Understanding Students' Self-reported Use of ChatGPT in Higher Education: A Technology Acceptance Perspective on Privacy and Security Concerns

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***Abstract*—As Artificial Intelligence (AI) tools like ChatGPT become more ubiquitous in higher education, they have created new opportunities for assisting students' learning, as well as raised privacy and security concerns. While many AI-powered learning tools are becoming available, there are inconsistencies in students' usage patterns, which indicates that both enabling and inhibiting factors are at play. The study analyzes the relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), Privacy and Security Concerns (PSC), and Self-Reported Actual Usage (SRAU) in a Gulf Cooperation Council (GCC) higher education environment using a Technology Acceptance Model (TAM) perspective. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the collected data. The findings show that the highest correlation with Behavioral Intention (β = 0.495, p < 0.001) is Perceived Ease of Use, followed by Perceived Usefulness (β = 0.303, p < 0.001). Among the behavioral variables, Behavioral Intention positively affects self-reported actual usage (β = 0.209, p < 0.001), while privacy and security concerns have a negative effect on self-reported actual usage (β = −0.247, p < 0.001). Significant indirect effects of PU and PEOU on Self-Reported Actual Usage through Behavioral Intention were also observed. The model accounts for 54.1% of the variance for Behavioral Intention and 14.7% for the Self-Reported Actual Usage, indicating that other contextual factors may affect students' AI usage behavior. The results bring empirical evidence to light on students' self-reported use of ChatGPT and offer practical implementation tips for higher education institutions aiming to foster responsible and sustainable AI use by enhancing usability, showcasing educational benefits, bolstering privacy safeguards, and establishing responsible AI practices.**

***Keywords*—ChatGPT, Technology Acceptance Model (TAM), artificial intelligence in education, higher education, privacy and security concerns, self-reported actual usage, Partial Least Squares Structural Equation Modeling (PLS-SEM)**

I. Introduction

The use of ChatGPT as a learning assistant in higher education has increased significantly in recent years. AI tools are being increasingly used in a way that enhances students' learning, from retrieving information, generating content, solving problems, and programming, to academic writing. Even if ChatGPT is increasingly accessible and able to be used for education, its use among students is still inconsistent. Some students are more likely to embrace technology in their learning process, while others are less likely due to their varying perceptions in terms of usefulness, usability, privacy, and security [1]. Recognizing those factors that might be either promoting or hindering students' sustained use of ChatGPT, as well, can be a crucial topic for higher education institutions looking to responsibly incorporate AI into their teaching and learning.

The Technology Acceptance Model (TAM) has been one of the most popular theories used to understand users' acceptance of technology in various settings, as first proposed by Davis [2]. The two most important factors for the Technology Acceptance Model (TAM) are Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These constructs have been found to be useful in explaining and predicting the behavioral intentions of users to adapt to emerging technologies across studies. However, current AI uses raise other issues beyond ease of use and perceived value. With generative AI tools like ChatGPT, with which students are engaging, privacy, security, and responsible data management are emerging as increasingly critical concerns [1].

In recent years, it has been constantly shown that students' intention to adopt AI-supported learning technology includes the perceived usefulness of the technology, such as ChatGPT [3]. Meanwhile, it is becoming well established that privacy, security, and personal data protection concerns threaten to prevent students from converting positive intentions into Self-Reported Actual Usage habits [4]. Therefore, explaining student engagement with AI-supported learning technologies based on their positive perceptions of usefulness and ease of use may only partially account for this engagement. To have a more holistic understanding, it is important to consider both the factors that can facilitate and those that can hinder the use of AI tools in students' academic pursuits.

Besides perceived usefulness and perceived ease of use, previous research has found that other contextual factors have an impact on students' behavioral intentions toward ChatGPT [5]. Previous studies have documented factors such as institutional support, peer influence, trust in technology, and organizational practices as influencing the decision to adopt technology [6]. The results suggest that the use of AI technologies by students is shaped not just by the properties of the technology, but also by the context in which it is integrated and implemented in education.

In light of the above issues, the present study focuses on students' Self-Reported Actual Usage (SRAU) of ChatGPT from the perspective of the Technology Acceptance Model (TAM) by examining the relationships between Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, and Privacy and Security Concerns in a higher education context in the Gulf Cooperation Council (GCC). This study does not introduce any new technology acceptance model, but rather

presents empirical evidence regarding the association between the factors of Privacy and Security Concerns with students' self-reported usage behavior, in addition to the enabling mechanisms described by TAM. This research will help to understand the promotional and oppositional aspects of ChatGPT usage and give practical insights that will help universities build trustworthy and sustainable learning environments with the assistance of AI.

II. Literature Review

The most common theoretical model used in the research to explore the use of AI in higher education is the TAM, whose most common results of behavioral intention are perceived usefulness and perceived ease of use [3]. Empirical research in different contexts shows that perceived usefulness has a more important effect on behavioral intention than perceived ease of use [7]. However, the effects of social influence, enabling conditions, privacy, and security are context sensitive, and thus, it can be concluded that the extensions to the base TAM model would be context sensitive. The incorporation of other constructs, such as trust, contributes greatly to explaining power in the model, with perceived trust acting as a key mediator, enhancing the relationship between perceived usefulness, perceived ease of use, and behavioral intention [6]. Prolonged TAM models with more constructs have significantly enhanced predictive accuracy in AI adoption settings. The relationship between perceived ease of use and attitude is partially mediated by perceived benefit, and behavioral intention is partially mediated by perceived benefit [8]. Likewise, the inclusion of perceived value and task-technology fit into expanded TAM frameworks contributes to a better explanation of adoption intentions [1]. Trust is a critical mediating variable that substantially improves the relationship between the perceived usefulness, perceived ease of use, and behavioral intention [6]. These findings indicate that AI adoption involves considerations of both instrumental aspects of technology and affective and ethical aspects that foster user trust [1].

A. Contextual Moderators and External Factors

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework performance expectancy and effort expectancy portray strong effects on behavioral intention in diverse populations of students [9]. The social influence plays a significant moderating role between perceived trust and behavioral intention, which provides the critical significance of peer recommendations and institutional guidance [6]. Motivational factors and especially hedonic motivation are direct determinants and moderators, enhancing the effect of the facilitating conditions on adoption [10]. The effect of personal innovativeness and effort expectancy varies across studies, with some contexts showing that the relationships are not significant [11]. The institutional-level issues have a significant impact on the trends of adoption regardless of personal perceptions. Perceived support at the university is seen to be a core facilitator of adoption as it substantially impacts both awareness and perceived usefulness via infrastructure provision and policy clarity [6]. On the other hand, the challenge of perceived risk of over-reliance on AI and academic integrity issues moderate the adoption-intention relationship [1]. For Vocational Education, the simplicity of the technical aspects is identified as one contributing factors for the adoption, while barrier to implementation varies between levels of education [12]. Income inequality can be considered as new invisible technological barriers and socioeconomic status can predict the willingness to use a premium feature and willingness to try an AI tool [7]. These contextual findings emphasize how adoption mechanisms must not be solely associated to certain phenomena but rather to individual perceptions and institutional readiness, as well as to increased structural inequalities.

B. Privacy, Security, and Ethical Concerns as Adoption Barriers

Students report that data breaches and unauthorized access are causes for a great deal of anxiety [1]. Students are showing signs of serious concerns that can be correlated to the security and privacy of the data and the potential over-dependency on the AI tools that can hinder skill development in relation to critical thinking and problem-solving skills [1]. Like students in the U.S., and Bangladeshi university students also offer greater concerns over data security than their U.S. counterparts, thereby data security issues are cultural contextual and contingent [4]. Even though privacy may seem like an advantage over something that is actually harmful, it can be a critical disconnect between good and bad [13]. Academic integrity and ethical usage, risks of plagiarism, and transparency of AI usage play a significant role in decision making to use AI [14]. The students are clearly able to differentiate between the three preconditions: institutional policies, ethical AI literacy and faculty guidance for successful adoption of AI. Fuzzy thinking about how to use AI and loss of trust, because of the lack of clear institutional guidance and the lack of clear AI governance schemes [15]. Data protection regulations, such as General Data Protection Regulation (GDPR), is still not uniformly applied in institutions, and there is still confusion among students regarding the protection of their personal data [16]. Furthermore, the inequity issue brought up by algorithmic bias concerns and inequitable access to premium features because of socioeconomic status leads to equity issues beyond the individual adoption decision to systemic educational inequality [17].

C. Contextual and Disciplinary Differences in Adoption Patterns

Patterns of adoption indicate that there is a significant variation in patterns of adoption across academic disciplines, with different student populations exhibiting different levels of adoption [18]. Perceived value and usefulness are more significant drivers of adoption in specialized settings like dental education than ease of use or social factors [19]. The contexts of medical and pharmacy education indicate that habit formation and performance expectancy are important predictors of behavioral intention in contexts of medical and pharmacy education [9]. The contexts of learning a language show distinctive patterns of adoption in which the perceived enjoyment plays a critical role in influencing the behavioral intention through various pathways [20]. Adoption fundamentally depends on socioeconomic context, with students in developing countries prioritizing free tools and depending on smartphones to access them, and institutional

support availability in developing countries varies dramatically [17]. The relationship between technical innovation and local context dictates adoption outcomes, and requires subtle insight into how generalist AI tools need to be tailored to specific teaching and learning settings. Comparative study across different geographic settings shows that institutional support and social persuasion come out as good predictors of the difference in adoption across different geographic settings [7]. Geographic and institutional differences imply that one-size-fits-all methods of adopting technology are not sufficient, and rather that context-sensitive implementation models that take into account local infrastructure, regulatory frameworks, and student populations are necessary [4].

D. Trust, Motivation, and Sustainable Adoption

Trust is an experience-based construct, and the frequency of use, length of use and self-perceived proficiency in use is more predictive of trust than demographic factors [21]. The initial trust towards AI systems, along with perceived usefulness, plays an important role in influencing behavioral intention as well as actual use [22]. Nevertheless, the limitations of institutional trust are based on the lack of transparency when it comes to the data practices, the ambiguous AI governance framework, and the perceived incompatibility of the interests of AI developers and the protection of student privacy [15]. Faculty members' attitudes toward using AI and institutional policies toward using AI also significantly impact students' confidence; clear policies can minimize misunderstandings and encourage students to use AI [23]. The predictive validity of a behavioral intention is high with relation to Self-Reported Actual Usage across contexts, in the case of Peruvian students, the intention accounts for 58.8% of the variance of the actual use of the context [7]. However, enabling conditions, which include technology assistance, infrastructure and institutional scaffolds, influence the necessity to move positive intentions into regular use [6]. This formation of a habit may be considered one of the most powerful predictors of adoption in any other environment, which means that once students start having habits with ChatGPT, further use could be regarded as self-sustaining [9]. The shift in trial use to routine adoption needs institutional settings that normalize AI use by integrating it into the curriculum, modeling its use by faculty, and providing a structure of peer support. Continued adoption is not based on the initial euphoria but on continuous perception of usefulness, ease of access, and institutional support of responsible use [9].

Table 1. Summary of previous studies and research gaps in the literature

REF	Study Focus	Key Findings	Identified Gap
[1]	TAM Core Constructs	PU is the strongest predictor of BI, followed by PEOU.	Limited integration of real-world barriers, like privacy concerns, into the core TAM.
[3]	Examined using TAM Models	Incorporating additional constructs increases model fit; trust mediates PU/PEOU-BI relationships.	Few studies examine interaction effects between multiple mediators simultaneously.
[4]	Privacy Concerns	Privacy concerns significantly reduce Self-Reported Actual Usage (SRAU) despite high BI; effects are stronger in developing nations.	Insufficient research on mechanisms linking privacy concerns to behavioral disengagement.
[5]	Institutional Support	Institutional support predicts both awareness and PU; university guidance affects adoption intention.	Limited longitudinal evidence on the sustainability of institutional support effects.
[6]	Discipline Variations	Different disciplines illustrate varying acceptance levels toward AI tools.	Minimal research on discipline-specific adoption drivers and pedagogical integration patterns.
[7]	Global Context Differences	Social influence and socioeconomic disparities shape adoption differently across regions.	Underexplored cross-cultural mechanisms explaining adoption variability.
[8]	Trust Development	Trust is experience-driven (usage frequency, duration, proficiency) rather than demographic-based.	Need for longitudinal studies tracking trust evolution from initial use to sustained adoption.
[9]	Academic Integrity Concerns	Students identify plagiarism risks and unclear policies as adoption barriers.	Limited research on how institutional AI literacy training modifies integrity concerns.
[10]	Facilitating Conditions	Technical infrastructure, support accessibility, and institutional scaffolding enable intention-action translation.	Insufficient investigation of which facilitating conditions are most impactful in resource-constrained settings.
[11]	Behavioral Intention-Self-Reported Actual Usage Gap	BI explains substantial variance in SRAU, indicating significant unmeasured factors affecting usage.	Exploratory research is needed on psychological and contextual factors explaining unexplained variance.
[12]	Habit Formation	Habit significantly predicts BI in various contexts; routine use becomes self-sustaining.	Limited understanding of habit development timelines and conditions facilitating transition from trial to routine.
[13]	Hedonic Motivation	Enjoyment and perceived playfulness significantly influence adoption in specialized contexts.	Insufficient research on how pedagogical context moderates enjoyment-adoption relationships.
[14]	Technical Simplicity	Tool simplicity significantly influences adoption as a primary driver.	There is a gap in understanding how complexity tolerance varies by student population and discipline.
[15]	Data Security Awareness	The majority voice concern about data breaches; inconsistent institutional compliance with regulations.	Minimal research on whether AI literacy training effectively addresses security concerns.
[16]	Socioeconomic Barriers	How to access and rely on free tools that are dependent on a smartphone in developing countries.	Limited investigation of how institutional provision of equitable access affects adoption equity.
[17]	Social Influence Moderation	Social influence plays a role in moderating the trust-BI relationship, and peer recommendations are found to be critical for adoption.	Few studies examine how peer influence operates differently across disciplinary and cultural contexts.
[18]	Faculty Influence	The effects of faculty attitudes on student confidence are significantly under-exploited (modeling effects).	Insufficient research on training programs enhancing faculty adoption, which cascades to student adoption.
[19]	Ethical Decision-Making	Students weigh up the practical and ethical issues; they need more structured institutional arrangements.	Limited empirical investigation of how ethical reasoning frameworks influence adoption decisions.
[20]	AI Literacy Gaps	Students do not have a full understanding of the mechanisms of AI and its limitations, and concerns affect adoption.	Exploratory research needed on optimal AI literacy curriculum components for adoption enablement.
[21]	Sustainability of Adoption	High adoption rates are present at initial stages, but there is a lack of evidence of sustained usage.	Longitudinal studies tracking adoption trajectories beyond initial enthusiasm are needed.

Table 1 highlights several recurring patterns in the existing literature. While most studies confirm the importance of Perceived Usefulness, Perceived Ease of Use, trust, institutional support, and facilitating conditions in promoting ChatGPT adoption, considerably less attention has been devoted to understanding the factors that constrain Self-Reported Actual Usage after positive intentions have been formed. In addition, Privacy and Security Concerns are reported as important barriers, but are not well incorporated into the existing technology acceptance models. The literature also shows that certain contextual conditions (disciplinary culture, socioeconomic status, and institutional support) can affect students' adoption behaviors and can influence the transition from adoption intention to adoption practice.

While there have been numerous studies that have contributed to the understanding of AI adoption in higher education, there are still gaps to be addressed. First, there are a few studies that have studied Self-Reported Actual Usage, and a lot of studies that have studied Behavioral Intention. Second, Privacy and Security Concerns are commonly cited as contextual obstacles, but lack direct inclusion in technology acceptance models. Third, there is limited empirical evidence for how much Privacy and Security Concerns hinder Self-Reported Actual Usage when there are positive perceptions of usefulness and ease of use [24–29].

To address these gaps, this study examines students' self-reported use of ChatGPT from a Technology Acceptance Model perspective by incorporating Privacy and Security Concerns as a contextual factor influencing Self-Reported Actual Usage. The proposed framework investigates the relationships among Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and Self-Reported Actual Usage (SRAU), while examining whether Privacy and Security Concerns act as a barrier to students' engagement with ChatGPT in academic environments. Based on these observations, the research questions and research objectives presented in Table 2 were formulated.

Table 2. Research Questions (RQ) and Research Objectives (RO)

RQ	RO
RQ1: To what extent does Perceived Usefulness influence students' Behavioral Intention to use ChatGPT?	RO1: To examine the effect of Perceived Usefulness on Behavioral Intention.
RQ2: To what extent does Perceived Ease of Use influence students' Behavioral Intention to use ChatGPT?	RO2: To examine the effect of Perceived Ease of Use on Behavioral Intention.
RQ3: How does Behavioral Intention affect Self-Reported Actual Usage of ChatGPT?	RO3: To analyze the effect of Behavioral Intention on Self-Reported Actual Usage.
RQ4: Do Privacy and Security Concerns Negatively Influence Self-Reported Actual Usage of ChatGPT?	RO4: To assess the effect of Privacy and Security Concerns on Self-Reported Actual Usage.
RQ5: How well does the examination using the TAM model explain students' intention and self-reported use of ChatGPT?	RO5: To evaluate the explanatory and predictive capability of the examined TAM-based model.

The Hypotheses are formulated as follows:

H1: PU positively influences BI to use ChatGPT.

H2: PEOU positively influences BI to use ChatGPT.

H3: BI positively influences SRAU of ChatGPT.

H4: Privacy & Security Concerns (PSC) negatively influence SRAU of ChatGPT.

Fig. 1 illustrates the proposed framework and summarizes the research problem, the identified challenges, and the study's proposed solution and contribution.

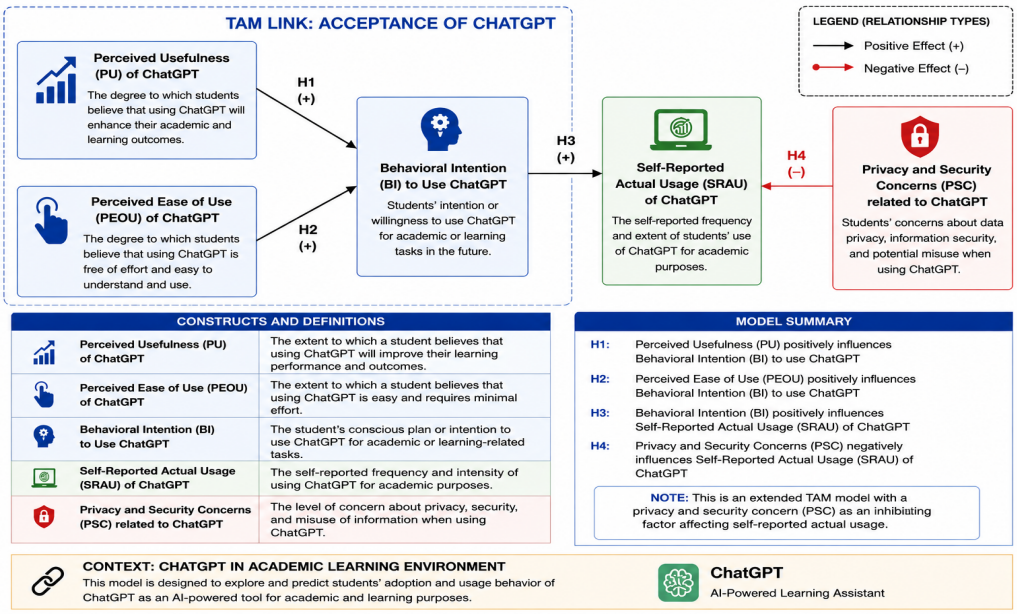


Fig. 1. Proposed framework.

III. Materials and Methods

A. Research Design

The research design used in this study is a quantitative research design because it aims to investigate the proposed model at the university level. Data was collected through a survey-based approach where students were distributed a structured questionnaire. The methodology is concerned with data quality, which is ensured by thorough screening and

statistical validation processes. Measurement and structural models were then tested to test research hypotheses and relationships.

1) Questionnaire development

The questionnaire consisted of five latent constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), Self-Reported Actual Usage (SRAU), and Privacy and Security Concerns (PSC). The SRAU construct was developed based on the latest research examining students' engagement with learning technologies that utilize AI tools and ChatGPT in higher education settings [24–29]. The indicators were measured as a reflective construct, Privacy and Security Concerns (PSC), because they are manifestations of the student's general concern about the protection of personal and academic information in the use of ChatGPT. While privacy and security are distinct concepts, they are inextricably linked when contemplating the risks of sharing information with AI systems, with student's likely thinking of them together when considering privacy and security. Thus, the two dimensions were amalgamated into one latent construct to represent students' general perception of information protection when using ChatGPT. The items were developed based on existing literature concerning privacy, security, trust, and the adoption of responsible AI in higher education and then adapted to the specific context of ChatGPT in higher education. The questionnaire was analyzed in the institutional ethics approval process to improve the clarity, relevance, and appropriateness of the questionnaire, prior to data collection.

All the measurement items were drawn from the existing technology acceptance literature and tailored to the domain of ChatGPT use in Higher Education [30–32]. Besides technology acceptance, recent research in education has focused on the wider implications of generative AI on assessment and feedback, learning quality and academic outcomes [33].

The PU and PEOU constructs were adapted mainly from the Technology Acceptance Model (TAM) by Davis [2], and the BI construct was adapted from the validated TAM and UTAUT constructs from previous studies [2, 34]. These items have been modified according to the previous study on technology acceptance and AI adoption in educational settings [2, 27, 29, 34, 35].

The SRAU construct was adapted from recent related studies that were conducted on the usage of AI and ChatGPT in academic environments. The PSC construct has been created based on a comprehensive search of the latest literature on privacy, security, trust, and data protection issues related to generative artificial intelligence technologies.

Each item was rated on a 5-point Likert scale from strongly disagree (1) to strongly agree (5). The questionnaire was pre-tested for clarity, relevance, and appropriateness for the target students in the institutional ethics approval process before distribution.

B. Data Collection and Survey Instrument

The study was carried out in a private higher education institution located in a Gulf Cooperation Council (GCC) country. An online questionnaire was used to gather data by sending the questionnaire to university students. The number of responses received was validated with data screening procedures. This sample was deemed adequate in terms of carrying out multivariate statistical analysis and structural equation modeling [30, 31].

Sampling Procedure: After ethical approval, an online survey link was sent via the university Moodle system, allowing all students enrolled to access and participate in the survey on a voluntary basis. Google Forms were used for data collection.

C. Data Screening and Cleaning

Prior to the statistical analysis, data quality was assessed. All the items in the questionnaire were set to be required, and so there were no missing values. In order to ensure consistency, the responses were screened for analysis. The free text entries were screened for duplicates and invalid entries. The design of the questionnaire was structured (Likert scale), and there were no missing records, so no further data imputation procedures were necessary.

1) Sample characteristics

The initial survey was an online survey sent via the university's Moodle platform. Following the screening and validation of data, valid responses were retained for analysis. The respondents came from various academic disciplines and levels of study. Of the students, 61.46% were female students and 38.54% were male students. The study involved students from various educational programs: Business (46.29%), Medical (31.66%), Engineering (18.67 %), and Information Technology and Information Systems (3.38 %). The majority (80.46%) responded that they are very proficient with digital technology, while over half (52.62%) said they spend over 3 h per day with AI tools. The detailed demographic profile of the respondents is given in Table 3. An entire questionnaire is available in the Appendix (Table A1).

Table 3. Demographic profile of respondents

Variable	Category	Frequency	Percentage (%)
Gender	Female	563	61.46
Gender	Male	353	38.54
GPA	>2 and <3	478	52.18
GPA	>3	369	40.28
GPA	<2	69	7.53
Field of Study	Business	424	46.29
Field of Study	Medical	290	31.66
Field of Study	Engineering	171	18.67
Field of Study	IT-IS	31	3.38
SRDP	G	737	80.46
SRDP	Non	100	10.92
SRDP	P	79	8.62
Year of Study	1	251	27.4
Year of Study	2	189	20.63
Year of Study	4	169	18.45
Year of Study	3	134	14.63
Year of Study	0(foundation)	96	10.48
Year of Study	5	77	8.41
ADAIU(D)	>3 h	482	52.62
ADAIU(D)	<1 & <3 h	366	39.96
ADAIU(D)	15–60 m	68	7.42

Note: SRDP: Self-Reported Digital Proficiency, G: Good; P: Poor, ADAIU (D): Average Daily AI Usage (Duration); h: hour, m: minutes.

2) Ethical considerations

Prior to data collection, ethical approval was obtained from the university research ethics committee. Prior to distributing surveys, the study questions, items, and methods were reviewed and approved. No one was forced or made to

participate, and participation was anonymous.

The survey was sent via the institution's Moodle platform to all students currently enrolled in the institution. Participants were given an informed consent statement in both Arabic and English that explained the purpose of the study, voluntary participation, confidentiality of responses, and the right to withdraw at any point without penalty before they were given the questionnaire.

There was no collection of personally identifiable information, and all responses were only for academic research purposes.

3) Data analysis approach

Data analysis was performed step by step: data screening and data preparation, measurement model evaluation, and structural model evaluation. The results were then interpreted to explore the relationships between the proposed constructs as well as the research questions and test the proposed hypotheses.

The model demonstrated adequate explanatory power of 54.1% (R^2 = 0.541). In contrast, the explanatory power for Self-Reported Actual Usage (R^2 = 0.147) was modest, suggesting that additional contextual factors beyond those included in the present model may influence students' reported ChatGPT usage behavior.

The model proposed was tested for its predictive relevance using PLSpredict. Results show good out-of-sample predictive ability of the model for Behavioral Intention (Q^2 predict = 0.535) and Self-Reported Actual Usage (Q^2 predict = 0.145).

The model fit was also evaluated by Standardized Root Mean Square Residual (SRMR), and obtained a value of 0.063, which is below the recommended value of 0.08, suggesting good model fit. The Normed Fit Index (NFI = 0.798) indicates a general model fit of a moderate level. However, the assessment of the model with the PLS-SEM method is based not only on global fit indicators, but also on an assessment of the quality of the measurement model, its explanatory power, its relevance for the prediction, and the significance of the structural relationships.

4) Common method bias assessment

The Common Method Bias (CMB) was observed using procedural and statistical methods. In terms of procedure, respondents' anonymity and confidentiality were guaranteed, participation was voluntary, and no personally identifying information was gathered. In addition, the questionnaire was examined and approved by the institutional research ethics committee before it was sent out.

Statistically, Harman's single-factor test was performed by loading all measurement items into an unrotated principal component analysis. The first factor accounted for 31.855% of the total variance, which is below the commonly accepted threshold of 50%, indicating that common method bias is unlikely to be a serious concern.

Additionally, a full collinearity assessment was conducted using variance INFLATION Factor (VIF) values. All VIF values ranged between 1.002 and 2.097, remaining below the conservative threshold of 3.3 as recommended [30, 31], further confirming that common method bias and multicollinearity were not significant threats to the validity of the results.

D. Measurement Model Assessment

The Measurement model was tested to measure the reliability and validity of the constructs. The internal consistency was checked, as well as the convergent validity, by examining factor loadings and indicators. The reliability of the individual indicators, internal consistency reliability, convergent validity, and discriminant validity were examined using the guidelines from PLS-SEM [30, 31] to evaluate the measurement model. In those cases where outer loadings were below the recommended level, the indicators were also checked for possible removal if removing them would enhance the reliability of the construct without compromising its conceptual validity. Thus, BI5 and PSC5 were dropped from the final model. The loading of BI5 was very low and negatively influenced the internal consistency of the Behavioral Intention construct. Likewise, the loading of PSC5 was very weak, showing that it did not sufficiently capture the underlying construct of Privacy and Security Concerns. The deletion of these indicators substantially increased Cronbach's alpha, Composite reliability, and Average variance extracted, while causing no disruption to the conceptual meaning of both constructs. The result of the refined measurement model showed good reliability and validity for all indicators retained in the model. Fig. 2 shows the finalized items that these exclusions greatly improved the quality of the measurement model.

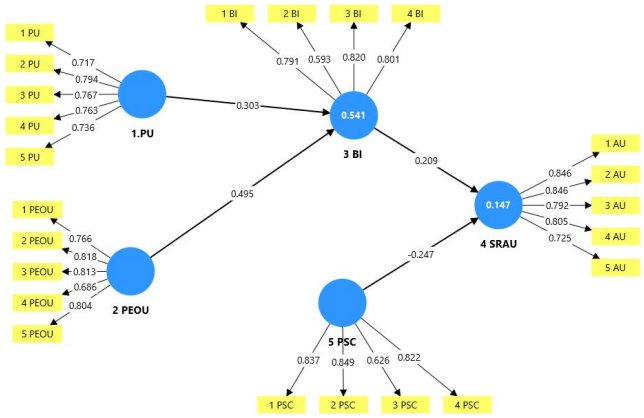


Fig. 2. Factor loading.

As a result, all reliability and validity indices are currently at the recommended value, as outlined in Table 4.

Table 4. Reliability and convergent validity assessment

Construct	Cronbachs alpha'	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
1 PU	0.812	0.815	0.869	0.571
2 PEOU	0.837	0.843	0.885	0.607
3 BI	0.748	0.774	0.841	0.572
4 SRAU	0.864	0.884	0.901	0.646
5 PSC	0.795	0.825	0.867	0.622

The results in Table 4 illustrate strong internal consistency and reliability, with all Cronbach's Alpha and Composite Reliability values exceeding the 0.70 threshold. The Average Variance Extracted (AVE) results for all constructs prove convergent validity because all paths exceed the standard 0.50 threshold with values between 0.571 and 0.646 as recommended [29, 30]. The metrics altogether illustrate that the measurement model exists as a strong and valid research instrument for subsequent structural evaluation.

The results of the HTMT presented in Table 5 overall support the discriminant validity among the study constructs. The majority of the HTMT values are below the conservative value of 0.85, and the HTMT value of Perceived Ease of Use and Behavioral Intention is 0.871. This is an above-acceptable value of 0.85 but below the more lenient value of 0.90 set for conceptually related constructs [30, 31]. Thus, the results suggest acceptable (although not unequivocal) discriminant validity for the relationship between these two constructs, and this is also supported by the fact that all other construct comparisons are satisfactory.

Table 5. Discriminant validity assessment (HTMT)

Construct	1 PU	2 PEOU	3 BI	4 SRAU	5 PSC
1 PU					
2 PEOU	0.82				
3 BI	0.809	0.871			
4 SRAU	0.381	0.371	0.366		
5 PSC	0.529	0.519	0.513	0.378	

E. Collinearity Assessment

Table 6 presents the Variance Inflation Factor (VIF) values for all retained measurement indicators. Assessing collinearity is important because excessive correlations among predictor variables can distort regression estimates and affect the interpretation of structural relationships in SEM analysis [30, 31]. The results indicate that all VIF values range from 1.213 to 2.097, remaining well below the recommended thresholds of 3.3 and 5.0 [30, 31]. Accordingly, multicollinearity is not considered a concern in the present study.

Table 6. Collinearity assessment (VIF)

Construct	Indicator	VIF
PU	PU1	1.535
PU	PU2	1.729
PU	PU3	1.633
PU	PU4	1.648
PU	PU5	1.45
PEOU	PEOU1	1.674
PEOU	PEOU2	1.905
PEOU	PEOU3	1.926
PEOU	PEOU4	1.46
PEOU	PEOU5	1.891
BI	BI1	1.497
BI	BI2	1.213
BI	BI3	1.697
BI	BI4	1.56
SRAU	SRAU1	2.083
SRAU	SRAU2	2.097
SRAU	SRAU3	1.818
SRAU	SRAU4	2.062
SRAU	SRAU5	1.696
PSC	PSC1	1.79
PSC	PSC2	1.929
PSC	PSC3	1.292
PSC	PSC4	1.8

F. Structural Model Analysis

Once the sufficiency of the measurement model had been confirmed, the structural model was tested to test the hypothesized relationships between the variables. Estimation of path coefficients was done to identify the strength and the significance of the relationships. The model was also tested to determine the explanatory power and the overall model fit.

It employed 10,000 sub-samples as recommended [30, 31] to conduct bootstrapping tests, which assessed the statistical significance of structural paths through t-value and p-value generation. Fig. 3 displays the path coefficients, which show that all proposed relationships illustrate high significance because Privacy Security Concerns (PSC) negatively affect Self-Reported Actual Usage (SRAU). The resampling method functions as an essential test because it permits researchers to evaluate model estimation stability through non-parametric testing while omitting the need for normal distribution data. The results section will explain how the validated structural paths lead to either acceptance or rejection of each research hypothesis.

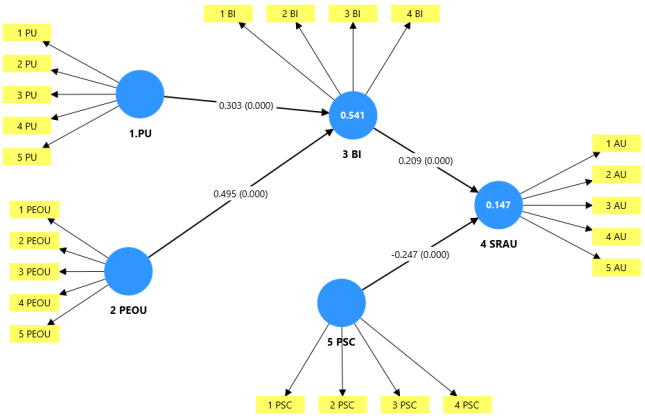


Fig. 3. Bootstrapping.

IV. Results

The explanatory and predictive power of the proposed model is shown in Table 7. The results indicate satisfactory explanatory power with the value of R^2 equal to 0.541, which indicates that the model is able to accommodate 54.1% of the variations in the variables. Although the model explains Behavioral Intention well, it explains only 14.7% of the variance in Self-Reported Actual Usage, suggesting that additional contextual variables influence students' reported AI use.

This finding implies that, while students might make high intentions to use ChatGPT, their reported usage behavior is likely affected by other factors beyond the scope of the current model (e.g., institutional policies, AI literacy, assessment practices, and students' learning preferences).

Table 7. Structural model evaluation (R^2 and Q^2 predict)

Construct	R^2	Adjusted R^2	Q^2 Predict
Behavioral Intention (BI)	0.541	0.54	0.535
Self-Reported Actual Usage (SRAU)	0.147	0.145	0.145

The values of effect size (f^2) for the structural relationships in the proposed model are shown in Table 8. The recommended guidelines define the f^2 values as small (0.02), medium (0.15), and large (0.35) effect sizes [30, 31]. The findings indicate that Perceived Ease of Use (PEOU) has a medium effect on Behavioral Intention (BI) ($f^2 = 0.284$), indicating that how easy it is for students to interact with ChatGPT is of medium influence on students' intention to use the technology. Perceived Usefulness (PU), on the other hand, shows a small effect on Behavioral Intention ($f^2 = 0.106$), which means that usefulness is still important but not as much as ease of use in the context of the present study.

For Self-Reported Actual Usage (SRAU), there are small effect sizes for both Behavioral Intention (BI) ($f^2 = 0.042$) and Privacy and Security Concerns (PSC) ($f^2 = 0.059$). The effect sizes of coping with Behavioral Intention (BI)

(f^2 = 0.042) and Privacy and Security Concerns (PSC) (f^2 = 0.059) are small for Self-Reported Actual Usage (SRAU). Both relationships are significant, but the relatively low effect sizes indicate that there are other contextual and behavioral factors that are not explicitly modeled in the current relationship that are influencing the students' reported usage behavior with ChatGPT. The low R^2 for SRAU and the fact that this observation is similar to that for the other measures indicate the need for further studies to examine other factors that influence AI usage behavior.

Table 8. Effect size assessment (f^2)

Path	f^2	Interpretation
PU → BI	0.106	Small
PEOU → BI	0.284	Medium
BI → SRAU	0.042	Small
PSC → SRAU	0.059	Small

The model fit indices used to assess the overall model validation of the proposed model, PLS-SEM, are shown in Table 8. The Standardized Root Mean Square Residual (SRMR) value of 0.063 is lower than the recommended value of 0.08, which means that the difference between the actual and the expected correlation matrices is not large [30–32].

The Normed Fit Index (NFI), as shown in Table 9, was 0.798, meaning that the global model fit was only at the moderate level. In contrast to PLS-SEM, however, the fit indices are not the only factors given special attention, but also explanatory power, predictive relevance, and significance of the structural relationships. The satisfactory SRMR value, coupled with the satisfactory reliability, validity, predictive relevance, and the satisfactory structural model results, validates the adequacy of the proposed framework to investigate students' self-reported use of ChatGPT in higher education.

Table 9. Model fit indices

Metric	Value	Recommended Threshold [30–32]
SRMR	0.063	<0.08
NFI	0.798	Closer to 1 indicates a better fit

The outcomes of the structural model assessment resulting from the PLS-SEM bootstrapping procedure can be seen in Fig. 3. Analysis focuses on the importance and magnitude of the hypothesized relationships between the constructs in the study. The path coefficient (β), the t-statistics, and the p-values were analyzed to test the proposed hypotheses.

The results provided in Table 10 show that all the proposed direct relationships are statistically significant ($p < 0.001$). The results indicate that the perceived usefulness positively affects Behavioral Intention ($\beta = 0.303$), thus supporting H1 and confirming that students have a higher intention to utilize the model of ChatGPT if they think that it is beneficial in the academic activity. The perceived ease of use has the highest positive relationship with Behavioral Intention ($\beta = 0.495$), supporting H2 and indicating that ease of interaction is one of the factors that can encourage adoption. Behavioral Intention significantly contributes to Self-Reported Actual Usage ($\beta = 0.209$), providing support for H3, where students with a high level of behavioral intention are more likely to use ChatGPT in their academic work. The negative correlation with Self-Reported Actual Usage ($\beta = -0.247$) supports H4, suggesting that privacy and security issues could hinder students' use of ChatGPT even as they recognize its potential value.

Table 10. Direct hypothesis testing

Hypothesized Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
1 PU → 3 BI	0.303	0.04	7.54	0.001
2 PEOU → 3 BI	0.495	0.044	11.334	0.001
3 BI → 4 SRAU	0.2·09	0.036	5.829	0.001
5 PSC → 4 SRAU	−0.247	0.035	7.137	0.001

Table 11 shows the significant indirect effects of the variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEU) on Self-Reported Actual Usage (SRAU) through the mediator: Behavioral Intention (BI). The results indicate significant indirect relationships for both PU → BI → SRAU ($\beta = 0.063$, $t = 4.345$, $p < 0.001$) and PEOU → BI → SRAU ($\beta = 0.103$, $t = 5.240$, $p < 0.001$). The indirect pathway between usefulness perception and ease of use, and between these dimensions and students' self-reported use of ChatGPT, indicates that students' perceptions of usefulness and ease of use have indirect effects on ChatGPT use via positive behavioral intention formation. Because the direct routes from Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to Self-Reported Actual Usage (SRAU) were not specified or tested in the structural model that was proposed, the results being reported ought to be read as statistically significant indirect effects, not as firm proof of full or even partial mediation.

Table 11. Indirect hypothesis testing

Specific Indirect Effect (Mediation Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
1 PU → 3 BI → 4 SRAU	0.063	0.015	4.345	0.001
2. PEOU → 3 BI → 4 SRAU	0.103	0.02	5.24	0.001

The indirect relationship results presented in Table 11 indicate that there are statistically significant indirect effects of PU and PEOU on SRAU through Behavioral Intention. The significant indirect effects confirm that students' perceptions of usefulness and ease of use influence actual engagement with ChatGPT primarily through the formation of positive behavioral intentions. The results of this study reinforce the ability of the examined using the TAM model to explain the learning technologies supported by AI.

At the 0.001 level of significance, all of the hypothesized explanations were confirmed. The results suggest that Perceived Usefulness and Perceived Ease of Use have a positive impact on Behavioral Intention, and Behavioral Intention has a positive impact on Self-Reported Actual Usage (SRAU). In contrast, Privacy and Security Concerns have a negative impact on students' reported behavior using ChatGPT. The findings indicate that students' self-reported use of ChatGPT is influenced by the core constructs of the TAM as well as privacy and security concerns. Moreover, the explanatory power of the model was greater for Behavioral Intention than for Self-Reported Actual Usage, which suggests that there are other factors that impact students' AI usage behavior that are not part of the present model.

V. Discussion

With Privacy and Security Concerns (PSC) in the higher education environment, this study explored self-reported ChatGPT usage among students from a Technology Acceptance Model (TAM) perspective. The results indicate that enabling factors (Perceived Usefulness and Perceived Ease of Use) as well as inhibiting factors (Privacy and Security Concerns) have an impact on students' self-reported use of AI-assisted learning tools. The results of the study support the proposed framework and show that both enabling and inhibiting factors affect learners' interaction with AI learning technologies. Perceived Usefulness and Perceived Ease of Use facilitate adoption through Behavioral Intention, yet Privacy and Security Concerns hinder adoption and can hinder adoption and reduce Self-Reported Actual Usage even when there is a positive perception of the technology. These findings have implications for the general understanding of the adoption of AI in higher education contexts, considering both the positive and perceived negative aspects.

The results indicate that both the Perceived Usefulness and Perceived Ease of Use have an effect on Behavioral Intention. However, the strongest predictor was Perceived Ease of Use, suggesting that ease of use is important to the students as a means of embedding ChatGPT in their learning activities. If students think the AI tools are easy to use, find them accessible and intuitive, they'll be more inclined to have a positive intention to use them. The outcomes of this study are consistent with the first two research purposes, and support the underlying premises of the use of TAM in AI-supported educational settings.

Two important differences stand out between the explanatory power of Behavioral Intention ($R^2 = 0.541$) and Self-Reported Actual Usage ($R^2 = 0.147$). Students tend to have positive intentions about using ChatGPT, but that doesn't necessarily lead to continued academic use. This implies that intention does not fully account for students' reported use of AI, and other contextual factors not included in the model have an impact on getting from intending to use AI to actually using it. Other contextual, institutional, and behavioral factors are likely to be important in real-world usage beyond the scope of these factors in the present model.

The most significant result of this study is that the Self-Reported Actual Usage is significantly and negatively influenced by the Privacy and Security Concerns. The findings suggest that students could be aware of the potential benefits and conveniences of using ChatGPT, but at the same time, they may be deterred by privacy and confidentiality concerns, as well as the management of personal and academic data. The results indicate that a positive perception of usefulness and ease of use does not completely account for students' reported usage of ChatGPT. Additionally, Privacy and Security Concerns serve as a significant contextual influence, and when considering students' AI adoption behavior, these need to be considered along with the core TAM constructs.

In addition to acceptance of technology, recent education research has been highlighting the broader impact of generative AI on assessment, feedback, learning quality, and academic performance [33]. As a result, it is becoming more crucial to understand what makes students likely to engage with AI technologies, to ensure responsible integration of AI into higher education. Thus, comprehending what facilitates or hinders student engagement with AI technologies becomes crucial for the effective integration of AI in education.

The results of the present study are not only important for the study of technology adoption, but also for the general issue of responsible use of AI in postsecondary education.

Together, these results indicate that there is a need for a balance between technical skills and user confidence when implementing ChatGPT. Motivation to engage comes from usability and perceived value, but can be a barrier to use if not addressed, due to privacy and security issues. This presents educational implications, both technical and governance, that need to be considered in the use of AI-powered learning solutions.

A. Key Insights

Overall, the findings suggest that the adoption mechanism comprises enabling and inhibiting factors:

- Drivers: intention will be stimulated if perceived usefulness and ease of use are high.
- Perceptions are transformed into action in terms of behavioral intention (Bridge).
- Barrier: Privacy concerns have a negative impact on usage despite good intentions.

B. Recommended Roadmap for Responsible AI Adoption in Higher Education

The empirical results have led to the development of a four-stage roadmap that is outlined in Fig. 4. Based on the empirical findings, a four-stage roadmap for responsible and sustainable use of AI-assisted learning technologies in higher education is proposed.

1) Stage 1: Enhance ease of use

In stage 1, the aim is to improve ease of use.

According to the result, Perceived Ease of Use is the most important factor influencing the behavioral intention. Hence, the creation and adoption of easily accessible, user-friendly and learnable AI tools that could be woven into the learning activities of institutions, is important. User-friendly interfaces, training programs, orientation sessions, and readily available technical support can help reduce the challenges associated with the first use and encourage positive engagement with AI technologies.

2) Stage 2: Demonstrate academic value

The results showed that the usefulness of ChatGPT had a significant impact on students' intention to use ChatGPT. To this end, it is crucial for universities to demonstrate the educational benefits of AI learning support. This can include showcasing successful applications, learning outcomes, best practices, and examining how AI tools can improve academic productivity, problem solving, and learning.

3) Stage 3: Strengthen privacy and security trust

Trust is also strongly related to the adoption of AI; there is a strong negative correlation between Privacy and Security Concerns and Self-Reported Actual Usage. Institutions need to have clear privacy policies, inform users about data collection and security measures, provide advice for safe usage of AI tools, and ensure compliance with privacy and security laws. These questions and issues can be mitigated and good use of AI technologies promoted.

4) Stage 4: Reinforce continuous usage

There is a positive correlation between the Behavioral Intention and the actual Self-Reported Using, which means further reinforcement is required to ensure that the behavior is maintained. Teaching and learning and assignments should be infused with activities based on Artificial Intelligence, feedback and support given continuously. Rethinking responsible and meaningful use of AI technologies will be one of the major steps to bringing technology to learning with AI technology.

The suggested roadmap emphasizes the importance of more than just technical solutions for successfully implementing AI. There is a need for a balance of usability, perceived value, privacy protection, and continued engagement for sustainable implementation. If these factors are considered collectively, HEIs can play a part in a responsible, trustworthy and effective use of AI-supported learning technologies.

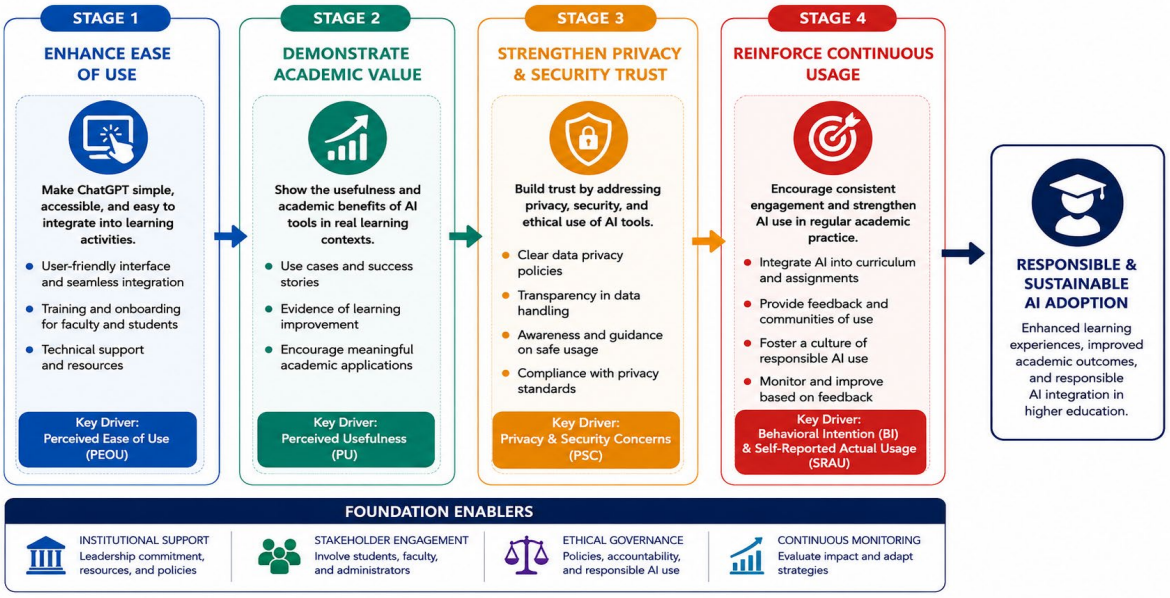


Fig. 4. Proposed roadmap.

VI. Conclusion

Based on the Technology Acceptance Model (TAM) and the addition of Privacy and Security Concerns (PSC), this study examined students' self-reported use of ChatGPT using the Technology Acceptance Model as the theoretical perspective. The goal of the study was to gain a more in-depth understanding of the adoption behavior of AI, as well as the factors that could hinder adoption despite positive perceptions of AI, which has led to a more holistic understanding of the factors that would enable and inhibit adoption behavior.

The The findings highlight the enduring relevance of classic TAM components to the field of AI's use in education. Perceived Usefulness and Perceived Ease of Use were found to positively influence Behavioral Intention; Perceived Ease of Use was found to be a better predictor. The results suggest that students' attitudes toward the use of ChatGPT will be more positive when it is easily accessible, is simple to use, and can be integrated into their learning activities. In addition, it found that the main predictions of TAM—namely that Behavioral Intention is positively related to Self-Reported Actual Usage—were confirmed, further supporting the notion that positive intentions can lead to Self-Reported Actual Usage of AI learning tools in practice. The model better reflects the nature of Behavioral Intention than Self-Reported Actual Usage.

One of the key findings that come from this study is that Privacy and Security Concerns are significant factors that hinder Self-Reported Actual Usage. The findings suggest that students could be aware of the educational benefits of using ChatGPT, but at the same time be reluctant to use it because of privacy, confidentiality, and data protection issues. This research is a step forward to the technology acceptance literature by adding empirical evidence that Perceived Usefulness and Perceived Ease of Use are significantly related to students' self-reported use of ChatGPT, while also showing that Privacy and Security Concerns are significant factors to consider when studying technology acceptance in a higher education environment in the Middle East region. If you want to learn about the use of AI in learning today, you need to know what helps and what doesn't.

In practice, the results provide valuable guidance to the HEIs who seek to integrate the possibilities provided by AI tools into their pedagogical practices. AI tools and their application should be more accessible and usable to universities and used responsibly, with awareness raised about data protection and privacy and clear policies developed to ensure data protection. Considering these factors can help foster better adoption of AI-powered learning technologies and trustworthy and sustainable learning.

While this study has provided some valuable contributions, there are some limitations that should be noted. The cross-sectional design prohibits the ability to investigate how adoption behavior changed over time, and the use of self-report responses could lead to response bias. Additionally, although the proposed model was found to have good explanatory power for Behavioral Intention, the model's explanatory power for Self-Reported Actual Usage was found to be less than satisfactory, meaning that other

functional or contextual factors may affect the involvement of students in using ChatGPT. Self-Reported Actual Usage is self-reported student perceptions of their use of ChatGPT, because it was based on the answers to the questionnaire, not on the actual use of the system. For later work, it might be useful to bring in behavioral trace data or actual system logs, so these findings can be checked and validated.

The authors would like to suggest future studies using longitudinal designs, exploring other factors including trust, facilitating conditions, and social influence, and testing the proposed framework in different educational institutions, cultural contexts, and AI-supported learning contexts.

Overall, this study adds to the body of evidence in AI adoption within higher education, revealing empirical evidence of the impact of perceived benefits and perceived risks on students' engagement with ChatGPT. The examined TAM-based framework provides valuable guidelines for future study and for the implementation of appropriate and effective approaches for integrating AI in higher education.

APPENDIX

Table A1. Questionnaire details

Construct	Code	Measurement Item	Source
Perceived Usefulness (PU)	CPU1	ChatGPT helps me improve the quality of my academic work.	Adapted from Ref. [2], refined based on TAM applications in educational technology contexts.
	CPU2	ChatGPT enhances my learning efficiency.	[2]
	CPU3	ChatGPT is useful for completing assignments faster.	[2]
	CPU4	ChatGPT improves my understanding of complex topics.	[2]
	CPU5	Overall, ChatGPT is beneficial for my studies.	[2]
Perceived Ease of Use (PEOU)	CPEOU1	It is easy to learn how to use ChatGPT.	Adapted from Ref. [2], refined using TAM-based educational technology studies [27, 29, 34, 35]
	CPEOU2	Interacting with ChatGPT is simple and understandable.	Same source
	CPEOU3	I find ChatGPT easy to use for academic tasks.	Same source
	CPEOU4	Using ChatGPT does not require much effort.	Same source
	CPEOU5	I can easily integrate ChatGPT into my study routine.	Same source
Behavioral Intention (BI)	CBI1	I intend to use ChatGPT regularly for academic purposes.	Adapted from Ref. [2] and UTAUT intention measures [34]
	CBI2	I will continue using ChatGPT in my studies.	Same source
	CBI3	I plan to use ChatGPT for future assignments.	Same source
	CBI4	I recommend ChatGPT to other students.	Same source
	CBI5	I am willing to increase my use of ChatGPT.	Same source
Self-Reported Actual Usage (SRAU)	SRAU1	I frequently use ChatGPT for academic tasks.	Adapted from recent AI and ChatGPT adoption literature and Refs. [27, 29] on AI-assisted learning.
	SRAU2	I rely on ChatGPT when studying or completing assignments.	Same source
	SRAU3	I use ChatGPT for idea generation and writing support.	Same source
	SRAU4	I actively use ChatGPT in my daily learning activities.	Same source
	SRAU5	ChatGPT is part of my regular study habits.	Same source
Privacy and Security Concerns (PSC)	PSC1	I am concerned that the personal or academic data I input into ChatGPT may not remain private.	Developed from contemporary literature on AI privacy, security, trust, and data protection in higher education [27, 29, 34, 35].
	PSC2	I worry that the information I share with ChatGPT might be used without my knowledge.	Same source
	PSC3	I hesitate to upload sensitive academic documents to ChatGPT.	Same source
	PSC4	I am concerned about the security measures used to protect information entered into ChatGPT.	Same source
	PSC5	My awareness of potential data privacy risks influences how I use ChatGPT.	Same source

ARTIFICIAL INTELLIGENCE USAGE STATEMENT

Grammarly was used during the writing process to improve the manuscript's grammar, spelling, and readability. Furthermore, only generative AI tools have been used to create the graphical representations of Figs. 1 and 4. The

conceptual content of these figures was developed entirely by the author.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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