Original Paper

Psychosocial Correlates of AI Chatbot Use for Emotional Support Among Young Adults: Cross-Sectional Study

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Abstract

Background: Generative AI chatbots are increasingly used for mental health–related purposes, yet little is known about the factors associated with such use or AI chatbot dependence.

Objective: This study examined factors associated with young adults' use of AI chatbots for emotional self-disclosure and mental health–related support, as well as the associations between AI chatbot use and dependence.

Methods: A cross-sectional online survey of individuals aged 18 to 29 years was conducted in Japan. Self-report measures assessed psychosocial factors (self-esteem and loneliness), mental health symptoms (anxiety and depression), AI chatbot use (emotional self-disclosure and mental health–related support), and AI chatbot dependence (emotional dependence and social anxiety–related dependence).

Results: Of 820 participants, 381 (46.5%) reported using AI chatbots for emotional self-disclosure at least once in the past month, including 65 (7.9%) who reported doing so every day or almost every day. In addition, 336 (41%) reported using AI chatbots for mental health–related support, including 53 (6.5%) who reported doing so every day or almost every day. Anxiety and depressive symptoms were combined into a composite measure of mental health symptoms because they are highly correlated. Multivariable logistic regression showed that greater mental health symptom severity, but not self-esteem or loneliness, was associated with both emotional self-disclosure (odds ratio [OR] 2.23, 95% CI 1.85-2.69; P<.001) and mental health–related support (OR 2.42, 95% CI 2.01-2.94; P<.001). Among emotional self-disclosure users (n=381), the frequency of emotional self-disclosure was positively associated with emotional dependence (β=0.334; P<.001) and social anxiety–related dependence (β=0.307; P<.001). Path analyses indicated that a model specifying psychosocial factors and mental health symptoms as antecedent variables to AI chatbot use and dependence fit the data better than an alternative model specifying AI chatbot use and dependence as the antecedent variables (comparative fit index [CFI]=0.994 vs 0.583; root mean square error of approximation [RMSEA]=0.033 vs 0.293). In this model, lower self-esteem and greater loneliness were associated with more severe mental health symptoms, which, in turn, were associated with greater AI chatbot dependence, primarily through direct pathways and, to a lesser extent, through more frequent emotional self-disclosure. Among emotional self-disclosure users, loneliness was the only significant psychosocial correlate of emotional dependence ($F_{1,369}$=7.78; P=.006).

Conclusions: Emotional engagement with AI chatbots was common in this sample of young adults in Japan. Findings suggest that young adults experiencing mental health symptoms may be more likely to use AI chatbots for emotional self-disclosure and mental health–related support, while loneliness may be particularly relevant to emotional dependence among users. These findings highlight the need to understand AI chatbot use not only as a technological behavior but also as part of young adults' broader emotional and help-seeking landscape.

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KEYWORDS

artificial intelligence; AI; chatbots; young adults; mental health; digital health; loneliness; self-esteem; anxiety; depression; technology dependence; help seeking

Introduction

AI Chatbot Use for Emotional and Mental Health–Related Support

Generative AI chatbots, such as ChatGPT and Gemini, have become increasingly integrated into everyday life. In addition to providing information and assisting with tasks, these systems can engage users in natural conversations, making them potential sources of emotional expression and support.

The use of AI chatbots for emotional and mental health–related purposes appears to be particularly relevant among young adults. In a 2025 Japanese industry survey of 1000 individuals aged 12 to 69 years who used AI chatbots at least once a week, respondents aged 20 to 29 years showed the highest proportion reporting that they could readily share emotions with AI chatbots (74.5%), compared with the proportion in the overall sample (64.9%) [1].

Relatedly, recent US survey findings suggest that some young people use AI systems for emotional and mental health–related support. McBain et al [2] found that 112 of 1058 US adolescents and young adults had used generative AI for mental health advice (weighted prevalence 13.1%). In that study, mental health advice was defined as seeking advice or help when feeling sad, angry, or nervous. Although some AI chatbots are general-purpose tools, others are designed specifically for companionship, mental health support, or other health-related purposes. A 2025 survey report published by Common Sense Media found that, among 1060 US adolescents, 12% had used AI companions for emotional or mental health support [3]. In that survey, AI companions included both purpose-built applications (eg, Character.AI and Replika) and general-purpose chatbots (eg, ChatGPT) when used for companionship. These findings suggest that AI systems are emerging as a source of emotional and mental health support for some young people, although their use for this purpose is not yet widespread.

Research on mental health help-seeking preferences provides additional context. A systematic review identified anonymity, privacy, immediacy, and accessibility as perceived benefits of online mental health support among young people [4]. More recently, a study found that US adults generally reported more favorable attitudes toward human mental health professionals than toward AI-based support, although heavy AI users viewed the 2 more similarly [5]. These findings highlight the importance of considering AI chatbot use within the broader context of mental health help-seeking preferences.

Psychosocial Factors and AI Chatbot Dependence

The emerging use of AI chatbots for emotional support has generated both enthusiasm and concern. On one hand, AI chatbots may offer a convenient source of support. Many users report finding AI-generated responses helpful and emotionally supportive [6]. On the other hand, concerns have emerged regarding excessive reliance on AI systems. In a 2025 health advisory, the American Psychological Association cautioned that users may come to view AI chatbots as substitutes for professional or interpersonal support and highlighted the potential risk of overdependence [7]. Empirical research has also linked compulsive ChatGPT use with greater anxiety, burnout, and sleep disturbance [8].

Despite these concerns, relatively little is known about the factors associated with emotional engagement with AI chatbots and AI chatbot dependence. Prior research has found that excessive internet use was associated with loneliness, lower self-esteem, depressive symptoms, and anxiety symptoms [9,10]. A recent meta-analysis of 32 studies similarly found that social media addiction was positively associated with anxiety, depression, and loneliness and negatively associated with self-esteem [11]. These findings suggest that individuals experiencing loneliness, low self-esteem, or mental health symptoms may be particularly likely to seek emotional support through AI-mediated interactions. However, it remains unclear whether these factors are associated with the use of AI chatbots for emotional self-disclosure and mental health–related support or with AI chatbot dependence. Furthermore, little is known about whether AI chatbot dependence varies according to psychosocial or sociodemographic characteristics among users.

Another question concerns how psychosocial factors, mental health symptoms, AI chatbot use, and AI chatbot dependence are related to one another. These associations may operate in more than 1 direction. Individuals with lower self-esteem, greater loneliness, or more severe anxiety or depressive symptoms may be more likely to disclose emotions to AI chatbots and subsequently report stronger AI chatbot dependence. Conversely, frequent emotional reliance on AI chatbots may be associated with greater AI chatbot dependence and poorer mental health. Given the limited empirical evidence on these relationships, research examining which directional structure is more consistent with the observed data is needed.

Study Objectives

This study targeted young adults and aimed to investigate (1) whether psychosocial factors (ie, self-esteem and loneliness) and mental health symptoms (ie, anxiety and depressive symptoms) were associated with the use of AI chatbots for emotional self-disclosure and/or mental health–related support; (2) the relationships among psychosocial factors, mental health symptoms, AI chatbot use, and AI chatbot dependence, including which of the 2 alternative directional models was more consistent with the data; and (3) sociodemographic and psychosocial correlates of AI chatbot dependence among individuals who used AI chatbots for emotional self-disclosure.

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Methods

Study Design

This study used a cross-sectional online survey design to examine psychosocial factors, mental health symptoms, AI chatbot use, and AI chatbot dependence among young adults.

Recruitment

Participants were recruited using a nonprobability sampling approach, an online survey platform with a registered research panel, during February 2026. Eligibility was limited to individuals aged 18 to 29 years, with no additional eligibility criteria. Potential participants were selected based on age information registered with the survey panel. Eligible registered panel members were invited to participate in the survey by the survey provider. The questionnaire was administered in Japanese.

The online questionnaire was pretested for usability and technical functionality before data collection. It consisted of 7 questionnaire pages containing 42 required response items presented in a fixed order, preceded by separate study information and survey instructions pages and followed by a completion page. Respondents could review and revise their answers before submission. The dataset provided to the researchers did not contain personally identifying information.

To account for potential exclusions, we aimed to collect approximately 1200 responses. A total of 1200 individuals completed the survey, of whom 380 (31.7%) were excluded because they failed an embedded attention check item, resulting in a final analytic sample of 820 (68.3%) participants. The numbers of individuals invited, those who viewed or started the questionnaire, and those who discontinued before submission were unavailable from the survey provider. Therefore, view, participation, and completion rates could not be calculated.

Ethical Considerations

The study protocol was approved by the Tottori University Institutional Review Board (25A193). The survey platform allowed each registered member to submit the questionnaire only once. Before participation, respondents were provided with information about the study and indicated their informed consent by selecting a checkbox. Participation was voluntary, and respondents could discontinue the survey at any time. Participants received reward points through the survey platform.

Measures

Psychosocial Factors

Self-esteem was assessed using the 10-item Rosenberg Self-Esteem Scale (RSES) [12]. Participants rated each item on a 4-point Likert scale ranging from 1="strongly disagree" to 4="strongly agree." After reverse scoring negatively worded items, responses were summed to yield a total score, with higher scores indicating greater self-esteem. We used the validated Japanese version [13]. The validation study demonstrated satisfactory internal consistency and a factor structure comparable to that of the original English version. For descriptive purposes, scores less than 15 were categorized as indicating low self-esteem, and scores of 15 or higher were categorized as indicating normal-to-high self-esteem, consistent with a previously published scoring convention using the 10 to 40 scale [14]. Self-esteem was treated as a continuous variable in all inferential analyses.

Loneliness was assessed using the 3-item UCLA Loneliness Scale (UCLA-LS-3) [15], adapted from the UCLA-LS-3 [16]. Participants rated how often they experienced feelings of loneliness on a 4-point scale ranging from 1="never" to 4="always." Item scores were summed, with higher scores indicating greater loneliness. The validated Japanese version was used [17]. In the Japanese validation study, the 3-item version demonstrated acceptable internal consistency (Cronbach α=0.790).

Mental Health Symptoms

Anxiety symptoms were assessed using the validated Japanese version of the Generalized Anxiety Disorder–7 (GAD-7) scale [18,19]. In a Japanese validation study, a cutoff score of 10 demonstrated a sensitivity of 70.6% and a specificity of 93.5% for identifying generalized anxiety disorder. Participants rated anxiety symptoms on a 4-point scale ranging from 0="not at all" to 3="nearly every day." Total scores ranged from 0 to 21, with higher scores indicating greater anxiety symptom severity. Scores of 10 or higher were used to identify participants with clinically significant anxiety symptoms, consistent with validation evidence for the Japanese version.

Depressive symptoms were assessed using the validated Japanese version of Patient Health Questionnaire–9 (PHQ-9) [20,21]. In a Japanese validation study, a cutoff score of 10 demonstrated a sensitivity of 90.5% and a specificity of 76.6% for detecting major depressive disorder. Participants rated depressive symptoms on a 4-point scale ranging from 0="not at all" to 3="nearly every day." Total scores ranged from 0 to 27, with higher scores indicating greater depressive symptom severity. Scores of 10 or higher were used to identify participants with clinically significant depressive symptoms, consistent with validation evidence for the Japanese version.

AI Chatbot Use

The 2 items assessing AI chatbot use were developed for the present study. Both items referred to AI chatbots, with ChatGPT and Gemini provided as examples. Participants were not asked to identify the specific AI chatbot platforms they used.

AI chatbot use for emotional self-disclosure was assessed using a single item informed by a recent study examining emotional sharing with conversational AI [1]. This item was intended to capture emotional disclosure, rather than specifically assessing the intention to obtain support or advice. Participants were asked how frequently they disclosed their emotions or personal concerns to AI chatbots during the past month. Responses were rated on a 5-point scale ranging from 1="never" to 5="every day or almost every day," with higher scores indicating more frequent emotional self-disclosure.

AI chatbot use for mental health–related support was assessed using a single item informed by prior research on generative AI use for emotional and mental health support [2]. This item was

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intended to capture more intentional support-seeking behavior. Participants were asked how frequently they had used AI chatbots to obtain advice or support when experiencing negative emotions during the past month, with sadness, anger, and anxiety provided as examples. No additional definitions of advice or support were provided to participants. Responses were rated on a 5-point scale ranging from 1="never" to 5="every day or almost every day." This measure assessed support-seeking behavior rather than the receipt of a structured psychological intervention.

AI Chatbot Dependence

AI chatbot dependence was assessed using 2 subscales from the Generative AI Dependence Tendency Scale for High School and University Students [22], a validated 22-item measure developed to assess dependence tendencies toward generative AI. The original scale consists of 5 factors: emotional dependence, anxiety about generative AI responses, prolonged use, use while doing other activities, and social anxiety.

In the present study, only the emotional dependence and social anxiety subscales were used because they were most relevant to the study objectives. The emotional dependence subscale consists of 5 items assessing emotional reliance on generative AI. The social anxiety subscale consists of 4 items assessing reliance on AI-mediated interactions in the context of discomfort with interpersonal communication, including a preference for consulting AI rather than other people.

In the original validation study, Cronbach α was 0.891 for the full scale, 0.873 for emotional dependence, and 0.784 for social anxiety. No established gold-standard measure of generative AI dependence was used in the original validation study. Instead, criterion-related validity was evaluated by comparing scale scores across categories of self-reported generative AI use frequency ($F_{3,617}$=13.80; P<.01).

Participants rated each item on a 4-point scale ranging from 1="not at all true of me" to 4="very true of me." Mean scores were calculated for each subscale, with higher scores indicating greater emotional dependence on AI chatbots and greater social anxiety–related dependence on AI chatbots, respectively. In the present sample of active AI chatbot users, internal consistency was good for the emotional dependence subscale (Cronbach α=0.80) and the social anxiety subscale (Cronbach α=0.81).

Statistical Analysis

All statistical analyses were conducted using R (version 4.6.0; R Foundation for Statistical Computing). All statistical tests were 2-tailed, and statistical significance was set at P<.05. We calculated descriptive statistics to summarize participants' sociodemographic characteristics, psychosocial factors, mental health symptoms, and AI chatbot use and dependence. We conducted Pearson correlation analyses to examine associations among self-esteem, loneliness, anxiety symptoms, and depressive symptoms.

Anxiety and depressive symptoms were highly correlated (r=0.88). In preliminary multivariable models, this overlap prevented reliable separation of their unique contributions: variance inflation factors (VIFs) were elevated at approximately 4.1 and 3.9, and the depressive symptom coefficient reversed sign relative to its bivariate association, indicating suppression. We therefore combined the 2 variables into a single standardized mental health symptoms composite, calculated as the mean of the standardized anxiety and depressive symptom scores. This composite was used in place of the separate anxiety and depression variables in subsequent multivariable models. Anxiety and depressive symptoms were retained as separate variables in descriptive correlation analyses to document their overlap.

We conducted 2 multivariable logistic regression analyses to identify psychosocial and mental health factors associated with AI chatbot use. The dependent variables were AI chatbot use for emotional self-disclosure and AI chatbot use for mental health–related support, each dichotomized as 0="no use" and 1="use at least once per month." Self-esteem, loneliness, and the mental health symptoms composite were entered simultaneously as predictors**,** with age, gender, and marital status included as covariates.

Among participants who reported emotional self-disclosure to AI chatbots at least once per month (n=381), we calculated Spearman rank-order correlations to examine associations among psychosocial factors, emotional self-disclosure frequency, AI chatbot dependence dimensions, anxiety symptoms, and depressive symptoms.

To examine whether the data were consistent with a hypothesized structure linking psychosocial factors, mental health symptoms, AI chatbot use, and AI chatbot dependence, we specified and compared 2 nonnested path models using the *lavaan* package. Because the data are cross-sectional, this comparison evaluates relative model fit and cannot establish causal or temporal ordering. In these models, mental health symptoms were represented by the composite described above. The 2 models were estimated using robust maximum likelihood, with observed exogenous variables treated as random (fixed.x=FALSE). Both models were fitted to the same analytic sample and the same set of 6 observed variables to ensure comparability of the likelihood-based information criteria. Model fit was evaluated using robust global fit indices, including the scaled chi-square statistic, comparative fit index (CFI), Tucker-Lewis Index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The 2 nonnested models were also compared using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Fit was interpreted using commonly cited criteria: CFI≥0.95, TLI≥0.95, RMSEA≤0.06, and SRMR≤0.08 [23].

For the better-fitting model, we report both unstandardized (B) and standardized (β) path coefficients. Parameter estimates, SEs, and CIs were obtained from the same model specification estimated by maximum likelihood with bootstrapping. To account for potential nonnormality, bias-corrected bootstrap 95% CIs were calculated using 1000 resamples. Indirect effects were calculated as the product of the constituent path coefficients and were considered statistically significant when the bias-corrected bootstrap 95% CI did not include 0.

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Finally, we conducted separate analyses of covariance (ANCOVAs) among participants who reported emotional self-disclosure to AI chatbots at least once per month to examine whether emotional dependence and social anxiety–related dependence varied as a function of sociodemographic characteristics and psychosocial factors. Age, self-esteem, and loneliness were included as continuous predictors, whereas gender, marital status, living arrangement, and household income were included as categorical predictors. Type 3 sums of squares were used to account for unequal group sizes across categories.

Results

Participant Characteristics

Participant characteristics are presented in Table 1. The mean age of participants was 25.05 (SD 3.29) years, and 527 (64.3%) identified as women. Of 820 participants, most were not married (n=692, 84.4%) and lived with family members (n=518, 63.2%), whereas approximately one-third lived alone (n=254, 31%).

The mean self-esteem score was 23.47 (SD 5.71), and 87 (10.6%) participants met the criterion for low self-esteem. The mean loneliness score was 7.44 (SD 2.57). Regarding mental health symptoms, 267 (32.6%) participants reported moderate to severe anxiety symptoms, and 348 (42.4%) reported moderate to severe depressive symptoms.

Nearly half of the participants (381/820, 46.5%) reported using AI chatbots for emotional self-disclosure at least once per month, including 65 (7.9%) who reported doing so every day or almost every day. In addition, 336 (41%) participants reported using AI chatbots for mental health–related support at least once per month, including 53 (6.5%) who reported doing so every day or almost every day. Among participants who reported emotional self-disclosure to AI chatbots at least once per month (n=381), the mean emotional dependence and social anxiety–related dependence scores were 2.59 (SD 0.66) and 2.62 (SD 0.72), respectively.

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Table 1. Participant characteristics and variable summary (N=820).

Variables	Participants
Sociodemographic characteristics	
Age (years), mean (SD; range)	25.05 (3.29; 18-29)
Gender, n (%)	
Woman	527 (64.3)
Man	293 (35.7)
Marital status, n (%)	
Married	128 (15.6)
Not married	692 (84.4)
Living arrangement, n (%)	
Living alone	254 (31)
Living with family	518 (63.2)
Living in a student or company dormitory	15 (1.8)
Living in a welfare or support facility	9 (1.1)
Other	24 (2.9)
Household income (¥)[a], n (%)	
<3 million	287 (35)
3-10 million	439 (53.5)
>10 million	94 (11.5)
Psychosocial factors	
Self-esteem, mean (SD; range)	23.47 (5.71; 10-40)
Self-esteem, n (%)	
Low self-esteem (scores <15)	87 (10.6)
Normal-to-high self-esteem (scores ≥15)	733 (89.4)
Loneliness, mean (SD; range)	7.44 (2.57; 3-12)
Mental health symptoms	
Anxiety symptoms, mean (SD; range)	6.59 (6.21; 0-21)
Anxiety symptoms, n (%)	
No or minimal-to-mild anxiety symptoms (scores 0-9)	553 (67.4)
Moderate to severe anxiety symptoms (scores ≥10)	267 (32.6)
Depressive symptoms, mean (SD; range)	8.59 (7.61; 0-27)
Depressive symptoms, n (%)	
No or minimal-to-mild depressive symptoms (scores 0-9)	472 (57.6)
Moderate to severe depressive symptoms (scores ≥10)	348 (42.4)
AI chatbot interaction and dependence	
AI chatbot use for emotional self-disclosure, n (%)	
Never	439 (53.5)
Once a month	94 (11.5)
A few times a month	116 (14.1)
A few times a week	106 (12.9)
Every day or almost every day	65 (7.9)
AI chatbot use for mental health–related support, n (%)	
Never	484 (59)

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Variables	Participants
Once a month	98 (12)
A few times a month	104 (12.7)
A few times a week	81 (9.9)
Every day or almost every day	53 (6.5)
Emotional dependence on AI chatbots[b], mean (SD; range)	2.59 (0.66; 1-4)
Social anxiety–related dependence on AI chatbots[b], mean (SD; range)	2.62 (0.72; 1-4)

[a]¥1=US $0.0063, as of November 2, 2026.

[b]Emotional dependence and social anxiety–related dependence are reported among participants who used AI chatbots for emotional self-disclosure at least once per month (n=381).

Associations Among Psychosocial Factors and Mental Health Symptoms

Pearson correlations among psychosocial factors and mental health symptoms are presented in Multimedia Appendix 1. Anxiety and depressive symptoms were strongly correlated (r=0.88; P<.001), supporting their combination into a single mental health symptom composite for subsequent multivariable analyses.

Psychosocial and Mental Health Factors Associated With AI Chatbot Use

The results of the 2 multivariable logistic regression analyses are presented in Table 2. Neither self-esteem nor loneliness was significantly associated with AI chatbot use for emotional self-disclosure or mental health–related support. In contrast, the mental health symptoms composite was significantly associated with both types of AI chatbot use. Higher mental health symptom scores were associated with greater odds of AI chatbot use for emotional self-disclosure (odds ratio [OR] 2.23, 95% CI 1.85-2.69; P<.001) and use for mental health–related support (OR 2.42, 95% CI 2.01-2.94; P<.001). Each 1-unit increase in the mental health symptoms composite was associated with approximately twice the odds of AI chatbot use.

Table 2. Multivariable logistic regression models of AI chatbot use for emotional self-disclosure and mental health–related support (N=820).

Predictors	Model 1		Model 2	
	Emotional self-disclosure, OR[a] (95% CI)	P value	Mental health–related support, OR (95% CI)	P value
Psychosocial factors				
Self-esteem	1.02 (0.99-1.05)	.22	1.02 (0.99-1.06)	.13
Loneliness	1.04 (0.97-1.12)	.25	1.02 (0.95-1.10)	.54
Mental health symptoms (standardized composite)[b]	2.23 (1.85-2.69)	<.001	2.42 (2.01-2.94)	<.001
Sociodemographic factors				
Age (years)	0.98 (0.93-1.03)	.38	0.94 (0.90-0.99)	.02
Gender (men vs women)[c]	1.09 (0.79-1.48)	.61	1.03 (0.75-1.42)	.85
Marital status (not married vs married)[c]	0.88 (0.57-1.36)	.57	0.88 (0.56-1.37)	.55

[a]OR: odds ratio.

[b]The mental health symptoms composite was calculated as the mean of the standardized anxiety and depressive symptom scores.

[c]Women and married participants were the reference categories for gender and marital status, respectively.

Among sociodemographic variables, older age was significantly associated with lower odds of AI chatbot use for mental health–related support (OR 0.94, 95% CI 0.90-0.99; P=.02) but was not significantly associated with use for emotional self-disclosure (P=.38). Gender and marital status were not significantly associated with either form of AI chatbot use.

Bivariate Associations Among Emotional Self-Disclosure Users

Among participants who reported emotional self-disclosure to AI chatbots at least once per month (n=381), Spearman rank correlations were calculated among psychosocial factors, mental health symptoms, emotional self-disclosure frequency, and AI chatbot dependence dimensions. Emotional self-disclosure frequency was positively correlated with emotional dependence (ρ=0.34; P<.001) and social anxiety–related dependence

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(ρ=0.32; *P*<.001). The full results are presented in Multimedia Appendix 2.

Path Analysis and Model Comparison

The fit indices for the 2 nonnested path models are presented in Table 3. Model 1, an AI-initiated structure in which AI chatbot use and dependence were specified as preceding mental health symptoms, showed poor fit to the data (CFI=0.583, TLI=0.106, RMSEA=0.293, SRMR=0.135). In contrast, model 2, in which psychosocial factors and mental health symptoms were specified as preceding AI chatbot use and dependence, fit the data well (CFI=0.994, TLI=0.987, RMSEA=0.033, SRMR=0.028), with all indices meeting conventional criteria and a nonsignificant scaled chi-square test statistic (χ^2_6=8.4; *P*=.21). Model 2 also had lower AIC (7384.02 vs 7610.46) and BIC (7443.16 vs 7665.66) values than model 1, further supporting its better relative fit. Model 2 was therefore retained as the final model. Because the data are cross-sectional and the models were nonnested, this comparison indicates which structure fit the data better, rather than establishing causal or temporal ordering.

Table 3. Goodness-of-fit indexes for the hypothesized and competing path models (N=381).

Fit indices	Model 1 (AI-initiated)[a]	Model 2 (psychosocial- or symptoms-initiated)[b]	Recommended criterion[c]
Scaled χ^2 (*df*)[d]	212.3 (7)	8.4 (6)	—[e]
P value (for χ^2)	<.001	.21	≥.05
CFI[f]	0.583	0.994	≥0.95
TLI[g]	0.106	0.987	≥0.95
RMSEA[h]	0.293	0.033	≤0.06
SRMR[i]	0.135	0.028	≤0.08
AIC[j]	7610.46	7384.02	Lower preferred
BIC[k]	7665.66	7443.16	Lower preferred

[a]Model 1 specifies an AI-initiated structure in which AI chatbot use and dependence are specified as preceding mental health symptoms, which in turn relate to self-esteem and loneliness.

[b]Model 2 specifies the hypothesized structure in which self-esteem and loneliness relate to mental health symptoms, which relate to AI chatbot use frequency and AI chatbot dependence dimensions, both directly and indirectly through emotional self-disclosure frequency.

[c]Recommended fit-index criteria were informed by Hu and Bentler [23]. Lower AIC and BIC values indicate better relative model fit.

[d]The chi-square values are robust scaled test statistics, and CFI, TLI, and RMSEA are robust fit indices.

[e]Not applicable.

[f]CFI: comparative fit index.

[g]TLI: Tucker-Lewis Index.

[h]RMSEA: root mean square error of approximation.

[i]SRMR: standardized root mean square residual.

[j]AIC: Akaike information criterion.

[k]BIC: Bayesian information criterion.

Parameter Estimates for the Final Model

Parameter estimates for the final model are presented in Table 4. Lower self-esteem and greater loneliness were significantly associated with more severe mental health symptoms (β=−0.175 and β=0.351, respectively). Mental health symptoms were, in turn, significantly associated with more frequent emotional self-disclosure to AI chatbots, although this association was modest in magnitude (β=0.119; *P*=.02).

Mental health symptoms were associated with both dependence dimensions mainly through direct paths, with direct effects of β=0.202 for emotional dependence and β=0.165 for social anxiety–related dependence. Indirect effects through emotional self-disclosure were statistically significant but small (B=0.028 for emotional dependence, 95% CI 0.004-0.055; B=0.028 for social anxiety–related dependence, 95% CI 0.006-0.059), accounting for only a small proportion of the respective total effects. Emotional self-disclosure itself was moderately associated with both emotional dependence (β=0.334) and social anxiety–related dependence (β=0.307). Overall, the model suggests that mental health symptoms were related to AI chatbot dependence largely through direct pathways, with a smaller additional pathway through more frequent emotional self-disclosure.

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Table 4. Unstandardized and standardized estimates for the final model (model 2; N=381)a.

Path (predictor→outcome)	B[b] (SE[c]; 95% CI[d])	β[e]	*P* value
Direct effects			
Psychosocial factors→mental health symptoms			
Self-esteem→mental health symptoms	−0.028 (0.009; −0.046 to −0.010)	−0.175	.002
Loneliness→mental health symptoms	0.135 (0.023; 0.093 to 0.181)	0.351	<.001
Mental health symptoms→AI chatbot use			
Mental health symptoms→emotional self-disclosure	0.132 (0.057; 0.016 to 0.243)	0.119	.02
AI chatbot use→AI dependence			
Emotional self-disclosure→emotional dependence	0.212 (0.028; 0.155 to 0.269)	0.334	<.001
Emotional self-disclosure→social anxiety–related dependence	0.215 (0.035; 0.150 to 0.286)	0.307	<.001
Mental health symptoms→AI dependence			
Mental health symptoms→emotional dependence	0.143 (0.039; 0.068 to 0.220)	0.202	<.001
Mental health symptoms→social anxiety–related dependence	0.127 (0.042; 0.034 to 0.213)	0.165	.003
Indirect effects (via emotional self-disclosure)			
Mental health symptoms→emotional dependence	0.028 (0.013; 0.004 to 0.055)	—[f]	.03
Mental health symptoms→social anxiety–related dependence	0.028 (0.013; 0.006 to 0.059)	—	.03
Total effects			
Mental health symptoms→emotional dependence	0.170 (0.042; 0.090 to 0.250)	—	<.001
Mental health symptoms→social anxiety–related dependence	0.156 (0.045; 0.064 to 0.243)	—	.001

[a]The mental health symptoms composite was calculated as the mean of standardized anxiety and depressive symptom scores. Point estimates were obtained using maximum likelihood, and SEs and CIs were obtained using 1000 bootstrap resamples. Reported *P* values are based on bootstrap SEs; for indirect and total effects, statistical significance is additionally indicated by CIs that exclude 0. Standardized estimates are reported for direct effects only.

[b]B refers to the unstandardized estimate.

[c]SE refers to the bootstrap SE.

[d]CI refers to the bias-corrected bootstrap 95% CI for the unstandardized estimate.

[e]β refers to the fully standardized path coefficient.

[f]The standardized estimate is not reported. Standardized estimates are provided for direct effects only.

Sociodemographic and Psychosocial Factors Associated With AI Chatbot Dependence

Separate ANCOVAs were conducted among participants who reported emotional self-disclosure to AI chatbots at least once per month (n=381) to examine whether AI chatbot dependence varied as a function of sociodemographic characteristics and psychosocial factors (Multimedia Appendix 3).

For emotional dependence, loneliness emerged as the only significant factor ($F_{1,369}$=7.78; *P*=.006). Greater loneliness was associated with higher levels of emotional dependence on AI chatbots. Age, self-esteem, gender, marital status, living arrangement, and household income were not significantly associated with emotional dependence.

For social anxiety–related dependence, no factors reached statistical significance. The association between loneliness and social anxiety–related dependence was not statistically significant ($F_{1,369}$=3.34; *P*=.07). All remaining factors were nonsignificant.

Discussion

Principal Results and Comparison With Prior Work

The present study investigated how psychosocial factors and mental health symptoms were associated with AI chatbot use and AI chatbot dependence among young adults in Japan. The findings indicated that emotional engagement with AI chatbots was relatively common and that mental health symptoms were associated with both emotional self-disclosure and mental health–related support. Among emotional self-disclosure users, more frequent self-disclosure was associated with both emotional dependence and social anxiety–related dependence. In exploratory analyses, loneliness was significantly associated with emotional dependence but not with social anxiety–related dependence. Path analyses suggested that a model specifying psychosocial factors and mental health symptoms as antecedent variables was more consistent with the data.

The prevalence of emotional engagement with AI chatbots was noteworthy. Of 820 participants, 381 (46.5%) reported disclosing emotions or personal concerns to AI chatbots at least

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once during the past month, including 65 (7.9%) who reported doing so every day or almost every day. Similarly, 336 (41%) participants reported using AI chatbots for mental health–related support at least once during the past month, including 53 (6.5%) who reported doing so every day or almost every day.

These findings can be considered alongside a recent Japanese survey in which 74.5% of respondents aged 20 to 29 years reported that they could readily share emotions with AI chatbots [1]. Although direct comparison is limited by differences in samples and measurement, the findings highlight the distinction between perceived ease of sharing emotions and actual self-disclosure behavior.

The proportion of participants reporting AI use for mental health–related support appeared higher than that reported by McBain et al [2]. Direct comparison is limited because the studies differed in measurement, sample characteristics, cultural context, and timing. Nevertheless, these differences may also point to possible explanations. First, the rapid adoption of generative AI may have increased emotional and mental health–related use over time; McBain et al [2] collected data approximately 1 year before the present study, and accessibility has increased substantially in the interim. Second, the populations differed: the present study focused on young adults aged 18 to 29 years, whereas McBain et al [2] included individuals aged 12 to 21 years, who may have less autonomy and more limited independent access to generative AI tools. Finally, cultural and structural factors may influence the attractiveness of AI-mediated support in Japan. Cultural norms around emotional disclosure and professional help-seeking may make anonymous support particularly appealing. Japanese individuals often show greater reluctance to seek professional help than individuals in the United States [24]. In addition, limited access to mental health professionals may increase the value of readily accessible support [25]. Thus, AI chatbots may be particularly attractive to young adults who experience distress but are hesitant to disclose concerns to others or face barriers to professional care. This interpretation is consistent with research identifying privacy and accessibility as perceived advantages of online mental health support among young people [4]. However, evidence that adults generally favor human professionals over AI-based support suggests that AI may serve as an additional rather than a replacement source of support [5].

Beyond prevalence, the present findings provide insight into the psychosocial characteristics associated with AI chatbot use. Contrary to expectations, self-esteem and loneliness were not associated with AI chatbot use for either emotional self-disclosure or mental health–related support. In contrast, mental health symptoms, indexed by a composite of anxiety and depressive symptoms, were significantly associated with both forms of use.

In a recent US study of 1003 young adults aged 18 to 25 years, Maheux et al [26] found that using generative AI for socioemotional support was associated with greater anxiety and depressive symptoms. This finding is consistent with the present results, although Maheux et al [26] examined motivations for generative AI use, whereas our study assessed the frequency of emotional self-disclosure and mental health–related support. The present results suggest that AI chatbot use may be more closely tied to current mental health symptoms than to broader psychosocial factors such as self-esteem and loneliness. Individuals experiencing elevated distress may be particularly likely to seek readily available forms of support, making AI chatbots an appealing resource during periods of emotional difficulty.

The path analyses further clarified the relationships among these variables. A model specifying psychosocial factors and mental health symptoms as antecedent variables to AI chatbot use and dependence fit the data well and substantially better than the reverse-direction alternative. Within this model, lower self-esteem and greater loneliness were associated with more severe mental health symptoms, which were directly associated with both emotional dependence and social anxiety–related dependence. Indirect associations through emotional self-disclosure were statistically significant but small. Because the models were estimated using cross-sectional data, the better-fitting model indicates relative consistency with the data rather than confirmation of the hypothesized direction.

This interpretation should be considered cautiously. The present findings do not rule out the possibility that AI chatbot dependence contributes to later psychological difficulties. The American Psychological Association noted concerns that some individuals may increasingly rely on AI chatbots in place of professional or interpersonal support, potentially reducing engagement with other forms of help [7]. More frequent emotional self-disclosure was associated with stronger AI chatbot dependence in the present study. Over time, frequent reliance on AI chatbots could reduce engagement with interpersonal or professional sources of support, which may contribute to later difficulties.

Finally, loneliness emerged as a unique correlate of emotional dependence on AI chatbots among active users. Loneliness was not associated with whether participants used AI chatbots for emotional self-disclosure or mental health–related support. Among those who did use them, however, greater loneliness was associated with stronger emotional dependence. This pattern suggests that loneliness may be less relevant to whether young adults use AI chatbots but more relevant to the degree of emotional reliance among those who do use them. One possible explanation is that individuals experiencing loneliness may derive a greater sense of emotional connection from AI interactions, leading to stronger emotional dependence. This interpretation is broadly consistent with emerging work suggesting that AI companions can provide perceived social connection for some users [27]. Because this finding was based on an exploratory analysis involving multiple predictors, it should be interpreted cautiously.

Limitations

Several limitations should be noted. First, the cross-sectional design precludes conclusions about causality or temporal ordering. Although the hypothesized model fit better than its directional reversal, the retained model represents 1 plausible account rather than a validated causal pathway; longitudinal research is needed. Second, all variables were assessed by self-report and may be subject to reporting biases. Third,

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participants were recruited through a nonprobability online survey platform with a registered research panel, which may have introduced selection bias and limited the representativeness of the sample. Participation also required internet access and the ability to complete an online questionnaire, potentially underrepresenting individuals with limited digital access or literacy. Differences in AI literacy, which was not assessed, may also have influenced participants' AI chatbot use and the generalizability of the findings. The sample was also restricted to young adults in Japan, further limiting generalizability. In addition, educational attainment, current student status, and occupation were not assessed, limiting our ability to examine their potential associations with AI chatbot use and dependence.

Fourth, the 2 central AI-use measures were assessed using single items developed for the present study, and their psychometric properties have not been formally established. Finally, AI chatbot dependence was assessed using selected subscales from a measure originally validated among high school and university students; although both subscales showed acceptable internal consistency, further psychometric evaluation in broader young adult populations is warranted. Given the rapid evolution of generative AI, the findings should be interpreted within the technological context in which the data were collected.

Conclusions

In conclusion, the present study suggests that AI chatbots are used by a substantial proportion of young adults in this sample to disclose emotions and personal concerns, as well as to seek mental health–related support. AI chatbot use appeared more closely tied to current mental health symptoms than to broader psychosocial factors, while loneliness was particularly relevant to emotional dependence among users. The cross-sectional design precludes causal conclusions. Nevertheless, the results highlight the value of understanding AI chatbot use not simply as a technological behavior but also within the broader context of young adults' emotional experiences and help-seeking behaviors.

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Data Availability

The data are not publicly available because they contain participant-level survey responses related to mental health and AI use, and public sharing was not included in the informed consent approved by the institutional review board. Aggregated results are reported in the article and supplementary materials.

Generative AI Use

The authors declare that they used ChatGPT (GPT-5.5 and 5.6; OpenAI) for proofreading or editing text or language polishing.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Intercorrelations among major psychosocial factors and mental health symptoms (N=820).
[DOCX File , 28 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Spearman correlations and corresponding *P* values among emotional self-disclosure users (N=381).
[DOCX File , 18 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Analysis of covariance (ANCOVA) results for AI chatbot dependence by sociodemographic and psychosocial factors among emotional self-disclosure users (N=381).
[DOCX File , 29 KB-Multimedia Appendix 3]

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Abbreviations

AIC: Akaike information criterion
ANCOVA: analysis of covariance
BIC: Bayesian information criterion
CFI: comparative fit index
GAD-7: Generalized Anxiety Disorder–7
JSPS: Japan Society for the Promotion of Science
OR: odds ratio
PHQ-9: Patient Health Questionnaire–9
RMSEA: root mean square error of approximation
RSES: Rosenberg Self-Esteem Scale
SRMR: standardized root mean square residual
TLI: Tucker-Lewis Index
UCLA-LS-3: 3-item UCLA Loneliness Scale
VIF: variance inflation factor

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