

RESEARCH ARTICLE

Bridging the mental health treatment gap with artificial intelligence: Public perspectives on tele-mental health services

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Abstract

Background: The incorporation of artificial intelligence (AI) into tele-mental health services has progressed rapidly in recent years; nevertheless, public acceptance of AI in psychotherapy remains ambiguous due to apprehensions regarding trust, privacy, usability, and cultural suitability. Therefore, real-world evidence is essential to understand what factors influence individuals' willingness to adopt AI-based mental health care.

Objective: Using an extended technology acceptance model that accounts for ethical and sociocultural factors, this study examined factors influencing individuals' adoption of AI-based tele-mental health services.

Methods: A self-administered bilingual questionnaire was used to conduct a cross-sectional online survey of 432 participants between January and June 2024. Perceived usefulness, perceived ease of use, trust and privacy, cultural fit, future readiness, familiarity with AI, and behavioral intention were all included in the proposed model. Multiple linear regression, exploratory and confirmatory factor analyses, and reliability analysis were used to analyze the data.

Results: The measurement model demonstrated satisfactory psychometric properties, including acceptable internal consistency (Cronbach's $\alpha = 0.790\text{--}0.910$), convergent validity (average variance extracted > 0.500), and discriminant validity based on the Fornell–Larcker criterion. Exploratory and confirmatory factor analyses supported a five-factor structure with good model fit (comparative fit index = 0.940; Tucker–Lewis index = 0.930; root mean square error of approximation = 0.055). Regression analysis indicated that perceived usefulness ($\beta = 0.430, p < 0.001$), trust and privacy ($\beta = 0.270, p < 0.001$), perceived ease of use ($\beta = 0.180, p = 0.002$), and cultural fit ($\beta = 0.100, p = 0.037$) were significant predictors of behavioral intention, collectively explaining 61% of the variance ($R^2 = 0.610$). In contrast, future readiness and familiarity with AI were not statistically significant, and the corresponding hypotheses were not supported.

Conclusion: In Saudi Arabia, perceived functional value, ethical trust, usability, and cultural alignment are more important factors in the public's acceptance of AI-based tele-mental health services than past experiences or general optimism about AI. These results highlight the significance of prioritizing data security, cultural sensitivity, and reliable system design when developing and implementing AI-based mental health services.

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Citation: Alhur AA, Alhur AA, Altuwayrib S, Alshammari SA, Almutairi N. Bridging the mental health treatment gap with artificial intelligence: Public perspectives on tele-mental health services. *Health Psychol Res.* 2026;14(2):0414. doi: 10.36922/hpr.0414

Received: November 30, 2025**Revised:** February 5, 2026**Accepted:** February 24, 2026**Published online:** June 3, 2026

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Keywords: Artificial intelligence; Tele-mental health; Public perception; Technology acceptance model; Perceived usefulness; Trust and privacy; Ease of use; Cultural fit; Behavioral intention; Saudi Arabia

1. Introduction

Artificial intelligence (AI) is increasingly recognized as an effective approach to mitigating the global mental health treatment disparity, especially as tele-mental health services are increasingly incorporated into healthcare systems.¹⁻³ AI-based solutions enhance the capabilities of mental health professionals, facilitate early screening and monitoring, and enable scalable therapies such as digital cognitive-behavioral therapy, conversational agents, and virtual triage systems.^{4,5} These technologies offer accessible, cost-effective options for those in underserved or rural areas, where a shortage of skilled mental health practitioners remains a significant issue.⁶⁻⁸

A growing body of research indicates that AI-based tele-mental health therapies may diminish stigma, boost participation, and enable early detection of mental health issues.^{9,10} Clinical outcomes for anxiety and depression facilitated by AI-assisted telehealth systems are progressively comparable to those attained by conventional in-person treatment.¹¹⁻¹³ Woebot, Wysa, and Meru Health are some of the most well-known systems that demonstrate how AI-driven support can improve therapist-led therapy by continuously monitoring patients and providing psychological support between sessions.¹⁴⁻¹⁶ At the same time, predictive AI models are employed to assess the likelihood of an individual attempting suicide and to prevent relapse, demonstrating their potential to assist in complex clinical decision-making.¹⁷⁻¹⁹

Even with these advances in technology and medicine, AI cannot be used effectively in mental health treatment unless the public is willing to accept it and use it.²⁰⁻²² Previous studies indicate that the tendency to embrace AI-driven health technology is influenced by perceived usefulness, perceived ease of use, and trust in data privacy and algorithmic fairness.²³⁻²⁵ Ease of use, privacy, and reducing stigma are often cited as the primary factors influencing the use of tele-mental health services.²⁵⁻²⁷ At the same time, challenges such as limited digital literacy, insufficient transparency, and poor cultural alignment continue to hinder equitable adoption.²⁸⁻³⁰

In addition to usability and functionality, ethical and social considerations significantly influence public perceptions of AI-assisted mental health treatment. Individual perceptions of privacy, data security, openness, and fairness in algorithmic decision-making are closely

linked to their level of trust.³¹⁻³³ Previous studies have consistently highlighted the importance of explainable AI, human oversight, and cultural sensitivity in fostering trust in digital mental health systems. Without such protections, AI-driven solutions may exacerbate existing disparities by being unjust, marginalizing certain individuals, or failing to provide equitable access for all.^{34,35} Consequently, policymakers and clinicians are increasingly supporting governance frameworks that enhance transparency, accountability, and cultural sensitivity in the development and implementation of AI-driven mental health interventions.³⁶⁻³⁹

1.1. Research model and hypotheses

The technology acceptance model (TAM) underpins this study, describing technology use in terms of two core cognitive beliefs: perceived usefulness (PU) and perceived ease of use (PEOU).⁴⁰ TAM has been tested in many different areas of information systems and digital health, and it has been shown to be a strong predictor of users' willingness to adopt new technologies.^{41,42} However, an increasing number of scholars state that when TAM is used in complex, high-risk fields like healthcare—where ethical, cultural, and trust-related factors affect how users make decisions—it needs to be expanded to include more context.⁴³⁻⁴⁵

1.2. Theoretical integration of extended constructs

When individuals decide whether or not to use AI-based tele-mental health services, they consider more than just how easy they are to use and how useful they are. Users have to share sensitive psychological information, trust algorithmic outputs, and use systems that could affect their mental health. Consequently, perceptions of trust, cultural acceptance, and future readiness emerge as crucial contextual elements that impact the operation of TAM constructs.⁴⁶⁻⁴⁸ Rather than treating these variables as parallel predictors, this study conceptualizes them as contextual and ethical extensions of TAM, thereby strengthening its applicability in mental health settings.

Trust and privacy may enhance TAM beliefs, as users who have confidence in AI systems are more likely to perceive them as beneficial and acceptable. Cultural acceptance is a sociocultural boundary condition that affects how people perceive AI-based services as legitimate and appropriate in a given social setting. Future readiness

reflects a forward-looking orientation toward technological innovation, influencing individuals' openness to using AI even when its usefulness is recognized.

While the present study focuses on direct effects on behavioral intention, these constructs are theoretically interconnected and jointly shape adoption decisions. Their inclusion provides a more integrated and context-sensitive extension of TAM suitable for AI-based mental health services.

1.3. Core technology acceptance model constructs

1.3.1. Perceived ease of use

Perceived ease of use refers to the degree to which an individual believes that using AI-based tele-mental health services would require minimal effort.⁴⁹ Rooted in TAM, PEOU has been consistently shown to influence adoption by reducing cognitive burden and facilitating positive user experiences.^{49,50} In mental health contexts, ease of interaction is particularly important, as users may already experience emotional or psychological strain.

- (i) H1: PEOU positively influences behavioral intention to use AI-based tele-mental health services.

1.3.2. Perceived usefulness

Perceived usefulness is defined as the extent to which an individual believes that using AI-based tele-mental health services will enhance access to care, improve service quality, or support mental health outcomes.⁵¹ TAM posits PU as the strongest predictor of behavioral intention, particularly in healthcare contexts where perceived value directly affects willingness to adopt digital solutions.⁵²

- (i) H2: PU positively influences behavioral intention to use AI-based tele-mental health services.

1.4. Ethical and contextual extensions of technology acceptance model

1.4.1. Trust and privacy

Trust and privacy originate from ethical- and risk-based adoption theories and are widely applied in digital health research.⁵³ Trust reflects confidence in the reliability, fairness, and clinical appropriateness of AI systems, while privacy concerns relate to perceptions of data security and responsible information handling.⁵⁴ In mental healthcare, where confidentiality and stigma are prominent concerns, trust is not only a direct predictor of adoption but also a factor that shapes users' evaluation of usefulness and ease of use.⁵⁴

- (i) H3: Trust and privacy positively influence behavioral intention to use AI-based tele-mental health services.

1.4.2. Cultural acceptance (cultural fit)

Cultural acceptance refers to the extent to which AI-based tele-mental health services conform to users' language preferences, values, and social and religious norms.⁵⁵ Prior research in digital health adoption emphasizes that technologies perceived as culturally incongruent may be rejected regardless of their usability or effectiveness.^{56,57} In Saudi Arabia, cultural norms strongly influence mental health perceptions and help-seeking behaviors, making cultural acceptance a critical sociocultural factor for adoption.⁵⁸⁻⁶⁰

- (i) H4: Cultural acceptance positively influences behavioral intention to use AI-based tele-mental health services.

1.4.3. Future readiness

Future readiness reflects individuals' expectations regarding the role of AI in future healthcare systems and their openness to long-term technological integration.^{61,62} Drawing on innovation diffusion and technology readiness literature, future readiness captures the temporal and attitudinal dimensions of adoption. Users who perceive AI as an inevitable and legitimate component of future care may be more inclined to adopt AI-based services.

- (i) H5: Future readiness positively influences behavioral intention to use AI-based tele-mental health services.

1.4.4. Familiarity with artificial intelligence

Familiarity represents prior exposure to AI technologies and tele-mental health services.⁶³ While familiarity is often assumed to facilitate adoption by reducing uncertainty, prior research suggests its influence may be indirect or context-dependent, particularly in high-risk health domains where trust and perceived value may outweigh prior experience alone.⁶⁴

- (i) H6: Familiarity positively influences behavioral intention to use AI-based tele-mental health services.

2. Conceptual framework

The conceptual research model guiding this investigation is shown in [Figure 1](#). PU and PEOU are positioned as key cognitive determinants of behavioral intention in the model, which is based on the TAM. Ethical and sociocultural extensions, which directly influence adoption and shape users' perceptions of usefulness, trust, privacy, and cultural acceptance, are incorporated. Contextual factors reflecting innovation orientation and prior exposure include familiarity and future readiness. The model acknowledges theoretical relationships among the constructs and provides a coherent and context-sensitive

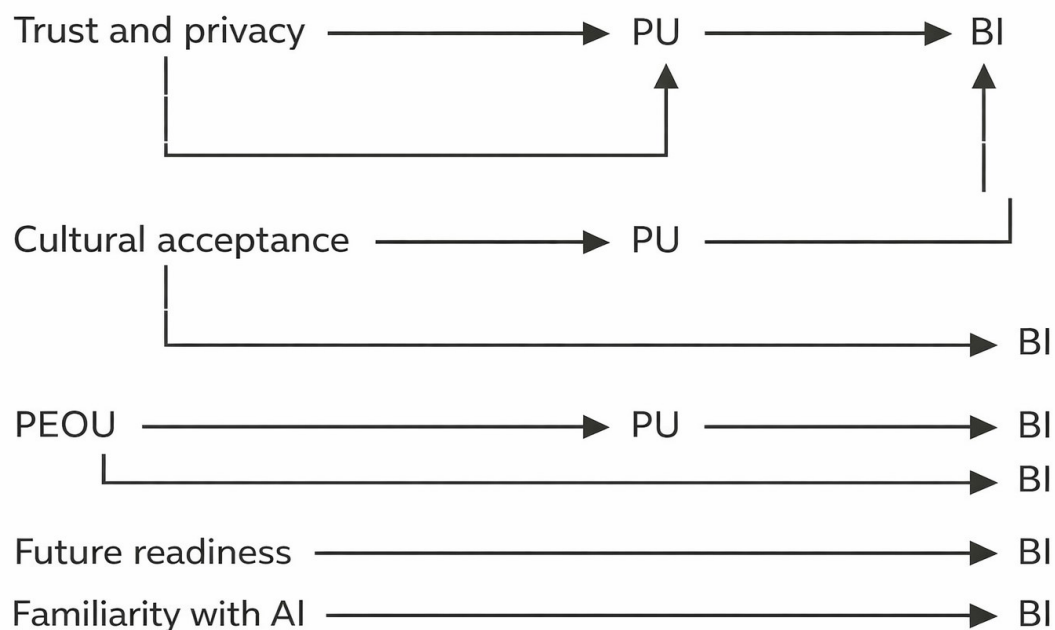


Figure 1. Conceptual research model extending the technology acceptance model for AI-based tele-mental health services
Abbreviations: AI: Artificial intelligence; BI: Behavioral intention; PU: Perceived usefulness.

extension of TAM for AI-based tele-mental health services, although the present study empirically examines only their direct effects on behavioral intention.

2.1. Study design and research process

To investigate public perceptions and acceptance of AI-based tele-mental health services in Saudi Arabia, a quantitative cross-sectional survey design was employed. A survey-based approach was selected due to its effectiveness in gathering attitudes, perceptions of emerging health technologies, and ethical considerations from a broad participant pool.

The research process comprised four steps: (i) instrument development and cultural adaptation; (ii) pilot testing and validation; (iii) large-scale online survey data collection; and (iv) psychometric and inferential statistical analyses to assess measurement properties and test hypothesized relationships. A self-administered bilingual (Arabic–English) questionnaire, distributed electronically, was used to collect data between January and June 2024.

2.2. Participants, inclusion criteria, and sampling strategy

The target population consisted of adults aged 18 years and older residing in Saudi Arabia. Participants were included if they provided informed consent electronically and were able to read and comprehend either Arabic or English.

Exclusion criteria comprised individuals younger than 18 years old, those who did not complete the survey, and participants who declined to provide consent. The study aimed to capture the general public's perceptions rather than clinical assessments; therefore, no restrictions were applied based on occupation, educational background, or prior experience with mental health services.

Convenience sampling was employed, with recruitment facilitated through professional and community organizations, university networks, and online platforms. This approach is commonly used in perception-focused and exploratory studies in digital health. However, it has inherent limitations regarding representativeness, potentially skewing toward younger individuals, those with higher educational attainment, or individuals with greater interest in digital technologies. Consequently, this sampling strategy may limit the generalizability of findings to populations with restricted internet access or lower digital literacy. Section 4 discusses the impact of this sampling structure on external validity.

The final analysis included 432 valid responses. This sample size provided sufficient statistical power for factor analysis and multivariate modelling, exceeding the minimum threshold established by Cochran's formula for proportions, assuming a 50% prevalence, a 5% margin of error, and a 95% confidence level.

2.3. Instrument development and construct measurement

The questionnaire was grounded in the TAM and extended to incorporate ethical, sociocultural, and contextual factors relevant to AI-based mental health services. The extended constructs included trust and privacy, cultural alignment, future readiness, familiarity with AI, behavioral intention, and related ethical and clinical perceptions. TAM consisted of two primary constructs: PU and PEOU. The items were adapted from prior literature on TAM and digital health adoption, trust in AI, privacy concerns, and culturally sensitive healthcare technologies.

The final instrument consisted of 40 items covering informed consent, demographic information, and the underlying constructs. A five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5), was used to assess all construct-related items. This scale was selected due to its widespread validation in studies of technology acceptance and health behaviors, effectively balancing respondent cognitive load with psychometric requirements. To measure familiarity, a five-point scale was employed to capture varying levels of prior exposure rather than agreement.

[Appendix 1](#) presents the complete bilingual questionnaire for clarity, while [Appendix 2](#) provides a comprehensive codebook linking items to constructs, variable names, and scoring methodologies.

2.4. Validity assessment, item treatment, and pilot testing

Experts in digital health, psychology, and health informatics conducted thorough evaluations, demonstrating both face and content validity. Reviewers assessed each item's relevance, clarity, and cultural appropriateness, resulting in minor wording adjustments. To evaluate comprehension and preliminary reliability, the instrument underwent pilot testing with 30 participants.

Exploratory factor analysis was employed to examine the instrument's underlying dimensional structure. Concepts with similar content, such as PU and PEOU, exhibited significant empirical relationships, and certain items were grouped based on factor loadings. Item grouping preserved the construct's conceptual integrity and reflected the empirical framework; no items were removed without theoretical justification. [Appendix 3](#) illustrates the treatment of the initial items and their final factor assignments, enhancing clarity.

2.5. Data collection procedure

Prior to participation, participants reviewed an informed

consent statement and accessed the survey via an electronic link. Participation was voluntary, anonymous, and uncompensated. No personally identifiable information was collected. Participants completed the survey within approximately 10–12 minutes. [Appendix 4](#) provides details on consent procedures and ethical protections, while [Appendix 5](#) provides additional insights into translation and cultural adaptation.

2.6. Data analysis strategy and statistical rigor

Data analysis was conducted using SPSS Statistics (version 26, IBM Corp., USA) following export of the data from Microsoft Excel (Version 2603, Microsoft, USA). Descriptive statistics were computed to characterize the sample and examine distributions. Internal consistency was evaluated using Cronbach's α , composite reliability, and average variance extracted (AVE). Exploratory factor analysis employed principal component extraction with varimax rotation, and confirmatory factor analysis was used to assess the fit of the measurement model.

Multiple linear regression analysis examined direct predictors of behavioral intention, aligning with the study's exploratory objectives and sample characteristics. Although structural equation modeling offers advantages for analyzing intricate structural relationships, it was not applied in this investigation. Standardized coefficients were reported, multicollinearity was assessed using variance inflation factors and tolerance values, and model assumptions were verified prior to interpretation to ensure rigor. Discriminant validity was assessed using the Fornell–Larcker criterion.

Based on the validated measurement framework, future research is recommended to employ comprehensive structural equation modeling to examine potential mediating or moderating relationships among constructs.

2.7. Ethical considerations

Ethical approval was obtained from the Institutional Review Board of the University of Hail (approval no. H-2025-210). All participants provided electronic informed consent prior to participation. Data were collected anonymously, stored securely, and analyzed in aggregate form in accordance with institutional and international ethical standards.

3. Results

3.1. Sample characteristics

[Table 1](#) presents the demographic details of the study participants. The sample included 432 participants, with a nearly equal gender distribution: 51.6% female and 48.4% male. Most participants were young adults: 66.2% were aged 18–34, 21.1% were 35–44, and 12.7% were ≥ 45 .

In terms of education, 71% of participants held at least a bachelor's degree, including 26.8% with a master's or higher. Students constituted the largest occupational group (41.7%), followed by healthcare professionals (24.5%) and information technology professionals (18.2%). These distributions indicate that the majority of the sample were younger, well-educated, and had professional or academic backgrounds relevant to digital and health technologies.

Descriptive statistics and internal consistency measures for all study constructs are summarized in Table 2. All constructs demonstrated satisfactory reliability, with Cronbach's α and composite reliability values exceeding recommended thresholds. AVE values were above 0.50 for all constructs, supporting convergent validity. PU and behavioral intention had the highest mean scores, indicating generally favorable perceptions of AI-based tele-mental health services.

Exploratory factor analysis using principal component extraction with varimax rotation yielded a five-factor solution (Table 3), accounting for 68.7% of the total variance. Items loaded cleanly onto their respective factors, with all retained loadings exceeding 0.730. The first factor comprised items related to PEOU and PU, indicating a strong empirical association between these TAM constructs. The second factor captured trust and privacy items, while the third factor reflected cultural fit. Behavioral intention items loaded distinctly on the fourth factor, and future readiness items loaded on the fifth factor. No substantial cross-loadings were observed, and

the factor structure demonstrated clear separation among constructs.

Table 1. Demographic characteristics of study participants

Characteristic	<i>n</i>	%
Gender		
Male	209	48.4
Female	223	51.6
Age (years)		
18–24	118	27.3
25–34	168	38.9
35–44	91	21.1
≥45	55	12.7
Education level		
High school or lower	97	22.5
Bachelor's degree	191	44.2
Master's degree or higher	116	26.8
Occupation		
Student	180	41.7
Healthcare professional	106	24.5
Information technology/technology professional	79	18.2
Other	67	15.5

Table 2. Reliability and descriptive statistics of study constructs

Construct	Item	Mean	SD	Cronbach's α	CR	AVE
Familiarity with artificial intelligence	3	3.61	0.91	0.83	0.84	0.57
Perceived ease of use	4	3.78	0.86	0.86	0.87	0.59
Perceived usefulness	5	3.94	0.82	0.88	0.89	0.64
Trust and privacy	5	3.71	0.79	0.81	0.82	0.53
Cultural fit	3	3.69	0.88	0.79	0.8	0.57
Behavioral intention	3	3.85	0.9	0.91	0.91	0.68
Future readiness	3	3.74	0.84	0.82	0.83	0.55

Note: Scale range = 1–5.

Abbreviations: AVE: Average variance extracted; CR: Composite reliability; SD: Standard deviation.

Table 3. Results of exploratory factor analysis: Rotated component matrix (varimax rotation)

Item (abbreviated)	Factor 1 (PEOU/PU)	Factor 2 (trust/privacy)	Factor 3 (cultural fit)	Factor 4 (BI)	Factor 5 (future readiness)
Learning to use AI-based services is easy	0.820	-	-	-	-
Overall, AI-based tele-mental health is useful	0.790	-	-	-	-
Trust AI-based tele-mental health	-	0.830	-	-	-
Need clear explanations of AI decisions	-	0.810	-	-	-
Respect cultural values	-	-	0.850	-	-
Accessible to people with disabilities	-	-	0.780	-	-
Intend to use in the future	-	-	-	0.910	-
Recommend to others	-	-	-	0.870	-
AI is essential in five years	-	-	-	-	0.760
Government should promote AI	-	-	-	-	0.730

Notes: Factor loadings < 0.400 were suppressed. The total variance explained was 68.7%

Abbreviations: AI: Artificial intelligence; BI: Behavioral intention; PEOU: Perceived ease of use; PU: Perceived usefulness.

Confirmatory factor analysis evaluated the adequacy of the measurement model. As reported in Table 4, the model demonstrated satisfactory fit across all indices. The χ^2/df ratio was 2.410, indicating an acceptable level of model parsimony. Incremental fit indices exceeded recommended thresholds (comparative fit index = 0.940; Tucker–Lewis index = 0.930), reflecting good comparative fit. Absolute fit indices also indicated strong model performance, with root mean square error of approximation = 0.055 and standardized root mean square residual = 0.046, both well below established cut-off values. All standardized factor loadings were statistically significant ($p < 0.001$) and exceeded 0.600. Combined with AVE values > 0.500 and composite reliability values > 0.700, these results support the adequacy of the measurement model and confirm convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion. As presented in “Table 5”, the square roots of AVE for all constructs (0.730–0.820) exceeded the corresponding inter-construct correlations. Inter-construct correlations were moderate, with the highest observed correlation ($r = 0.610$) remaining below the

square root of AVE for the respective constructs. These results confirm that each latent variable exhibits adequate discriminant validity and represents a distinct construct within the measurement model.

Multiple linear regression analysis examined predictors of behavioral intention to adopt AI-based tele-mental health services. The overall model was statistically significant ($F[6, 425] = 33.400, p < 0.001$), accounting for 61% of the variance in behavioral intention ($R^2 = 0.610$; adjusted $R^2 = 0.590$).

Based on “Table 6”, PU was the strongest predictor ($\beta = 0.430, p < 0.001$), followed by trust and privacy ($\beta = 0.270, p < 0.001$) and PEOU ($\beta = 0.180, p = 0.002$). Cultural fit also demonstrated a statistically significant effect ($\beta = 0.100, p = 0.037$). Future readiness ($\beta = 0.060, p = 0.151$) and familiarity ($\beta = 0.050, p = 0.227$) were not significant predictors.

A summary of the hypothesis-testing results is provided in Table 7. H1–H4 were supported, confirming significant effects of PEOU, PU, trust and privacy, and cultural fit on behavioral intention. H5 and H6, examining the effects of future readiness and familiarity, were not supported.

Table 4. Confirmatory factor analysis and model fit indices

Fit index	Recommended threshold	Obtained value
χ^2/df	<3.000	2.410
CFI	≥ 0.900	0.940
TLI	≥ 0.900	0.930
RMSEA	≤ 0.080	0.055
SRMR	≤ 0.080	0.046

Notes: All standardized factor loadings were significant ($p < 0.001$). Average variance extracted > 0.50 and composite reliability > 0.70 confirm convergent validity. Abbreviations: CFI: Comparative fit index; RMSEA: Root mean square error of approximation; SRMR: Standardized root mean square residual; TLI: Tucker–Lewis index.

4. Discussion

This study examined the acceptance of AI-based tele-mental health services as a psychologically sensitive healthcare interaction, rather than merely a digital technology adoption decision. The findings indicate a layered evaluation process, in which users first assess functional value (“usefulness and ease of use”), then

evaluate emotional and informational safety (“trust and privacy”), and finally consider social legitimacy (“cultural fit”).

While TAM traditionally explains intention primarily through performance beliefs,^{40–45} the findings of this study suggest that adoption in AI-mediated mental health care depends on the willingness to disclose personal psychological information to a non-human agent. In contrast to general digital health acceptance studies,^{17,22} behavioral intention here reflects a relational trust judgment rather than a purely utilitarian evaluation. This extends contextualized TAM approaches that emphasize environment-dependent determinants of adoption^{42,45} by demonstrating that, in sensitive health domains, psychological safety is the central mechanism linking cognition to intention.

Perceived usefulness strongly predicted behavioral intention; however, in mental health contexts, it reflects emotional utility rather than task efficiency. Individuals evaluate whether the service reduces barriers to seeking help, such as hesitation, embarrassment, or delayed disclosure. AI systems provide continuous availability and non-judgmental interaction, features previously described as enhancing engagement between sessions^{14,21} and expanding access to care.^{6,7} While previous studies have indicated these benefits primarily as accessibility improvements,^{3,33} the present findings suggest that their importance lies in reshaping the help-seeking experience into a psychologically manageable first step. Thus, PU serves both as a performance expectancy,^{49–52} and a means of reducing emotional burden, thereby extending the existing literature on digital mental health adoption.^{10,17}

Table 5. Discriminant validity (Fornell–Larcker criterion)

Construct	Perceived usefulness	Perceived ease of use	Trust and privacy	Cultural fit	Behavioral intention	Future readiness
Perceived usefulness	0.800^a	-	-	-	-	-
Perceived ease of use	0.610	0.770^a	-	-	-	-
Trust and privacy	0.590	0.540	0.730^a	-	-	-
Cultural fit	0.470	0.430	0.450	0.750^a	-	-
Behavioral intention	0.550	0.490	0.520	0.480	0.820^a	-
Future readiness	0.440	0.410	0.390	0.420	0.460	0.740^a

Note: ^aSquare root of average variance extracted.

Table 6. Multiple linear regression analysis predicting behavioral intention

Predictor	B	Standard error	β	<i>t</i>	<i>p</i>
Perceived usefulness	0.412	0.042	0.430	9.870	<0.001
Trust and privacy	0.268	0.043	0.270	6.310	<0.001
Perceived ease of use	0.183	0.044	0.180	4.120	0.002
Cultural fit	0.097	0.047	0.100	2.080	0.037
Future readiness	0.061	0.042	0.060	1.440	0.151
Familiarity	0.053	0.044	0.050	1.210	0.227

Model summary: $R^2 = 0.610$; adjusted $R^2 = 0.590$; $F(6, 425) = 33.400$; $p < 0.001$.

Table 7. Summary of hypothesis testing

Hypothesis	Path	Result
H1	PEOU $\rightarrow$ BI	Supported ($p = 0.002$)
H2	PU $\rightarrow$ BI	Supported ($p < 0.001$)
H3	Trust and privacy $\rightarrow$ BI	Supported ($p < 0.001$)
H4	Cultural fit $\rightarrow$ BI	Supported ($p = 0.037$)
H5	Future readiness $\rightarrow$ BI	Not supported
H6	Familiarity $\rightarrow$ BI	Not supported

Abbreviations: AI: Artificial intelligence; BI: Behavioral intention; PEOU: Perceived ease of use; PU: Perceived usefulness.

Trust and privacy had a substantial influence on behavioral intention, indicating that acceptance of AI-based tele-mental health services is fundamentally a decision about personal disclosure. In mental health interactions, users must reveal sensitive experiences, making the perceived security and ethical handling of information central to adoption. Prior literature emphasizes transparency, explainability, and data governance as technical determinants of trust;^{25,28-30} however, the present findings support a more relational interpretation, consistent with ethical analyses of AI therapy.^{15,29} Privacy concerns, therefore, pose a threat to emotional vulnerability beyond mere data security risks. Consistent with evidence that privacy concerns limit sustained engagement with AI-based mental health systems,^{14,53} participants appeared willing to use AI when disclosures were perceived as secure, contained, and non-judgmental. Trust thus acts as the gateway through which PU translates into willingness to seek support.

Cultural fit significantly influenced behavioral intention, suggesting that adoption depends on the perceived social legitimacy of the help-seeking process. Help-seeking in many contexts is shaped by social expectations and stigma surrounding mental illness.⁵⁸ Technologies perceived as culturally incongruent may be rejected despite their functionality.⁵⁵⁻⁵⁷ Rather than simple localization, cultural alignment provides ethical and social permission to engage with care by reducing perceived exposure associated with formal psychiatric consultation. This aligns with research showing that culturally responsive digital mental health services improve engagement³¹⁻³³ and are particularly relevant in environments where social norms strongly influence disclosure behavior. These findings indicate that cultural acceptance functions as a legitimacy condition, enabling trust to translate into intention.

The findings reveal that future readiness and familiarity were not significant predictors of behavioral intention, indicating that general openness to AI does not necessarily translate into willingness to use AI for psychological support. Technology readiness models typically predict adoption in consumer and educational contexts.⁶¹⁻⁶⁴ However, mental health applications require users to disclose personal information. Individuals comfortable with AI in everyday contexts may still hesitate to rely on it for emotional or psychological purposes. This supports prior observations that perceived risk and trust outweigh prior experience in healthcare AI acceptance^{17,53} and extends TAM by demonstrating domain-specific boundary conditions. Adoption is governed by relational and ethical considerations rather than technological optimism.

These findings clarify the conditions under which AI-based mental health tools can achieve clinical impact. Implementation should prioritize confidence-building mechanisms rather than technological promotion. Transparent communication about data handling and

oversight is essential to maintain public confidence.^{25,28-30} Designing culturally appropriate interaction styles can reduce perceived stigma and engagement barriers,^{31-33,58} while hybrid human-AI models may maintain professional legitimacy and preserve privacy benefits.^{2,7,21} Importantly, increasing general digital literacy alone is unlikely to substantially improve adoption, because willingness arises primarily from perceived emotional safety, rather than familiarity with technology.⁵⁹⁻⁶⁴

5. Limitations and future directions

This research is subject to several limitations. The reliance on convenience sampling may limit the representativeness of the study, as it tends to over-represent participants who are more comfortable with online platforms. Furthermore, the applicability of these findings to broader adult or clinical populations, which may encompass diverse perspectives, is constrained by the high proportion of student participants.

Self-administered questionnaires were employed to collect responses; however, the sensitive nature of mental health topics may introduce social desirability bias, potentially affecting reported intentions. To determine whether perceived trust and cultural legitimacy facilitate genuine engagement, future studies should combine behavioral usage data with stratified sampling methods.

This study demonstrates that the desire to utilize AI-based tele-mental health services is influenced more by perceptions of psychological safety than by familiarity with technology. Usefulness prompts reflection, whereas engagement is shaped by cultural legitimacy and trust. These findings extend TAM by demonstrating that technology adoption in emotionally sensitive healthcare contexts follows a relational trust pathway rather than a general technology readiness pathway. They emphasize that AI systems should be designed as secure tools for delivering care, rather than replacements for healthcare professionals.

6. Conclusion

This study highlights that the public is receptive to AI-based tele-mental health services when these services are perceived as practical, reliable, user-friendly, and culturally relevant. The most significant predictor of intention to adopt was PU, emphasizing the importance of developing AI tools that demonstrate clear therapeutic advantages, provide valuable support, and enhance user experience. The public's concern for data protection, transparency, security, and ethical considerations is reflected in the strong influence of trust and privacy on behavioral intentions. Acceptance was also shaped by

cultural compatibility, particularly in regions such as Saudi Arabia, where social and religious conventions profoundly affect discussions surrounding mental health.

It is noteworthy that adoption was not strongly influenced by prior experience with AI or general openness to new technologies, suggesting that functional and ethical considerations carry greater weight than mere interest or exposure. These findings emphasize several critical areas that developers and policymakers should prioritize, including ensuring that individuals maintain control, promoting algorithmic equity, and accounting for cultural variations. As AI advances, its thoughtful integration into mental health systems has the potential to address persistent gaps in care, enhancing the accessibility, scalability, and stigma-free nature of mental health services globally.

Acknowledgments

The authors thank the participants for their time and the Institutional Review Board of the University of Hail for guidance during the ethical review process.

Funding

None.

Conflict of interest

The authors declare no competing interests.

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Ethics approval and consent to participate

This study was approved by the Institutional Review Board of College of Public Health and Health Informatics, University of Hail, Saudi Arabia (approval no.: H-2025-210; January 2, 2024). Participation was voluntary and anonymous. All participants provided electronic informed consent prior to participation. Data were collected anonymously, stored securely, and analyzed in aggregate form in accordance with institutional and international ethical standards.

Consent for publication

Not applicable. No identifiable individual data are included in this study.

Availability data

De-identified data, the analysis codebook, and the questionnaire (Appendices 1 and 2) are available from the corresponding author upon reasonable request.

References

1. Pandit Sharma S. Role of AI in business decision process of companies in Nepal: a case study of Inira Diamond Pvt Ltd. Theseus Repository. 2025. Accessed January 27, 2026. <https://www.theseus.fi/handle/10024/891703>
2. Babu A, Joseph AP. Artificial intelligence in mental healthcare: transformative potential vs the necessity of human interaction. *Front Psychol*. 2024;15:1378904. doi: 10.3389/fpsyg.2024.1378904
3. Karimian Kelhini F. The role of artificial intelligence in transforming mental healthcare: bridging gaps, enhancing accessibility, and personalizing interventions. *SSRN*. 2025. doi: 10.2139/ssrn.5217663
4. World Health Organization. Mental health and COVID-19: early evidence of the pandemic's impact. World Health Organization. Published March 2, 2022. Accessed January 27, 2026. <https://iris.who.int/server/api/core/bitstreams/b516621b-1d79-4f5c-a36d-9149b28f6576/content>
5. Alhur AA, Al-Kahtani NK. Generative Artificial Intelligence In Health Informatics Education: A Comprehensive Bibliometric Assessment Of Cognitive Outcome Research (2019–2025). *IJASIS*. 2026;12(1s):895-915. doi: 10.29284/r2man269
6. Poudel U, Jakhar S, Mohan P, Nepal A. AI in mental health: a review of technological advancements and ethical issues in psychiatry. *Issues Ment Health Nurs*. 2025;46(7):693-701. doi: 10.1080/01612840.2025.2502943
7. Mansoor M, Ansari K. Artificial intelligence-driven analysis of telehealth effectiveness in youth mental health services: insights from SAMHSA data. *J Pers Med*. 2025;15(2):63. doi: 10.3390/jpm15020063
8. Bobkov A, Cheng F, Xu J, *et al*. Telepsychiatry and artificial intelligence: a structured review of emerging approaches to accessible psychiatric care. *Healthcare (Basel)*. 2025;13(11):1348. doi: 10.3390/healthcare13111348
9. Alhur A, Alhur AA. The acceptance of digital health: what about telepsychology and telepsychiatry? *J Syst Inf*. 2022;18(2):18-35. doi: 10.21609/jsi.v18i2.1143
10. Alavi N, Moghimi E, Stephenson C, *et al*. Comparison of online and in-person cognitive behavioral therapy in individuals diagnosed with major depressive disorder: a non-randomized controlled trial. *Front Psychiatry*. 2023;14:1113956. doi: 10.3389/fpsyg.2023.1113956
11. Zhang M, Scandiffio J, Younus S, *et al*. The adoption of AI in mental health care: perspectives from mental health professionals. *JMIR Form Res*. 2023;7(1):e47847. doi: 10.2196/47847
12. Hornstein S, Forman-Hoffman V, Nazander A, Ranta K, Hilbert K. Predicting therapy outcome in a digital mental health intervention for depression and anxiety: a machine learning approach. *Digit Health*. 2021;7:20552076211060659. doi: 10.1177/20552076211060659
13. Al-Remawi M, Ali Agha ASA, Al-Akayleh F, Aburub F, Abdel-Rahem RA. Artificial intelligence and machine learning techniques for suicide prediction: integrating dietary patterns and environmental contaminants. *Heliyon*. 2024;10(24):e40925. doi: 10.1016/j.heliyon.2024.e40925
14. Paul MK, Kulal N, Singla A, *et al*. Leveraging technology to bridge the psycho-social care gap in mental health care: a case series. *Indian J Psychol Med*. 2025. doi: 10.1177/02537176251400527
15. Benda N, Desai P, Reza Z, *et al*. Patient perspectives on AI for mental health care: cross-sectional survey study. *JMIR Ment Health*. 2024;11:e58462. doi: 10.2196/58462
16. Rahsepar Meadi M, Sillekens T, Metselaar S, van Balkom A, Bernstein J, Batelaan N. Exploring the Ethical Challenges of Conversational AI in Mental Health Care: Scoping Review. *JMIR Ment Health*. 2025;12:e60432. doi: 10.2196/60432
17. Alhur A. Curricular analysis of digital health and health informatics in medical colleges across Saudi Arabia. *Cureus*. 2024. doi: 10.7759/cureus.66892
18. Chew HSJ, Achananuparp P. Perceptions and needs of artificial intelligence in health care to increase adoption: scoping review. *J Med Internet Res*. 2022;24(1):e32939. doi: 10.2196/32939
19. Chaturvedi U, Chauhan SB, Singh I. The impact of artificial intelligence on remote healthcare: enhancing patient engagement, connectivity, and overcoming challenges. *Intell Pharm*. 2025;3(5):323-329. doi: 10.1016/j.ipha.2024.12.003

20. Jabir AI, Lin X, Martinengo L, *et al.* Attrition in conversational agent-delivered mental health interventions: systematic review and meta-analysis. *J Med Internet Res.* 2024;26:e48168.
doi: 10.2196/48168
21. Timmons AC, Duong JB, Simo Fiallo N, *et al.* A call to action on assessing and mitigating bias in artificial intelligence applications for mental health. *Perspect Psychol Sci.* 2023;18(5):1062-1096.
doi: 10.1177/17456916221134490
22. Sharma A, Lin IW, Miner AS, Atkins DC, Althoff T. Human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. *Nat Mach Intell.* 2023;5(1):46-57.
doi: 10.1038/s42256-022-00593-2
23. Shatte AB, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. *Psychol Med.* 2019;49(9):1426-1448.
doi: 10.1017/S0033291719000151
24. Cai Y, Wang F, Wang H, Qian Q. Public sentiment analysis and topic modeling regarding ChatGPT in mental health on Reddit: negative sentiments increase over time. *arXiv.* Preprint posted online November 27, 2023.
doi: 10.48550/arXiv.2311.15800
25. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med.* 2019;25(1):44-56.
doi: 10.1038/s41591-018-0300-7
26. Torous J, Roberts LW. Needed innovation in digital health and smartphone applications for mental health: transparency and trust. *JAMA Psychiatry.* 2017;74(5):437-438.
doi: 10.1001/jamapsychiatry.2017.0262
27. Hollis C, Falconer CJ, Martin JL, *et al.* Annual Research Review: Digital health interventions for children and young people with mental health problems: a systematic meta-review. *J Child Psychol Psychiatry.* 2017;58(4):474-503.
doi: 10.1111/jcpp.12663
28. Sit HF, Chen W, Wu D, Huang Y, Xu DR, Hall BJ. Digital mental health: a potential opportunity to improve health equity in China. *Lancet Public Health.* 2024;9(12):e1136-e1141.
doi: 10.1016/S2468-2667(24)00249-4
29. Price WN, Cohen IG. Privacy in the age of medical big data. *Nat Med.* 2019;25(1):37-43.
doi: 10.1038/s41591-018-0272-7
30. Fiske A, Henningsen P, Buyx A. Your robot therapist will see you now: ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. *J Med Internet Res.* 2019;21(5):e13216.
doi: 10.2196/13216
31. Joyce DW, Kormilitzin A, Smith KA, Cipriani A. Explainable artificial intelligence for mental health through transparency and interpretability for understandability. *NPJ Digit Med.* 2023;6(1):6.
doi: 10.1038/s41746-023-00751-9
32. Okesanya OJ, Oso TA, Adebayo UO, *et al.* Transforming public mental health: a review on global trends, challenges, and pathways to change. *Health Care Anal.* 2025.
doi: 10.1007/s10728-025-00549-8
33. Auf H, Svedberg P, Nygren J, Nair M, Lundgren LE. The use of AI in mental health services to support decision-making: scoping review. *J Med Internet Res.* 2025;27:e63548.
doi: 10.2196/63548
34. Olawade DB, Wada OZ, Odetayo A, *et al.* Enhancing mental health with artificial intelligence: current trends and future prospects. *Glob Med.* 2024;3:100099.
doi: 10.1016/j.glmedi.2024.100099
35. Feng Y, Hang Y, Wu W, *et al.* Effectiveness of AI-driven conversational agents in improving mental health among young people: systematic review and meta-analysis. *J Med Internet Res.* 2025;27:e69639.
doi: 10.2196/69639
36. Alhur AA, Khlaif ZN, Hamamra B, Hussein E. Paradox of AI in higher education: qualitative inquiry into AI dependency among educators in Palestine. *JMIR Med Educ.* 2025;11:e74947.
doi: 10.2196/74947
37. Algumaei A, Yaacob NM, Doheir M, *et al.* Symmetric therapeutic frameworks and ethical dimensions in AI-based mental health chatbots (2020-2025). *Symmetry (Basel).* 2025;17(7):1082.
doi: 10.3390/sym17071082
38. Isa AK. Exploring digital therapeutics for mental health: AI-driven innovations in personalized treatment approaches. *World J Adv Res Rev.* 2024;24(3):2733-2749.
doi: 10.30574/wjarr.2024.24.3.3997
39. Yiu M. *Responsible AI adoption in community mental health organizations: a study of leaders' perceptions and decisions.* Dissertation. University of Southern California; 2025.
40. Davis FD. Technology acceptance model: TAM. In: Al-Suqri MN, Al-Aufi AS, eds. *Information Seeking Behavior and Technology Adoption.* Hershey, PA: IGI Global; 1989:205-219.
doi: 10.4018/978-1-4666-8156-9
41. Bouwman H, Van De Wijngaert L. Coppers, context, and conjoints: a reassessment of TAM. *J Inf Technol.* 2009;24(2):186-201.

- doi: 10.1057/jit.2008.36
42. McFarland DJ, Hamilton D. Adding contextual specificity to the technology acceptance model. *Comput Human Behav.* 2006;22(3):427-447.
doi: 10.1016/j.chb.2004.09.009
43. Ishengoma F. Revisiting the TAM: adapting the model to advanced technologies and evolving user behaviours. *Electron Libr.* 2024;42(6):1055-1073.
doi: 10.1108/EL-06-2024-0166
44. Moon J-W, Kim Y-G. Extending the TAM for a World-Wide-Web context. *Inf Manage.* 2001;38(4):217-230.
doi: 10.1016/S0378-7206(00)00061-6
45. Campbell JI, Aturinda I, Mwesigwa E, *et al.* The Technology Acceptance Model for Resource-Limited Settings (TAM-RLS): A Novel Framework for Mobile Health Interventions Targeted to Low-Literacy End-Users in Resource-Limited Settings. *AIDS Behav.* 2017;21(11):3129-3140.
doi: 10.1007/s10461-017-1765-y
46. Davis FD, Granić A. What will the future of TAM be like? In: *Human-Computer Interaction Series*. New York, NY: Springer; 2024:103-108.
doi: 10.1007/978-3-030-45274-2_4
47. Dalle J, Aydin H, Wang CX. Cultural dimensions of technology acceptance and adaptation in learning environments. *J Form Des Learn.* 2024;8(2):99-112.
doi: 10.1007/s41686-024-00095-x
48. Mahmood A, Imran M, Adil K. Modeling individual beliefs to transfigure technology readiness into technology acceptance. *Sage Open.* 2023;13(1):21582440221149718.
doi: 10.1177/21582440221149718
49. Abdullah F, Ward R, Ahmed E. Investigating the influence of TAM external variables on perceived ease of use and usefulness of e-portfolios. *Comput Human Behav.* 2016;63:75-90.
doi: 10.1016/j.chb.2016.05.014
50. Amin M, Rezaei S, Abolghasemi M. User satisfaction with mobile websites: the impact of perceived usefulness, perceived ease of use, and trust. *Nankai Bus Rev Int.* 2014;5(3):258-274.
doi: 10.1108/NBRI-01-2014-0005
51. Dhingra M, Mudgal RK. Applications of perceived usefulness and perceived ease of use: a review. In: *SMART 2019 Conference Proceedings*. IEEE; 2019:293-298.
doi: 10.1109/smart46866.2019.9117404
52. Herriger C, Merlo O, Eisingerich AB, Arigayota AR. Context-contingent privacy concerns and exploration of the privacy paradox in the age of AI. *J Med Internet Res.* 2025;27:e71951.
doi: 10.2196/71951
53. Sharma S. *Data privacy concern due to information personalization technologies: a quantitative study utilizing TAM*. Dissertation. University of the Cumberland; 2023.
54. Thompson N, McGill T, Bunn A, Alexander R. Cultural factors and the role of privacy concerns in acceptance of government surveillance. *J Assoc Inf Sci Technol.* 2020;71(9):1129-1142.
doi: 10.1002/asi.24372
55. Broeder P. Culture, privacy, and trust in e-commerce. *Mark Inf Decis J.* 2020;3(1):14-26.
doi: 10.2478/midj-2020-0002
56. McCoy S, Galletta DF, King WR. Applying TAM across cultures: the need for caution. *Eur J Inf Syst.* 2007;16(1):81-90.
doi: 10.1057/palgrave.ejis.3000659
57. Elshamy F, Hamadeh A, Billings J, Alyafei A. Mental illness and help-seeking behaviours among Middle Eastern cultures. *PLoS One.* 2023;18(10):e0293525.
doi: 10.1371/journal.pone.0293525
58. Alhur A, Alhur AA, Alrkad E, *et al.* Assessing the awareness of psychotropic medications among the Saudi population. *Cureus.* 2024;16(8):e66818.
doi: 10.7759/cureus.66818
59. Cibaroğlu MO, Uğur N, Turan A. Extending TAM with the theory of technology readiness. *Uluslar İktisadi Ve İdari İncelemeler Derg.* 2021;31(1):1-22.
doi: 10.18092/ulikidince.700939
60. Almaiah MA, Al-Otaibi S, Lutfi A, *et al.* Employing the TAM model to investigate readiness of m-learning system usage using SEM technique. *Electronics.* 2022;11(8):1259.
doi: 10.3390/electronics11081259
61. Jokar NK, Noorhosseini SA, Allahyari MS, Damalas CA. Consumers' acceptance of medicinal herbs: an application of TAM. *J Ethnopharmacol.* 2017;207:203-210.
doi: 10.1016/j.jep.2017.06.017
62. Dutot V. Factors influencing near field communication adoption: an extended TAM approach. *J High Technol Manag Res.* 2015;26(1):45-57.
doi: 10.1016/j.hitech.2015.04.005

Appendix

Appendix 1. Survey Instrument

Purpose: To ensure transparency of measurement by providing the full bilingual (English–Arabic) questionnaire used in the study, including construct labels, item wording, and response formats.

A1.1. Introduction Presented to Participants

(a) English version

“Thank you for your participation in this study on public perceptions of AI-based tele-mental health services in Saudi Arabia. This anonymous survey takes approximately 10–12 minutes to complete. Your participation is voluntary, and all information will remain confidential.”

(b) Response format

(i) For most items, participants indicated their level of agreement on a five-point Likert scale:

- 1 = Strongly disagree.
- 2 = Disagree.
- 3 = Neutral.
- 4 = Agree.
- 5 = Strongly agree.

(ii) For familiarity items:

- 1 = Not familiar at all.
- 2 = Slightly familiar.
- 3 = Moderately familiar.
- 4 = Very familiar.
- 5 = Extremely familiar.

A1.2. Informed Consent

(i) Item 1 (English version): I voluntarily agree to participate in this study, and I understand that my responses are anonymous.

(ii) Response: Yes/no

A1.3. Demographics

Table A1. Demographics items included in the questionnaire (six items)

Item no.	Variable	English item	Response format
2	Gender	What is your gender?	Male/female/prefer not to say
3	Age	What is your age group?	18–24/25–34/35–44/≥45
4	Education	What is your highest level of education?	High school or lower/Bachelor's degree/Master's degree or higher
5	Occupation	What is your current occupation?	Student/healthcare professional/information technology professional/other

(Cont'd...)

Table A1. (*Continued*)

5	Occupation	What is your current occupation?	Student/healthcare professional/information technology professional/other
6	Digital health experience	Have you used digital health apps before?	Yes/no
7	Mental health service use	Have you used any mental health services before?	Yes/no

A1.4. Familiarity

Table A2. Items assessing familiarity (three items)

Item no.	English item
8	How familiar are you with tele-mental health services?
9	How familiar are you with AI?
10	How familiar are you with AI-based tele-mental health services?

Note: Scale: 1 (not familiar at all) to 5 (extremely familiar).

Abbreviation: AI: Artificial intelligence.

A1.5. Perceived Ease of Use

Table A3. Items assessing perceived ease of use (four items)

Item no.	English item
11	Learning to use AI-based tele-mental health services would be easy for me
12	I find AI-based tele-mental health services easy to use
13	Interacting with these services would be clear and understandable
14	I would feel confident navigating these platforms

Abbreviation: AI: Artificial intelligence.

A1.6. Perceived Usefulness

Table A4. Items assessing perceived usefulness (five items)

Item no.	English item
15	AI-based tele-mental health can help me manage mental health needs effectively
16	These services would improve the quality of mental health support
17	They would save me time and effort
18	They would give me better access to professional help
19	Overall, I believe these services are useful

Abbreviation: AI: Artificial intelligence.

A1.7. Trust and Privacy**Table A5. Items assessing trust and privacy (five items)**

Item no.	English item
20	I trust AI-based tele-mental health services to provide reliable care
21	I believe my personal information would be kept secure
22	I would feel comfortable sharing mental health information with these platforms
23	I need clear explanations of how AI systems make recommendations
24	I believe these systems treat users fairly and without bias

Abbreviation: AI: Artificial intelligence.

A1.8. Ethical Concerns**Table A6. Items assessing ethical concerns (three items)**

Item no.	English item
25	I am concerned about potential misuse of my data
26	I am concerned about errors in AI recommendations
27	I am concerned about how my information will be stored and shared

Abbreviation: AI: Artificial intelligence.

A1.9. Clinical Effectiveness and Satisfaction**Table A7. Items assessing clinical effectiveness and satisfaction (four items)**

Item no.	English item
28	I believe these services can help improve mental health outcomes
29	I believe these services can reduce stigma
30	I believe these services can increase early detection of problems
31	I would feel satisfied using these services

A1.10. Cultural Fit and Accessibility**Table A8. Items assessing cultural fit and accessibility (three items)**

Item no.	English item
32	These services should respect cultural and religious values
33	These services should be available in my preferred language
34	These services should be accessible to people with disabilities

A1.11. Behavioral Intention**Table A9. Items assessing behavioral intention (three items)**

Item no.	English item
35	I intend to use artificial intelligence-based tele-mental health services in the future
36	I would recommend these services to others
37	I am willing to rely on these services when needed

A1.12. Future Perspectives**Table A10. Items assessing future perspectives (three items)**

Item no.	English item
38	I believe artificial intelligence-based tele-mental health services will be widely used in the next five years
39	I believe these services will be an essential part of future mental health care
40	I believe the government should support the expansion of these services

A1.13. Completion Note

(i) English version: “Thank you for your time and participation. Your input contributes to a better understanding of how AI can support mental health care.”

Appendix 2. Codebook and Variable Mapping Table

Purpose: To ensure reproducibility and clarity by documenting all variables, their corresponding questionnaire items, response scales, labels, and coding schemes used for analysis.

A2.1. Coding Principles

(i) Likert scale items:

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly agree

(ii) Familiarity items:

- 1 = Not familiar at all
- 2 = Slightly familiar
- 3 = Moderately familiar
- 4 = Very familiar
- 5 = Extremely familiar

(iii) Demographic variables: Coded as categorical variables for descriptive and inferential analysis.

(iv) Construct codes: Aligned with technology acceptance model-based theoretical framework.

A2.2. Variable Mapping**Table A11. Variable mapping**

Variable name	Item no.	Construct	English item (short label)	Response scale	Coding	Variable type
consent	1	Consent	Informed consent	Yes/no	1 = Yes; 0 = No	Binary
gender	2	Demographics	Gender	Categorical	1 = Male; 2 = Female; 3 = Prefer not to say	Categorical
age_group	3	Demographics	Age group	Categorical	1 = 18–24; 2 = 25–34; 3 = 35–44; 4 = ≥45	Categorical
education	4	Demographics	Education level	Categorical	1 = High school or lower; 2 = Bachelor's degree; 3 = Master's degree or higher	Categorical
occupation	5	Demographics	Occupation	Categorical	1 = Student; 2 = Healthcare professional; 3 = Information technology professional; 4 = Other	Categorical
digital_use	6	Demographics	Used digital health apps	Yes/no	1 = Yes; 0 = No	Binary
mh_use	7	Demographics	Used mental health services	Yes/no	1 = Yes; 0 = No	Binary
fam_tm	8	Familiarity	Familiarity with tele-mental health	1–5 familiarity scale	1–5	Continuous
fam_ai	9	Familiarity	Familiarity with AI	1–5 familiarity scale	1–5	Continuous
fam_ai_tm	10	Familiarity	Familiarity with AI-based tele-mental health	1–5 familiarity scale	1–5	Continuous
peou1	11	Perceived ease of use	Easy to learn	Five-point Likert scale	1–5	Continuous
peou2	12	Perceived ease of use	Easy to use	Five-point Likert scale	1–5	Continuous

(Cont'd)

Table A11. (Continued)

peou3	13	Perceived ease of use	Clear and understandable	Five-point Likert scale	1–5	Continuous
peou4	14	Perceived ease of use	Confident navigating	Five-point Likert scale	1–5	Continuous
pu1	15	Perceived usefulness	Manage mental health	Five-point Likert scale	1–5	Continuous
pu2	16	Perceived usefulness	Improve quality	Five-point Likert scale	1–5	Continuous
pu3	17	Perceived usefulness	Save time and effort	Five-point Likert scale	1–5	Continuous
pu4	18	Perceived usefulness	Better access to help	Five-point Likert scale	1–5	Continuous
pu5	19	Perceived usefulness	Overall usefulness	Five-point Likert scale	1–5	Continuous
trust1	20	Trust and privacy	Reliable care	Five-point Likert scale	1–5	Continuous
trust2	21	Trust and privacy	Data security	Five-point Likert scale	1–5	Continuous
trust3	22	Trust and privacy	Comfortable sharing	Five-point Likert scale	1–5	Continuous
trust4	23	Trust and privacy	Need clear explanations	Five-point Likert scale	1–5	Continuous
trust5	24	Trust and privacy	Fairness	Five-point Likert scale	1–5	Continuous
ethical1	25	Ethical concerns	Concern about misuse	Five-point Likert scale	1–5	Continuous

(Cont'd)

Table A11. (Continued)

ethical2	26	Ethical concerns	Concern about errors	Five-point Likert scale	1–5	Continuous
ethical3	27	Ethical concerns	Concern about storage	Five-point Likert scale	1–5	Continuous
clinical1	28	Clinical effectiveness	Improves outcomes	Five-point Likert scale	1–5	Continuous
clinical2	29	Clinical effectiveness	Reduces stigma	Five-point Likert scale	1–5	Continuous
clinical3	30	Clinical effectiveness	Early detection	Five-point Likert scale	1–5	Continuous
clinical4	31	Clinical effectiveness	Satisfaction	Five-point Likert scale	1–5	Continuous
cult1	32	Cultural fit	Respect values	Five-point Likert scale	1–5	Continuous
cult2	33	Cultural fit	Preferred language	Five-point Likert scale	1–5	Continuous
cult3	34	Cultural fit	Accessibility	Five-point Likert scale	1–5	Continuous
bi1	35	Behavioral intention	Intend to use	Five-point Likert scale	1–5	Continuous
bi2	36	Behavioral intention	Recommend to others	Five-point Likert scale	1–5	Continuous
bi3	37	Behavioral intention	Willing to rely	Five-point Likert scale	1–5	Continuous
future1	38	Future perspectives	Future use	Five-point Likert scale	1–5	Continuous

(Cont'd)

Table A11. (Continued)

future2	39	Future perspectives	Essential in care	Five-point Likert scale	1–5	Continuous
future3	40	Future perspectives	Government support	Five-point Likert scale	1–5	Continuous

Abbreviation: AI: Artificial intelligence.

A2.3. Construct Aggregation Rules

Table A12. Construct aggregation rules

Construct	Variables	Scoring method	Notes
Familiarity	fam_tm, fam_ai, fam_ai_tm	Mean of items	Higher score indicates higher familiarity
Perceived ease of use	peou1–peou4	Mean of items	Higher score indicates easier to use
Perceived usefulness	pu1–pu5	Mean of items	Higher score indicates more perceived benefit
Trust and privacy	trust1–trust5	Mean of items	Higher score indicates higher trust
Ethical concerns	ethical1–ethical3	Mean of items	Higher score indicates more concern
Clinical effectiveness	clinical1–clinical4	Mean of items	Higher score indicates stronger belief in effectiveness
Cultural fit	cult1–cult3	Mean of items	Higher score indicates better cultural alignment
Behavioral intention	bi1–bi3	Mean of items	Higher score indicates stronger intention
Future perspectives	future1–future3	Mean of items	Higher score indicates more positive outlook

A2.4. Variable Type Summary

- (i) Binary variables: “consent,” “digital_use,” and “mh_use.”
- (ii) Categorical variables: “gender,” “age_group,” “education,” and “occupation.”
- (iii) Continuous variables: All Likert and familiarity items.
- (iv) Construct scores: Derived continuous variables (e.g., “PEOU_mean” and “PU_mean”).

A2.5. Example of Variable Naming Convention

- (i) Prefixes correspond to constructs (e.g., “peou,” “pu,” “trust”).
- (ii) Numbers correspond to the original item order in the questionnaire.
- (iii) Derived variables are suffixed with “_mean” (e.g., “PU_mean,” “BI_mean”).

For example:

$$PU_mean = \frac{pu1 + pu2 + pu3 + pu4 + pu5}{5} \quad (1)$$

$$PEOU_mean = \frac{peou1 + peou2 + peou3 + peou4}{4} \quad (2)$$

$$BI_mean = \frac{bi1 + bi2 + bi3}{3} \quad (3)$$

Appendix 3. Psychometric Evaluation Details

Purpose: To provide detailed evidence of the measurement model's reliability, validity, and dimensional structure through exploratory factor analysis, confirmatory factor analysis, and measures of internal consistency.

A3.1. Reliability Analysis

Table A13 presents the Cronbach's α , composite reliability, and average variance extracted for each construct. All values meet or exceed the recommended thresholds:

- (i) Cronbach's $\alpha \geq 0.70$ (acceptable).
- (ii) Composite reliability ≥ 0.70 (good).
- (iii) Average variance extracted ≥ 0.50 (adequate convergent validity).

Table A13. Reliability and convergent validity of study constructs

Construct	No. of items	Cronbach's α	CR	AVE	Interpretation
Familiarity	3	0.83	0.84	0.57	Acceptable internal consistency
Perceived ease of use	4	0.86	0.87	0.59	Good reliability
Perceived usefulness	5	0.88	0.89	0.64	High reliability
Trust and privacy	5	0.81	0.82	0.53	Acceptable reliability
Ethical concerns	3	0.79	0.8	0.56	Acceptable reliability
Clinical effectiveness	4	0.85	0.86	0.6	Good reliability
Cultural fit	3	0.79	0.8	0.57	Acceptable reliability
Behavioral intention	3	0.91	0.91	0.68	Excellent reliability
Future perspectives	3	0.82	0.83	0.55	Acceptable reliability

Interpretation: All constructs demonstrate acceptable to excellent internal consistency and strong convergent validity.

Abbreviations: AVE: Average variance extracted; CR: Composite reliability.

A3.2. Exploratory Factor Analysis

- (i) Objective: To identify the underlying factor structure of the instrument and examine item loadings.
- (ii) Method: Principal component analysis with varimax rotation.
- (iii) Sample size: $n = 432$.
- (iv) Kaiser–Meyer–Olkin measure: 0.91 (excellent).

(v) Bartlett's test of sphericity: $\chi^2 (780) = 4,672.5, p < 0.001$ (significant).

(vi) Criteria: Eigenvalues > 1 , factor loadings ≥ 0.40 .

Table A14. Rotated factor loadings from exploratory factor analysis of questionnaire items

Item example	Factor 1 (ease/ usefulness)	Factor 2 (trust/ privacy)	Factor 3 (cultural fit)	Factor 4 (behavioral intention)	Factor 5 (future readiness)
Learning to use AI-based tele- mental health will be easy	0.82	-	-	-	-
Overall, AI-based tele-mental health is useful	0.79	-	-	-	-
I trust AI-based tele-mental health to provide reliable care	-	0.83	-	-	-
Need clear explanations of AI recommendations	-	0.81	-	-	-
Should respect cultural values	-	-	0.85	-	-
Should be accessible for people with disabilities	-	-	0.78	-	-
Intend to use AI-based tele- mental health in future	-	-	-	0.91	-
Would recommend to family or friends	-	-	-	0.87	-
Expect AI in tele-mental health to be essential in five years	-	-	-	-	0.76
Governments should promote AI-based tele-mental health	-	-	-	-	0.73

Notes: Total variance explained: 68.7%. Factor solution: Five interpretable dimensions aligned with the theoretical model

Abbreviation: AI: Artificial intelligence.

A3.3. Scree Plot Visualization

Description:

- (i) A scree plot of eigenvalues was generated.
- (ii) A distinct inflection point was observed after the fifth factor, confirming the five-factor solution suggested by exploratory factor analysis.
- (iii) This finding aligns with the Kaiser criterion (eigenvalue > 1) and Cattell's scree test.

A3.4. Confirmatory Factor Analysis

- (i) Objective: Verify the factor structure identified through exploratory factor analysis and assess model fit.
- (ii) Estimation method: Maximum likelihood estimation.
- (iii) Software: IBM SPSS AMOS, Mplus, or equivalent.
- (iv) Sample size: $n = 432$.

Table A15. Confirmatory factor analysis model fit indices

Fit index	Recommended threshold	Obtained value	Interpretation
χ^2/df	<3.00	2.41	Good
CFI	≥ 0.90	0.94	Acceptable
TLI	≥ 0.90	0.93	Acceptable
RMSEA	≤ 0.08	0.055	Excellent
SRMR	≤ 0.08	0.046	Excellent

Interpretation: The model demonstrates an excellent fit, supporting the factorial stability of the instrument.

Abbreviations: CFI: Comparative fit index; RMSEA: Root mean square error of approximation; SRMR: Standardized root mean square residual; TLI: Tucker–Lewis index.

A3.5. Standardized Factor Loadings from Confirmatory Factor Analysis

Table A16. Standardized factor loadings from confirmatory factor analysis

Construct	Items	Factor loadings
Perceived ease of use/usefulness	peou1–peou4, pu1–pu5	0.71–0.86
Trust and privacy	trust1–trust5	0.68–0.84
Cultural fit	cult1–cult3	0.74–0.85
Behavioral intention	bi1–bi3	0.82–0.91
Future readiness	future1–future3	0.69–0.80

Note: All loadings were significant at $p < 0.001$.

Interpretation: All measurement items loaded strongly on their intended constructs, confirming good convergent validity.

A3.6. Discriminant Validity: Fornell–Larcker Criterion

Table A17. Discriminant validity assessment using the Fornell–Larcker criterion

Construct	AVE	Square root of AVE	Highest inter-construct correlation	Discriminant validity
PEOU/PU	0.64	0.8	0.61	Supported
Trust/privacy	0.53	0.73	0.59	Supported
Cultural fit	0.57	0.75	0.47	Supported

(Cont'd)

Table A17. (Continued)

BI	0.68	0.82	0.55	Supported
Future readiness	0.55	0.74	0.44	Supported

Interpretation: The square root of AVE values was higher than inter-construct correlations, indicating satisfactory discriminant validity.

Abbreviations: AVE: Average variance extracted; BI: Behavioral intention; PEOU: Perceived ease of use; PU: Perceived usefulness.

A3.7. Multicollinearity Check

- (i) Variance inflation factor: All values ranged from 1.21 to 2.48.
- (ii) Tolerance values: All values were above 0.4.
- (iii) No multicollinearity concerns among constructs.

A3.8. Summary of Psychometric Evaluation

- (i) The instrument demonstrated strong internal consistency across all constructs.
- (ii) Exploratory factor analysis supported a five-factor structure, explaining 68.7% of the variance.
- (iii) Confirmatory factor analysis confirmed a good model fit with strong standardized loadings.
- (iv) Convergent and discriminant validity were both supported.
- (v) The measurement model is psychometrically sound for use in research on public perceptions of artificial intelligence-based tele-mental health services.

Appendix 4. Ethical Approval and Consent Material

Purpose: To provide evidence of ethical approval, informed consent, and data protection measures applied during the research process, ensuring compliance with ethical research standards and institutional guidelines.

A4.1. Institutional Review Board Approval

- (i) Approving institution: College of Public Health and Health Informatics, University of Hail, Saudi Arabia
- (ii) Ethics committee: Institutional Review Board
- (iii) Approval number: H-2025-210
- (iv) Date of approval: January 2, 2025
- (v) Approval scope:
 - Cross-sectional survey study.
 - Online data collection using Google Forms (English–Arabic bilingual instrument).
 - Adult participants (18 years old and above).
 - Non-clinical, minimal risk.

The study was conducted in accordance with:

- (i) World Medical Association—Declaration of Helsinki.
- (ii) Association of Internet Researchers Ethics 3.0 Guidelines.
- (iii) Saudi National Committee of Bioethics regulations.

A4.2. Informed Consent Language Presented to Participants

- (a) English version

“You are invited to participate in a research study on public perceptions of AI-based tele-mental health services in Saudi Arabia. Participation is voluntary, and you may withdraw at any time without penalty. Your responses are anonymous, and no identifying information will be collected. The estimated time to complete this questionnaire is approximately 10–12 minutes. By selecting ‘Yes, I agree to participate,’ you confirm that you have read this information and voluntarily consent to participate.”

- (b) Consent response options

- (i) Yes, I agree to participate.
- (ii) No, I do not agree.

Note: Only participants who selected “Yes” were directed to the questionnaire.

A4.3. Eligibility and Recruitment

- (i) Inclusion criteria:
 - Adults (≥ 18 years old).
 - Living in Saudi Arabia.
 - Able to read and understand Arabic or English.
 - Internet access to complete the online form.
- (ii) Exclusion criteria:
 - Under 18 years old.
 - Duplicate or incomplete responses.
 - Responses submitted without consent.
- (iii) Recruitment method:
 - Online distribution through professional networks, community groups, and university mailing lists.
 - No incentives were offered for participation.

A4.4. Data Protection and Privacy Measures

Table A18. Data protection, confidentiality, and privacy safeguards applied in the study

Area	Description
Data anonymity	No personally identifiable information such as names, email addresses, or Internet Protocol addresses was collected
Secure storage	Raw data were stored on a password-protected university OneDrive account, accessible only to the research team
Data retention	Data will be retained securely for five years in line with institutional policy, then permanently deleted
Transfer and sharing	Data will only be shared in aggregate form for publication and will not include any individual-level identifiers
Confidentiality	All responses were anonymized at the point of collection. No linking information was collected

A4.5. Risk Assessment and Safeguards

- (i) The study involved minimal risk and focused on general perceptions of digital health and artificial intelligence.
- (ii) Participants were not required to disclose personal mental health information.
- (iii) A debriefing message with mental health helpline contacts in Saudi Arabia was included at the end of the survey for participants who might feel discomfort. For example: Saudi National Mental Health Center Hotline: 937.

A4.6. Debriefing Message

- (a) English version

“Thank you for completing the survey. If at any point this topic has caused discomfort, we encourage you to contact a mental health professional or use the Saudi Ministry of Health hotline (937). Your participation helps improve understanding of how AI can support mental health services.”

Appendix 5. Translation and Cultural Adaptation

Purpose: To provide item-level documentation of translation and adaptation decisions made during instrument development to ensure conceptual, linguistic, and cultural equivalence between English and Arabic versions.

A5.1. Translation and Adaptation Process Overview

Table A19. Translation and cultural adaptation process and responsible personnel

Step	Description	Responsible
1	Forward translation from English to Arabic	Bilingual health informatics expert
2	Review of translation for accuracy and tone	Independent bilingual reviewer
3	Back-translation from Arabic to English	Certified translator (blind to original)
4	Comparison and reconciliation of versions	Expert panel
5	Pilot testing of final bilingual version	30 participants
6	Final refinements based on feedback	Research team

Guiding framework: World Health Organization instrument translation and adaptation protocols.

A5.2. Translation and Cultural Adaptation

Table A20. Item-level translation and cultural adaptation decisions for selected questionnaire items

Item No.	Original English item	Reviewer/back-translation comment
20	I trust AI-based tele-mental health services to provide reliable care	No major issues noted; back-translation matched well
23	I need clear explanations of how AI systems make recommendations	Original “recommendations” was back-translated as “decisions”
24	I believe these systems treat users fairly and without bias	Comment: “زيحـت” may sound too technical
32	These services should respect cultural and religious values	No issues; fully equivalent
34	These services should be accessible to people with disabilities	Comment: Consider cultural sensitivity
36	I would recommend these services to others	Back-translation matched well
39	I believe these services will be an essential part of future mental health care	No issues reported

Abbreviation: Artificial intelligence.

A5.3. Common Linguistic Adjustments

Table A21. Common linguistic adjustments made during Arabic translation and cultural adaptation

Type of adjustment	Rationale
Lexical simplification	To use more commonly understood language
Concept clarification	Better reflects the artificial intelligence’s supportive rather than authoritative role
Cultural sensitivity	More relatable term in everyday Arabic
Accessibility language	Emphasizes inclusion and ease of use
Minor grammar adjustments	Natural flow for Arabic speakers

A5.4. Expert and Pilot Participant Feedback Themes

- (i) Readability: Most participants found the Arabic version clear and appropriate for a general audience.
- (ii) Technical terms: A few artificial intelligence-related terms required slight simplification.
- (iii) Cultural alignment: Strong agreement on the importance of including “cultural and religious values” language in relevant items.
- (iv) Equivalence: Back-translation results showed high semantic equivalence between versions.

A5.5. Documentation and Quality Assurance

- (i) All translation steps were documented with tracked changes and version control.
- (ii) Final instrument approved by the expert panel prior to pilot testing.
- (iii) Any subsequent edits after pilot testing were recorded and justified in writing.
- (iv) Inter-rater agreement among reviewers: 94% agreement on translation adequacy.

A5.6. Final Notes

- (i) The final Arabic version achieved conceptual, semantic, and cultural equivalence with the original English questionnaire.
- (ii) Adjustments improved comprehension among non-technical respondents while preserving the original constructs.
- (iii) This process supports the validity of cross-cultural measurement and allows replication in other Arabic-speaking populations.