JKSCI

한국컴퓨터정보학회논문지
Journal of The Korea Society of Computer and Information
Vol. 30 No. 11, pp. 329-339, November 2025
https://doi.org/10.9708/jksci.2025.30.11.329

Understanding Young Users' Continued Use of AI Chatbots for Mental Health: A TAM and PSI Perspective

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[Abstract]

AI chatbots have rapidly grown in popularity among Chinese adolescents and young adults as tools for emotional support and mental-health assistance. To investigate the factors driving their continued use, this study integrates the Technology Acceptance Model (TAM) with parasocial interaction (PSI) theory. Survey data from 398 participants were analyzed using partial least squares structural equation modeling (PLS-SEM). The results show that emotional support and perceived ease of use positively influence perceived usefulness, while both perceived usefulness and PSI significantly predict continued usage intention. Moreover, perceived usefulness mediates the effects of emotional support and ease of use on sustained engagement. Although the study is limited by its focus on a single cultural context and a Chinese-only youth sample, the findings highlight design strategies-such as embedding empathy cues, enhancing usability, and fostering a sense of social connection-that can strengthen the long-term adoption of AI chatbots for mental-health support.

▸ **Key words**: AI chatbot, emotional support, perceived usefulness, ease of use, parasocial interaction, mental health, continued use

[요 약]

인공지능(AI) 챗봇은 중국의 청소년과 청년층 사이에서 감정적 지지와 정신 건강 지원 수단으로 점차 널리 활용되고 있다. 본 연구는 이러한 챗봇의 지속적 사용을 설명하기 위해 기술수용모형(Technology Acceptance Model, TAM)과 준사회적 상호작용(Parasocial Interaction, PSI) 이론을 통합하였다. 중국 청년 398명을 대상으로 한 설문조사를 부분최소제곱 구조방정식모형(PLS-SEM)으로 분석한 결과, 감정적 지지와 지각된 사용 용이성은 지각된 유용성에 긍정적 영향을 미쳤으며, 지각된 유용성과 PSI는 지속 사용 의도를 유의하게 예측하는 것으로 나타났다. 또한 지각된 유용성은 감정적 지지와 사용 용이성이 지속 사용 의도에 미치는 영향에서 매개 역할을 하였다. 본 연구의 표본은 중국 청년층에 한정되어 있으므로, 연구 결과를 전 세계 청년층으로 일반화하기에는 한계가 있다.연구 결과는 특정 문화적 맥락에 한정된다는 제약이 있으나, 공감적 단서 설계, 사용 편의성 제고, 사회적 연결감 강화와 같은 전략이 AI 챗봇의 장기적 활용을 촉진하는 데 기여할 수 있음을 시사한다.

▸ **주제어**: AI 챗봇, 감정적지지, 지각된 유용성, 사용 용이성, 준사회적 상호작용, 정신 건강, 지속적 사용

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• Received: 2025. 08. 04, Revised: 2025. 09. 26, Accepted: 2025. 11. 04.
• This thesis is an extension of the thesis presented at the 72nd Summer Conference of the Korean Computer Information Society (Understanding Young Users' Continued Use of AI Chatbots for Mental Health: A TAM and PSI Perspective) in 2025

http://www.ksci.re.kr pISSN:1598-849X | eISSN:2383-9945

I. Introduction

Artificial intelligence (AI) has surged from research labs into daily routines, reshaping scores of industries and social practices [1]. Since John McCarthy characterized the field in 1955 as "the science and engineering of making intelligent machines" [2], progress was steady but largely invisible to the average person—until recent breakthroughs made the technology almost friction-free to use. AMD CEO Lisa Su, for example, credits the meteoric rise of tools such as ChatGPT to their unprecedented ease of adoption.

Nowhere is that accessibility more consequential than in mental-health care. In many Asian settings, limited clinical capacity, stigma, and uneven resource distribution leave large gaps in support. Round-the-clock, non-judgmental AI chatbots are well placed to fill those gaps and scale interventions for adolescents and young adults [3].

Early evidence is encouraging. One study reports that 91.2 % of users find ChatGPT helpful in managing anxiety—though privacy concerns linger [3]. Machine-learning risk-screening models can already flag mental-health issues with AUC scores of 0.94 or higher [4]. Surveys show that Generation Z embraces AI chiefly because they perceive it as both easy to handle and genuinely useful [5]; the technology's ability to personalize dialogue only heightens its appeal [6].

As natural-language processing and machine-learning techniques mature, organizations are deploying context-aware chatbots across education, finance, health care, and especially psychological counseling [7]. By stripping away time and distance barriers, these agents create conversational spaces where users feel freer to open up—prompting human-computer-interaction researchers to design systems that are not only functional but therapeutic.

This study was exempt from formal ethics review because it involved anonymous survey data and posed minimal risk to participants. Against this backdrop, the present study models what persuades adolescents and young adults to keep using AI chatbots for emotional support. Drawing on the Technology Acceptance Model and parasocial-interaction theory, we test how usability, perceived usefulness, empathy cues, and quasi-social bonding combine to sustain engagement. The results aim to close critical gaps in digital-mental-health scholarship while guiding more human-centered—and ethically grounded—AI design. While prior work has integrated TAM and PSI in adjacent domains, few studies have applied this lens systematically to AI chatbots designed for mental-health contexts. Recent research highlights that digital mental-health adoption is influenced not only by ease of use and usefulness but also by affective resonance[8], Recent research highlights that digital mental-health adoption is influenced not only by ease of use and usefulness but also by affective resonance (Lee & Lee, 2023),ethical trust[9], and sustained relational[10] bonds—factors that remain underexplored in unified models. Unlike prior work that primarily examined media or streaming contexts, this study uniquely situates TAM-PSI integration within AI-based mental-health support, emphasizing empathy cues and relational bonding as key extensions of traditional acceptance frameworks.By explicitly situating TAM-PSI integration within adolescent mental-health support, this study advances theory by demonstrating how parasocial bonding and empathy cues extend the explanatory scope of technology-adoption frameworks.

Accordingly, the contribution of this research lies in extending classical acceptance theories toward affective and relational dimensions in AI-mediated care, offering theoretical refinement and context-specific design guidance for digital mental-health tools.

II. Theory and hypothesis

1. Emotional Support

Unlike the delayed, one-way broadcasts of earlier media, today's generative-AI chatbots talk back in real time, collapsing distance and giving users instant evidence of whether the exchange is helping [11]. Drawing loosely on insights from online-learning studies [12], we can think of the chatbot's emotional scaffolding as a three-strand braid. First comes climate: a warm tone and mindful wording carve out a space that feels both safe and respectful. Next is sensitivity: sentiment-analysis and text-generation routines pick up on subtle mood shifts, then adjust replies on the fly. Finally, there is a youth-centred stance: the system affirms the user's perspective and poses gentle, open-ended questions that invite honest self-expression. Together, these strands tighten users' trust in the bot's ability to steady their emotions, which in turn boosts perceived usefulness (PU) and nudges them toward sticking with the service.

H1: Emotional Support will have a positive (+) effect on PU.

2. Perceived Ease of Use

Perceived Ease of Use (PEOU) refers to "the degree to which a person believes that using a particular system would be free of effort" [13]. In the context of emotionally supportive chatbots, PEOU specifically reflects whether young users can seek emotional support with minimal cognitive effort during conversations, setup, and function use. As Roose (2022) emphasized in relation to ChatGPT, "This is the first time such a powerful tool has been made available to the public via a free and user-friendly web interface," underscoring the decisive role of high ease of use in the rapid adoption of generative AI tools [14].

Prior studies have consistently found that PEOU exerts a positive influence on perceived usefulness (PU) across diverse technology domains. For instance, Davis(1989) foundational TAM work demonstrated that systems requiring less effort are judged as more beneficial. Subsequent research in e-learning[15], mobile health applications [16] and AI-based counseling tools[17] confirms that when users perceive a system as intuitive and effortless, they are more likely to evaluate it as useful.Building on the Technology Acceptance Model (Davis, 1989), numerous extensions such as TAM2 (Venkatesh & Davis, 2000) and UTAUT (Venkatesh et al., 2003) have consistently demonstrated that perceived ease of use is a fundamental antecedent of perceived usefulness (PU)across digital platforms. These models emphasize that when users experience low cognitive effort and intuitive system design, they are more likely to perceive the system as useful and valuable. These findings suggest that ease of use not only lowers entry barriers but also enhances perceptions of functional value, providing robust theoretical justification for Hypothesis 2.

H2: PEOU will have a positive (+) effect on PU.

3. Perceived Usefulness

Perceived Usefulness (PU) is a core construct in the Technology Acceptance Model (TAM) [13], used to assess the extent to which an individual expects a technology to enhance their performance. In the scenario of emotionally supportive chatbots, PU refers to the extent to which young users believe that the tool can effectively provide emotional support and psychological comfort. Existing research has shown that PU significantly predicts both actual usage behavior [18] and user satisfaction [19]. For example, an empirical study at a UK university confirmed that PU positively influences system usage frequency and learner satisfaction in e-learning contexts [20]. By analogy, when young users recognize that emotionally supportive chatbots can deliver tangible benefits such as emotional relief and stress reduction, particularly within digital mental-health contexts, their usage intentions and satisfaction are also

expected to increase.

H3: PU will have a positive (+) effect on Use Intention.

H5: PU will mediate the relationship between Emotional Support and Use Intention.

H6: PU will mediate the relationship between PEOU and Use Intention.

4. Parasocial Interaction

Parasocial interaction (PSI) was first articulated in communication research to capture the one-sided emotional ties audiences cultivate with media personalities—news anchors, celebrities, or fictional characters—even though no true two-way exchange occurs [10]. Viewers nevertheless experience these bonds as “quasi-social,” imagining a sense of intimacy and trust with the figure on the screen [21]. Scholars have since extended PSI to human-machine contexts, finding it highly revealing for studies of AI-mediated emotional assistance [22].

Recent progress in generative dialogue and anthropomorphic interface design allows conversational agents to display seemingly empathic replies, share “personal” details, and provide comfort, thereby eliciting social reciprocity and emotional projection from users [23]. Even when fully aware that the entity is non-human, individuals may come to regard it as a friend—showing trust, dependence, and genuine relief from distress [24]. In mental-health settings, PSI is a potent driver of engagement and repeat use, offering a key explanatory pathway for sustained interaction with AI companions [25]. Incorporating PSI into our model therefore not only clarifies the mechanisms of acceptance but also guides the personalised, relationship-centred design of future emotional-support bots.

H4: PSI will have a positive (+) effect on Use Intention.

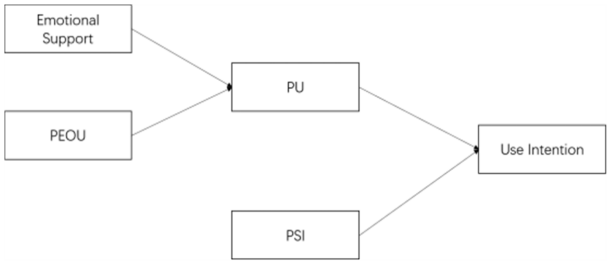

Fig. 1. Proposed research model.

III. Methods and analysis

1. Item Sources

Emotional Support was measured using three items adapted from Nick et al. (2018), e.g., "I feel cared for and supported when I interact with the AI chatbot."

Perceived Usefulness (PU) was assessed with three items from Al-Hattami (2023), e.g., "The AI chatbot improves my mental-health experience."

Perceived Ease of Use (PEOU) employed three items from Liu and Hsu (2022), e.g., "Using the AI chatbot for emotional support is effortless."

Parasocial Interaction (PSI) was measured with reference to three items from Du et al. (2025), e.g., "My AI chatbot feels like a close companion."

Use Intention was evaluated using three items based on Ode et al. (2025), e.g., "I intend to continue using AI chatbots for emotional support.“

2. Sample and Procedure

The target population of this study included Chinese international students in South Korea, undergraduate students at Chinese universities, and Chinese employees with less than three years of work experience. All respondents reported interacting with AI chatbots (such as ChatGPT, Deepseek, Doubao, or Grok) multiple times per week, with each participant regularly using at least one of these tools. Participants were selected based on their recent and routine experiences of using AI chatbot applications for emotional communication, ensuring that the sample closely aligned with the research objectives. This study was exempt from

formal ethics review because it involved anonymous survey data and posed minimal risk to participants. All respondents provided informed consent before completing the questionnaire.A total of 398 valid questionnaires were collected via Wenjuanxing (www.wjx.cn) between April and May 2025.Participants ranged in age from 18 to 35 years (M = 23.8), and 62.8% were male. Demographic information of the respondents is presented in Table 1. The sample size determination followed the guideline proposed by Barclay et al. [31], According to the widely cited "10-times rule," a PLS-SEM study should include a sample size at least ten times larger than the greatest number of structural paths converging on any latent variable.

With 398 valid responses, our dataset comfortably exceeds this guideline. We first ran descriptive statistics to profile participants and screen the data. Next, we assessed the measurement model's reliability as well as its convergent and discriminant validity. Finally, we estimated the structural model to test the hypothesised paths. The sections that follow detail these analyses and discuss the study's key contributions.

Table 1. Demographic information

Particulars	Description	Values	%
Gender	Male	193	48.5
	Female	205	51.5
Age	18-24	23	5.8
	25-29	166	41.7
	30-33	134	33.7
	33-35	75	18.8
Annual income	less than 5,000 (USD)	91	22.9
	5,001-15,000_(USD)	125	31.4
	15,001-,30000(USD)	120	30.2
	More than 30,001	62	15.6
Education level	College and below	45	11.3
	University	173	54.8
	Master's degree	99	24.9
	Doctor degree	81	20.4

IV. Data Analysis and Results

To verify the measurement model, both reliability and validity were rigorously examined to confirm that each construct was accurately represented by its indicators. The results showed that all factor loadings met or exceeded 0.7. Reliability was further supported by Cronbach's alpha and composite reliability values, which all surpassed the standard criterion of 0.7, indicating strong internal consistency[32]. In addition, the average variance extracted (AVE) for each construct was above 0.5, confirming satisfactory convergent validity. Detailed statistics related to these reliability and validity checks are provided in Table 2.

These assessments ensured the measurement model met the recommended psychometric thresholds before testing the structural paths.

Furthermore, to address potential concerns regarding common-method variance (CMV), both procedural and statistical remedies were applied. Harman's single-factor test showed that the first factor accounted for less than 50% of the total variance, and all full collinearity variance inflation factors (VIFs) were below 3.3. These results suggest that CMV is unlikely to pose a serious threat to the validity of the findings.

Table 2. Reliability and Validity of Measurement Constructs

Construct	Loadings	VIF	Cronbach's alpha	CA	CR	AVE
Emotional Support (ES)			0.787	0.788	0.876	0.702
ES1	0.828	1.607				
ES2	0.851	1.716				
ES3	0.834	1.635				
PEOU			0.824	0.826	0.895	0.739
PEOU1	0.859	1.939				
PEOU2	0.868	1.858				
PEOU3	0.852	1.788				
PU			0.830	0.837	0.898	0.746
PU1	0.841	1.799				
PU2	0.866	1.955				
PU3	0.884	1.973				
parasocial interaction PSI			0.845	0.848	0.906	0.763
PSI1	0.857	1.961				
PSI2	0.878	2.031				
PSI3	0.885	2.090				

Use Intention (UI)			0.837	0.842	0.902	0.754
UI1	0.849	1.795				
UI2	0.865	2.052				
UI3	0.890	2.106				

Discriminant validity was assessed following the Fornell and Larcker approach, which requires that the square root of each construct's AVE (shown on the diagonal of the correlation matrix) be greater than any inter-construct correlation[33]. Based on this criterion, the lowest square root of AVE ($\sqrt{AVE}$ = 0.838) was higher than the highest inter-construct correlation (0.497), thereby supporting discriminant validity. thereby supporting discriminant validity [34]. Table 3 details these results. The heterotrait-monotrait (HTMT) ratio of correlations was also used to verify discriminant validity, and all HTMT values fell below the 0.9 threshold, further confirming adequate separation between constructs[35]. Model fit was checked using the Standardized Root Mean Square Residual (SRMR), with a value of 0.053—well below the 0.09 cutoff—demonstrating that the model is suitable for path analysis [36].

Table 3. Discriminant validity (Fornell-Larcker criterion)

	ES	PEOU	PSI	PU	UI
ES	0.838				
PEOU	0.423	0.860			
PSI	0.340	0.374	0.874		
PU	0.301	0.398	0.390	0.863	
UI	0.438	0.497	0.448	0.462	0.868

Table 4. Discriminant validity (HTMT)

	ES	PEOU	PSI	PU	UI
ES					
PEOU	0.525				
PSI	0.417	0.448			
PU	0.369	0.477	0.462		
UI	0.539	0.596	0.530	0.551	

The predictive capability of the model was primarily assessed through the coefficient of determination (R^2). Adjusted R^2 values for Perceived Usefulness (PU) and Use Intention (UI) were 0.176 and 0.295, respectively. According to the commonly accepted benchmarks (0.75 = substantial, 0.50 = moderate, 0.25 = weak), these values indicate that the model demonstrates weak-to-moderate explanatory power for the endogenous constructs. Although the explanatory strength is limited, it still provides meaningful insights into the directional relationships among the variables and supports the overall validity of the proposed framework. These results indicate that the model exhibits weak-to-moderate explanatory power for the endogenous variables. While the explanatory strength is not particularly high, it still provides meaningful insights into the relationships among the constructs and supports the relevance of the proposed research model. After confirming the overall explanatory adequacy of the model, effect size (f^2) was calculated to evaluate the relative contribution of exogenous variables. Furthermore, effect size (F^2) was calculated to evaluate the contribution of exogenous variables to the endogenous constructs. The observed F^2 values correspond to the standard thresholds for small (0.02), medium (0.15), and large (0.35) effects.

Table 5. Effect Size (f^2) of Exogenous Variables

	f-square
ES -> PU	0.026
PEOU -> PU	0.109
PSI -> UI	0.121
PU -> UI	0.138

Following the evaluation of reliability, validity, and explanatory strength, the structural model was tested to examine the hypothesized paths. At the 0.05 significance level, structural relationships were evaluated using a nonparametric bootstrapping procedure, with 5,000 resamples drawn from the original data to estimate t-values for path significance testing. A pathway was considered statistically significant if its t-value exceeded 1.96. As presented in Table 6, the results of the structural equation modeling indicated that all hypothesized paths were significant: emotional support positively influenced perceived usefulness

(β = 0.161, t = 3.533, p < 0.001), perceived ease of use significantly affected perceived usefulness (β = 0.330, t = 7.533, p < 0.001), perceived usefulness had a significant impact on use intention (β = 0.339, t = 7.614, p < 0.001), and parasocial interaction also significantly influenced use intention (β = 0.316, t = 6.844, p < 0.001). Accordingly, all four hypotheses (H1–H4) were supported.

Table 6. Hypothesis Testing Results

Hypothesis	Constructs	Coefficient	Sample Mean	Standard Deviation	t-value	p-value	Decision
H1	ES -> PU	0.161	0.163	0.046	3.533	0.000 ***	Supported
H2	PEOU -> PU	0.330	0.331	0.044	7.533	0.000 ***	Supported
H3	PU -> UI	0.339	0.339	0.044	7.614	0.000 ***	Supported
H4	PSI -> UI	0.316	0.318	0.046	6.844	0.000 ***	Supported

Notes: ***p<0.001, **p<0.01, *p<0.05

As shown in Table 7, the mediation analysis revealed that perceived usefulness mediated the effect of emotional support on use intention (β = 0.054, t = 3.014, p = 0.003), providing support for the mediation hypothesis (H5). Similarly, the effect of perceived ease of use on use intention was also mediated by perceived usefulness (β = 0.112, t = 4.939, p < 0.001), thus supporting hypothesis H6. These results indicate that perceived usefulness acts as a significant mediator in both relationships. The detailed results of the mediation tests are presented in Figure 2.

Table 7. Mediation Analysis Results

Hypothesis	Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-Value	p-Value	Mediation
H5	ES -> PU -> UI	0.054	0.056	0.018	3.014	0.003	Mediation
H6	PEOU -> PU -> UI	0.112	0.113	0.023	4.939	0.000	Mediation

Notes: ***p<0.001, **p<0.01, *p<0.05

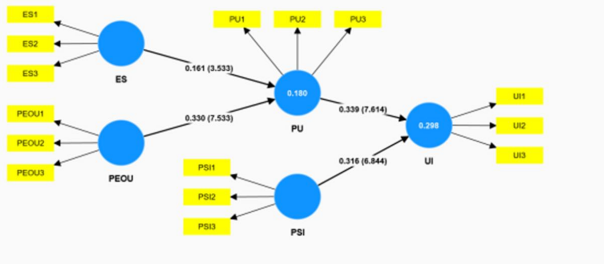

Fig. 2. Results of PLS-SEM analysis for this study.

V. Discussion and Conclusion

1. Discussion

The structural model indicates that AI-mediated emotional support markedly elevates users' perceptions of an assistant's value for mental-health care. When adolescents feel genuinely comforted, they are more inclined to judge the tool as useful—underscoring the design imperative for empathetic, responsive features. Perceived ease of use likewise exerts a strong, positive effect on perceived usefulness: the more intuitive the interface, the more readily users can access resources, which in turn strengthens their appraisal of the assistant's utility.

Perceived usefulness emerges as the most powerful direct predictor of continued-use intention. Users who clearly recognize an assistant's benefits are far more likely to rely on it regularly, suggesting that iterative refinements to core functions and personalised feedback will be critical for sustaining engagement.

Although the observed effect sizes were generally small, their consistency across constructs suggests practical levers for scalable improvement. Even modest gains in perceived usefulness and empathy can accumulate into meaningful increases in user retention for mental-health chatbots.

Parasocial interaction further contributes to retention; a convincing sense of companionship and understanding deepens users' motivation to return.

Perceived usefulness also operates as a partial mediator: it channels some of the positive influence of emotional support and ease of use into

continued-use intention. Enhancing empathy and usability therefore yields both direct gains in engagement and indirect gains via heightened usefulness perceptions.

Taken together, the results recommend a design strategy centred on three pillars—emotional resonance, Theoretically, this study extends the Technology Acceptance Model by incorporating parasocial interaction as an affective mechanism within AI-mediated mental-health contexts, Theoretically, this study extends the Technology Acceptance Model by incorporating parasocial interaction as an affective mechanism within AI-mediated mental-health contexts, offering an integrative view that bridges cognitive and emotional dimensions of technology use.

These findings also carry managerial relevance: developers and service providers should prioritise building empathetic dialogue systems, as emotional resonance not only improves user perceptions but also aligns with broader trends in mental-health service innovation. Similarly, investments in interface design and usability directly translate into more sustained engagement, suggesting that resources allocated to user experience (UX) teams may yield disproportionate long-term returns. Finally, strengthening parasocial features—such as personalised conversations, continuity of interaction, and adaptive emotional responses—can serve as a low-cost but impactful strategy to foster loyalty, which is critical in competitive digital health markets.While the statistical effects were modest, their consistency across constructs underscores actionable priorities for developers seeking scalable improvements in AI-based emotional support systems.

2. Theoretical Implications

Seen through a theoretical lens, our work nudges three strands of scholarship forward. To begin with, we drag the classic Technology Acceptance Model into the therapy-bot arena, braiding emotional support, ease of use, usefulness, and parasocial connection into one pathway that predicts whether people stick around. In doing so, we show that TAM still has room to stretch when the setting is as delicate as mental health.

Next, the findings reveal that usefulness is more than an end-point verdict; it acts as the footbridge that carries warmth and usability over to repeat visits. Put plainly, young users keep an AI companion close only after deciding it genuinely helps.

Finally, by folding parasocial interaction into the adoption map, we move the theory beyond its celebrity-fan roots and into human-machine alliances. Even a faint feeling that “this bot gets me” turns out to oil the gears of acceptance.

Taken together, these three threads offer a sturdier conceptual fabric for anyone hoping to design—or study—emotionally attuned chatbots.

On a practical level, this study offers actionable recommendations for the design and promotion of AI-driven mental health support tools among youth. First, young users are highly sensitive to the emotional support and interactive experience provided by AI chatbots, indicating that developers should enhance AI tools’ emotional understanding and responsiveness to increase user trust and emotional connection. Second, the ease of use and personalized experience of AI tools are critical for improving users’ willingness to use them. Development teams should prioritize user-friendly interfaces, streamlined processes, and personalized content delivery to lower the operational threshold. Third, AI chatbots can offer unbiased, round-the-clock support for young users in environments where mental health resources are limited or cultural and social barriers exist, thus expanding the accessibility and equity of mental health services.

3. Limitations and Future Research

While our data illuminate why many adolescents warm to chatbot companions, a few blind spots deserve mention. First, because all participants

were Chinese-with many residing in Korea at the time-it would be inappropriate to generalize these findings beyond that cultural context. This limitation constrains the external validity of the results, which should therefore be interpreted as context-specific to Chinese youth rather than as representative of global populations. Adoption patterns may vary in other populations, so our findings should be replicated across different cultural and demographic groups in future studies.

Second, although this study relied on self-reported survey data collected at a single time point, future work could incorporate longitudinal or experimental designs to capture changes in user trust and emotional bonding over time. Additionally, incorporating behavioral data such as actual chatbot usage logs could further strengthen construct validity.

Ethically, this study involved minimal risk and anonymous data collection, but future research should continue to adhere to strict privacy safeguards, especially when targeting under-25 populations. Researchers are encouraged to examine participants' perceptions of data transparency and algorithmic fairness to enhance public trust in AI-mediated mental-health support.

Despite these limitations, the present findings provide a valuable foundation for understanding how emotional support, perceived ease of use, usefulness, and parasocial interaction jointly shape young users' willingness to continue using AI chatbots for mental-health care.

ACKNOWLEDGEMENT

This work was supported by Kyonggi University's Graduate Research Assistantship 2025.

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Appendix

Construct	Item
Emotional Support (ES)	
ES1	The AI assistant comforts me when I'm feeling down.
ES2	The AI assistant makes me feel listened to and understood.
ES3	I feel cared for and supported when I interact with my AI assistant.
PEOU	
PEOU1	AI assistant makes mental health info easy to access.
PEOU2	AI assistant simplifies decisions about seeking support.
PEOU3	Using AI assistant for mental health is effortless.
PU	
PU1	AI assistant improves my mental health experience.
PU2	AI assistant saves time finding support.
PU3	AI assistant provides new ways to get help.
parasocial interaction PSI	
PSI1	My AI assistant brings me comfort and connection.
PSI2	I feel supported when chatting with my AI assistant.
PSI3	My AI assistant's presence makes me feel less lonely.
Use Intention (UI)	
UI1	I intend to keep using AI tools.
UI2	I will continue using AI tools.
UI3	I plan to use AI tools regularly, as I do now.