
116. Verano-Tacoronte, D.; Bolívar-Cruz, A.; Sosa-Cabrera, S. Are university teachers ready for generative artificial intelligence? Unpacking faculty anxiety in the ChatGPT era. *Education and Information Technologies* **2025**, doi:10.1007/s10639-025-13585-7.

 doi:10.20944/preprints202505.0338.v1

117. Belkina, M.; Daniel, S.; Nikolic, S.; Haque, R.; Lyden, S.; Neal, P.; Grundy, S.; Hassan, G.M. Implementing generative AI (GenAI) in higher education: A systematic review of case studies. *Computers and Education: Artificial Intelligence* **2025**, *8*, 100407, doi:10.1016/j.caeai.2025.100407.
118. Kim, J.; Klopfer, M.; Grohs, J.R.; Eldardiry, H.; Weichert, J.; Cox, L.A.; Pike, D. Examining Faculty and Student Perceptions of Generative AI in University Courses. *Innovative Higher Education* **2025**, doi:10.1007/s10755-024-09774-w.
119. Simpson, A.; Day, C.; Goulding, J.; Asha, J. Australian teachers' perceptions of effectiveness in a performative culture. *Teaching and Teacher Education* **2022**, *109*, 103542, doi:10.1016/j.tate.2021.103542.
120. Alkhaldi, F.K.; Altaei, S. Emirates Leading Experience in Employing Artificial Intelligence. In *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success*, Hamdan, A., Hassanien, A.E., Razzaque, A., Alareeni, B., Eds.; Springer International Publishing: Cham, 2021; pp. 241-251, doi:10.1007/978-3-030-62796-6_14.
121. Karkouti, I. Integrating Technology in Qatar's Higher Education Settings: What Helps Faculty Accomplish the Job. *Technology, Knowledge and Learning* **2021**, *28*, doi:10.1007/s10758-021-09553-y.
122. Aljaber, A. E-learning policy in Saudi Arabia: Challenges and successes. *Research in Comparative and International Education* **2018**, *13*, 176-194, doi:10.1177/1745499918764147.
123. Zalat, M.M.; Hamed, M.S.; Bolbol, S.A. The experiences, challenges, and acceptance of e-learning as a tool for teaching during the COVID-19 pandemic among university medical staff. *PLoS One* **2021**, *16*, e0248758, doi:10.1371/journal.pone.0248758.
124. Laabidi, Y.; Laabidi, H. Barriers Affecting Successful Integration of ICT in Moroccan Universities. *Journal of English Language Teaching and Linguistics* **2016**, *1*, doi:10.21462/jeltl.v1i3.29.
125. Eden, C.; Adeniyi, I. Harnessing technology integration in education: Strategies for enhancing learning outcomes and equity. *World Journal of Advanced Engineering Technology and Sciences* **2024**, *11*, 001-008, doi:10.30574/wjaets.2024.11.2.0071.
126. Ali, O.; Murray, P.A.; Momin, M.; Dwivedi, Y.K.; Malik, T. The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technological Forecasting and Social Change* **2024**, *199*, 123076, doi:10.1016/j.techfore.2023.123076.
127. Ayaz, A.; Yanartaş, M. An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports* **2020**, *2*, 100032, doi:10.1016/j.chbr.2020.100032.
128. Hughes, L.; Malik, T.; Dettmer, S.; Al-Busaidi, A.S.; Dwivedi, Y.K. Reimagining Higher Education: Navigating the Challenges of Generative AI Adoption. *Information Systems Frontiers* **2025**, doi:10.1007/s10796-025-10582-6.
129. Wang, K.; Ruan, Q.; Zhang, X.; Fu, C.; Duan, B. Pre-Service Teachers' GenAI Anxiety, Technology Self-Efficacy, and TPACK: Their Structural Relations with Behavioral Intention to Design GenAI-Assisted Teaching. *Behav Sci (Basel)* **2024**, *14*, 373, doi:10.3390/bs14050373.
130. Balalle, H.; Pannilage, S. Reassessing academic integrity in the age of AI: A systematic literature review on AI and academic integrity. *Social Sciences & Humanities Open* **2025**, *11*, doi:10.1016/j.ssaho.2025.101299.
131. An, Y.; Yu, J.H.; James, S. Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education* **2025**, *22*, 10, doi:10.1186/s41239-025-00507-3.
132. Nur, A.A.; Leibbrand, C.; Curran, S.R.; Votruba-Drzal, E.; Gibson-Davis, C. Managing and minimizing online survey questionnaire fraud: lessons from the Triple C project. *International Journal of Social Research Methodology* **2024**, *27*, 613-619, doi:10.1080/13645579.2023.2229651.