Artificial Intelligence Chatbots for Mental Health Support: Exploring the Attitudes of Young Adults in Greece

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Article

Artificial Intelligence Chatbots for Mental Health Support: Exploring the Attitudes of Young Adults in Greece

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Abstract

The adoption of artificial intelligence (AI) chatbots within mental health care has accelerated significantly, reflecting a growing trend toward leveraging digital tools to enhance accessibility and provide immediate support. We conducted a study to explore young adults' perceptions of AI chatbots as tools for mental health support, assess their level of trust in AI technologies, and analyze factors associated with the formation of these attitudes. We carried out a cross-sectional study in October 2025. Attitudes toward AI chatbots for mental health support were assessed using the Artificial Intelligence in Mental Health Scale (AIMHS), while trust in AI was measured with the Short Trust in Automation Scale (S-TIAS). AIMHS score reflected moderately positive attitudes toward AI chatbots for mental health support, while S-TIAS scores indicated a moderate level of trust in AI. A significant positive correlation was found between AIMHS and S-TIAS scores. Multivariable analysis revealed that greater daily use of social media/websites and higher self-perceived digital competence were significantly associated with more positive attitudes toward these chatbots. Increased daily use of social media/websites was significantly related to higher trust in AI. In conclusion, attitudes toward AI and trust in AI were moderately positive. Several factors influence individuals' attitudes toward AI.

Keywords: mental health; chatbots; artificial intelligence; trust; attitudes; young adults

1. Introduction

The increasing prevalence of mental health disorders among young people constitutes a significant global public health concern [1–3]. Mental illness among adolescents and young adults accounts for approximately 45% of the total global burden of disease in individuals aged 10–24 years [2], with suicide identified as the third leading cause of mortality among those aged 15–29 years [4]. According to the World Health Organization, in 2021 nearly one in seven individuals worldwide, approximately 1.1 billion people, were living with a mental disorder [5]. Mental health conditions represent a major cause of substantial disruption to daily functioning and are often associated with prolonged psychological suffering. Anxiety and depressive disorders are the most prevalent mental health conditions globally; however, a considerable proportion of affected individuals lack access to effective mental health care [5]. Among individuals diagnosed with a mental health disorder, approximately 24% experienced moderate to severe functional impairment, while 8% had not sought professional assistance and 5% had not consulted a mental health professional at any point [6,7].

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Numerous barriers to the delivery and utilization of mental health services, such as male gender, lower levels of educational attainment, and the presence of anxiety disorders, have been identified as significant contributors to limited access to care [7]. Evidence further indicates that individuals who experience a common mental disorder at some point in their lives frequently encounter stigma, discrimination, and violations of their human rights [5,8]. Stigma within mental health care settings operates across three interrelated levels: (a) the structural level, which encompasses social systems, public policies, and legislation; (b) the interpersonal level, involving knowledge, attitudes, and interactions between health care providers and individuals receiving care; and (c) the intrapersonal level, which refers to the internalized effects of stigma, including direct experiences and awareness of prevailing public attitudes [9]. Stigma is often accompanied by negative stereotypes, prejudice, and discriminatory practices, and affects all dimensions of psychiatric care, contributing to delayed help-seeking, increased morbidity, and reduced quality of life among affected individuals [10]. Consequently, the destigmatization of mental disorders and the early identification of emotional dysregulation are critical priorities, particularly through the application of innovative technological advances. In this context, artificial intelligence (AI) and machine learning algorithms have been increasingly recognized for their potential to offer novel and scalable solutions in mental health care [11].

Previous research has demonstrated that young people frequently experience symptoms of mental health disorders, particularly anxiety and depression, which are associated with an elevated risk of academic burnout across a broad range of student age groups [12,13]. The intensification of burnout, alongside symptoms of anxiety and depression among adolescents and young adults, has been linked to adverse outcomes, including reduced academic performance and increased emotional exhaustion. Conversely, resilience and self-efficacy have been identified as protective factors that may mitigate symptoms of anxiety and depression among young people [14]. Individuals with higher levels of resilience and self-efficacy exhibit a greater capacity to cope with adversity, manage negative emotions, and withstand excessive psychological stress. Furthermore, the mental health status of adolescents and young adults has significant long-term implications for their life trajectories and interpersonal relationships. Poor mental health during this developmental period is associated with increased risks of academic dropout, impaired personal development, diminished career motivation, and reduced quality of relationships in future workplace environments [14–16].

The rapid advancement of AI has already exerted a substantial influence on contemporary society. Over recent years, AI has transformed a wide range of industries, with its expanding applications receiving increasing attention within the health care sector. In particular, generative AI—referring to algorithms and models capable of producing novel content based on large datasets—has emerged as a fundamental component of modern health care systems. Generative AI tools have demonstrated considerable potential to reshape health care delivery and practice [17,18]. The notable capabilities of large language models (LLMs), which leverage vast volumes of medical data and domain-specific knowledge, have introduced innovative opportunities in clinical decision-making, patient communication, and health data management [19]. Within this context, AI-based conversational agents, commonly referred to as chatbots, have gained prominence as tools capable of supporting mental health care through interactive dialogue. These systems can assess aspects of mental health status and provide early support and intervention, particularly among adolescents and young adults [20]. AI-driven conversational agents are designed to simulate human interaction via text- or voice-based communication, utilizing machine learning techniques to interpret, comprehend, and respond to human language and emotional states. Such chatbots are capable of processing conversational content, detecting emotional cues, and exhibiting human-like, context-specific behavioral patterns [21].

In this context, we conducted a study to investigate young adults' perceptions of the use of AI chatbots for mental health support. Additionally, our study examined levels of trust in AI-based technologies. Moreover, we explored several factors that may influence attitudes toward the use of AI chatbots for mental health support and trust in AI-based technologies.

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2. Materials and Methods

2.1. Study Design

A cross-sectional study was conducted in Greece using an online survey administered in October 2025. Study sample included young adults aged 18-24 years old. The questionnaire was developed in Google Forms and disseminated via Facebook and Instagram, resulting in a convenience sample. Eligibility criteria required participants: (a) to be adults aged 18-24 years old; (b) to maintain an active account on at least one social media platform; (c) and to provide informed consent prior to completing the questionnaire. The study adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines [22].

The sample size was estimated using G*Power software (version 3.1.9.2). The calculation was based on the following parameters: (a) a Type I error probability of 5%, (b) statistical power of 95%, (c) five independent variables, and (d) a small effect size ($f^2 = 0.04$). This analysis indicated a required sample size of 327 participants.

2.2. Measurements

The demographic variables assessed included: (a) gender, (b) age, (c) self-perceived financial status on a scale ranging from 0 (very poor) to 10 (very good), (d) daily duration of social media or/and website use, and (e) self-reported competence in digital technologies, such as smartphones, personal computers, AI applications, and tablets, measured on a scale from 0 (very poor) to 10 (very good).

Attitudes toward AI-based mental health chatbots were assessed using the Artificial Intelligence in Mental Health Scale (AIMHS) [23]. The AIMHS consists of five items grouped into two factors: Technical Advantages (2 items) and Personal Advantages (3 items). The technical advantages factor includes statements such as “Artificial intelligence chatbots cannot achieve empathy levels comparable to those of a human therapist” and “Artificial intelligence chatbots can demonstrate better problem-solving skills compared to a human therapist”. The personal advantages factor includes items addressing access to mental health care, such as reducing geographic and financial barriers and providing continuous availability. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Factor scores were calculated by summing item responses and dividing by the number of items, resulting in scores from 1 to 5, with higher scores indicating more positive attitudes toward AI mental health chatbots. Two negatively worded items were reverse-scored. The validated Greek version of the AIMHS [23] was used in this study. Internal consistency was acceptable, with Cronbach’s alpha values of 0.703 for technical advantages and 0.847 for personal advantages.

Trust in Artificial Intelligence was assessed using the Short Trust in Automation Scale (S-TIAS) [24]. This instrument comprises three items rated on a 7-point Likert scale, ranging from 1 (not at all) to 7 (extremely). The overall score is calculated as the mean of the item responses, producing a range from 1 to 7, with higher scores indicating greater trust in AI and, consequently, more positive attitudes toward its use. For this study, the validated Greek version of the S-TIAS version [25] was employed. The scale demonstrated excellent internal consistency, with a Cronbach’s alpha of 0.893.

2.3. Ethical Issues

Ethical approval was obtained from the Ethics Committee of the Faculty of Nursing, National and Kapodistrian University of Athens (Protocol Approval No. 01, September 14, 2025). Participation was voluntary and anonymous. All participants were fully informed about the study’s objectives and procedures and provided written informed consent prior to participation. The study was conducted in accordance with the principles outlined in the Declaration of Helsinki [26].

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2.4. Statistical Analysis

Categorical variables are summarized as frequencies and percentages, while continuous variables are presented using means, standard deviations (SD), medians, and interquartile ranges. The distribution of continuous variables was assessed using the Kolmogorov–Smirnov test and Q–Q plots, which indicated normality. Demographic variables served as independent variables, whereas attitudes toward AI mental health chatbots and trust in AI were treated as dependent variables. Given that the dependent variables were continuous and normally distributed, simple and multivariable linear regression analyses were performed. Initially, simple linear regressions were conducted, followed by the construction of final multivariable models. Multicollinearity was evaluated using variance inflation factors (VIFs), with values greater than 5 indicating potential multicollinearity. Model assumptions were checked by examining histograms of residuals for normality, and scatterplots of residuals versus predicted values for homoscedasticity and linearity [27]. Results are reported as unadjusted and adjusted beta coefficients, 95% confidence intervals (CIs), and p-values. Additionally, Pearson's correlation coefficient was used to assess the correlation between AIMHS and S-TIAS scores. P-values less than 0.05 were considered statistically significant. We used the IBM SPSS 28.0 (IBM Corp. Released 2021. IBM SPSS Statistics for Windows, Version 28.0. Armonk, NY: IBM Corp) for the analysis.

3. Results

3.1. Demographic Characteristics

The final sample consisted of 332 participants. Among them, 76.2% (n=253) were females, while 23.8% (n=79) were males. The mean age was 19.00 years (SD = 1.34), with a median of 19 years (interquartile range = 1). The mean self-perceived financial status score was 5.62 (SD = 1.83; median = 6; interquartile range = 2). Participants reported an average daily use of social media/websites of 4.74 hours (SD = 2.56; median = 4; interquartile range = 3). The mean score for self-perceived competence in digital technologies was 7.70 (SD = 1.63; median = 8; interquartile range = 2).

3.2. Study Scales

The mean score on the AIMHS was 2.76 (SD = 0.70; median = 2.80; interquartile range = 0.80). Moreover, mean score for the factor "technical advantages" was 1.80 (SD = 0.76; median = 1.50; interquartile range = 1.00), while for the factor "personal advantages" was 3.40 (SD = 0.89; median = 3.67; interquartile range = 1.00). The mean score on the S-TIAS was 3.39 (SD = 1.26; median = 3.67; interquartile range = 1.92).

A statistically significant positive correlation was observed between AIMHS and S-TIAS scores, indicating that higher levels of trust in AI were associated with more favorable attitudes toward AI-based mental health chatbots. Pearson's correlation coefficient between S-TIAS score and AIMHS score, score on the factor "technical advantages", and score on the factor "personal advantages" was 0.453 (p-value<0.01), 0.490 (p-value<0.01), and 0.314 (p-value<0.01), respectively.

3.3. Dependent Variable: Artificial Intelligence in Mental Health Scale

Table 1 presents the results of the linear regression analysis with the technical advantages factor of the AIMHS as the dependent variable. In the final multivariable model, greater daily use of social media/websites (adjusted b = 0.037, 95% CI: 0.005 to 0.069, p = 0.022) and higher self-perceived competence in digital technologies (adjusted b = 0.064, 95% CI: 0.013 to 0.114, p = 0.014) were significantly associated with more positive attitudes toward AI mental health chatbots. Model diagnostics confirmed that assumptions were met: residuals followed a normal distribution (Supplementary Figure 1), homoscedasticity and linearity were observed (Supplementary Figure 2), and VIFs showed no evidence of multicollinearity among independent variables (Table 1).

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Table 1. Univariate and multivariable linear regression analyses with "technical advantages" score as the dependent variable (n=332).

Independent variables	Univariate models			Multivariable model[a]			VIF
	Unadjusted coefficient beta	95% CI for beta	P-value	Adjusted coefficient beta	95% CI for beta	P-value	
Males vs. females	0.169	-0.022 to 0.360	0.083	0.173	-0.017 to 0.363	0.075	1.027
Age	0.019	-0.042 to 0.080	0.538	0.003	-0.058 to 0.065	0.915	1.065
Financial status	-0.056	-0.100 to -0.012	0.013	-0.033	-0.079 to 0.014	0.171	1.143
Daily use of social media/websites	0.037	0.005 to 0.069	0.022	0.037	0.005 to 0.069	0.022	1.028
Competence in digital technologies	0.067	0.116 to 0.017	0.009	0.064	0.013 to 0.114	0.014	1.066

[a] R^2 for the multivariable model = 4.1%; p-value for ANOVA = 0.002 CI: confidence interval; VIF: variance inflation factor.

Table 2 summarizes the linear regression analysis with the personal advantages factor of the AIMHS as the dependent variable. In the final multivariable model, females demonstrated significantly more positive attitudes toward AI mental health chatbots regarding personal advantages (adjusted b = –0.261, 95% CI: –0.487 to –0.034, p = 0.024). Model diagnostics confirmed that assumptions were met: residuals followed a normal distribution (Supplementary Figure 3), homoscedasticity and linearity were observed (Supplementary Figure 4), and VIFs showed no evidence of multicollinearity among independent variables.

Table 2. Univariate and multivariable linear regression analyses with "personal advantages" score as the dependent variable (n=332).

Independent variables	Univariate models			Multivariable model[a]			VIF
	Unadjusted coefficient beta	95% CI for beta	P-value	Unadjusted coefficient beta	95% CI for beta	P-value	
Males vs. females	-0.232	-0.456 to -0.008	0.042	-0.261	-0.487 to -0.034	0.024	1.027
Age	0.001	-0.072 to 0.071	0.995	-0.010	-0.084 to 0.064	0.781	1.065
Financial status	-0.054	-0.106 to -0.002	0.041	-0.066	-0.122 to -0.011	0.020	1.143
Daily use of social media/websites	0.008	-0.030 to 0.045	0.679	0.001	-0.038 to 0.037	0.982	1.028

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Competence in digital technologies	0.001	-0.058 to 0.060	0.966	0.021	-0.039 to 0.081	0.498	1.066

[a] R^2 for the multivariable model = 1.5%; p-value for ANOVA = 0.082 CI: confidence interval; VIF: variance inflation factor.

3.4. Dependent Variable: Short Trust in Automation Scale

Table 3 presents the linear regression analysis with the S-TIAS score as the dependent variable. In the final multivariable model, greater daily use of social media/websites was significantly associated with increased trust in AI (adjusted b = 0.088, 95% CI: 0.034 to 0.141, p = 0.001). Model diagnostics confirmed that assumptions were met: residuals followed a normal distribution (Supplementary Figure 5), homoscedasticity and linearity were observed (Supplementary Figure 6), and variance inflation factors (VIFs) showed no evidence of multicollinearity among independent variables.

Table 3. Univariate and multivariable linear regression analyses with score on the Short Trust in Automation Scale as the dependent variable (n=332).

Independent variables	**Univariate models**			**Multivariable model[a]**			**VIF**
	Unadjusted coefficient beta	**95% CI for beta**	**P-value**	**Unadjusted coefficient beta**	**95% CI for beta**	**P-value**	
Males vs. females	0.157	-0.163 to 0.478	0.336	0.148	-0.172 to 0.469	0.364	1.027
Age	0.027	-0.075 to 0.129	0.602	0.010	-0.093 to 0.114	0.846	1.065
Financial status	-0.051	-0.125 to 0.024	0.183	-0.037	-0.115 to 0.042	0.360	1.143
Daily use of social media/websites	0.092	0.039 to 0.144	0.001	0.088	0.034 to 0.141	0.001	1.028
Competence in digital technologies	0.038	-0.046 to 0.122	0.375	0.038	-0.047 to 0.123	0.384	1.066

[a] R^2 for the multivariable model = 2.8%; p-value for ANOVA = 0.015 CI: confidence interval; VIF: variance inflation factor.

4. Discussion

The results of this study reflect the attitudes of young adults toward AI mental health chatbots and trust in AI. We found that young people who mention high levels of trust presented more favorable attitudes toward AI-based mental health chatbots. Our multivariable analysis revealed that greater daily use of social media/websites and higher self-perceived digital competence were significantly associated with more positive attitudes toward these chatbots. Additionally, females reported significantly more positive attitudes regarding personal benefits. Increased daily use of social media/websites was also significantly related to higher trust in AI.

 doi:10.20944/preprints202604.1996.v1

Notably, female participants in the present study exhibited significantly more positive attitudes toward AI-based mental health chatbots, particularly with respect to perceived personal benefits. This finding is consistent with previous research on technology adoption, which suggests that the perceived usefulness of online safety and support chatbots may be influenced by gender-specific factors [28]. Literature further indicates that females are more likely to hold favorable views toward such technologies when they are perceived as practical and beneficial, whereas men may require additional motivational factors to facilitate engagement [29,30].

Within the existing body of literature, the findings of the present study are consistent with prior research demonstrating that trust is closely associated with young people's acceptance of generative AI tools, including conversational chatbots [31–34]. Previous studies have indicated that the development of trust in AI systems involves both cognitive and affective processes. In this context, research has shown that conversational and agent-based chatbots exhibit minimal differences in perceived trustworthiness and effectiveness [29]. Moreover, earlier investigations have emphasized users' experiences and acceptance across several key dimensions, including perceived system capabilities and limitations, educational and learning enhancement benefits, efficiency of interactions, challenges related to system adaptation, limited emotional engagement, and users' willingness to continue utilizing chatbots despite identified constraints [32]. Users' willingness and motivation to follow chatbot-provided advice have also been shown to influence behavioral intentions and overall levels of trust in AI systems [35]. Accordingly, existing evidence suggests that trust is closely linked to individuals' propensity to use chatbot-recommended support features, as well as to user-related characteristics. In particular, self-efficacy, state anxiety, learning styles, and personality traits, such as neuroticism, have been identified as prominent predictors of trust and engagement with chatbots [29,31,36]. A limited number of studies have also explored factors influencing trust in chatbots across different age groups. These studies have reported age-related differences, indicating that older adults tend to exhibit lower levels of trust in automated processes compared to younger users [28]. Older individuals have been found to prioritize pragmatic benefits, such as perceived usefulness and ease of use of the technology [37,38]. In contrast, younger users appear to be more influenced by hedonic factors that contribute to emotional and psychological satisfaction [39]. The literature further suggests that while personalized and human-like chatbot interactions are generally well received, inappropriate responses or inaccurate assumptions can result in diminished user interest and engagement [40]. At the same time, the constant accessibility and convenience of chatbots may foster increased user dependence, with some individuals preferring chatbot-mediated interactions over communication with friends or family members. Notably, chatbots are often perceived as non-judgmental environments, which may facilitate greater comfort in sharing sensitive or personal information.

In the context of the increasing demand for accessible mental health support among young people, the present study addresses a critical gap in understanding how young adults perceive and engage with automated mental health support systems, particularly AI-based conversational agents. Previous research has demonstrated that AI-driven chatbots can yield moderate to substantial effect sizes in improving psychiatric outcomes, including symptoms of anxiety, depression, hopelessness, agency, and self-efficacy among student populations [34,41–43]. The findings of this study reflect young adults' familiarity with mental health chatbots and underscore the potential impact of AI-enabled conversational technologies as tools for enhancing mental well-being particularly given that young adults tend to prioritize affective attributes related to emotional support and psychological comfort [44]. Comparable results have been reported in earlier studies. For example, young adults (mean age; 18.8 years) experiencing depressive symptoms during the COVID-19 pandemic who engaged with a cognitive behavioral therapy (CBT)-based mental health chatbot demonstrated significant reductions in depressive symptom severity as measured [45]. Similarly, a randomized trial in China found that university students exhibited significant reductions in both anxiety and depression symptoms following the use of a mobile-based therapy chatbot [46]. These findings align with conclusions from other studies, which indicated that chatbot-delivered psychotherapy resulted

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in significant improvements in depressive symptoms among participants with clinically diagnosed anxiety or depression [47,48]. Comparable outcomes were also reported by a systematic review and meta-analysis, which identifies conversational agents as safe, feasible, acceptable, and usable interventions among patients with cancer, leading to significant improvements in physical activity levels, anxiety, pain, and overall quality of life [49]. Collectively, these findings suggest that CBT-based chatbots and other digital mental health interventions represent feasible and engaging therapeutic approaches that facilitate accessible and self-guided mental health support for young people experiencing depressive symptoms [50]. This conclusion is further supported by prior evidence indicating that higher levels of user engagement with chatbots are associated with improved mental health outcomes, more favorable user experiences, greater acceptability, and enhanced treatment efficacy among individuals with depression [51].

In summary, the significance of the present study lies in its dual methodological approach, employing both an attitude measure (i.e., the Attitudes toward Intelligent Mental Health Support) and a trust measure (i.e., the Scale of Trust in Automated Systems). This combined approach offers a multidimensional contribution to the fields of Human–Computer Interaction and digital health research [52,53]. While the attitude scale assesses perceived ease of use and perceived usefulness, the trust scale captures individuals' willingness to accept vulnerability, reflecting the psychological threshold that young adults must overcome to share sensitive emotional information with automated systems. These findings underscore the necessity of advancing toward more personalized and age-responsive digital therapeutics that support both instrumental adoption and the development of a therapeutic alliance, thereby more effectively serving vulnerable youth populations [33,45,54–56]. Digital mental health interventions, particularly AI-based chatbots, represent promising tools for stress management among young people. However, their acceptance and sustained use depend on multiple interacting factors, including accessibility, usability, personalization, perceived social support, and cultural sensitivity [57]. Ultimately, sustainable anxiety relief among young people is likely to depend on the integration of personalized and community-oriented digital mental health tools, which can function as pivotal mechanisms for long-term stress regulation and anxiety reduction within youth populations [58,59].

5. Limitations

Despite the contributions of the present study, several limitations should be acknowledged. First, the cross-sectional design restricts the ability to draw causal inferences regarding associations among demographic factors, attitudes towards AI mental health chatbots, and trust in AI. Longitudinal or experimental studies are required to better assess changes in perceptions over time and to establish causal pathways. Second, the reliance on self-reported measures may introduce response bias, including social desirability bias and recall bias. Participants' reported attitudes toward AI-based mental health chatbots and levels of trust may not fully correspond to their actual behaviors or long-term usage patterns. Future research could benefit from integrating objective usage data or behavioral analytics to triangulate self-reported findings. Third, the study sample consisted of young adults in Greece, which may limit the generalizability of the results to broader youth populations or to individuals with different educational, socioeconomic, or cultural backgrounds. Moreover, the specific national and cultural context may influence attitudes toward mental health, technology, and AI, suggesting that findings should be interpreted with caution when extrapolating to other settings. Additionally, the use of convenience sampling via social media likely introduced a selection bias, potentially overrepresenting young people who are more familiar with technology. Random and representative samples of young adults could add further to this research field. Finally, the study did not directly assess clinical mental health outcomes or symptom severity using diagnostic instruments. As such, while participants expressed favorable attitudes and perceived benefits, conclusions regarding the effectiveness of chatbots as therapeutic interventions remain limited. Future research should integrate validated clinical measures to evaluate efficacy alongside user acceptance.

 doi:10.20944/preprints202604.1996.v1

6. Conclusions

This study examined young people's behaviors and acceptance of mental health chatbots, with particular emphasis on perceived usefulness, trust, and overall attitudes toward these digital mental health interventions. The findings indicate that young adults generally demonstrate a positive disposition toward mental health chatbots, identifying accessibility, anonymity, and convenience as key advantages. Higher levels of engagement were associated with more favorable perceptions of user experience and increased acceptance, suggesting that the quality of interaction plays a critical role in shaping user attitudes. Furthermore, the present study highlights the potential of mental health chatbot interventions to support psychological well-being among young individuals, reinforcing their role as complementary tools within mental health care systems. Although existing research points to the widespread use of AI chatbots alongside improvements in certain mental health outcomes, concerns regarding technology dependence among young people remain. AI chatbot usage is relatively prevalent among university students; however, instances of overuse and excessive dependence have also been reported. Notably, higher levels of chatbot use and dependence have been associated with increased depressive symptoms, although the directionality and causality of this relationship require further empirical investigation [60]. Additionally, broader examinations of bias in artificial intelligence systems indicate that while access to AI technologies may be equitable, outcomes generated by these systems are not inherently equal or unbiased. Given that AI chatbots are developed and trained by humans, they may inadvertently reflect or reinforce existing biases embedded within their design or training data. Although the development of AI expert systems is largely grounded in established literature and data-driven frameworks, the potential for biased or unfair outcomes remains a critical concern [61–63]. In conclusion, mental health chatbots represent a viable and increasingly accepted form of digital support among young people. Enhancing features such as personalization, responsiveness, transparency, and trustworthiness may further improve their effectiveness and adoption. With appropriate safeguards and ethical considerations, AI-based chatbots have the potential to become valuable components of integrated and sustainable mental health care ecosystems.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org, Figure S1: Histogram of the residuals with "technical advantages" score as the dependent variable, figure S2: Scatterplot of residuals versus predicted values with "technical advantages" score as the dependent variable, figure S3: Histogram of the residuals with "personal advantages" score as the dependent variable, figure S4: Scatterplot of residuals versus predicted values with "personal advantages" score as the dependent variable, figure S5: Histogram of the residuals with score on the Short Trust in Automation Scale as the dependent variable, figure S6: Scatterplot of residuals versus predicted values with score on the Short Trust in Automation Scale as the dependent variable.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIMHS	AI Mental Health Scale
CBT	Cognitive Behavioral Therapy
CIs	Confidence Intervals
SD	Standard Deviation
S-TIAS	Short Trust in Automation Scale
VIFs	Variance Inflation Factors

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