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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

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Background: The use of ChatGPT among university students has gained a recent popularity. The current study aimed to assess the factors driving the attitude and usage of ChatGPT as an example of generative artificial intelligence (genAI) among university students in the United Arab Emirates (UAE).

Methods: This cross-sectional study was based on a previously validated Technology Acceptance Model (TAM)-based survey instrument termed TAME-ChatGPT. The self-administered e-survey was distributed by emails for students enrolled in UAE universities during September–December 2023 using a convenience-based approach. Assessment of the demographic and academic variables, and the TAME-ChatGPT constructs' roles in ChatGPT attitude and usage was conducted using univariate followed by multivariate analyses.

Results: The final study sample comprised 608 participants, 91.0% of whom heard of ChatGPT while 85.4% used ChatGPT before the study. Univariate analysis indicated that a positive attitude to ChatGPT was associated with the three TAME-ChatGPT attitude constructs namely, lower perceived risks, lower anxiety, and higher scores on the attitude to technology/social influence. For the ChatGPT usage, univariate analysis indicated that positive attitude to ChatGPT use was associated with being male, Arab in nationality, and lower point grade average (GPA) as well as the four ChatGPT usage constructs namely, higher perceived usefulness, lower perceived risks of use, higher scores on the behavior/cognitive construct and higher scores on the ease-of-use construct.

In multivariate analysis, only TAME-ChatGPT constructs explained the variance in attitude towards ChatGPT (80.8%) and its usage (76.9%).

Conclusion: The findings indicated that ChatGPT usage is commonplace among university students in the UAE. The determinants of use included the perceived usefulness, lower perceived risks, cognitive and behavioral factors, perceived ease of use, while the attitude was determined by lower perceived risks, lower anxiety, and higher scores for attitude to technology/social influence. These factors should be considered for understanding the motivators for successful adoption of genAI including ChatGPT in higher education.

KEYWORDS

AI in education, higher education, large language models, attitude, ChatGPT

1 Introduction

The integration of technology is becoming an indispensable component to improve the quality of higher education (Haleem et al., 2022; Criollo-C et al., 2023; Okoye et al., 2023). Recently, the incorporation of various generative artificial intelligence (genAI) models in education received a significant attention (Kamalov et al., 2023; King and Prasetyo, 2023; Mijwil et al., 2023; Yu and Guo, 2023). The genAI role in higher education represents a paradigm shift which could redefine the fundamental aspects of teaching and learning methodologies (Ouyang and Jiao, 2021; Yu, 2024).

The emergence of genAI exemplified by popular tools such as ChatGPT (OpenAI, San Francisco, CA), could mark a revolution rather than an evolution which could reshape the entire educational landscape (Caleb et al., 2023; Fütterer et al., 2023; Johnson, 2023). The potential educational benefits of genAI including ChatGPT especially in health education attracted significant research attention within a short time span (Ogunleye et al., 2024; Sallam, 2024; Sallam et al., 2024). Generative AI tools are characterized by a remarkable ability to understand and respond to natural language queries (Bandi et al., 2023). On one hand, these capabilities of genAI models offer innovative educational benefits. These benefits include enhancing personalized learning experiences and providing realistic simulations which would help to create an engaging educational content; thus, improving student engagement and learning outcomes (Kurtz et al., 2024; Salinas-Navarro et al., 2024a,b). For example, (Kıyak and Emekli, 2024) showed the efficiency of ChatGPT in generating medical multiple-choice questions (MCQs) in a recent review. However, the same tools, including ChatGPT, pose valid challenges and ethical concerns igniting controversy in aspects such as bias, cybersecurity, plagiarism and academic dishonesty (Michel-Villarreal et al., 2023; Sallam, 2023; Salazar et al., 2024; Williams, 2024).

Specifically, the concerns regarding genAI include but are not limited to the following aspects. First, a decline in the critical thinking and problem-solving skills can occur among students due to the over-reliance on technology (Sallam et al., 2023b). Second, variability in the ability to get access to novel technologies within and between different societies can put students lacking such an ability at a disadvantage creating a digital divide (Ragnedda and Muschert, 2013; Kitsara, 2022). Third, genAI integration into educational practices requires adaptation from the educators, who may display hesitancy or lack of the needed support due to perceived barriers or misconceptions (Karen et al., 2023; Ng et al., 2023; Barakat et al., 2024). Fourth, the rapid emergence and evolution of genAI models could surpass the pace of developing policies and regulations for successful implementation and responsible use of these tools (Chan, 2023; Dempere et al., 2023; Lim et al., 2023). In turn, this could potentially create significant challenges in establishing standardized practices for governing higher education. Fifth, the impact of genAI on the job market necessitates a thorough re-evaluation of the competencies and skills acquired during higher education to ensure the preparation of graduates capable to adapt in a rapidly changing work environment (Bukartaite and Hooper, 2023; Gupta, 2024; Tayan et al., 2024).

Educators and students have been shown to increasingly utilize genAI models with ChatGPT being among the most popular of these tools (Ansari et al., 2023; Ibrahim et al., 2023; von Garrel and Mayer, 2023; Abdaljaleel et al., 2024). Therefore, it is important to understand how these genAI models are perceived and utilized especially among students. Such an inquiry could be viewed as a critical factor for successful implementation of genAI models including ChatGPT into the educational framework (Chan and Hu, 2023; Sallam et al., 2024).

The implications of this research area are far-reaching. Understanding the factors driving the genAI adoption in higher education can inform the development of effective implementation strategies (Kamalov et al., 2023). Additionally, this area of research could shed light on the broader implications of genAI for the future of higher education and the job market (Michel-Villarreal et al., 2023). Such a quest involves the assessment of demographic, academic, psychological, social, and economic aspects driving the attitude towards this novel technology (Farina and Lavazza, 2023; Ibrahim et al., 2023; Zarifhonarvar, 2023; Abdaljaleel et al., 2024). In addition, this investigation can help to embrace genAI tools as constructive assets within educational settings, rather than viewing this inevitable technology as a challenge (de Winter et al., 2023).

A comprehensive framework for assessing the determinants of adopting a novel technology is the Technology Acceptance Model (TAM) (Davis, 1989; Bagozzi et al., 1992; Marangunić and Granić, 2015). Based on the TAM framework, a recently developed and validated instrument termed "TAME-ChatGPT" described several factors as drivers of the attitude to ChatGPT and its usage among university students (Sallam et al., 2023a). These factors include the perceived usefulness, behavioral and cognitive factors, general perceived risks and the perceived risks of use, the perceived ease of use, anxiety, attitude to technology and social influence (Sallam et al., 2023a).

Based on the TAME-ChatGPT tool, the current study aimed to unravel the factors driving the adoption of ChatGPT among university students in the United Arab Emirates (UAE). The UAE presents a unique setting for this investigation, given its diverse cultural composition and rapidly evolving higher education landscape with aspiration to achieve top tier quality in education (Badry, 2019). The UAE has placed AI at the core of its national agenda, establishing a deep commitment to embedding AI within its economic and technological strategies (Alkhaldi and Altaei, 2021; Shwedeh et al., 2024). A pioneering step in this direction was the early establishment of the Ministry of State for Artificial Intelligence, Digital Economy & Remote Work Applications. As the first entity of its kind worldwide, this ministry coordinates AI governance and policy, positioning the UAE as a leader in the global AI landscape (Dahabreh, 2023). Furthermore, the UAE hosts the world's first dedicated AI research university at the graduate level, highlighting its strategic educational initiatives aimed at developing a proficient workforce to meet the demands of an AI-driven future (Science/AAAS Custom Publishing Office, 2023). The current study implications could help in contributing to the growing literature assessing the determinants of generative AI implementation in higher education. Additionally, this study sought to provide insights that can guide educators and academic policymakers regarding the students' perspectives on ChatGPT which can consequently help to enrich their educational experience.

2 Methods

2.1 Study design

This study adopted a validated survey instrument based on the technology acceptance model (TAM) and specifically tailored to measure the attitude towards ChatGPT among university students (Sallam et al., 2023a). The survey instrument validity was confirmed in a recently published multinational study among university students in five Arab countries (Abdaljaleel et al., 2024).

This study utilized a self-administered electronic survey, distributed via email to university students in the UAE. The survey employed a non-probability, convenience sampling approach, hosted using Google Forms, and distributed by the authors based in the UAE (W.E., M.A.-S., W.G., N.A., and D.M.). The questionnaire was offered simultaneously in both Arabic and English languages to accommodate the linguistic preferences and cultural diversity among university students in the UAE. The survey was accessible from 20 September 2023 to 8 December 2023. Participation in the study was entirely voluntary, with no incentives for participation. To reduce the effect of non-response bias, responding to all items were mandatory for successful completion of the questionnaire with the exception of self-reported latest cumulative grade point average (GPA).

The minimum required sample size was calculated at 384 based on the formula: $n = (Z^2 \times P \times (1 - P))/e^2$, where: $Z = 1.96$ for 95% confidence interval (CI), P as the expected true proportion (set at 50%), and e as the desired precision (set at ±0.05), and the latest estimate of the total number of university students in the UAE as retrieved from the UAE Ministry of Education official website in the academic year 2019/2020 (The UAE Ministry of Education, 2024). Calculation of the minimum sample size was done using the EPITOOLS sample size to estimate a proportion or apparent prevalence with specified precision available from Epitools – Epidemiological Calculators (2024).

2.2 Ethical considerations

This study was approved by the Institutional Review Board (IRB) at Gulf Medical University (Reference number: IRB-COD-FAC-49-APRIL-2023). Obtaining the informed consent to participation was ensured by the inclusion of a mandatory item at the beginning of the electronic survey to explicitly indicate consent for participation.

2.3 Survey instrument

The electronic survey started with an introductory section which outlined the study objectives. This was followed by the mandatory informed consent item: "Do you agree to participate in this study?" Agreement with "yes" as an answer allowed the participant to proceed to the subsequent survey sections, whereas disagreement as indicated by "no" response resulted in closure of the survey.

The following section assessed the socio-demographic and academic data including the following variables: (1) age (as a scale variable); (2) sex (male vs. female); (3) nationality (Arab vs. non-Arab); (4) college/faculty affiliation (health-related (Health Sciences and Public Health colleges), vs. non-health-related (Art and Sciences, Law, Business, Engineering, Military, Electrical Engineering, Communication, Arts, and Sciences, and Social Sciences colleges)); (5) current educational level (undergraduate vs. postgraduate); and (6) the latest self-reported GPA (optional item), later classified into four categories as follows: <2.50, 2.50–2.99, 3.00–3.49, and 3.50–4.00.

The next section comprised two preliminary questions: first, "Have you heard of ChatGPT before the study?" (Yes vs. No), where a "No" response led to the survey submission. A "Yes" response led to the second question, "Have you used ChatGPT before the study?" (Yes vs. No). Respondents who had not used ChatGPT were directed to a set of 13 attitude TAME-ChatGPT scale questions, whereas those who had used ChatGPT proceeded to a comprehensive set of 25 TAME-ChatGPT items addressing both attitude to ChatGPT and its usage.

The survey items comprising the constructs of the TAME-ChatGPT, are outlined in Appendix. Each item was evaluated using a 5-point Likert scale, where "strongly agree" was scored as 5, "agree" as 4, "neutral/no opinion" as 3, "disagree" as 2, and "strongly disagree" as 1. For the TAME-ChatGPT items indicative of a negative attitude (perceived risk, anxiety, and perceived risk of use), the scoring was reversed.

The attitude scale encompassed three constructs: a perceived risk sub-scale with 5 items, an anxiety sub-scale with 3 items, and an attitude to technology/social influence sub-scale with 5 items. The usage scale comprised four constructs: perceived usefulness sub-scale with 6 items, behavior/cognitive factors sub-scale with 3 items, perceived risk of ChatGPT use sub-scale with 3 items, two of which were also present in the perceived risk construct, and perceived ease of use subs-scale with 2 items (Appendix).

2.4 Statistical and data analyses

Statistical analyses were conducted using IBM SPSS Statistics Version 26.0 (Armonk, NY: IBM Corp). The association between categorical variables was evaluated using the Chi-squared test (χ^2). The Chi-squared test was selected for its effectiveness in determining statistical significance between categorical variables in a contingency table. This choice was supported by the sufficient sample size, which ensured that the expected frequency in each cell of the table was adequate. For the analysis involving categorical and scale variables, the Mann–Whitney *U* (M-W) and Kruskal-Wallis H (K-W) tests were employed. These non-parametric tests are appropriate for datasets where a normal distribution cannot be assumed. Specifically, the M-W test was utilized to compare two independent groups when the dependent variable was a scale variable that is not normally distributed. For comparisons involving more than two groups, the K-W test, which extends the M-W test, was applied. The selection of these tests was done following the determination of non-normal distribution of the scale variables via the Kolmogorov–Smirnov test ($p < 0.001$ for all). The level of statistical significance was determined at $p < 0.050$.

For the multivariate analysis, predictor variables were included based on $p < 0.100$ in univariate analysis. The selection of a less stringent threshold allowed an exploratory approach in model building for the identification of potentially important variables which could have been overlooked with a more conservative *p* value cutoff.

Multivariate regression analysis was employed to assess the influence of multiple predictors simultaneously, accounting for their interdependencies. The overall significance of the regression model was evaluated, which was crucial to determine whether the set of variables in the model significantly predicted the outcome variable, compared to a model with no predictors. This evaluation was reported as an F-test in the Analysis of Variance (ANOVA) table provided in regression analysis output, testing the null hypothesis that no relationship existed between the dependent and independent variables. To ensure the reliability of the regression analysis, the Variance Inflation Factor (VIF) was used to assess multicollinearity among predictors. A VIF value >3.0 was used as a conservative threshold to flag variables that might excessively inflate variances, which helped to prevent the inclusion of highly correlated variables that could distort the true relationship between predictors and the outcome.

Scores for each construct of the TAME-ChatGPT scale were calculated by dividing the total scores by the number of items within that construct, resulting in a score range of 1–5. The overall TAME-ChatGPT scores were based on the mean of the scores for scale items divided by the number of items in each scale. The scoring classification for both the TAME-ChatGPT and its individual constructs was categorized as follows: a score range of 1.00 to 2.33 indicated disagreement (negative), 2.34 to 3.67 indicated neutral position, and 3.68 to 5.00 indicated agreement (positive). The internal consistency of the seven TAME-ChatGPT constructs were ensured by the following Cronbach's α values: perceived usefulness = 0.888, behavior/cognitive factors = 0.796, perceived risk of use = 0.638, perceived ease of use = 0.779, perceived risk = 0.846, anxiety = 0.867, and attitude to technology/social influence = 0.904. The Cronbach's α value for the overall TAME-ChatGPT usage scale was 0.797, while the value for the overall attitude scale was 0.736. The calculated Cronbach's α values indicated an acceptable level of consistency within the TAME-ChatGPT constructs (Tavakol and Dennick, 2011).

3 Results

3.1 General features of the study sample

A total of 608 responses were collected over the period 20 September 2023 to 8 December 2023. Most of the participants were females, less than 21 years in age, Arabs, enrolled in non-health-related colleges, and undergraduates. For age as a scale variable, the overall mean age of the participants was 20.9 ± 3.5 (median: 20, interquartile range (IQR): 19–22). The latest self-reported cumulative GPA data were available from 520 participants out of the 608 participants (85.5%). The vast majority of participants heard of ChatGPT (91.0%) or used ChatGPT before the study (85.4%, Table 1). Subsequent analysis was conducted among those who heard of ChatGPT for the attitude constructs ($n = 553$), and among those who indicated ChatGPT usage before the study for the usage constructs ($n = 472$).

3.2 Analysis of TAME-ChatGPT usage constructs

The highest average score for the TAME-ChatGPT usage constructs was observed for the ease of use construct with a mean score of 4.36 ± 0.74 followed by the perceived usefulness construct with a mean score of 3.97 ± 0.80, behavior/cognitive construct with a mean score of 3.73 ± 0.97, and finally the perceived risk of use construct with a mean score of 2.06 ± 0.77 (Figure 1).

Univariate analysis of the demographic factors associated with each TAME-ChatGPT usage construct revealed statistically significant higher scores among males, Arabs, participants in non-health-related colleges, and postgraduates that for both the perceived usefulness construct and the behavior/cognitive construct (Table 2).

3.3 Attitude towards ChatGPT based on TAME-ChatGPT constructs

The highest average score for the TAME-ChatGPT attitude sub-scales was observed for the technology/social influence construct with a mean score of 3.95 ± 0.82 followed by the perceived risk construct with a mean score of 2.08 ± 0.79, and finally the anxiety construct with a mean score of 2.07 ± 0.92 (Figure 2).

Univariate analysis of the demographic factors associated with each TAME-ChatGPT attitude constructs revealed statistically significant higher scores among males, Arabs, and participants in non-Health-related colleges for attitude to technology/social influence construct (Table 3).

3.4 Univariate analysis of the attitude and usage of ChatGPT based on TAME-ChatGPT constructs

To assess the overall factors influencing the usage of ChatGPT, univariate analysis revealed that the following demographic variables

TABLE 1 General features of the study sample (N = 608).

Variable	Category	Count	Percentage
Age	≤ 20 years	347	57.1
	> 20 years	261	42.9
Sex	Male	287	47.2
	Female	321	52.8
Nationality	Arab	412	67.8
	Non-Arab	196	32.2
College[a]	Health-related	155	25.5
	Non-Health-related	453	74.5
Latest self-reported cumulative GPA[b]	< 2.50	54	10.4
	2.50–2.99	90	17.3
	3.00–3.49	173	33.3
	3.50–4.00	203	39.0
Educational level	Undergraduate	580	95.4
	Postgraduate	28	4.6
Have you heard of ChatGPT before this study?	Yes	553	91.0
	No	55	9.0
Have you used ChatGPT before this study?	Yes	472	85.4
	No	81	14.6

[a]College: Health-related included Health Sciences and Public Health colleges, while non-Health-related included Art and Sciences, Law, Business, Engineering, Military, Electrical Engineering, Communication, Arts, and Sciences, and Social Sciences colleges.
[b]GPA: Grade point average with information available from 520 participants.

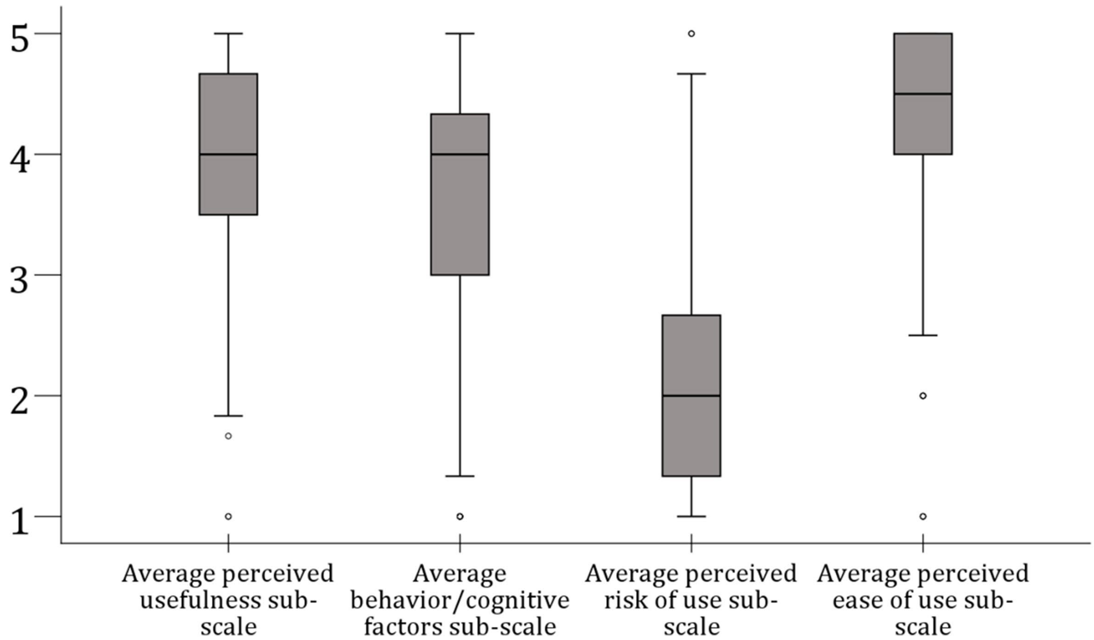

FIGURE 1
Box plots showing the distribution of scores across the four TAME-ChatGPT usage constructs.

were significantly associated with higher ChatGPT usage scores: being a male, an Arab in nationality, and lower self-reported latest GPA (Table 4). Additionally, the four TAME-ChatGPT constructs were significantly associated with higher ChatGPT usage scores as follows: higher perceived usefulness, higher scores of the behavior/cognitive factors, lower perceived risk of use, and higher perceived ease of use (Table 4).

TABLE 2 The demographic determinants of ChatGPT use based on TAME-ChatGPT usage constructs.

Variable	Category	Average perceived usefulness sub-scale		Average behavior/ cognitive factors sub-scale		Average perceived risk of use sub-scale		Average perceived ease of use sub-scale	
		Mean ± SD[c]	*p* value[d]	Mean ± SD	*p* value	Mean ± SD	*p* value	Mean ± SD	*p* value
Age	≤ 20 years	3.95 ± 0.78	0.292	3.72 ± 0.97	0.730	2.00 ± 0.73	0.076	4.35 ± 0.71	0.361
	> 20 years	4.01 ± 0.83		3.74 ± 0.97		2.15 ± 0.82		4.39 ± 0.77	
Sex	Male	4.14 ± 0.77	**<0.001**	3.89 ± 0.96	**<0.001**	2.04 ± 0.82	0.569	4.39 ± 0.75	0.329
	Female	3.82 ± 0.80		3.57 ± 0.96		2.07 ± 0.72		4.34 ± 0.73	
Nationality	Arab	4.05 ± 0.81	**<0.001**	3.86 ± 0.92	**<0.001**	2.08 ± 0.82	0.692	4.38 ± 0.76	0.120
	Non-Arab	3.81 ± 0.76		3.45 ± 1.02		2.02 ± 0.65		4.32 ± 0.68	
College[a]	Health-related	3.81 ± 0.81	**0.013**	3.44 ± 1.03	**<0.001**	2.11 ± 0.79	0.428	4.28 ± 0.78	0.131
	Non-Health-related	4.02 ± 0.79		3.82 ± 0.94		2.04 ± 0.77		4.39 ± 0.72	
Cumulative GPA[b]	< 2.50	4.23 ± 0.79	**<0.001**	4.17 ± 0.83	**<0.001**	1.91 ± 0.76	0.352	4.33 ± 0.87	0.854
	2.50–2.99	4.11 ± 0.78		3.85 ± 0.92		2.12 ± 0.80		4.46 ± 0.62	
	3.00–3.49	4.06 ± 0.82		3.85 ± 1.01		1.99 ± 0.76		4.35 ± 0.75	
	3.50–4.00	3.79 ± 0.81		3.56 ± 0.93		2.11 ± 0.77		4.38 ± 0.71	
Educational level	Undergraduate	3.97 ± 0.79	**0.013**	3.72 ± 0.97	**0.001**	2.06 ± 0.76	0.428	4.38 ± 0.72	0.131
	Postgraduate	3.99 ± 1.01		3.83 ± 1.11		2.10 ± 1.01		4.07 ± 0.98	

[a]College: Health-related included Health Sciences and Public Health colleges, while non-Health-related included Art and Sciences, Law, Business, Engineering, Military, Electrical Engineering, Communication, Arts, and Sciences, and Social Sciences colleges.
[b]GPA: Grade point average.
[c]SD: Standard deviation.
[d]*p* value: Calculated using the Mann–Whitney and Kruskal Wallis tests.
Statistically significant *p* values are highlighted in bold style.

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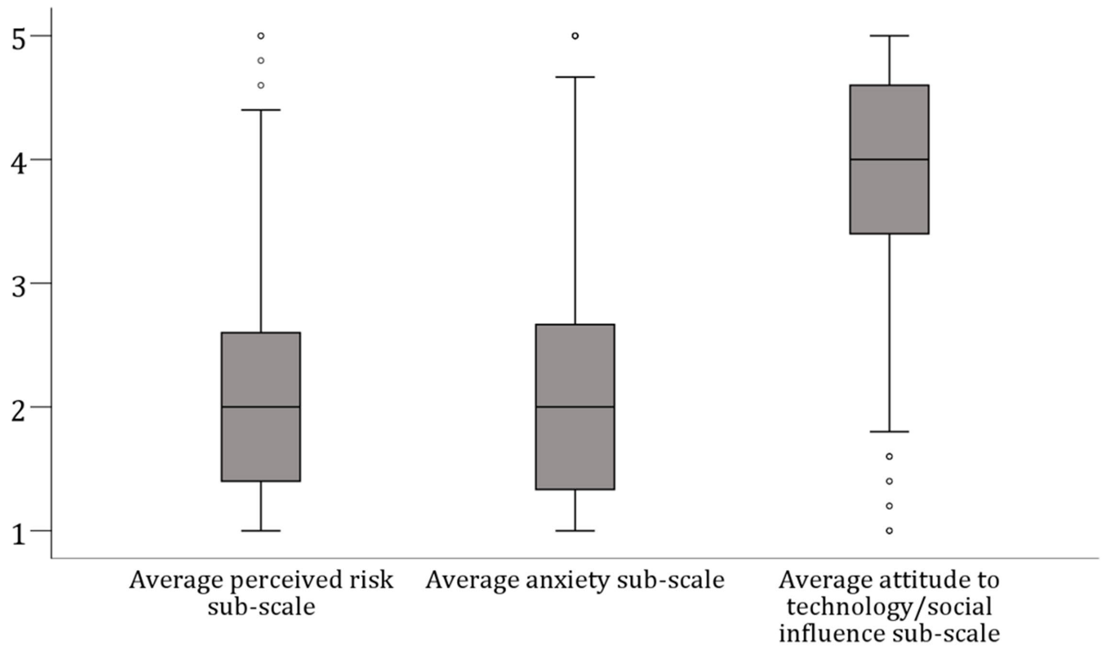

FIGURE 2
Box plots showing the distribution of scores across the three TAME-ChatGPT attitude constructs.

TABLE 3 The demographic determinants of attitude to ChatGPT based on TAME-ChatGPT attitude constructs.

Variable	Category	Average perceived risk sub-scale		Average anxiety sub-scale		Average attitude to technology/ social influence sub-scale	
		Mean ± SD[c]	*p* value[d]	Mean ± SD	*p* value	Mean ± SD	*p* value
Age	≤ 20 years	2.02 ± 0.76	0.106	2.01 ± 0.90	0.058	3.92 ± 0.80	0.175
	> 20 years	2.15 ± 0.82		2.16 ± 0.94		3.99 ± 0.85	
Sex	Male	2.07 ± 0.81	0.673	2.13 ± 0.96	0.199	4.12 ± 0.77	**<0.001**
	Female	2.08 ± 0.76		2.01 ± 0.89		3.79 ± 0.83	
Nationality	Arab	2.07 ± 0.83	0.500	2.06 ± 0.94	0.770	4.02 ± 0.81	**0.001**
	Non-Arab	2.08 ± 0.69		2.07 ± 0.89		3.79 ± 0.83	
College[a]	Health-related	2.08 ± 0.82	0.969	2.09 ± 0.97	0.988	3.77 ± 0.84	**0.001**
	Non-Health-related	2.07 ± 0.78		2.06 ± 0.90		4.01 ± 0.81	
Cumulative GPA[b]	< 2.50	1.88 ± 0.75	0.270	2.01 ± 0.90	0.457	4.22 ± 0.78	**0.022**
	2.50–2.99	2.18 ± 0.84		2.23 ± 0.98		3.92 ± 0.87	
	3.00–3.49	2.04 ± 0.79		2.01 ± 0.89		4.03 ± 0.84	
	3.50–4.00	2.07 ± 0.76		2.07 ± 0.93		3.86 ± 0.83	
Educational level	Undergraduate	2.08 ± 0.78	0.139	2.08 ± 0.92	0.138	3.94 ± 0.81	0.253
	Postgraduate	1.92 ± 0.98		1.87 ± 1.00		3.98 ± 1.10	

[a]College: Health-related included Health Sciences and Public Health colleges, while non-Health-related included Art and Sciences, Law, Business, Engineering, Military, Electrical Engineering, Communication, Arts, and Sciences, and Social Sciences colleges.
[b]GPA: Grade point average.
[c]SD: Standard deviation.
[d]*p* value: Calculated using the Mann–Whitney and Kruskal Wallis tests.
Statistically significant *p* values are highlighted in bold style.

For the attitude towards ChatGPT, univariate analysis showed that the three TAME-ChatGPT constructs were the only variables having significant associations with the overall TAME-ChatGPT attitude score with lower perceived ChatGPT risk, lower anxiety, and higher scores on attitude to technology/social influence being linked with higher attitude scores (Table 5).

TABLE 4 Univariate analysis associated with TAME-ChatGPT usage.

Variable	Category	Overall TAME-ChatGPT usage categories[b]			p value, χ^2
		Negative	Neutral	Positive	
		Count (%)	Count (%)	Count (%)	
Age	≤ 20 years	1 (0.3)	179 (62.2)	108 (37.5)	0.456, 1.571
	> 20 years	2 (1.1)	107 (58.2)	75 (40.8)	
Sex	Male	2 (0.9)	123 (53.2)	106 (45.9)	**0.006**, 10.316
	Female	1 (0.4)	163 (67.6)	77 (32.0)	
Nationality	Arab	3 (0.9)	177 (54.6)	144 (44.4)	**<0.001**, 16.013
	Non-Arab	0 (0)	109 (73.6)	39 (26.4)	
College	Health-related	0 (0)	76 (67.9)	36 (32.1)	0.144, 3.876
	Non-Health-related	3 (0.8)	210 (58.3)	147 (40.8)	
Cumulative GPA	< 2.50	1 (2.4)	20 (47.6)	21 (50.0)	**0.049**, 12.658
	2.50–2.99	0 (0)	38 (53.5)	33 (46.5)	
	3.00–3.49	1 (0.7)	71 (53.0)	62 (46.3)	
	3.50–4.00	1 (0.6)	113 (68.1)	52 (31.3)	
Educational level	Undergraduate	2 (0.4)	271 (60.4)	176 (39.2)	0.056, 5.761
	Postgraduate	1 (4.3)	15 (65.2)	7 (30.4)	
Perceived usefulness categories	Disagreement	3 (18.8)	13 (81.3)	0 (0)	**<0.001**, 201.836
	Neutral	0 (0)	126 (97.7)	3 (2.3)	
	Agreement	0 (0)	147 (45.0)	180 (55)	
Behavior/cognitive factors categories	Disagreement	3 (5.4)	53 (94.6)	0 (0)	**<0.001**, 132.198
	Neutral	0 (0)	103 (88.8)	13 (11.2)	
	Agreement	0 (0)	130 (43.3)	170 (56.7)	
Perceived risk of use categories[a]	Disagreement	1 (0.3)	214 (62.4)	128 (37.3)	**<0.001**, 78.008
	Neutral	0 (0)	69 (57.0)	52 (43.0)	
	Agreement	2 (25.0)	3 (37.5)	3 (37.5)	
Perceived ease of use categories	Disagreement	2 (28.6)	5 (71.4)	0 (0)	**<0.001**, 124.765
	Neutral	0 (0)	60 (93.8)	4 (6.3)	
	Agreement	1 (0.2)	221 (55.1)	179 (44.6)	

[a]Agreement indicated lower perceived risk of use based on reverse coding of the items.
[b]TAME-ChatGPT usage categories based on the average scores were classified as 1.00–2.33 (negative), 2.34–3.67 (neutral), and 3.68–5.00 (positive).
Statistically significant p values are highlighted in bold style.

3.5 Multivariate analysis of the determinants of ChatGPT usage

The regression model for the predictors of ChatGPT usage showed a high degree of explanatory power with an R^2 value of 0.774 indicating that 77.4% of the variation in the usage of ChatGPT were accounted for by the predictors included in the model. Nationality was the only demographic variable with a significant association with TAME-ChatGPT usage score ($p = 0.025$), suggesting that being Arab in nationality was linked with higher usage scores.

On the other hand, the four TAME-ChatGPT usage constructs were associated with the overall TAME-ChatGPT usage scores as follows: higher perceived usefulness (B = 0.398, $p < 0.001$), higher scores on the behavior/cognitive factors (B = 0.276, $p < 0.001$), lower perceived risk of use (B = 0.265, $p < 0.001$), and higher perceived ease of use scores (B = 0.368, $p < 0.001$, Table 6).

3.6 Multivariate analysis of the determinants of attitude towards ChatGPT

For the predictors of the attitude towards ChatGPT, the regression model showed a high degree of explanatory power with an R^2 value of 0.808. Using this model, the three TAME-ChatGPT attitude constructs were associated with the attitude scores as follows: lower perceived risk (B = 0.418, $p < 0.001$), lower anxiety scores (B = 0.479, $p < 0.001$), and higher scores in the attitude to technology/social influence construct (B = 0.413, $p < 0.001$, Table 7).

4 Discussion

The current study highlighted a notable increase in the usage of ChatGPT among university students, with a substantial increase compared to earlier studies from different world regions. The findings

TABLE 5 Univariate analysis associated with the overall TAME-ChatGPT attitude score.

Variable	Category	Overall TAME-ChatGPT attitude categories[c]			p value, χ^2
		Negative	Neutral	Positive	
		Count (%)	Count (%)	Count (%)	
Age	≤ 20 years	1 (0.3)	179 (62.2)	108 (37.5)	0.086, 4.914
	> 20 years	2 (1.1)	107 (58.2)	75 (40.8)	
Sex	Male	2 (0.9)	123 (53.2)	106 (45.9)	0.126, 4.143
	Female	1 (0.4)	163 (67.6)	77 (32.0)	
Nationality	Arab	3 (0.9)	177 (54.6)	144 (44.4)	0.787, 0.479
	Non-Arab	0 (0)	109 (73.6)	39 (26.4)	
College	Health-related	0 (0)	76 (67.9)	36 (32.1)	0.067, 5.410
	Non-Health-related	3 (0.8)	210 (58.3)	147 (40.8)	
Cumulative GPA	< 2.50	1 (2.4)	20 (47.6)	21 (50.0)	0.184, 8.814
	2.50–2.99	0 (0)	38 (53.5)	33 (46.5)	
	3.00–3.49	1 (0.7)	71 (53.0)	62 (46.3)	
	3.50–4.00	1 (0.6)	113 (68.1)	52 (31.3)	
Educational level	Undergraduate	2 (0.4)	271 (60.4)	176 (39.2)	0.437, 1.655
	Postgraduate	1 (4.3)	15 (65.2)	7 (30.4)	
Perceived risk categories[a]	Disagreement	148 (41.5)	209 (58.5)	0 (0)	**<0.001**, 201.097
	Neutral	7 (3.9)	159 (89.3)	12 (6.7)	
	Agreement	0 (0)	9 (50.0)	9 (50)	
Anxiety categories[b]	Disagreement	152 (39.1)	237 (60.9)	0 (0)	**<0.001**, 227.671
	Neutral	3 (2.3)	123 (92.5)	7 (5.3)	
	Agreement	0 (0)	17 (54.8)	14 (45.2)	
Attitude to technology/social influence categories	Disagreement	13 (65.0)	7 (35.0)	0 (0)	
	Neutral	56 (35.0)	104 (65.0)	0 (0)	**<0.001**, 29.956
	Agreement	86 (23.1)	266 (71.3)	21 (5.6)	

[a]Agreement indicated lower perceived risk based on reverse coding of the items.
[b]Agreement indicated lower anxiety based on reverse coding of the items.
[c]TAME-ChatGPT usage categories based on the average scores were classified as 1.00–2.33 (negative), 2.34–3.67 (neutral), and 3.68–5.00 (positive).
Statistically significant p values are highlighted in bold style.

of this study revealed that 85% of the participating university students in the UAE have already used ChatGPT. An early study conducted during February–March 2023 among university students in health schools in Jordan reported that only 11% used ChatGPT at the time (Sallam et al., 2023a). A subsequent multinational study that involved university students in five Arab countries (Iraq, Kuwait, Egypt, Lebanon, and Jordan) during April–August 2023 reported ChatGPT usage at a rate of 25% (Abdaljaleel et al., 2024).

In a culturally different context, a study that was conducted during June–July 2023 revealed that 39% of medical students across Germany, Austria, and Switzerland previously engaged with AI-based chatbots including ChatGPT (Weidener and Fischer, 2024). Another multinational study among academics and university students in Brazil, India, Japan, United Kingdom, and United States, which was conducted in January 2023 indicated that a majority of students intend to use ChatGPT for support in university assignments and anticipate that their peers would endorse its usage (Ibrahim et al., 2023). A recently published study among marketing students in India indicated that 309 out of 425 students were aware of ChatGPT (73%), with daily usage among 19% of the participants (Gulati et al., 2024). Taken together, these results highlight a noticeable rise in the adoption of ChatGPT among university students and its evolving status to become a normal practice within this demographic group.

In this study, the univariate analysis identified a positive correlation between the attitude to technology/social influence in the context of general attitude to ChatGPT and the following demographic groups: being an Arab student, being a male participant, and affiliation in non-health colleges. This association might indicate the interplay of cultural and demographic factors in the adoption of new technologies such as ChatGPT. For example, Arab students might exhibit more positive attitude to innovative AI technologies possibly due to its utility in overcoming language barriers (Chen, 2023; Mijwil et al., 2023b; Barwise et al., 2024). Nevertheless, this justification remains tentative considering the studies showing inferior performance of ChatGPT in non-English languages (Żammit, 2023; Liu et al., 2024; Sallam and Mousa, 2024). Sex also appeared to play a role in ChatGPT acceptance, with previous evidence suggesting that females may face more technical challenges and perceive greater risks

TABLE 6 Regression analysis of the predictors influencing ChatGPT usage based on the TAME-ChatGPT constructs.

Model	Coefficients[a]			T statistic	*p* value	VIF[c]
	Unstandardized Coefficients		Standardized Coefficients			
	B	SE[b]	Beta			
Constant	0.561	0.142		3.955	**<0.001**	
Sex	−0.003	0.023	−0.003	−0.109	0.913	1.068
Nationality	−0.057	0.026	−0.055	−2.243	**0.025**	1.085
Cumulative GPA	−0.017	0.012	−0.035	−1.434	0.152	1.070
Educational level	−0.033	0.058	−0.014	−0.576	0.565	1.029
Perceived usefulness	0.398	0.027	0.460	14.643	**<0.001**	1.757
Behavior/cognitive factors	0.276	0.022	0.396	12.465	**<0.001**	1.798
Perceived risk of use	0.265	0.024	0.275	10.898	**<0.001**	1.139
Perceived ease of use	0.368	0.03	0.310	12.181	**<0.001**	1.158

[a]Dependent variable: Overall TAME-ChatGPT usage score.
[b]SE: Standard error.
[c]VIF: Variance inflation factor.
Statistically significant *p* values are highlighted in bold style. Adjusted $R^2 = 0.769$, SE = 0.23. ANOVA F statistic = 172.48, *p* value < 0.001.

TABLE 7 Regression analysis of the predictors influencing the attitude towards ChatGPT based on the TAME-ChatGPT constructs.

Model	Coefficients[a]			T statistic	*p* value	VIF[c]
	Unstandardized coefficients		Standardized coefficients			
	B	SE[b]	Beta			
Constant	0.285	0.073		3.907	**<0.001**	1.009
Age	0.031	0.02	0.029	1.547	0.123	1.016
College	0.029	0.022	0.024	1.287	0.199	1.678
Perceived risk	0.418	0.023	0.442	18.212	**<0.001**	1.670
Anxiety	0.479	0.022	0.537	22.173	**<0.001**	1.073
Attitude to technology/ social influence	0.413	0.018	0.438	22.539	**<0.001**	1.009

[a]Dependent variable: Overall TAME-ChatGPT usage score.
[b]SE: Standard error.
[c]VIF: Variance inflation factor.
Statistically significant *p* values are highlighted in bold style. Adjusted $R^2 = 0.808$, SE = 0.23; ANOVA F statistic = 460.12, *p* value < 0.001.

when using technology compared to males (Goswami and Dutta, 2016; Cai et al., 2017). The more positive attitude observed among students from non-health disciplines can be attributed to their specific academic fields. University students in technology-related disciplines might be more inclined towards embracing new technologies such as ChatGPT which is influenced by both the curricular content and personal interests. This notion is supported by a study by Margaryan et al. (2011), which found that engineering students were more likely to use technology tools for various purposes compared to social work students.

The univariate analysis of the usage constructs of TAME-ChatGPT in this study revealed the following findings. The lower perceived risk of ChatGPT use and higher agreement with behavior/cognitive factors, indicative of an instinctive impulse to utilize this novel technology, were associated with being male, Arab, enrolled in non-health colleges, and having a lower GPA. These associations may point to a greater tendency among these groups to embrace new technologies, likely influenced by a combination of cultural/societal norms and prior educational experiences as well as the attitudes towards the perceived risk.

The propensity of postgraduate students to exhibit these characteristics could be related to their extended experience with a variety of technologies. Consequently, this extended exposure could result in a more readiness to accept and engage with innovative technological tools such as ChatGPT. Likewise, students in non-health disciplines especially in technology-related colleges might be more regularly exposed to emerging technologies. Consequently, this exposure would lead to increased familiarity with novel technologies and a lower level of perceived risks. Additionally, the previous academic experience with novel technologies among these students could result in an innate readiness to engage with technological advancements such as ChatGPT.

The correlation of lower perceived risk from ChatGPT and more agreement with cognitive/behavioral factors with lower GPA categories was an interesting finding in this study. One possible explanation is that university students with lower academic performance are more inclined to experiment with novel technologies such as ChatGPT as a compensatory mechanism to improve their academic achievements. Another explanation could be related to the higher propensity to explore innovative tools including ChatGPT as a result of the lower level of perceived constraints of academic rigor. In all cases, this particular observation warrants further investigation to understand the underlying motivations and implications of ChatGPT adoption among university students with varying academic performances which may require tailoring the adoption of ChatGPT to the individual student needs.

In this study, the perceived usefulness of ChatGPT, behavioral/cognitive factors, perceived risk associated with ChatGPT usage, and the perceived ease of using ChatGPT were all significantly correlated with the overall ChatGPT usage score. Concerning the overall TAME-ChatGPT attitude score, lower perceived risk and anxiety were associated with more favorable attitudes towards ChatGPT, alongside a positive attitude towards technology and social influence. These findings contribute an additional evidence to the growing literature emphasizing the significance of various constructs in technology acceptance assessment tools, such as the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT2) in the adoption of ChatGPT in various settings (Foroughi et al., 2023; Habibi et al., 2023; Jo and Bang, 2023; Yilmaz et al., 2023). In turn, this can help to guide evidence-based strategies to govern ChatGPT use among other genAI models in higher education (Veras et al., 2023; Grájeda et al., 2024).

For example, a study among Polish university students using UTAUT2 found that habit was the most influential factor on behavioral intention in the context of ChatGPT use, followed by performance expectancy and hedonic motivation (Strzelecki, 2023). Moreover, behavioral intention had the most substantial effect on ChatGPT usage behavior, followed by habit and facilitating conditions (Strzelecki, 2023). Our results align with these findings, particularly regarding behavioral/cognitive factors, which are reflected in items indicating previous use of similar tools and frequent utilization of ChatGPT in university assignments. Performance expectations in our study were analogous to the perceived usefulness construct, while facilitating conditions are comparable to our perceived ease of use construct highlighting recurrence of similar themes for the factors driving the acceptance of ChatGPT as an innovative tool in higher education (Gupta and Yang, 2024). The perceived ease of use is particularly an important driver for the wide popularity of ChatGPT with a user-friendly interface and little technical requirements (Shaikh et al., 2023; Albayati, 2024). In turn, this perceived ease of use would render ChatGPT more appealing for students to try and continue using.

In line with our findings, the importance of usefulness and ease of use has been shown in a recent study by Almogren et al. (2024) among a group of undergraduate and postgraduate university students. Additionally, the effectiveness of AI tools was an important predictor of its acceptance and use among university students in a recent study conducted in Malaysia and Pakistan (Dahri et al., 2024). Moreover, effectiveness has been shown to positively influence ChatGPT usage frequency as shown in a recent study in a different context by de Winter et al. (2024). The importance of usefulness has also been shown through its influence on user satisfaction in a recent study addressing AI chatbots user experience (Xing and Jiang, 2024). Furthermore, the central role of perceived usefulness and ease of use of ChatGPT in learning has been demonstrated in a study involving nursing students (Savellon et al., 2024).

The significance of perceived risks in ChatGPT use, which includes concerns about cybersecurity (Mijwil et al., 2023a), bias (Ray, 2023), and inaccuracies (Borji, 2023; Sallam, 2023), was a critical determinant of both attitude to ChatGPT and its usage in this study. This finding was consistent with a recent qualitative study which utilized the UTAUT model and highlighted the role of privacy concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions in driving engagement with ChatGPT (Menon and Shilpa, 2023). This suggests that university students' collective perceptions of both benefits and risks posed by technologies such as ChatGPT play a key role to shape their engagement and adoption of this novel technology (Chan and Hu, 2023; Abdaljaleel et al., 2024).

In this study, multivariate regression analyses provided comprehensive insights into the predictors of ChatGPT usage, and attitudes as modeled by the TAME-ChatGPT constructs. The complex nature of ChatGPT perceptions and adoption were determined by several factors including the psycho-social determinants manifested in anxiety, behavior/cognitive and social influence constructs besides the individual perception of usefulness, usability, and perception of risks. Notably, the demographic and academic variables (e.g., age, sex, college, GPA) were not significant predictors of ChatGPT attitude or usage. This result suggests that practical aspects of this novel technology such as the usefulness, user-friendly nature, and potential risks were more impactful in determining usage than demographic attributes. Thus, the primary drivers of ChatGPT usage and attitudes are mainly rooted in students' psycho-social predispositions. These findings suggest that if ChatGPT among other genAI models are to be integrated in higher education, there is a necessity for strategies to enhance the perceived usefulness and ease of use for these models. Additionally, addressing the students' anxiety and perceived risks is required for positive engagement with genAI technology in education. Nevertheless, the demographic and academic variables can also be considered to achieve an intricate understanding of attitude and use of ChatGPT among university students.

Based on the results of this study, it is crucial for higher education institutions, policymakers, and educators to formulate new educational strategies to accommodate the transformative AI changes. These strategies should highlight the utility and accessibility of genAI tools and proactively address the potential apprehensions that students might encounter as shown recently by Oluwadiya et al. (2023). To enhance the perception of ease and usefulness of genAI models, higher education institutions are advised to launch AI integration initiatives that include raising awareness regarding the benefits of these tools in education (Ivanov et al., 2024). These initiatives should also focus on providing training sessions, tutorials, and practical, hands-on experiences for students and faculty alike to explore the full potential of genAI in education (Chiu, 2024). Furthermore, integrating these genAI tools into the curriculum can directly benefit learning and research by demonstrating their real-world applications (Sheikh Faisal et al., 2024). These applications include generating content for study materials, or simulating complex concepts, thereby enriching the educational experience (Yu, 2024). The better usability of ChatGPT compared to web-based tools in health education has been suggested in a recent research protocol by Veras et al. (2023). In another aspect, addressing psychological barriers such as anxiety and perceived risks associated with genAI technology is essential and can be effectively managed by shifting the cultural dynamics within educational institutions (Yusuf et al., 2024). Programs designed to familiarize students and faculties with genAI tools can facilitate the integration of this novel technology into higher education and alleviate fears, similar to initiatives seen with the introduction of digital learning tools in the past decade as reviewed recently by Fernández et al. (2023).

Although demographic and academic variables may not emerge as primary drivers in genAI adoption, their influence on technology interaction should not be overlooked. Tailored educational practices that consider these factors can significantly enhance genAI adoption rates. By acknowledging these subtle differences, educational policies can better accommodate a diverse students' strata, ensuring that the benefits of genAI are accessible to all students, regardless of their background (Sheikh Faisal et al., 2024). These strategic approaches can facilitate the adoption of genAI technologies and maximize their potential to enrich learning experiences and outcomes. Subsequently, this can help to prepare students to operate effectively in an increasingly digital AI-driven world (George, 2023).

The results of this study highlighted several areas for future research to enhance the collective understanding of genAI effects in different educational contexts. For example, longitudinal studies are essential to assess the long-term impact of genAI on learning outcomes and experiences, tracking changes in students' perceptions and academic performance over extended periods. Additionally, experimental designs like randomized controlled trials (RCTs) are recommended to establish causal links between genAI usage and educational outcomes, building on recent protocols such as the one conceived by Veras et al. (2023). Investigating genAI influence across different academic disciplines would also be beneficial, which would help to develop tailored integration strategies that address the specific needs and challenges for various academic disciplines. Moreover, considering the significant role of cultural context in technology adoption, cross-cultural studies could examine how different settings influence genAI acceptance and effectiveness. Lastly, with ongoing concerns about the ethical implications and risks of genAI, further research should focus on these areas, particularly privacy, data security, and bias, to ensure responsible and ethical use of genAI for students and educational institutions.

Finally, it is important to consider the findings of this study in light of several limitations as follows. The convenience sampling approach utilized with the inherent selection bias could limit the representativeness of the sample and generalizability of the findings. The selection bias is also expected considering the electronic distribution of the survey among students. An element of bias should be considered as well in light of more inclination of the students who previously engaged with ChatGPT or heard of it to participate in the study and express their opinions. Finally, the reliance on self-reported data could result in self-reporting bias.

5 Conclusion

This study elucidated the determinants of ChatGPT adoption among university students in the UAE. Addressing these factors could help to exploit ChatGPT potential for better learning experience and to help equip university students to responsibly use the current and future technological innovations. Students' familiarity with ChatGPT can provide an opportunity for genAI integration in higher education curricula and teaching methods.

The study highlighted the central role of individual and psycho-social factors as modeled in the TAME-ChatGPT constructs as significant factors driving the attitude towards ChatGPT and its usage. These insights can help higher education institutions, policymakers, and educators to formulate clear initiatives and guidelines that would help students in circumventing the ethical and practical aspects of genAI tool adoption in higher education.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Ethics statement

This study was approved by the Institutional Review Board (IRB) at Gulf Medical University (Reference number: IRB-COD-FAC-49-APRIL-2023). Obtaining the informed consent to participation was ensured by the inclusion of a mandatory item at the beginning of the electronic survey to explicitly indicate consent for participation. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. WE: Data curation, Investigation, Methodology, Writing – review & editing. MA-S: Data curation, Investigation, Methodology, Writing – review & editing. MB: Data curation, Investigation, Methodology, Writing – review & editing. SE: Data curation, Investigation, Methodology, Writing – review & editing. WG: Data curation, Investigation, Methodology, Writing – review & editing. NA: Data curation, Investigation, Methodology, Writing – review & editing. SH: Data curation, Investigation, Methodology, Writing – review & editing. DM: Data curation, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A1

Table A1.

TABLE A1 Full TAME-ChatGPT items.

Usage scale
A. Perceived usefulness
1. ChatGPT helps me to save time when searching for information
2. For me, ChatGPT is a reliable source of accurate information
3. I recommend ChatGPT to my colleagues to facilitate their academic duties
4. ChatGPT is more useful than other sources of information that I have used previously
5. I appreciate the accuracy and reliability of the information provided by ChatGPT
6. I believe that using ChatGPT can save time and effort in my university assignments and duties
B. Behavior/cognitive factors
7. I have used tools or techniques similar to ChatGPT in the past
8. I spontaneously find myself using ChatGPT when I need information for my university assignments and duties
9. I often use ChatGPT as a source of information in my university assignments and duties
C. Perceived risk of use REVERSED SCORE
10. I am concerned that using ChatGPT would get me accused of plagiarism
11. I am concerned about the potential security risks of using ChatGPT
12. I think that relying on technology like ChatGPT can disrupt my critical thinking skills
D. Perceived ease of use
13. It does not take a long time to learn how to use ChatGPT
14. ChatGPT does not require extensive technical knowledge
Attitude scale
A. Perceived risk REVERSED SCORE
1. I am concerned about the reliability of the information provided by ChatGPT
2. I am concerned that using ChatGPT would get me accused of plagiarism
3. I am concerned about the potential security risks of using ChatGPT
4. I am afraid that the use of the ChatGPT would be a violation of academic and university policies
5. I am concerned about the potential privacy risks that might be associated with using ChatGPT
B. Anxiety REVERSED SCORE
6. I am afraid of relying too much on ChatGPT and not developing my critical thinking skills
7. I am afraid of becoming too dependent on technology like ChatGPT
8. I am afraid that using ChatGPT would result in a lack of originality in my university assignments and duties
C. Technology/social influence
9. I am enthusiastic about using technology such as ChatGPT for learning and research
10. I believe technology such as ChatGPT is an important tool for academic success
11. I think that technology like ChatGPT is attractive and fun to use
12. I am always keen to learn about new technologies like ChatGPT
13. I trust the opinions of my friends or colleagues about using ChatGPT