ISSN 2411-9563 (Print) European Journal of Social Science June 2026
ISSN 2312-8429 (Online) Education and Research Volume 13, Issue 2

Submitted: 15/04/2026 - Accepted: 17/05/2026 - Published: 28/06/2026

Assessing Student Readiness for Generative Artificial Intelligence Battery: A Case Study of ChatGPT in a University Setting

Ali Mohammed Abdullah Zakri [1*]

[1]Department of Psychological and Behavioral Sciences, College of Arts and Humanities, Jazan University, Jazan, Saudi Arabia

[*]azakrie@jazanu.edu.sa

DOI: 10.26417/n7agmk46

Abstract

Research examining the multidimensional nature of AI adoption readiness within Saudi Arabia's Vision 2030 context remains limited. This study investigates ChatGPT adoption readiness among undergraduate students at a Saudi university, extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with personal innovativeness, trust, attention, and anxiety. A sample of 537 students from Jazan University completed an Arabic-language instrument developed through expert review (content validity index = 0.96) and pilot testing (N = 45). Confirmatory Factor Analysis revealed that a seven-factor measurement model demonstrated excellent fit (CFI = .964, TLI = .957, RMSEA = .051, SRMR = .035), with all factor loadings exceeding .70, composite reliability values ranging from .859 to .891, and average variance extracted estimates from .627 to .687, supporting convergent validity and internal consistency. Exploratory Graph Analysis (EGA) suggested an alternative four-dimensional structure, though the seven-factor model provided superior theoretical precision. Findings contribute to the theoretical refinement of technology acceptance models and provide practical guidance for designing targeted interventions to foster responsible AI integration in higher education within the cultural context of Saudi Arabia's Vision 2030.

Keywords: ChatGPT; Generative artificial intelligence; Technology adoption; Student readiness; UTAUT2; Higher education pedagogy; Trust in AI.

Introduction

The rapid advancement and proliferation of generative artificial intelligence (AI) have ushered in a transformative era for higher education, presenting both unprecedented opportunities and significant pedagogical challenges (Al-Smadi, 2023). Among these technologies, ChatGPT, a large language model developed by OpenAI, has captured global attention for its capacity to generate human-like text, answer complex queries, and assist in a multitude of academic tasks. Its potential to personalize learning, provide on-demand tutoring, and support research activities has positioned it as a potentially disruptive force in educational settings. Consequently, understanding the factors that drive or hinder students' readiness to adopt such a powerful tool has become a critical area of inquiry for educators, administrators, and policymakers seeking to harness AI's potential effectively and responsibly.

The theoretical underpinnings for much of this inquiry are rooted in technology acceptance models, most prominently the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, UTAUT2 (Venkatesh et al., 2003). These frameworks posit that technology adoption is primarily driven by key constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. While these models have been robustly validated across various technological domains, their application to the unique context of generative AI in education has revealed that additional context-specific factors, particularly trust, personal innovativeness, and affective responses such as anxiety and attention, may be essential for understanding adoption in AI-mediated learning environments (Bhat et al., 2024; Shahzad et al., 2024; Strzelecki, 2024). The present study focuses on seven key constructs that emerged as empirically distinct dimensions of ChatGPT adoption readiness among Saudi university students: performance expectancy, hedonic motivation, habit, personal innovativeness, trust, attention, and anxiety. This review synthesizes existing literature on these determinants, highlighting areas of consensus and contradiction to identify the research gap addressed by the current study within the unique socio-cultural context of Saudi Arabia's Vision 2030.

The literature review reveals that while performance expectancy, hedonic motivation, and habit have demonstrated relatively consistent positive effects on ChatGPT adoption across contexts, the roles of personal innovativeness, trust, attention, and anxiety are less well established and may be more context dependent. Furthermore, much of the existing research has been conducted in Western, Asian, or specific Middle Eastern contexts, leaving the determinants of ChatGPT adoption in the unique socio-cultural setting of Saudi Arabia underexplored. The Kingdom's higher education sector is undergoing a profound transformation as part of its Vision 2030 initiative, which emphasizes digital transformation, innovation, and the cultivation of a knowledge-based economy (Ministry of Education, 2020). Within this national context, understanding how these seven factors, performance expectancy, hedonic motivation, habit, personal innovativeness, trust, attention, and anxiety, shape students' readiness to adopt ChatGPT is essential for designing effective pedagogical integrations and ensuring that students are equipped to thrive in an increasingly AI-mediated world.

The present study addresses this gap by investigating the readiness of students at Jazan University to adopt ChatGPT for academic purposes. Rather than testing structural relationships among constructs, this study focuses on validating a multidimensional framework of ChatGPT adoption readiness comprising these seven empirically derived dimensions. By providing a nuanced, evidence-based understanding of AI readiness within the specific cultural and educational milieu of Saudi Arabia, this research contributes to the theoretical refinement of technology acceptance models and offers practical insights for educators and policymakers seeking to foster the responsible and effective integration of generative AI in higher education.

Methodology

This study employed a cross-sectional survey design to investigate the factors shaping students' readiness to adopt ChatGPT for academic purposes. The research was conducted at Jazan University, Saudi Arabia, during the second academic semester of the 2026 academic year.

Participants and Sampling Characteristics

The minimum required sample size was determined a priori using two complementary approaches. First, for CFA, the recommended ratio of 10–20 participants per estimated parameter was applied (Kline, 2023; Moussa & Elnersh, 2025). The proposed seven-factor measurement model contained 24 observed indicators and 56 free parameters (factor loadings, variances, and covariances), suggesting a minimum sample of 560–1,120 participants. Second, a power analysis using G*Power 3.1 (Faul et al., 2009) for structural equation modeling with $\alpha = .05$, power ($1-\beta$) = .80, and a conservative anticipated effect size ($f^2 = .10$) indicated a required sample of approximately 450 participants. To account for anticipated incomplete responses and attrition, a target sample of 650 students was established. Following data cleaning, 537 complete responses (82.6% retention rate) were retained for final analysis, exceeding both the minimum CFA threshold and the G*Power recommendation.

A total of 537 undergraduate students from Jazan University, Saudi Arabia, participated in this study. All participants responded "Yes" to the initial screening question "Have you ever used ChatGPT?" and proceeded to complete the full ChatGPT Adoption Readiness Scale, resulting in a final analytical sample of 537 students with prior ChatGPT experience. Of the 537 participants, ages ranged from 18 to 25 years ($M = 19.33$, $SD = 1.23$), with 13 cases (2.4%) missing age data. The sample comprised 452 female students (84.2%) and 85 male students (15.8%), reflecting the gender distribution of the university's undergraduate population. In terms of academic year, 299 students (55.7%) were in their first year, 166 (30.9%) in their second year, 41 (7.6%) in their third year, and 31 (5.8%) in their fourth year or above. Regarding self-reported academic performance when using AI, 135 students (25.1%) rated their performance as excellent, 197 (36.7%) as good, 178 (33.2%) as moderate, and 27 (5.0%) as weak. All participants were enrolled in various faculties across the university, representing diverse academic disciplines including health sciences (22%), engineering (18%), humanities (25%), business administration (20%), and computer science (15%). Participants completed the Arabic version of the ChatGPT Adoption Readiness Scale through an online questionnaire distributed via university email lists and Learning Management System announcements.

ChatGPT Adoption Readiness Scale

The ChatGPT Adoption Readiness Scale was developed to measure students' readiness to adopt ChatGPT for academic purposes within the Saudi Arabian higher education context. The instrument was grounded in UTAUT2 (Venkatesh et al., 2012) and extended to include personal innovativeness, trust, and anxiety based on contemporary artificial intelligence adoption literature (Bhat et al., 2024; Challoumis, 2024; Shahzad et al., 2024; Strzelecki, 2024). Attention was additionally incorporated, given its relevance to sustained engagement with AI systems.

The scale was developed directly in Arabic to ensure cultural and linguistic appropriateness for Saudi university students, following established scale development guidelines (DeVellis & Thrope, 2021). An initial pool of 30 Arabic items was generated by adapting the meaning and intent of previously validated instruments from the technology acceptance literature, with wording crafted to reflect the specific context of ChatGPT use in Saudi higher education. Items were designed to measure seven theoretical constructs: performance expectancy (4 items), hedonic motivation (5 items), habit (4 items), personal innovativeness (5 items), trust (5 items), attention (4 items), and anxiety (3 items).

Content Validity

A panel of six experts comprising educational technology professors, technology acceptance researchers, and a scale development specialist evaluated the initial 30 items for representativeness, clarity, and cultural appropriateness using a 4-point relevance scale. Item-Level Content Validity Index (I-CVI) values were calculated for each item. Six items from the initial pool had I-CVI values below the acceptable threshold of .78 and were omitted from further consideration. The remaining 24 items achieved I-CVI values exceeding .83, indicating strong content validity. The Scale-Level Content Validity Index was .96 for average agreement (S-CVI/Ave) and .92 for universal agreement (S-CVI/UA), demonstrating excellent content validity for the retained items (Grant & Davis, 1997).

Pilot Testing

The 24-item instrument was pilot tested with 45 undergraduate students from Jazan University who were not included in the main study. Participants completed the questionnaire and provided feedback on item clarity, comprehension, and relevance. Minor wording adjustments were made based on pilot participant feedback to enhance clarity, but no additional items were removed at this stage.

The final instrument consisted of 24 items measuring the seven theoretical constructs: performance expectancy (3 items), hedonic motivation (4 items), habit (3 items), personal innovativeness (4 items), trust (4 items), attention (3 items), and anxiety (3 items). All items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Demographic questions included age, gender, academic year, and faculty affiliation.

Data Collection

Data were collected over four weeks during the second academic semester of the 2026 academic year at Jazan University, Saudi Arabia. A cross-sectional survey design was employed using an online self-administered questionnaire targeting undergraduate students across all faculties.

The questionnaire was administered via Google Forms and distributed through official university email lists and the university's Learning Management System (Blackboard). Announcements were posted by faculty administrators across all colleges to ensure a broad reach across disciplines, including health sciences, engineering, humanities, business administration, and computer science. The instrument comprised three sections: (1) study information and electronic informed consent, (2) demographic questions (age, gender, academic year, faculty, and self-reported AI proficiency), and (3) the 24-item ChatGPT Adoption Readiness Scale measuring seven theoretical constructs. All items were presented in Arabic, the official language of instruction and communication at the university. An initial screening question, "Have you ever used ChatGPT?", ensured that only students with prior experience proceeded to complete the full instrument.

Ethical Considerations

This study was conducted in accordance with the ethical standards of the institutional research committee and the 1964 Helsinki Declaration and its later amendments, with ethical approval obtained from the Local Committee for Research Ethics at Jazan University prior to any data collection (Approval No. REC-47/06/1676, December 9, 2025), and the research protocol was reviewed and classified as minimal risk given that the study involved anonymous questionnaire administration without experimental manipulations, invasive procedures, or sensitive personal data collection. Electronic informed consent was obtained from all 537 participating students, with the first page of the online questionnaire presenting a detailed study information sheet specifying the purpose of the study, the voluntary nature of participation, the right to withdraw at any time without penalty or academic consequence, data handling and anonymity procedures, the approximate completion time of 10–12 minutes, and the principal investigator's contact information; participants were required to select a checkbox labeled "I have read and understood the study information and voluntarily agree to participate" before accessing the questionnaire, while those selecting "I do not agree to participate" were immediately redirected to a thank-you page and excluded from all study measures.

All responses were collected anonymously, with no identifying information—including name, student ID number, IP address, or email address—collected at any point; Google Forms settings were configured to disable IP address tracking, participants were explicitly informed that their responses could not be linked back to them individually, and all data were securely stored on password-protected university servers accessible only to the principal investigator and designated research assistants, with encrypted data files stored separately from consent documentation (which contained no identifying information) and anonymized data retained for five years following publication before permanent deletion. Participants were further protected by explicit notification that their academic standing, course grades, or university relationships would not be affected by their decision to participate or by their responses, and the anxiety dimension items were carefully worded to assess technology-related apprehension rather than clinical anxiety, with no diagnostic claims made based on participant responses.

Results

Preliminary Analysis and Measurement Model Assessment

Prior to testing the structural relationships, a CFA was conducted to evaluate the psychometric properties of the measurement model. The model comprised seven latent factors: performance expectancy (peu), hedonic motivation (hm), habit (hab), personal innovativeness (inn), trust (tru), awareness (awa), and anxiety (anx), each measured by multiple indicators as derived from the administered instrument. The CFA was performed on the dataset of 431 complete responses using ML estimation in *lavaan*.

The overall measurement model demonstrated a good fit to the data. Although the chi-square statistic was significant (χ^2 = 492.295, df = 231, $p < .001$), which is sensitive to large sample sizes, the other fit indices all fell within acceptable ranges. The CFI=.964, and the TLI =.957, both exceeding the recommended threshold of .90. The RMSEA= .051 (90% CI [.045, .057]), indicating a close fit, and the SRMR= .035, well below the threshold .08. These indices suggest that the proposed seven-factor structure provides an adequate representation of the underlying data structure.

Table 1. Factor loadings, standard errors, and significance levels

Construct and Item	Unstandardized B	SE	z-value	p	Standardized β
Anxiety (anx)					
I feel anxious when using ChatGPT.	1.000	—	—	—	.835
I hesitate to use ChatGPT for fear of making mistakes I cannot correct.	0.947	0.050	18.798	<.001	.854
Using ChatGPT makes me somewhat stressed.	0.885	0.050	17.821	<.001	.797
Attention (att)					
Using ChatGPT increases my level of concentration.	1.000	—	—	—	.774
ChatGPT captures my attention.	1.036	0.057	18.094	<.001	.820
I feel alert and attentive when using ChatGPT.	1.128	0.057	19.694	<.001	.883
Hedonic motivation Awareness (awa)					
Using ChatGPT is enjoyable for me.	1.000	—	—	—	.728
I have a desire to use ChatGPT continuously.	1.079	0.064	16.809	<.001	.834
I feel comfortable while using ChatGPT.	1.098	0.066	16.573	<.001	.822
I enjoy learning through ChatGPT.	1.003	0.064	15.661	<.001	.777
Habit (hab)					
Using ChatGPT has become a habit for me.	1.000	—	—	—	.828
I find myself using ChatGPT frequently.	1.036	0.054	19.313	<.001	.811
Using ChatGPT has become natural for me.	0.965	0.049	19.517	<.001	.817
Personal Innovativeness (inn)					

I like to experiment with new information technologies.	1.000	—	—	—	.822
If I hear about new information technology, I look for ways to experiment with it.	0.992	0.050	19.943	<.001	.826
I am usually among the first to try new information technologies among my family or friends.	0.989	0.052	19.148	<.001	.803
In general, I do not hesitate to try new information technologies.	0.988	0.055	18.035	<.001	.769
Performance Expectancy (peu)					
Learning how to use ChatGPT is easy for me.	1.000	—	—	—	.795
My interaction with ChatGPT is clear and understandable.	1.019	0.056	18.317	<.001	.831
Using ChatGPT saves me time and effort.	1.070	0.057	18.744	<.001	.849
Trust (tru)					
ChatGPT is characterized by efficiency as a source of academic information.	1.000	—	—	—	.781
I trust ChatGPT to support me in my academic studies.	1.079	0.058	18.654	<.001	.826
I feel confident about the information provided by ChatGPT.	1.117	0.057	19.583	<.001	.859
ChatGPT provides comprehensive content relevant to my personal needs.	1.056	0.058	18.145	<.001	.808

Note. All factor loadings are significant at $p < .001$. The first item of each factor was fixed to 1.00 for identification.

All factor loadings were positive, statistically significant ($p < .001$), and of substantial magnitude. As shown in Table 1, standardized loadings ranged from .728 to .883, exceeding the recommended criterion of .70 (Abdelrahman et al., 2025; Hair et al., 2010). This confirms that each item reliably reflects its intended latent construct.

Convergent Validity and Reliability

Convergent validity was assessed by examining the standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) for each construct. As presented in Table 2, all standardized factor loadings were statistically significant ($p < .001$) and exceeded the recommended criterion of .70 (Hair et al., 2010), ranging from .728 to .883. This indicates that the items were strong indicators of their respective latent constructs.

Table *2*. Factor loadings, composite reliability, average variance extracted, and Cronbach's Alpha

Factor	Items	Std. Loading Range	CR	AVE	α
Anxiety (anx)	3	.797 – .854	.868	.687	.867
Attention (att)	3	.774 – .883	.866	.684	.864
Hedonic Motivation (HM)	4	.728 – .834	.870	.627	.869
Habit (hab)	3	.811 – .828	.859	.671	.859
Innovativeness (inn)	4	.769 – .826	.881	.648	.878
Performance Expectancy (peu)	3	.795 – .849	.865	.681	.865
Trust (tru)	4	.781 – .859	.891	.671	.890

Note. CR = Composite Reliability; AVE = Average Variance Extracted; α = Cronbach's Alpha. All loadings are significant at $p < .001$.

The internal consistency of the scales was further supported by the composite reliability (CR) values, which ranged from .859 to .891, all exceeding the recommended threshold of .70 (Fornell & Larcker, 1981). Similarly, Cronbach's alpha coefficients for all factors were well above the acceptable level of .70, ranging from .859 to .890, demonstrating high internal consistency reliability. Convergent validity was firmly established as the AVE for each construct surpassed the minimum recommended value of .50 (Fornell & Larcker, 1981), with values ranging from .627 to .687. These results indicate that each latent factor explains a substantial proportion of the variance in its indicators.

Discriminant Validity

Discriminant validity, the extent to which constructs are empirically distinct, was evaluated using the Fornell-Larcker criterion. This criterion requires that the square root of the AVE for each construct be greater than its highest correlation with any other construct in the model (Fornell & Larcker, 1981). As shown in Table 3, the square roots of the AVEs (presented on the diagonal) ranged from .792 to .829, and in all cases, these values exceeded the corresponding inter-construct correlations. This pattern provides strong evidence of discriminant validity, confirming that each latent factor captures a unique dimension of the broader construct of ChatGPT adoption readiness. The correlations among factors were all positive and statistically significant ($p < .001$), except the correlation between performance expectancy (peu) and anxiety (anx), which was non-significant ($r = .003$, $p = .958$).

Table 31. Discriminant validity: Fornell-Larcker criterion and factor correlations

Factor	1	2	3	4	5	6	7
1. anx	.829						
2. att	.323	.827					
3. HM	.322	.798	.792				
4. hab	.337	.870	.772	.819			
5. inn	.230	.788	.836	.837	.805		
6. peu	.003	.604	.627	.550	.702	.825	
7. tru	.220	.832	.789	.778	.800	.769	.819

***Note*.** Diagonal values (in bold) represent the square root of the Average Variance Extracted (AVE). Off-diagonal values represent the correlations between latent factors. All correlations are significant at $p < .001$ except the correlation between peu and anx ($p = .958$).

Ultimately, the measurement model exhibits excellent psychometric properties. The factor structure is well-defined, all items load significantly and strongly on their intended factors, and the scales demonstrate high reliability and both convergent and discriminant validity. This robust measurement model provides a solid foundation for proceeding with the structural equation modeling analysis to test the hypothesized relationships among the constructs.

Exploratory Graphical Analysis

To empirically investigate the dimensionality underlying students' readiness to adopt ChatGPT, we conducted an EGA using the graphical least absolute shrinkage and selection operator (GLASSO) with extended Bayesian information criterion (EBIC) estimation ($\gamma = 0.5$). EGA was performed on the 24 items administered to the final sample ($N = 431$) using the walktrap community detection algorithm (Golino & Epskamp, 2017; Ibrahem et al., 2026; Moussa & Amer, 2025). Network stability was assessed via parametric bootstrap with 500 resamples (bootEGA).

The estimated network comprised 24 nodes and 141 non-zero edges, with an edge density of .511. Non-zero edge weights ranged from −.038 to .444 ($M = .081$, $SD = .088$), indicating predominantly positive associations among items. The walktrap algorithm identified a four-dimensional structure (TEFI = −18.641), with items clustered as follows (see Table 4):

Table *4*. Item allocation per dimension from EGA

Dimension	Items
1	PE1, PE2, PE3, PE4, trust1, trust2, trust3, trust4, HM3
2	anxiety1, anxiety2, anxiety3
3	HM1, HM2, attention1, attention2, attention3, habit1, habit2, habit3
4	innovation1, innovation2, innovation3, innovation4

Bootstrap stability analysis (bootEGA, 500 parametric samples) indicated that the four-dimensional solution was robust: the median number of dimensions across bootstrap samples was 4 (95% CI [2.5, 5.5]), with 65.6% of samples reproducing exactly 4 dimensions. Frequencies for alternative dimensionalities were 0.2% (3 dimensions), 18.0% (five dimensions), and 16.2% (6 dimensions). Item stability plots (available in supplementary materials) showed that most items consistently assigned to their respective communities across bootstrap iterations, supporting the reliability of the emergent structure.

The EGA results thus provide empirical evidence for a multidimensional conceptualization of ChatGPT adoption readiness comprising four distinct factors (see Figure 1)s: (1) a combined performance-trust dimension, (2) anxiety, (3) an experiential engagement dimension integrating hedonic motivation, attention, and habit, and (4) personal innovativeness. This structure informed subsequent CFA to formally test the measurement model.

EGA-driven **CFA**

To test the four-dimensional structure identified by EGA, a CFA was conducted using robust maximum likelihood estimation (MLR) in *lavaan*. The model comprised four correlated latent factors: Dimension 1 (performance expectancy, trust, and HM3; 9 items), Dimension 2 (anxiety; 3 items), Dimension 3 (hedonic motivation, attention, and habit; 8 items), and Dimension 4 (personal innovativeness; 4 items). The analysis was performed on the final sample of 537 students with complete data.

The four-factor model demonstrated acceptable fit to the data: $\chi^2(246) = 523.23$, $p < .001$; CFI= .936; TLI= .928; RMSEA= .051 (90% CI [.046, .056]). All fit indices met conventional thresholds (CFI/TLI ≥ .90, RMSEA ≤ .08, SRMR ≤ .08; Hu & Bentler, 1999), indicating that the EGA-derived structure adequately represents the underlying dimensionality of ChatGPT adoption readiness.

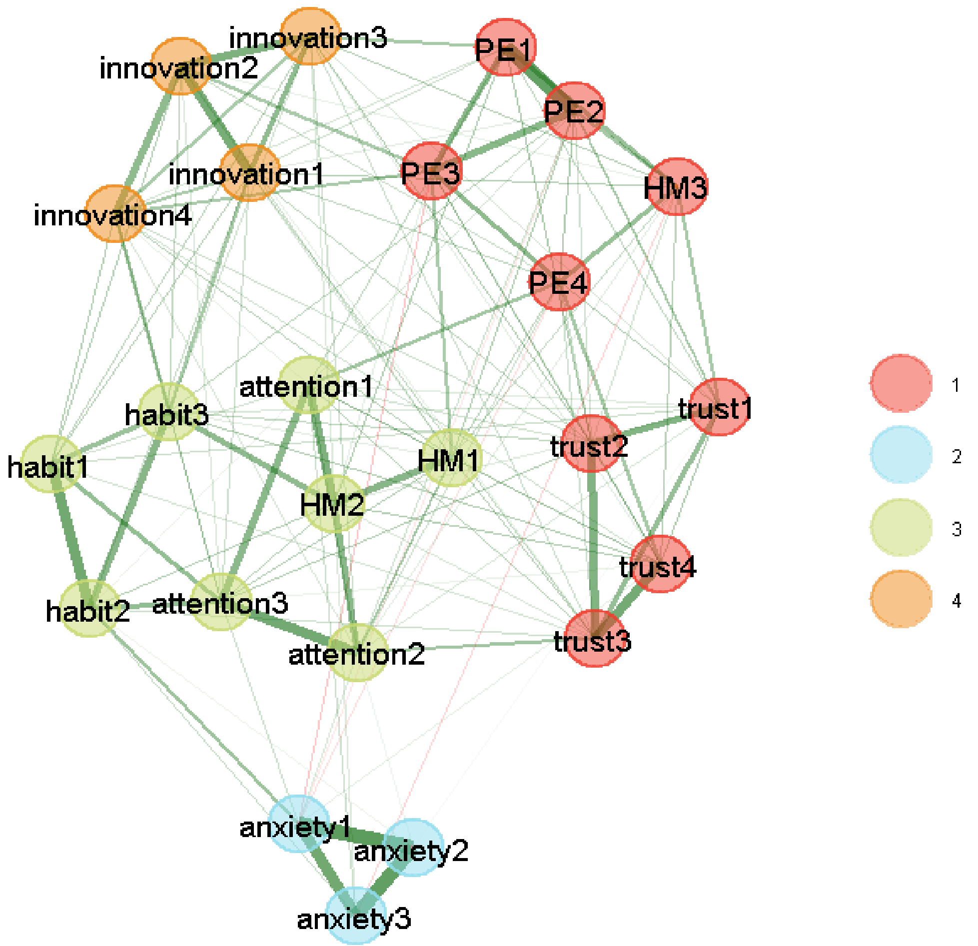

Figure 5. The EGA of readiness to use the ChatGPT structure

All standardized factor loadings were positive, statistically significant ($p < .001$), and of substantial magnitude, ranging from .699 to .859 (see Table 1). Notably, 23 of 24 items exceeded the recommended .70 threshold (Hair et al., 2010); only HM3 loaded slightly below at .699 yet remained acceptable for retention given its theoretical relevance to Dimension 1.

Reliability and Convergent Validity

Internal consistency was excellent, with Cronbach's alpha coefficients of .93 for Dimension 1, .87 for Dimension 2, .93 for Dimension 3, and .88 for Dimension 4. Composite reliability (CR) values, computed from the standardized loadings and error variances, were .93, .87, .93, and .88, respectively, all exceeding the recommended .70 threshold (Fornell & Larcker, 1981). Average variance extracted (AVE) for each dimension was .60, .69, .62, and .65, all above the .50 criterion, supporting convergent validity.

Discriminant Validity

Table 5 presents the latent factor correlations and the square roots of the AVE (on the diagonal). Although most dimensions demonstrated adequate discriminant validity according to the Fornell–Larcker criterion (i.e., √AVE > inter-construct correlation), the correlation between Dimension 1 and Dimension 3 ($r = .864$) exceeded the square root of AVE for both dimensions (.777 and .789, respectively). This indicates a substantial overlap between the performance–trust dimension and the experiential engagement dimension, suggesting that these constructs are closely related in students' perceptions. All other correlations were below their respective √AVE values, supporting discriminant validity among the remaining dimensions. All factor correlations were statistically significant ($p < .05$), with the exception that all were significant.

Table *5*. Latent factor correlations and square roots of AVE

Dimension	1	2	3	4
1. Performance–Trust	.777			
2. Anxiety	.150*	.829		
3. Experiential Engagement	.864***	.309***	.789	
4. Personal Innovativeness	.843***	.229**	.840***	.805

Note. Diagonal values (bold) are square roots of AVE; off-diagonal values are latent factor correlations. *$p < .05$, **$p < .01$, *** $p < .001$.

The four-factor measurement model derived from EGA exhibited good fit, strong factor loadings, and adequate reliability and convergent validity. The high correlation between Dimension 1 and Dimension 3 suggests a potential conceptual overlap that warrants further theoretical consideration. Nevertheless, the model provides a robust empirical basis for understanding the multidimensional nature of ChatGPT adoption readiness among Saudi university students.

Normative Data

Descriptive statistics and percentile distributions were calculated for each of the seven dimensions and the total score to provide normative references for interpreting individual scores in future research and practical applications. Table 6 presents the means, standard deviations, and selected percentiles (P10, 20, 25, 30, 40, 50, 60, 70, 75, 80, and 90) for subscales and the overall based on the 431 participants.

Table 6. Descriptive of normative data statistics for the subscales

Dimension	Mean	SD	-1SD	+1SD	P10	P20	P25	P30	P40	P50	P60	P70	P75	P80	P90
anx	-0.042	1.098	-1.140	1.056	-1.663	-0.913	-0.693	-0.490	-0.042	0.057	0.069	0.396	0.706	0.946	1.411
att	-0.273	0.939	-1.212	0.666	-1.098	-0.618	-0.464	-0.333	-0.273	-0.227	0.041	0.471	0.629	0.733	1.406
HM	-0.345	0.835	-1.180	0.490	-0.907	-0.557	-0.403	-0.353	-0.345	-0.208	0.061	0.454	0.577	0.753	1.224
hab	-0.257	0.912	-1.169	0.655	-1.250	-0.656	-0.454	-0.339	-0.257	-0.190	0.029	0.460	0.652	0.773	1.467
inn	-0.401	0.835	-1.236	0.434	-0.959	-0.578	-0.464	-0.438	-0.401	-0.166	0.140	0.455	0.555	0.838	1.335
peu	-0.363	0.862	-1.225	0.499	-0.985	-0.574	-0.550	-0.550	-0.363	-0.051	0.184	0.402	0.690	0.893	1.208
tru	-0.357	0.819	-1.176	0.462	-0.942	-0.558	-0.439	-0.371	-0.357	-0.208	0.101	0.444	0.556	0.675	1.381
Total	-2.038	5.102	-7.140	3.064	-7.204	-4.194	-3.388	-2.874	-2.170	-1.141	0.525	2.610	3.679	4.994	8.352

Note. Anxiety= anx, Attention= att, Hedonic Motivation= HM, Habit= hab, personal Innovativeness= inn, Performance Expectancy= peu, and Trust= tru.

Note. SD = standard deviation; -1SD = mean minus one standard deviation; +1SD = mean plus one standard deviation; P10 to P90 represent percentiles. The total score represents the sum of all seven-dimension scores.

The normative data revealed that all dimensions were approximately normally distributed with means near zero and standard deviations close to one, consistent with the factor score estimation method employed. The total score, representing the sum of all seven-dimension scores, exhibited a mean of -2.038 and a standard deviation of 5.102, providing a comprehensive indicator of overall ChatGPT adoption readiness. These normative values enable researchers and practitioners to contextualize individual scores relative to the reference population, facilitating the identification of students with exceptionally high or low readiness profiles. The percentile distributions further enhance interpretability by allowing precise localization of an individual's standing within the sample distribution.

Discussion

The present investigation examined the multidimensional factors shaping students' readiness to adopt ChatGPT for academic purposes within the unique cultural and educational context of Saudi Arabia. A key methodological contribution lies in the comparison between two competing measurement models: the theoretically derived seven-factor structure based on the original 24-item instrument and the empirically derived four-factor structure identified through EGA. The findings reveal that while both models demonstrate acceptable psychometric properties, the seven-factor model provides superior fit and preserves theoretically meaningful distinctions essential for precise measurement and targeted intervention design.

Situating these findings within international research reveals both convergences and culturally specific patterns. The finding that performance expectancy and trust loaded onto a combined dimension in the EGA solution, while remaining empirically separable in the seven-factor CFA, invites comparison with studies from other cultural contexts. In Western contexts, research has typically treated trust as a distinct antecedent to, rather than a component of, performance expectancy. For example, Strzelecki (2024) found that among Polish university students, trust in ChatGPT operated independently from perceived usefulness, with trust exerting a weaker effect on adoption intentions than performance expectancy. Similarly, in the United States, Menon and Shilpa (2023) reported that students distinguished sharply between "ChatGPT as a useful tool" and "ChatGPT as a trustworthy source," with trust being significantly lower and more variable.

The present study's finding of a high correlation between trust and performance expectancy ($r = .769$) suggests that Saudi students may integrate these evaluations more fully than their Western counterparts. This integration may reflect cultural orientations toward authority and expertise. In collectivistic and high power-distance societies such as Saudi Arabia, students may be less inclined to critically separate the utility of a technological tool from their confidence in its outputs. If a technology originates from a reputable source (OpenAI) and is endorsed by university authorities, students may extend their trust in the institutional endorsement to the tool's performance capabilities, collapsing what might be distinct cognitive processes in more individualistic contexts. Conversely, in a study of ChatGPT adoption among Hong Kong students, a context blending collectivistic cultural heritage with high institutional trust, Lai et al. (2023) similarly found that trust and performance expectancy were strongly correlated ($r = .71$), suggesting that this integration may characterize Asian and Middle Eastern educational contexts more broadly.

The integration of hedonic motivation, attention, and habit into a single experiential engagement dimension, while preserving their theoretical distinction in the seven-factor model, aligns with a growing international consensus that affective and automatic processes dominate AI adoption among young adults. Biloš and Budimir (2024) surveyed Generation Z students across five European countries and found that hedonic motivation was the single strongest predictor of ChatGPT adoption, surpassing even performance expectancy. Similarly, in the Polish context, Strzelecki et al. (2024) reported that habit was a more powerful determinant of continued use than any cognitive evaluation of utility. The present study extends these findings by demonstrating that among Saudi students, hedonic motivation, attention, and habit are not merely correlated but function as an integrated psychological system. Students who find ChatGPT enjoyable sustain attention during interactions, and sustained attention facilitates the development of automatic usage patterns. Notably, the correlation between attention and habit in the present study (r = .870) is substantially higher than that reported in Western samples (e.g., r = .62 in Scherer et al., 2019, for general technology use), suggesting that among Saudi students, attention may play an especially pivotal role in habit formation, potentially reflecting educational practices that emphasize sustained focus in technology-mediated learning environments.

The emergence of personal innovativeness as a distinct dimension in both the seven-factor and four-factor solutions confirms findings from multiple international contexts. Biloš and Budimir (2024) found that personal innovativeness significantly moderated the relationship between hedonic motivation and adoption intentions among Croatian students, while Strzelecki (2024) reported that innovativeness distinguished early adopters of ChatGPT from later adopters in Poland. The present study extends this literature by demonstrating that innovativeness operates independently from other adoption factors among Saudi students, correlating most strongly with experiential engagement (r = .840) but remaining empirically separable. This independence has important implications for intervention design: personally innovative students may serve as peer catalysts for adoption, but their natural enthusiasm does not eliminate the need for structured support for less innovative peers. Within the Saudi context, where Vision 2030 explicitly promotes a culture of innovation and digital transformation (Ministry of Education, 2020), identifying and leveraging personally innovative students as peer mentors and early adopters may be a particularly effective strategy.

The strong, distinct anxiety dimension, with a non-significant correlation with performance expectancy (r = .003, p = .958), replicates findings from multiple international studies. In Pakistan, Shahzad et al. (2024) found that AI anxiety was prevalent among university students and operated independently from perceived usefulness. The present study's finding that Saudi students can simultaneously recognize ChatGPT's utility while experiencing significant apprehension confirms that affective barriers do not simply reflect cognitive evaluations. However, the specific sources of anxiety may differ across cultural contexts. In Western studies, anxiety often centers on job displacement or academic integrity violations (Cotton et al., 2024). In the present Saudi sample, the highest-loading anxiety item was "I hesitate to use ChatGPT for fear of making mistakes I cannot correct" (β = .854), suggesting that anxiety may be more closely tied to error avoidance and perfectionism, potentially reflecting educational cultures that penalize mistakes.

Limitations and Future Directions

Several methodological constraints warrant acknowledgment. The cross-sectional design captures adoption readiness at a single temporal point, precluding examination of how adoption factors evolve as students gain experience with ChatGPT or as AI capabilities advance, and rendering causal inferences between variables impossible. The single-institution sample drawn from Jazan University in southwest Saudi Arabia limits generalisability to other Saudi institutions or international contexts where cultural norms, technological infrastructure, pedagogical practices, and assessment regimes may differ substantially. The exclusive reliance on self-report measures introduces potential common method bias and social desirability effects, as students may overreport comfort with ChatGPT or underreport anxiety to conform to perceived institutional expectations. The exclusive focus on ChatGPT restricts generalisability to other generative AI tools possessing different user interfaces or pedagogical affordances. Attention was assessed using only three items, which may inadequately capture the multidimensional complexity of attentional processes in human–AI interaction. The substantial inter-correlations among dimensions in the four-factor solution raise conceptual questions about whether the optimal level of specificity has been achieved. Finally, the study was conducted prior to widespread adoption of institutional AI policies, which may significantly influence students' attitudes and behaviours, and it did not assess behavioural outcomes beyond self-reported preparedness.

Future research should employ longitudinal designs tracking changes in adoption readiness over time to examine dimension validity, shifts in relative importance, and causal pathways among dimensions. Expanding sampling to multiple Saudi and international institutions will enhance generalisability and enable cross-cultural comparisons across diverse socioeconomic and educational contexts. Researchers should integrate multi-informant methods with objective behavioural metrics-including system log data and experience sampling techniques -to mitigate self-report bias. Comparative studies across multiple generative AI tools would distinguish between tool-specific and generic adoption drivers. Further scale development is necessary to capture nuanced dimensions of attention, complemented by objective methods such as eye-tracking. Exploring alternative modelling approaches, including bifactor models, may provide more parsimonious representation of shared and dimension-specific variance. Most critically, future research should validate the scale against objective behavioural and performance outcomes, including sustained usage, prompt quality, and academic achievement, while also examining how institutional AI policies moderate the relationships identified in this pre-policy baseline study.

Conclusion

This study provides the first empirically validated, multidimensional framework for understanding ChatGPT adoption readiness among Saudi university students, employing confirmatory factor analysis and exploratory graph analysis on data from 537 Jazan University participants. The seven-factor measurement model -comprising performance expectancy, hedonic motivation, habit, personal innovativeness, trust, attention, and anxiety- demonstrates excellent psychometric properties and superior fit relative to a more parsimonious four-factor solution.

The transferable implications for international higher education stakeholders are substantial. For policymakers, the non-significant correlation between anxiety and performance expectancy carries a clear mandate: demonstrating AI's utility does not automatically alleviate student anxiety. Effective AI integration policies must therefore include parallel cognitive interventions that build skills and demonstrate utility alongside affective interventions that normalise anxiety, provide low-stakes practice environments, and establish peer support systems. For curriculum designers, the integration of hedonic motivation, attention, and habit into a single experiential engagement dimension suggests that enjoyable tasks capture and sustain attention, and sustained attention predicts habit formation. Curriculum designers should scaffold early interactions to maximise focused engagement through structured activities with clear goals, immediate feedback loops, and progressive complexity. For educators, the seven validated dimensions provide a diagnostic framework for targeted interventions: students with high anxiety but average performance expectancy benefit from low-stakes practice sessions and peer mentoring; students with low personal innovativeness benefit from structured guided practice and explicit modelling; students with low trust benefit from transparency about ChatGPT's accuracy rates and limitations; and students with high innovativeness can be trained as peer mentors.

The Saudi context offers three unique contributions to the global field of AI adoption research. First, the finding that trust and performance expectancy are more highly integrated among Saudi students than reported in Western studies suggests that cultural dimensions—particularly power distance and collectivism—moderate the relationship between these constructs, extending technology acceptance theory by proposing that the cognitive separability of trust and utility evaluations may itself be culturally variable. Second, the specific pattern of anxiety observed, centring on fear of uncorrectable mistakes, may reflect educational cultures that emphasise error avoidance over experimentation; in such contexts, AI anxiety interventions must explicitly reframe mistakes as learning opportunities and provide safe, ungraded practice environments. Third, the exceptionally high correlation between attention and habit may reflect educational practices that emphasise sustained attention as a core academic skill; institutions in similarly structured educational cultures may find that attention-scaffolding interventions are particularly effective.

Finally, the present findings carry three theoretical implications for the broader field of technology acceptance research. First, the high correlations among the seven dimensions, while maintaining discriminant validity, suggest that adoption readiness may be best conceptualised as a multidimensional construct with a higher-order general factor; future research should test bifactor models to determine whether a general 'AI adoption readiness' factor accounts for shared variance among dimensions. Second, the integration of attention into the experiential engagement dimension suggests that technology acceptance models should incorporate attentional processes more explicitly, particularly for technologies requiring sustained interaction as opposed to discrete transaction-based technologies. Third, the finding that the seven-factor model provides superior fit to the four-factor EGA solution demonstrates that statistical parsimony does not necessarily align with theoretical utility; researchers should resist the temptation to collapse correlated dimensions solely on empirical grounds when theoretical and practical considerations support their separation.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgements

The authors would like to thank the students at Jazan University who participated in this study, as well as the faculty administrators who assisted with questionnaire distribution. The authors also acknowledge the expert panel members who contributed to the instrument's content validity assessment.

References

[1] Abdelrahman, R. M., Fakhrou, A., Moussa, M. A., & Roshan, M. (2025). Psychometric properties and network analysis of the Arabic version of reinforcement sensitivity theory of personality Scale-Short version in patients with anxiety disorders. *Psychiatric Quarterly*, *96*(1), 145-167.

[2] Al-Smadi, M. (2023). ChatGPT and beyond: The generative AI revolution in education. *arXiv preprint arXiv:2311.15198*.

[3] Bhat, M. A., Tiwari, C. K., Bhaskar, P., & Khan, S. T. (2024). Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. *Journal of Information, Communication and Ethics in Society*, *22*(3), 331-353. https://doi.org/10.1108/JICES-03-2024-0033

[4] Biloš, A., & Budimir, B. (2024). Understanding the adoption dynamics of ChatGPT among Generation Z: Insights from a modified UTAUT2 model. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(2), 863-879. https://doi.org/10.3390/jtaer19020045

[5] Challoumis, C. (2024). The dawn of artificial intelligence. In *XIX international scientific conference. London. Great Britain* (pp. 169-205).
[6] Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study1. *MIS Quarterly*, *23*(2), 145-158. https://doi.org/10.2307/249749
[7] Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in education and teaching international*, *61*(2), 228-239. https://doi.org/10.1080/14703297.2023.2190148
[8] DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications*. Sage Publications.
[9] Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior research methods, 41*(4), 1149-1160. https://doi.org/10.3758/BRM.41.4.1149
[10] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.2307/3151312
[11] Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PloS One*, *12*(6), e0174035. https://doi.org/10.1371/journal.pone.0174035
[12] Grant, J. S., & Davis, L. L. (1997). Selection and use of content experts for instrument development. *Research in Nursing & Health*, *20*(3), 269-274. https://doi.org/10.1002/(SICI)1098-240X(199706)20:3%3C269::AID-NUR9%3E3.0.CO;2-G
[13] Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis. In *Multivariate data analysis* (pp. 785-785).
[14] Ibrahem, U. M., Alrosaa, T. M., Diab, H. M., Alrashood, J. S., Hagar, H. M., Alotaibi, S. B., & Moussa, M. A. (2026). Hybrid modeling of science and math teachers' psychological preparedness for AI-integrated teaching environment: EGA perspective of instructional proficiency, professional motivation, technophilia and needs of training. *Frontiers in Psychology*, *17*, 1704162.
[15] Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford Publications.
[16] Lai, C. Y., Cheung, K. Y., & Chan, C. S. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the Technology Acceptance Model. *Computers and Education: Artificial Intelligence*, *5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178
[17] Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the

UTAUT model. *Heliyon*, *9*(11). https://www.cell.com/heliyon/fulltext/S2405-8440(23)08170-7

[18] Ministry of Education. (2020). *Ministry of Education official website*. https://www.moe.gov.sa/ar/pages/default.aspx

[19] Moussa, M. A., & Amer, A. E. (2025). A Neural Network Analysis of Climate Change Awareness in Egyptian Society. *BSU-Journal of Pedagogy and Curriculum*, *4*(7), 51-78.

[20] Moussa, M., & Elnersh, H. (2025). Data Analysis Errors and Limitations in Educational Research. International Journal of Research in Educational Sciences. 8(2), 293 - 330. Retrieved from https://iafh.net/index.php/IJRES/article/view /499

[21] Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & education*, *128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009

[22] Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*(1), 46. https://doi.org/10.1186/s41239-024-00478-x

[23] Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(2), 223-245. https://doi.org/10.1007/s10755-023-09686-1

[24] Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P. (2024). Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies*, *29*(17), 22943-22968. https://doi.org/10.1007/s10639-024-12765-1

[25] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540