

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

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## Abstract

**Background:** 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

**Methods:** 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.

**Results:** 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.

**Conclusions:** 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 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 (Alfirević et al., 2024; Bhullar et al., 2024). Universities, which are the longstanding pillars of human intellect are now at a critical juncture, grappling with the dualities of genAI innovation and disruption (Farrokhnia et al., 2024; Luo, 2024; Sallam, Al-Mahzoum, Sallam, et al., 2025). For university educators, the shift brought about by genAI evokes both the allure of unprecedented opportunities and the disquieting specter of obsolescence (Sallam, 2023; Strzelecki et al., 2024). Recent reports highlighted the growing uncertainty among university educators regarding genAI adoption, which may carry significant implications for higher education (Yilmaz & Karaoglan Yilmaz, 2023; Yusuf et al., 2024). This uncertainty is rooted not merely in technological unfamiliarity and perceived risks but in the very identity and purpose of education itself (Menon & Shilpa, 2023; Bouchard, 2024; Wang, Dang, et al., 2024).

A primary concern among educators is the perceived threat that genAI poses to their professional roles (Bearman et al., 2023; Şimşek, 2025). In higher education, genAI models have the ability to generate coherent course plans, automate students' assessments, and simulate dialogues and feedback (Alfirević et al., 2024; Davis & Lee, 2024; Law, 2024; Yusuf et al., 2024). 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 (Bozkurt et al., 2024; Capraro et al., 2024).

The second issue represents a deeper existential challenge to university educators, namely the preservation of originality and intellectual integrity in the genAI era (Preiksaitis & Rose, 2023; Lane et al., 2024; Tan & Maravilla, 2024). 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 (Caldwell, 2023; Haase & Hanel, 2023; Creely & Blannin, 2025). 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 (Bozkurt et al., 2024; Kostanek et al., 2024; Luo, 2024).

In higher education, resistance to genAI adoption is often reinforced by tradition—a defining trait of institutions that value historical continuity (Martin et al., 2015; Watermeyer et al., 2024). 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 (Moerschell, 2009; Gratz & Looney, 2020; Singh et al., 2023; Yu, 2023). Technological readiness among university educators, though critical, remains far from universal (Lloyd et al., 2012; El Alfy et al., 2017; Bayaga et al., 2021). Yet, history demonstrates that resistance to innovation seldom delays its ultimate course (Trouche, 2005; Shehata et al., 2024). From personal computers and internet search engines to smartphones and digital classrooms, higher education has consistently, albeit reluctantly adapted to technological change (Westberry et al., 2015; Marshall et al., 2024; Sitar-Tăut et al., 2024). 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. (Dempere et al., 2023; Kurtz et al., 2024).

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 (Granić, 2022; Giannakos et al., 2024; Jose et al., 2024; Mohamed et al., 2024). Far beyond novelty, genAI has the potential to revolutionize teaching, learning, and assessment by automating routine tasks, personalizing education, and enabling innovative instructional methods (Sallam, 2023; Sallam, Salim, Barakat, & Al-Tammemi, 2023; Omran Zailuddin et al., 2024). Yet, genAI adoption in higher education remains controversial (Hasanein & Sobaih, 2023; Khlaif et al., 2024). Concerns about academic integrity, faculty

readiness, and equitable access highlight the complexity of this transition (Chan, 2023; Currie, 2023). 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 (Alotaibi, 2024; Sallam, Al-Mahzoum, et al., 2024; Strzelecki, 2024c; Sallam, Al-Mahzoum, Alaraji, et al., 2025). 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 (Kong et al., 2024; Wang, Ruan, et al., 2024b).

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 (Abdaljaleel et al., 2024). 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 (Abdaljaleel et al., 2024). In the United Arab Emirates (UAE), similar patterns of genAI adoption have emerged, reflecting an emerging norm among university students in Arab countries (Sallam, Elsayed, et al., 2024). Globally, this trend has been corroborated by a multinational study conducted across Brazil, India, Japan, the United Kingdom, and the United States (Ibrahim et al., 2023). 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 (Mansour & Wong, 2024; Strzelecki, 2024b, 2024c).

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 (Abrahams, 2010; Gammoh, 2024; Monib et al., 2024). GenAI implications extend beyond technological novelty, challenging the very foundations of higher education—learning outcomes, academic integrity, and pedagogical frameworks (Van Wyk et al., 2023; Yusuf et al., 2024). 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 (Davis, 1989; Creswell & Guetterman, 2018; Liu et al., 2020). This study also sought to confirm the validity of the Ed-TAME-ChatGPT tool, which was specifically developed to assess educators' perspectives on ChatGPT (Barakat et al., 2025). 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. 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 (Barakat et al., 2025). 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 (Barakat et al., 2025). 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.

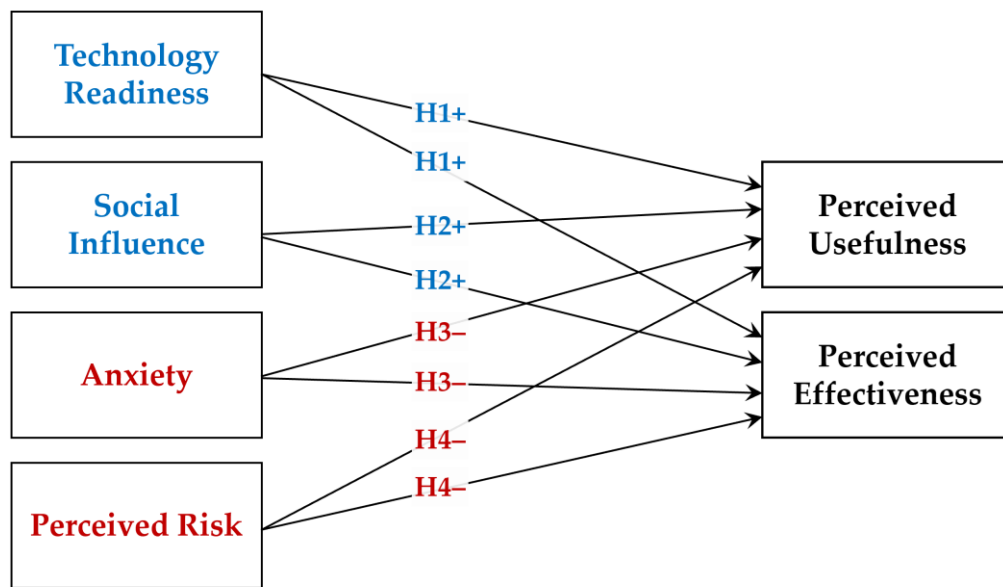


Figure 1. Conceptual Framework of the Study Based on the Ed-TAME-ChatGPT Constructs with Hypothesized Paths

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 (Johnson, 2014). 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 (Mundfrom et al., 2005; Koran, 2016). 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 (Barakat et al., 2025). 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 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) (Jasp Team, 2024). 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  $\alpha$ , with a threshold of  $\geq 0.60$  considered acceptable for reliability (Tavakol & Dennick, 2011; Taber, 2018).

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 ( $\rho$ ) was used (Schober et al., 2018). 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 (Kim, 2019). 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).

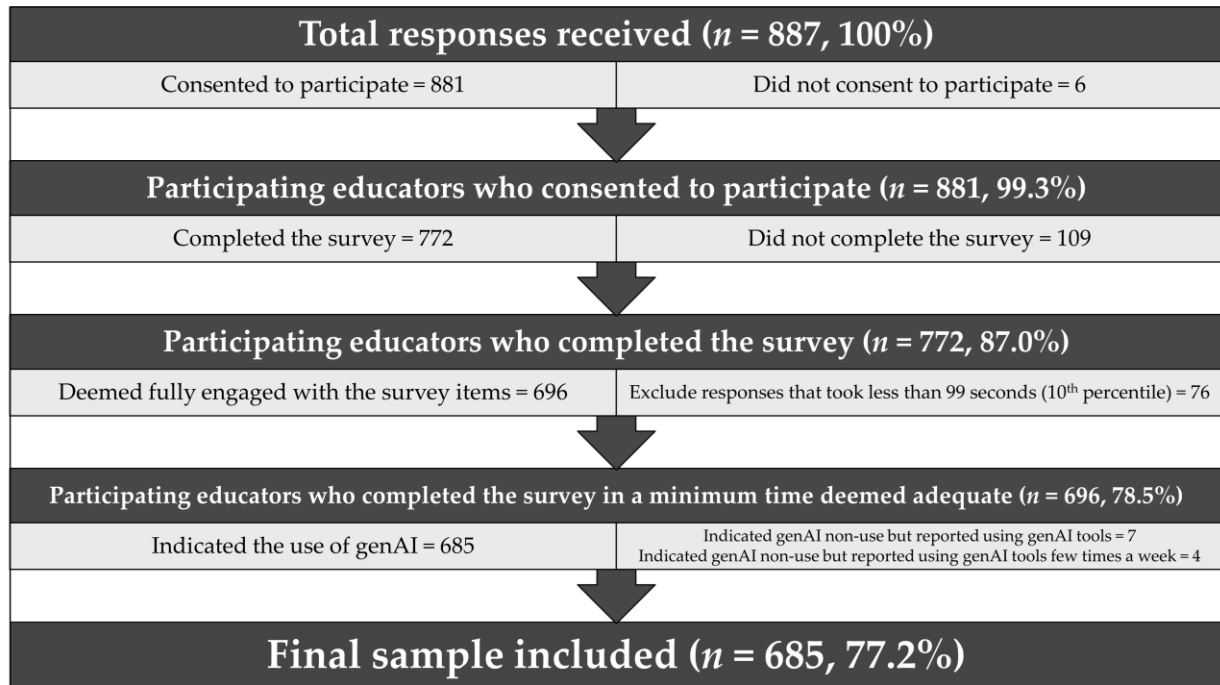


Figure 2. Participant recruitment and quality control (QC) measures implemented  
genAI: generative artificial intelligence.

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).

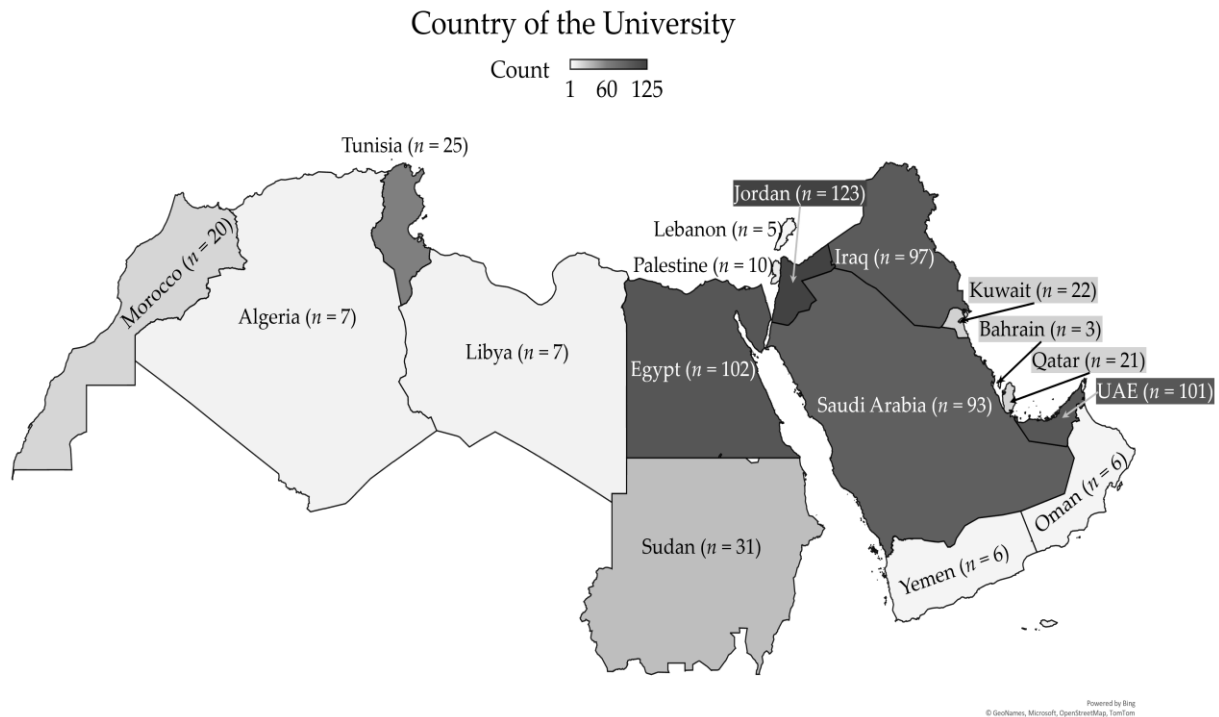


Figure 3. Distribution of study participants based on the country of their university affiliation

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.

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 <sup>1</sup>	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)

<sup>1</sup> 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).

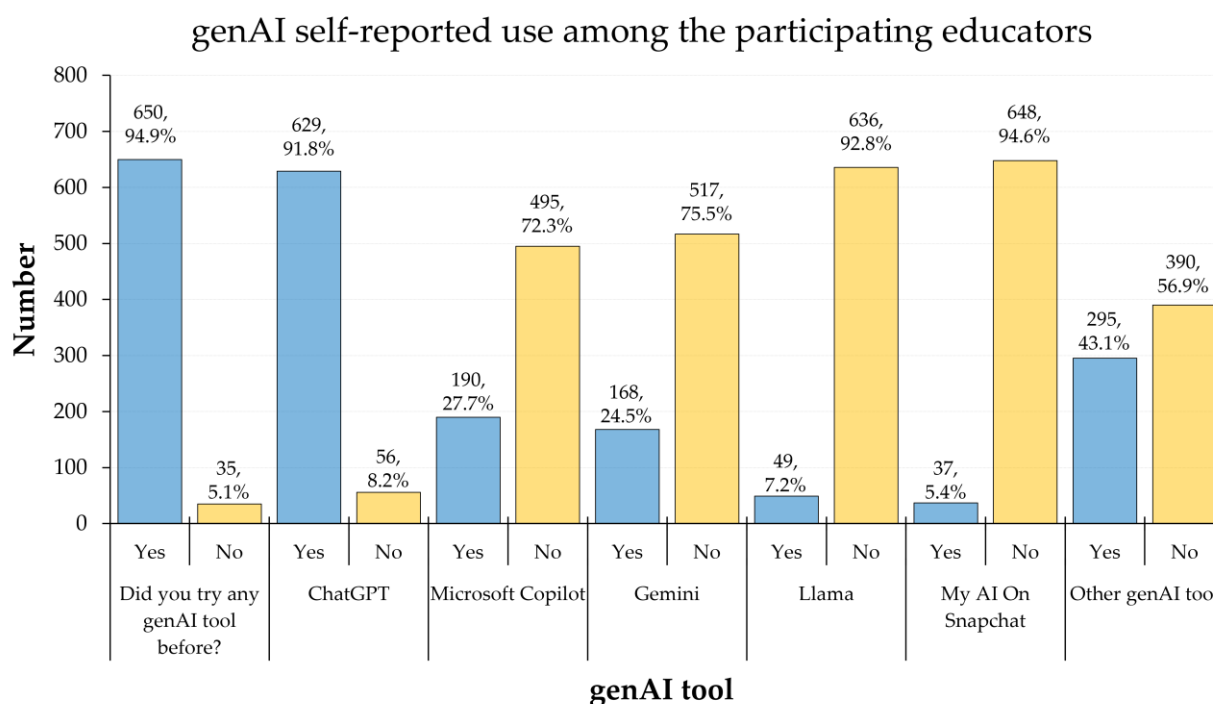


Figure 4. Distribution of generative AI (genAI) tools' used by the participating educators

The mean genAI use score among participants was  $2.00 \pm 1.23$ . 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		<i>p</i> value	genAI use score	<i>p</i> value
		Daily	Less than daily			
		Count (%)	Count (%)		Mean $\pm$ SD <sup>2</sup>	
Age	25–34 years	112 (56.0)	88 (44.0)	<0.001	2.17 $\pm$ 1.22	0.028
	35–44 years	98 (46.9)	111 (53.1)		1.89 $\pm$ 1.07	
	45–54 years	76 (42.9)	101 (57.1)		2.03 $\pm$ 1.34	
	55+ years	29 (29.3)	70 (70.7)		1.83 $\pm$ 1.33	
Sex	Male	202 (50.1)	201 (49.9)	0.009	2.03 $\pm$ 1.27	0.516
	Female	113 (40.1)	169 (59.9)		1.95 $\pm$ 1.18	
Nationality	GCC <sup>1</sup>	75 (70.1)	32 (29.9)	<0.001	2.64 $\pm$ 1.42	<0.001
	Levant and Iraq	100 (33.6)	198 (66.4)		1.85 $\pm$ 1.25	
	Egypt and Sudan	76 (43.9)	97 (56.1)		1.99 $\pm$ 1.06	
	Maghreb	42 (70.0)	18 (30.0)		1.90 $\pm$ 0.99	
	Others	22 (46.8)	25 (53.2)		1.60 $\pm$ 1.06	
In which	GCC	149 (60.6)	97 (39.4)	<0.001	2.37 $\pm$ 1.36	<0.001

country is your university?	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	

<sup>1</sup> GCC: Gulf Cooperation Council countries; <sup>2</sup> 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		<i>p</i> 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 <sup>1</sup>	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)	

<sup>1</sup> 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  $\chi^2$  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 <sup>1</sup>	0.065 (0.061 – 0.069)
Fit Measures	Standardized Root Mean Square Residual (SRMR)	0.046
Fit Measures	Goodness of Fit Index (GFI)	0.986
Reliability	Perceived Usefulness	$\alpha=0.877$
Reliability	Perceived Effectiveness	$\alpha=0.892$
Reliability	Technology Readiness	$\alpha=0.851$
Reliability	Social Influence	$\alpha=0.817$
Reliability	Anxiety	$\alpha=0.899$
Reliability	Perceived Risk	$\alpha=0.695$

<sup>1</sup> 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  $\alpha$  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:  $4.07 \pm 0.75$  and  $4.08 \pm 0.66$ , respectively) and Effectiveness ( $3.78 \pm 0.82$  and  $3.85 \pm 0.76$ ) 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).

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

<sup>1</sup> GCC: Gulf Cooperation Council countries; <sup>2</sup> SD: Standard deviation; <sup>3</sup>  $p$  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).

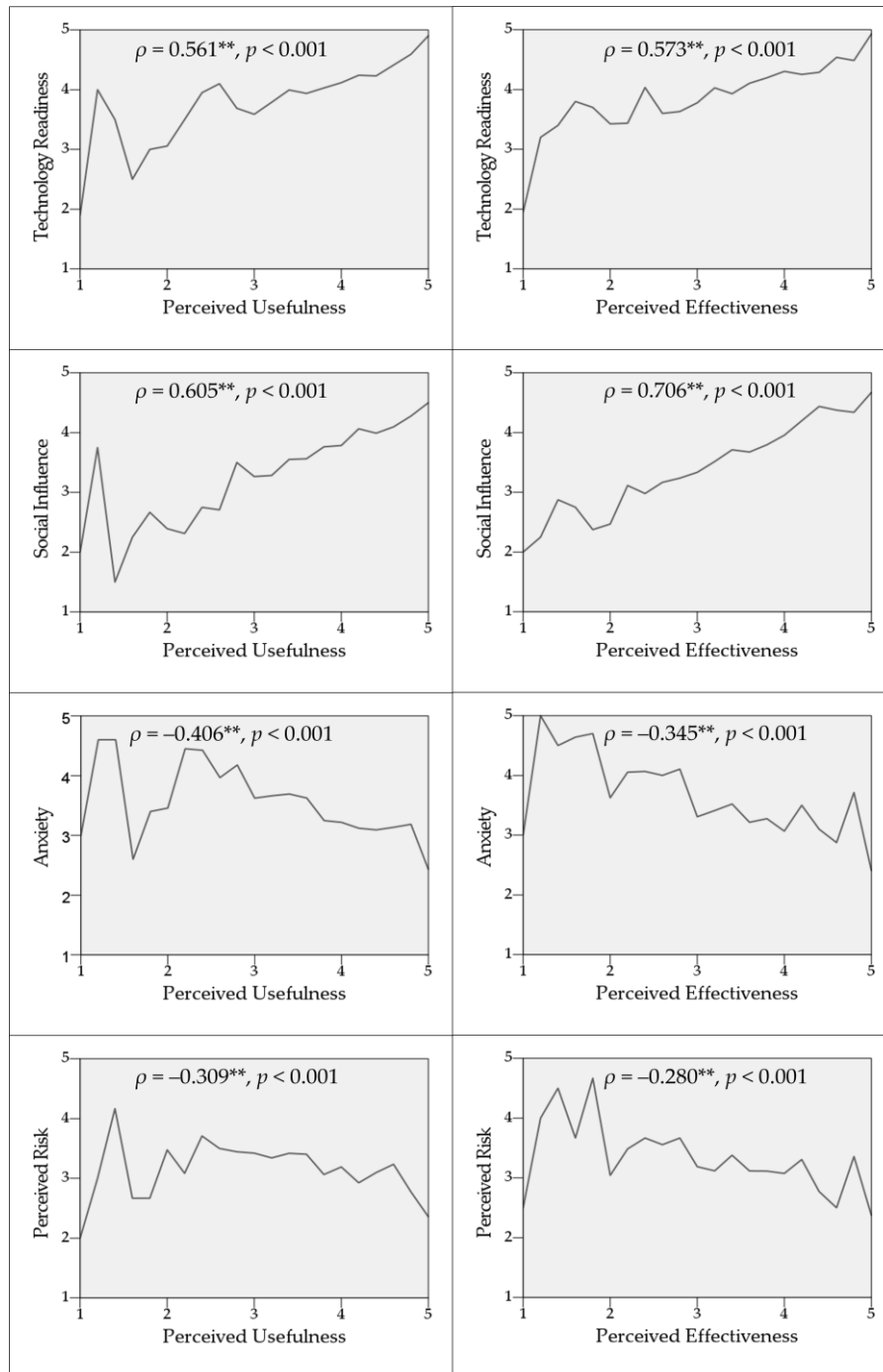


Figure 5. Univariate correlations between Ed-TAME-ChatGPT constructs and Perceived Usefulness and Effectiveness of Generative AI

\*\*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 Perceived Usefulness and 0.647 for Perceived Effectiveness. Social Influence emerged as the strongest positive predictor for both Perceived Usefulness ( $\beta = 0.445$ ,  $p < 0.001$ ) and Effectiveness ( $\beta = 0.531$ ,  $p < 0.001$ , Table 6). Technology Readiness was also significantly associated with more favorable attitudes ( $\beta = 0.325$  for Usefulness,  $\beta = 0.314$  for Effectiveness;  $p < 0.001$  for both). Anxiety negatively predicted both outcomes ( $\beta = -0.154$  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 ( $\beta = -0.098$ ,  $p = 0.019$ ), 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 <sup>2</sup>
Dependent Variable:	Perceived		B (95.0% CI <sup>1</sup> for B)	$\beta$		
<b>Usefulness</b>						
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	<b>0.019</b>	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	<b>&lt;0.001</b>	1.336
Anxiety			−0.124 (−0.181 to −0.067)	−0.154	<b>&lt;0.001</b>	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	<b>&lt;0.001</b>	1.364
Model $R^2 = 0.647$			Unstandardized Coefficients	Standardized Coefficients	p value	VIF
Dependent Variable:	Perceived		B (95.0% CI for B)	$\beta$		
<b>Effectiveness</b>						
Age			0.027 (−0.024 to 0.079)	0.035	0.302	2.242
Nationality			0.059 (0.018 to 0.100)	0.081	<b>0.005</b>	1.534
In which country is your university?			−0.054 (−0.097 to −0.011)	−0.070	<b>0.013</b>	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	<b>&lt;0.001</b>	1.336
Anxiety	-0.077 (-0.133 to -0.021)	-0.088	<b>0.007</b>	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	<b>&lt;0.001</b>	1.364

<sup>1</sup> CI: Confidence interval; <sup>2</sup> 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 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 (Al-Adwan et al., 2023; Al-Hattami, 2023; Adouani & Khenissi, 2024; Suliman et al., 2024). 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 (Eke, 2023; Mamo et al., 2024). 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 (Jiang et al., 2024).

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 (Adarkwah et al., 2023; Kiryakova & Angelova, 2023; Livberber & Ayvaz, 2023; Arowosegbe et al., 2024). 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 (Ogurlu & Mossholder, 2023). 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 (Kiryakova & Angelova, 2023). 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 (Au, 2023).

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 (Strzelecki, 2024a, 2024c, 2024b; Strzelecki & ElArabawy, 2024). While previous studies, including a systematic review by Deng et al. (Deng et al., 2025), and research from the UAE (Sallam, Elsayed, et al., 2024), Jordan (Sallam, Salim, Barakat, Al-Mahzoum, et al., 2023), Indonesia (Nagy et al., 2024), Nigeria (Ofem et al., 2024), Slovakia, Portugal, and Spain (Žáková et al., 2024), 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. (Al-kfairy, 2024; Bhat et al., 2024).

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 (Godoe & Johansen, 2012; Bruno et al., 2020; Uren & Edwards, 2023). Importantly, H1 reinforces the principle that access to technology, when paired with familiarity and self-efficacy, fosters engagement and skill development (Ng et al., 2023; Timotheou et al., 2023). 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. (Afzal et al., 2023). Thus, the positive association between Technology Readiness and genAI attitudes emphasizes the crucial role of institutional investment in digital literacy and continuous faculty development (Gicheru & Mwangi, 2023). 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 (Yfanti & Sakkas, 2024).

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 (Jang, 2024; Nevárez Montes & Elizondo-Garcia, 2025; Shata & Hartley, 2025). 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 (Straub, 2009; Amer jid Almahri et al., 2024; Acosta-Enriquez et al., 2025).

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 (Sallam, Al-Mahzoum, Alaraji, et al., 2025). Notably, Anxiety reflects more than technological unfamiliarity; it encompasses deeper concerns related to academic integrity, intellectual displacement, and the erosion of scholarly originality (Kim, Soh, et al., 2025; Verano-Tacoronte et al., 2025). 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 (Belkina et al., 2025). 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 (Kim, Klopfer, et al., 2025). These findings suggest that effectiveness perceptions are not merely individual judgments but are shaped by the academic settings in which educators operate (Simpson et al., 2022). 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 (Aljaber, 2018; Alkhaldi & Altaei, 2021; Karkouti, 2021). Conversely, regions with lower reported genAI competence may reflect resource limitations, restricted access to training, or a cultural hesitancy toward disruptive technologies (Laabidi & Laabidi, 2016; Zalat et al., 2021; Afzal et al., 2023). 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 (Eden & Adeniyi, 2024).

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 (Ali et al., 2024).

#### *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 (Ayaz & Yanartaş, 2020; Amer jid Almahri et al., 2024; Jang, 2024).

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 (Hughes et al., 2025).

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 (Wang, Ruan, et al., 2024a). 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 (Balalle & Pannilage, 2025). Institutions must therefore craft transparent, enforceable guidelines on acceptable genAI applications in both instruction and scholarship (An et al., 2025). 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 (An et al., 2025).

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 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. (Nur et al., 2024). 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.

#### **Abbreviations**

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

### **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.

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### **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. The manuscript is available as a preprint at: <https://www.preprints.org/manuscript/202412.0340/v1>

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### **Conflicts of Interest**

The authors declare no conflicts of interest.

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