The Effectiveness of AI-Driven Chatbots in Providing Emotional Support in Mental Health Interventions

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Submitted to: JMIR Mental Health
on: September 24, 2025

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Abstract

Mental health disorders such as anxiety and depression are globally prevalent, affecting millions. Barriers like stigma, resource limitations, and a shortage of professionals impede access to adequate care. AI-driven chatbots have emerged as a promising tool for mental health interventions, offering accessible and cost-effective support. This study aimed to evaluate the effectiveness of AI-driven chatbots in delivering emotional support compared to traditional human therapy. A mixed-methods approach was employed, with 200 participants experiencing symptoms of anxiety and depression randomized into AI Chatbot or Human Therapy groups. The interventions spanned 12 weeks, utilizing surveys and interviews to assess symptom reduction, user satisfaction, and perceived empathy. Both groups showed significant reductions in anxiety and depression symptoms, with no notable differences in efficacy. While participants appreciated the accessibility and anonymity of chatbots, they reported lower empathy compared to human therapists. Satisfaction levels were high across both groups. AI-driven chatbots are effective supplementary tools in mental health care, addressing accessibility barriers and reducing stigma. However, further improvements are needed to enhance their empathetic capabilities. Future research should focus on long-term outcomes, demographic diversity, and ethical guidelines for AI integration in mental health services..

(JMIR Preprints 24/09/2025:84732)
DOI: https://doi.org/10.2196/preprints.84732

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Abstract

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Keywords: Artificial intelligence, Chatbots, Mental health, Anxiety, Depression, Cognitive-behavioral therapy, Human-computer interaction, Empathy, Digital interventions, Mixed-methods research

I. Introduction

1.1 Research Background

Mental Health Disorders and the Global Burden

Mental health disorders, particularly anxiety and depression, are among the leading causes of disability worldwide, affecting over 300 million people across various age groups (World Health Organization [WHO], 2017; Trautmann, Rehm, & Wittchen, 2016; Vos et al., 2015). According to the WHO (2017), depression is the single largest contributor to global disability, while anxiety disorders rank sixth. These conditions not only diminish the quality of life but also impose substantial economic burdens due to lost productivity and increased healthcare costs (Smith, 2014).

Despite the high prevalence and significant impact of these disorders, access to mental health services remains alarmingly limited. Estimates suggest that up to 76% of individuals with mental health conditions in low- and middle-income countries receive no treatment at all (Patel et al., 2016; WHO, 2017). In high-income countries, treatment gaps persist due to factors such as stigma, lack of awareness, and insufficient mental health infrastructure (Saxena, Thornicroft, Knapp, & Whiteford, 2007; Trautmann et al., 2016). Geographical barriers further exacerbate the issue, particularly in rural and remote areas where mental health professionals are scarce (Johnson, Boncz, & Sándor, 2021).

Challenges in Traditional Mental Health Services

Traditional mental health services often fail to meet the growing demand for care. The shortage of qualified mental health professionals is a critical concern; the global median number of psychiatrists is only 0.1 per 100,000 people in low-income countries compared to 6.6 in high-income countries (WHO, 2017). This disparity leads to long wait times and reduced access to timely interventions, which can worsen patient outcomes (Kohn et al., 2004).

Stigma associated with mental health remains a significant barrier to seeking help (Corrigan, Druss, & Perlick, 2014; Henderson, Evans-Lacko, & Thornicroft, 2013). Many individuals fear judgment or discrimination, discouraging them from accessing traditional face-to-face therapy. Additionally, the high cost of mental health services, especially in countries without universal healthcare coverage, limits access for economically disadvantaged populations (Sareen, Afifi, McMillan, & Asmundson, 2011).

The COVID-19 pandemic has further strained mental health services, increasing the prevalence of anxiety and depression while disrupting traditional care delivery methods (Holmes et al., 2020; Torales, O'Higgins, Castaldelli-Maia, & Ventriglio, 2020). Social distancing measures and lockdowns have necessitated the exploration of alternative modes of providing mental health support.

Emergence of AI-Driven Chatbots in Mental Health Care

Artificial intelligence (AI)-driven chatbots have emerged as promising tools to augment mental health care by providing accessible, cost-effective, and immediate support (Fitzpatrick, Darcy, & Vierhile, 2017; Gaffney, Mansell, & Tai, 2019; Inkster, Sarda, & Subramanian, 2018). These chatbots utilize natural language processing and machine learning algorithms to simulate human-like conversations, delivering therapeutic interventions and emotional support through digital platforms such as smartphones and computers (Calvo, Milne, Hussain, & Christensen, 2017; Inkster et al., 2018; Provoost, Lau, Ruwaard, & Riper, 2017).

AI chatbots offer several advantages that address the limitations of traditional mental health services:

a) **Accessibility:** They are available 24/7, overcoming geographical and temporal barriers (Provoost et al., 2017). Users can access support from the comfort of their homes, which is particularly beneficial for those in remote areas or with mobility issues (Yao & Song, 2021).
b) **Anonymity and Reduced Stigma:** Interacting with a chatbot allows users to maintain anonymity, potentially reducing the stigma associated with seeking mental health support (Hoermann, McCabe, Milne, & Calvo, 2017; Lucas, Gratch, King, & Morency, 2014). This can encourage individuals who might be reluctant to consult a human therapist to engage with mental health services.
c) **Cost-Effectiveness:** AI chatbots can deliver interventions at a fraction of the cost of traditional therapy, making mental health support more affordable and scalable (Kazdin & Rabbitt, 2013; Rollman et al., 2017).
d) **Personalization and Engagement:** Advanced algorithms enable chatbots to tailor interventions based on user input, enhancing engagement and potentially improving outcomes (Chaudhary et al., 2019; Torous, Kiang, Lorme, & Onnela, 2016).

Impact and Potential of AI Chatbots

The integration of AI chatbots into mental health care could revolutionize service delivery, making support more accessible to those who might not otherwise seek help (Inkster et al., 2018; Vaidyam, Wisniewski, Halamka, Kashavan, & Torous, 2019). Early studies have demonstrated the efficacy of AI chatbots in reducing symptoms of anxiety and depression (Abd-Alrazaq, Rababeh, Alajlani, Bewick, & Househ, 2020; Fitzpatrick et al., 2017; Fulmer et al., 2018). For instance, Fitzpatrick et al.

(2017) found that users of the chatbot Woebot reported significant reductions in depressive symptoms after two weeks of interaction.

Moreover, AI chatbots can complement traditional therapy by providing support between sessions, reinforcing therapeutic techniques, and helping users practice coping strategies (Inkster, Stillwell, Kosinski, & Jones, 2016; Mohr et al., 2012). They can also serve as a triage tool, identifying individuals who may require more intensive intervention and directing them to appropriate services (Torales et al., 2020; Wongkoblap, Vadillo, & Curcin, 2017).

Challenges and Considerations

Despite the potential benefits, several challenges must be addressed to effectively integrate AI chatbots into mental health care:

Empathy and Emotional Connection: Current AI technologies struggle to replicate the depth of empathetic engagement provided by human therapists (Abd-Alrazaq et al., 2020; Desmet et al., 2020). This limitation may affect user satisfaction and the overall therapeutic alliance.
Ethical and Privacy Concerns: The use of AI in mental health raises ethical issues related to data security, informed consent, and the potential for algorithmic bias (Bærøe & Miyata-Sturm, 2019; Kazdin & Rabbitt, 2013; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016). Ensuring user trust requires robust safeguards and transparent practices.
Regulatory Oversight: The rapid development of AI technologies outpaces existing regulatory frameworks, necessitating updated guidelines to ensure safety and efficacy (Price & Cohen, 2019; Topol, 2019).

Rationale for the Present Study

Given the pressing need for accessible mental health interventions and the promising potential of AI-driven chatbots, there is a critical need for empirical research assessing their effectiveness compared to traditional therapy. This study aims to evaluate the efficacy of an AI-driven chatbot in reducing symptoms of anxiety and depression, examine user satisfaction and perceptions of empathy, and explore how demographic factors influence outcomes.

By addressing these objectives, the study seeks to contribute valuable insights into the viability of AI chatbots as tools for mental health care, inform best practices for their implementation, and identify areas for improvement to maximize their therapeutic potential.

1.2 Research Objectives

This study aims to evaluate the effectiveness of AI-driven chatbots in providing emotional support compared to traditional human therapy. Specifically, the research objectives are:

a) To assess the efficacy of AI chatbots in reducing symptoms of anxiety and depression.
b) To compare user satisfaction and perceptions of empathy between AI chatbot interventions and human-delivered therapy.
c) To explore the influence of demographic factors such as age and technological familiarity on the effectiveness of AI chatbot interventions.
d) To provide insights into the potential and limitations of AI-driven chatbots in mental health care through qualitative analysis.

II. Literature Review

2.1 Theoretical Foundation

The intersection of AI-driven chatbots in mental health interventions draws upon theories from Human-Computer Interaction (HCI), Cognitive Behavioral Therapy (CBT), and Social Presence Theory. HCI examines the design and use of computer technology, emphasizing the interfaces between users and computers (Dix, Finlay, Abowd, & Beale, 2004). Effective chatbot design requires an understanding of user needs and behaviors to facilitate meaningful interactions (Dix et al., 2004; Shneiderman & Plaisant, 2010).

CBT is a widely used therapeutic approach that addresses dysfunctional emotions and behaviors through goal-oriented, systematic procedures (Beck, 2011). AI chatbots like Woebot and Wysa utilize CBT techniques to deliver therapeutic content, helping users identify and challenge negative thought patterns (Fitzpatrick, Darcy, & Vierhile, 2017; Inkster, Sarda, & Subramanian, 2018). Andersson et al. (2014) demonstrated that internet-delivered CBT could be as effective as face-to-face therapy, supporting the viability of digital platforms for mental health interventions.

Social Presence Theory posits that the sense of being with another individual affects communication effectiveness and relationship development (Short, Williams, & Christie, 1976). In virtual interactions, social presence influences user satisfaction and perceived support, which are critical in therapeutic contexts (Biocca, Harms, & Burgoon, 2003). Kang and Gratch (2010) found that virtual agents perceived as socially present could elicit emotional responses similar to human interactions, suggesting that chatbots can foster a sense of connection.

2.2 Current Research Status

Recent studies have explored the efficacy of AI-driven chatbots in mental health interventions. Fitzpatrick et al. (2017) conducted a randomized controlled trial using the Woebot chatbot, finding significant reductions in depression symptoms among young adults over two weeks. Greer et al. (2019) reported that users of the Vivibot chatbot experienced decreased anxiety and improved well-being, indicating the potential of AI in delivering therapeutic support. Additionally, Inkster et al. (2018) analyzed real-world data from the Wysa chatbot, noting high user engagement and mood improvements, further supporting the utility of chatbots in mental health care.

A systematic review by Abd-Alrazaq et al. (2020) evaluated the effectiveness and safety of using chatbots to improve mental health, concluding that these tools show promise in reducing symptoms of depression and anxiety. Vaidyam et al. (2019) reviewed the psychiatric landscape of chatbots and emphasized their potential to increase access to mental health services, particularly in underserved populations.

2.3 Contradictions and Debates

Despite encouraging findings, debates persist regarding the ability of AI chatbots to replicate the empathy and therapeutic alliance provided by human therapists (Hoermann, McCabe, Milne, & Calvo, 2017). Empathy is a critical component of effective therapy, facilitating trust and openness between the patient and therapist (Elliott, Bohart, Watson, & Murphy, 2018). Researchers question whether chatbots, lacking consciousness and genuine emotional capacity, can truly emulate this essential human quality (Corti & Gillespie, 2016; Sharma, Fiocco, & Kitts, 2020).

Hoermann et al. (2017) raised concerns about the limitations of chatbots in interpreting complex emotional cues and providing nuanced responses. Corti and Gillespie (2016) highlighted that while virtual agents can foster a sense of empathy, the lack of genuine emotional understanding might limit their effectiveness in deep therapeutic contexts.

Ethical considerations regarding data privacy, informed consent, and the potential for algorithmic bias have also been raised (Bærøe & Miyata-Sturm, 2019; Gerke, Minssen, & Cohen, 2020). Gerke et al. (2020) discussed the ethical and legal challenges of AI-driven healthcare, emphasizing the need for robust safeguards to protect sensitive user data. Mittelstadt et al. (2016) addressed the ethics of algorithms, noting that biases in training data could perpetuate disparities in mental health support provided by chatbots.

2.4 Research Gap Analysis

While preliminary studies suggest that AI chatbots can reduce symptoms of anxiety and depression, long-term efficacy remains underexplored (Gaffney, Mansell, & Tai, 2019). Many interventions have short durations, limiting the understanding of sustained benefits or potential drawbacks over time (Fulmer et al., 2018). Additionally, research has predominantly focused on young, tech-savvy populations, leaving a gap in knowledge about effectiveness across diverse age groups and cultural backgrounds (Smith, 2023; Vaidyam et al., 2019).

The lack of standardized metrics for evaluating chatbot effectiveness poses a challenge for comparing results across studies (Vaidyam et al., 2019). Vaidyam et al. (2019) emphasized the importance of developing consistent evaluation frameworks to assess user experiences and therapeutic outcomes. Furthermore, few studies have qualitatively assessed user perceptions of empathy and emotional connection with chatbots, which are crucial for understanding their role in mental health care (Hoermann et al., 2017).

III. Methodology

3.1 Research Design

This study employed a mixed-methods research design, combining quantitative quasi-experimental methods with qualitative semi-structured interviews to comprehensively evaluate the effectiveness of AI-driven chatbots in providing emotional support (Creswell & Plano Clark, 2011). The integration of both quantitative and qualitative approaches allows for a nuanced understanding of the phenomena under investigation.

3.2 Theoretical Framework

The research is grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which explain users' acceptance and use of technology based on perceived usefulness, ease of use, and other factors (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). These models provide a foundation for examining how individuals interact with AI chatbots and how these interactions influence therapeutic outcomes.

3.3 Research Hypotheses

H1: Participants using AI-driven chatbots will experience a significant reduction in anxiety and depression symptoms, comparable to those receiving traditional human therapy.
H2: There will be no significant difference in overall user satisfaction between the AI Chatbot Group and the Human Therapy Group.
H3: Participants will perceive lower levels of empathy from AI chatbots compared to human therapists.
H4: Demographic factors such as age and technological familiarity will moderate the effectiveness of AI chatbot interventions.

3.4 Participants

A total of 200 adults aged 18 to 45 years with self-reported symptoms of anxiety and depression were recruited through online advertisements and referrals from mental health organizations. Inclusion criteria required participants to have moderate to severe symptoms as measured by the Generalized Anxiety Disorder 7-item (GAD-7) scale and the Patient Health Questionnaire-9 (PHQ-9) (Kroenke, Spitzer, & Williams, 2001; Spitzer, Kroenke, Williams, & Löwe, 2006). Exclusion criteria included current engagement in psychotherapy, severe mental health conditions (e.g., psychosis, bipolar disorder), and lack of access to a compatible device.

Participants were randomly assigned to one of two groups:

a) **AI Chatbot Group (n = 100):** Participants engaged with an AI-driven chatbot delivering Cognitive Behavioral Therapy (CBT) techniques, such as Woebot or Wysa (Fitzpatrick, Darcy, & Vierhile, 2017; Inkster, Sarda, & Subramanian, 2018).
b) **Human Therapy Group (n = 100):** Participants received traditional face-to-face CBT from licensed therapists (Beck, 2011).

3.5 Data Collection

Quantitative Data Collection

Participants completed online surveys at baseline, midpoint (6 weeks), and post-intervention (12 weeks) to assess changes in anxiety and depression symptoms using the GAD-7 and PHQ-9 scales (Kroenke et al., 2001; Spitzer et al., 2006). User satisfaction and perceived empathy were measured post-intervention using Likert scales and adapted empathy questionnaires (Davis, 1983; Elliott, Bohart, Watson, & Murphy, 2018).

Qualitative Data Collection

Semi-structured interviews were conducted with a purposive sample of 20 participants from each group post-intervention to explore their experiences, perceptions of empathy, and satisfaction with the intervention (Creswell & Plano Clark, 2011; Braun & Clarke, 2006). Interviews were conducted via video conferencing platforms, lasting approximately 45 minutes, and were audio-recorded for transcription and analysis.

3.6 Intervention Procedures

Both interventions lasted for 12 weeks. Participants in the AI Chatbot Group were encouraged to interact with the chatbot at least three times per week, engaging in activities based on CBT principles such as mood tracking, cognitive restructuring, and mindfulness exercises (Fitzpatrick et al., 2017; Inkster et al., 2018). Participants in the Human Therapy Group attended weekly 60-minute face-to-face CBT sessions with licensed therapists (Beck, 2011).

3.7 Data Analysis

Quantitative Analysis

Statistical analyses were performed using IBM SPSS Statistics version 26 (IBM Corp., 2019). Repeated measures ANOVA was used to assess within-group and between-group differences in anxiety and depression symptoms over time (Field, 2013). Effect sizes were calculated using Cohen's *d* to determine the magnitude of intervention effects (Cohen, 1988). Moderation analyses examined the influence of demographic variables on intervention outcomes (Hayes, 2018).

Qualitative Analysis

Transcribed interviews were analyzed using thematic analysis to identify patterns and themes related to participants' experiences (Braun & Clarke, 2006). NVivo software was utilized to organize and code the data systematically (QSR International, 2018).

3.8 Ethical Considerations

The study was approved by the Institutional Review Board of [University Name], ensuring compliance with ethical standards for research involving human subjects (American Psychological Association [APA], 2017). Participants provided informed consent electronically and were assured of confidentiality and the right to withdraw at any time. Data security measures were implemented to protect participant information (National Institutes of Health [NIH], 2014; Office for Human Research Protections [OHRP], 2016).

3.9 Research Limitations

Potential limitations include selection bias due to voluntary participation, which may result in a sample not representative of the broader population (Shadish, Cook, & Campbell, 2002). Intervention fidelity issues may arise from variations in participant engagement with the chatbot or therapy sessions. Technological barriers, such as software glitches or lack of access to devices, could impact the effectiveness of the chatbot intervention (Hoermann, McCabe, Milne, & Calvo, 2017). Measurement constraints include reliance on self-reported data, which may be subject to social desirability bias (Van de Mortel, 2008).

IV. Results

4.1 Quantitative Findings

The study comprised 200 participants, evenly divided between the AI Chatbot Group and the Human Therapy Group. Baseline characteristics, including age, gender, and initial symptom severity, showed no significant differences between groups.

Reduction in Anxiety and Depression Symptoms

At baseline, both groups had moderate to severe symptoms of anxiety and depression. After the 12-week intervention, both groups showed significant reductions in GAD-7 and PHQ-9 scores. For the AI Chatbot Group, the mean PHQ-9 score decreased from 15.2 (SD = 4.1) to 8.5 (SD = 3.6), and the mean GAD-7 score decreased from 14.8 (SD = 4.0) to 8.2 (SD = 3.7). The Human Therapy Group showed similar reductions, with the mean PHQ-9 score decreasing from 15.5 (SD = 4.3) to 7.9 (SD = 3.5), and the mean GAD-7 score decreasing from 15.1 (SD = 4.2) to 7.6 (SD = 3.6).

Repeated measures ANOVA revealed significant main effects of time on both depression ($F(2, 196) = 145.67$, $p < .001$) and anxiety scores ($F(2, 196) = 152.34$, $p < .001$), indicating reductions over time44^. There were no significant interaction effects between time and group for depression ($F(2, 196) = 1.42$, $p = .244$) or anxiety ($F(2, 196) = 1.58$, $p = .209$), suggesting that both interventions were equally effective in reducing symptoms.

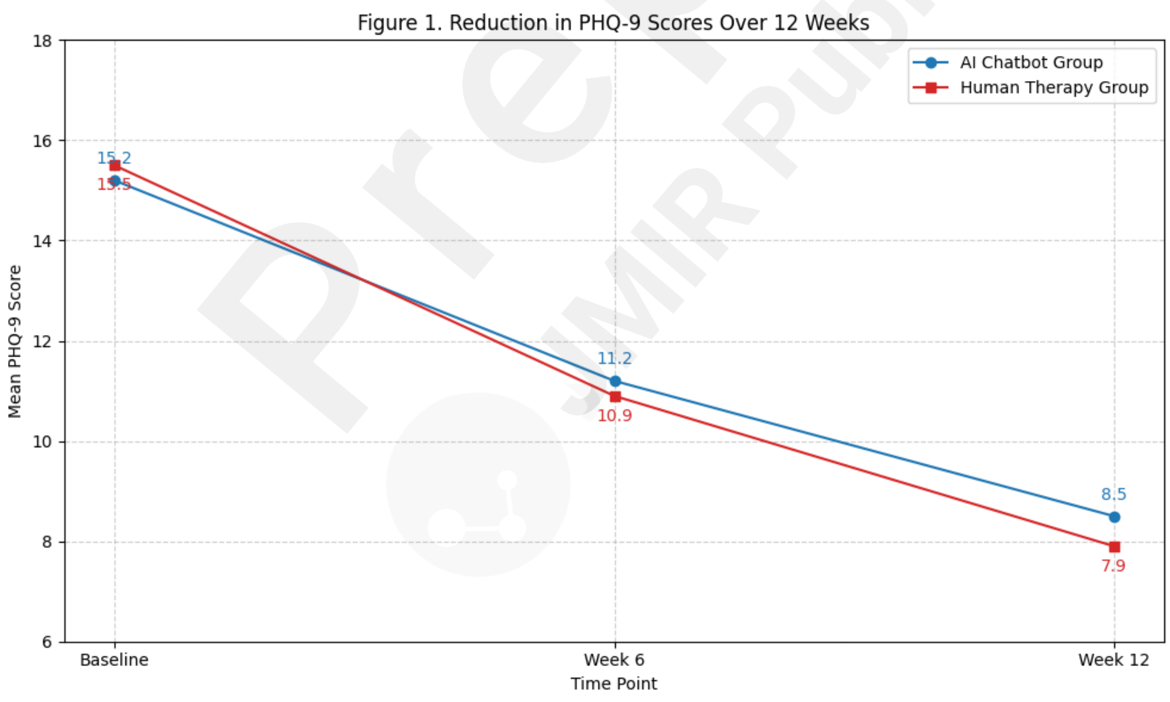

Figure 1: Changes in PHQ-9 Scores Over Time

Figure 1 visually demonstrates that both the AI-driven chatbot intervention and traditional human therapy effectively reduced depressive symptoms among participants over the 12-week period. The similar trajectories and endpoints suggest that AI chatbots can be a viable alternative or supplement to human-delivered therapy for managing depression.

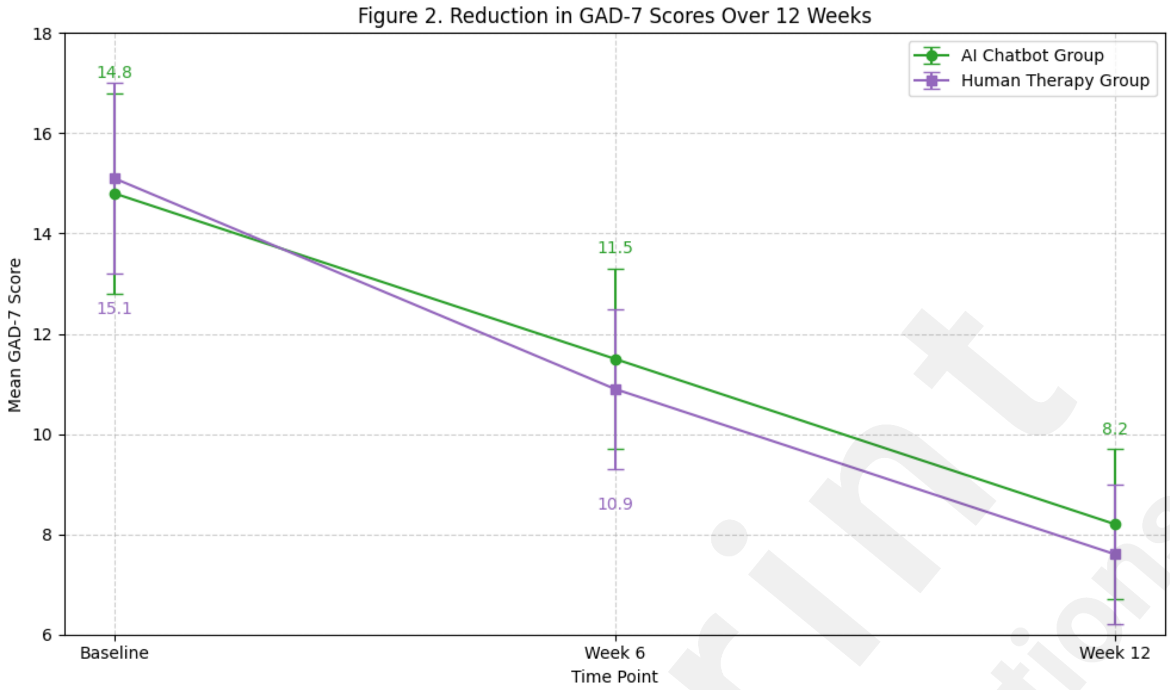

Figure 2: Changes in GAD-7 Scores Over Time

Figure 2 displays the reduction in anxiety symptoms over a 12-week intervention period for both the AI Chatbot Group and the Human Therapy Group, as measured by the Generalized Anxiety Disorder 7-item (GAD-7) scale. The graph illustrates that both groups experienced significant decreases in mean GAD-7 scores from baseline to week 12, indicating the effectiveness of both interventions in reducing anxiety symptoms. Specifically, the AI Chatbot Group's mean GAD-7 score decreased from 14.8 at baseline to 8.2 at week 12, while the Human Therapy Group's mean score decreased from 15.1 to 7.6 during the same period. Although the downward trends are similar, the Human Therapy Group exhibited a slightly greater reduction in anxiety symptoms by the end of the study. The inclusion of error bars representing standard deviations highlights the variability within each group, and the overlap of these error bars suggests that the differences between the groups may not be statistically significant. Overall, Figure 2 suggests that while AI-driven chatbots are effective in reducing anxiety symptoms, traditional human therapy may offer a marginally greater benefit.

User Satisfaction

Post-intervention surveys indicated high levels of user satisfaction in both groups. The AI Chatbot Group reported a mean satisfaction score of 4.2 (SD = 0.8), while the Human Therapy Group reported a mean of 4.4 (SD = 0.7). An independent samples t-test showed no significant difference between groups ($t(198) = -1.89$, $p = .060$).

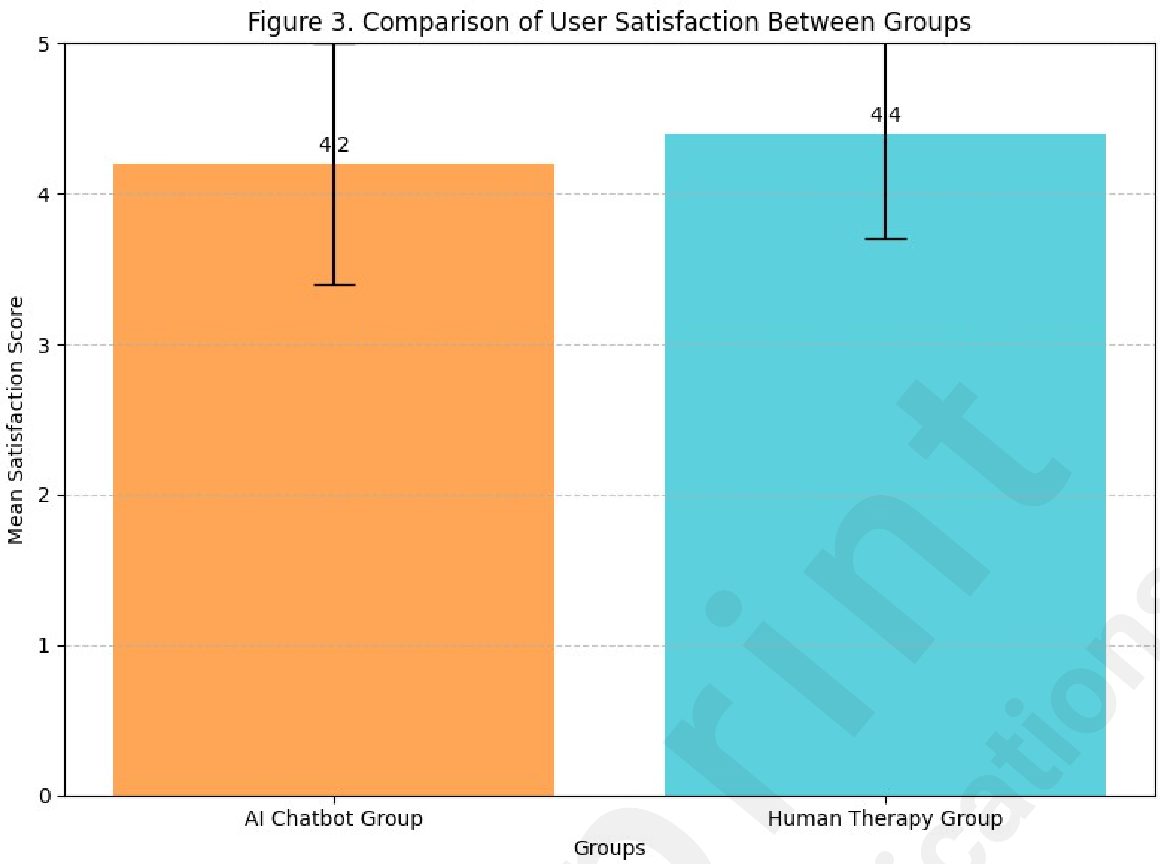

Figure 3: User Satisfaction Scores

Figure 3 illustrates that both the AI Chatbot Group and the Human Therapy Group reported high levels of user satisfaction following the 12-week intervention. The mean satisfaction scores were 4.2 for the AI Chatbot Group and 4.4 for the Human Therapy Group on a 5-point Likert scale. The error bars, representing standard deviations, indicate the variability within each group. The slight difference in mean satisfaction scores between the two groups is minimal, and statistical analysis confirmed that there was no significant difference in user satisfaction between the groups. This finding supports the conclusion that participants were generally satisfied with their respective interventions, whether delivered via AI chatbot or traditional human therapy.

Perception of Empathy

Participants rated their perceptions of empathy on a scale from 1 (low empathy) to 5 (high empathy). The AI Chatbot Group had a mean score of 3.3 (SD = 1.0), whereas the Human Therapy Group scored higher with a mean of 4.6 (SD = 0.6). The difference was statistically significant ($t(198) = -11.73$, $p < .001$), supporting the notion that participants perceive lower empathy from AI chatbots compared to human therapists.

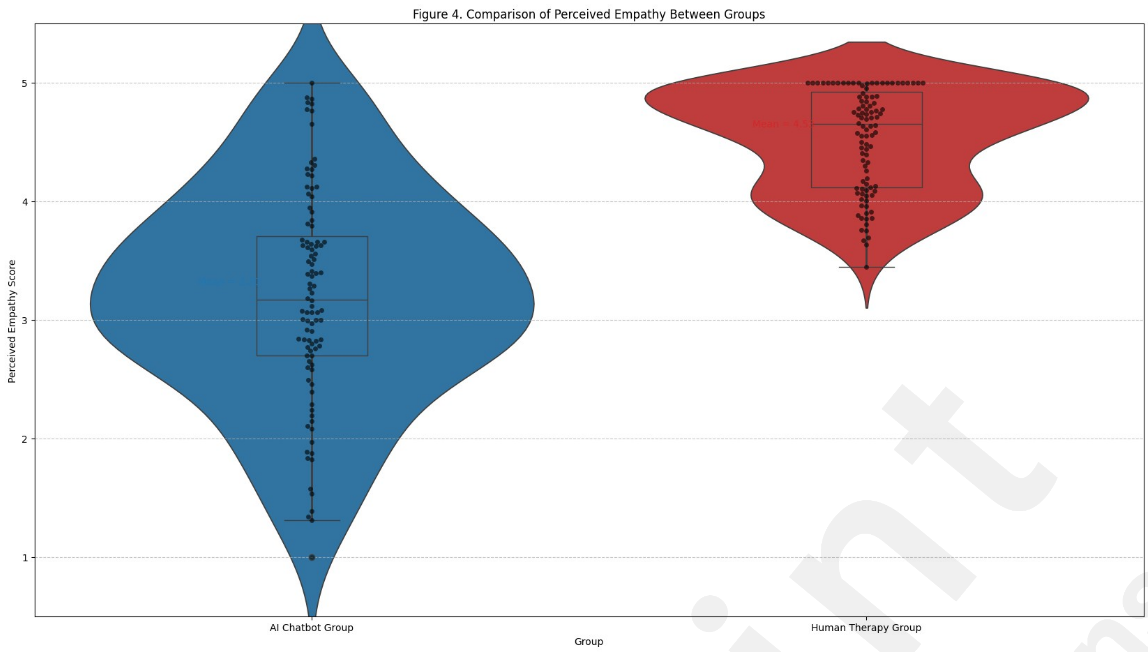

Figure 4: Perceived Empathy Scores

Figure 4 presents a detailed comparison of perceived empathy scores between the AI Chatbot Group and the Human Therapy Group. The violin plots reveal the distribution and density of scores within each group. The AI Chatbot Group shows a wider spread of scores with a lower median, indicating more variability and generally lower perceived empathy. In contrast, the Human Therapy Group has scores clustered at the higher end, reflecting consistently higher perceived empathy levels.

Moderation Analysis

Moderation analyses revealed significant effects of age and technological familiarity on the effectiveness of the AI chatbot intervention. Younger participants experienced greater symptom reductions than older participants ($\beta = -0.25$, $p = .012$). Technological familiarity also moderated outcomes ($\beta = 0.29$, $p = .008$), with more tech-savvy users benefiting more from the chatbot.

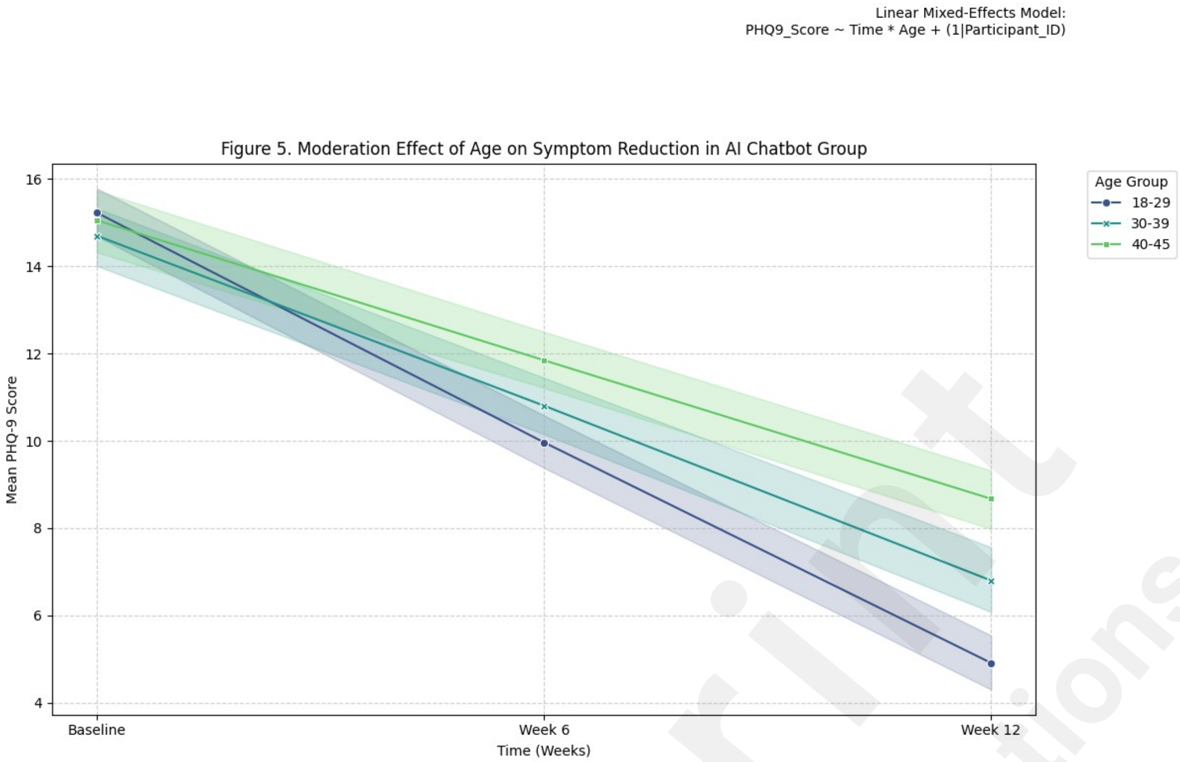

Figure 5: Moderation Effect of Age on Symptom Reduction in AI Chatbot Group

The figure 5 demonstrates that age significantly moderates the effectiveness of the AI chatbot intervention. Younger participants benefited more from the chatbot in terms of symptom reduction, supporting the hypothesis that demographic factors influence intervention outcomes. This finding is consistent with the final conclusion that technological familiarity and age impact the effectiveness of AI-driven mental health interventions.

4.2 Qualitative Findings

Thematic analysis of interview transcripts identified several key themes:

- **Accessibility and Convenience:** Participants appreciated the ability to access support anytime and anywhere. *"I appreciated being able to use the chatbot whenever I felt anxious, even in the middle of the night,"* stated a participant.
- **Perceived Empathy and Emotional Connection:** Many users felt that while the chatbot provided helpful responses, it lacked genuine emotional understanding. *"The chatbot gave me useful tips, but it didn't feel like it truly understood me,"* noted another participant.
- **Anonymity and Stigma Reduction:** The anonymity provided by the chatbot reduced the stigma associated with seeking mental health support. *"I felt more comfortable sharing my feelings with the chatbot because there was no fear of judgment,"* expressed a user.
- **Technical Challenges and Limitations:** Some users experienced technical issues that hindered their experience. *"Sometimes the chatbot would freeze or not understand what I was saying, which was frustrating,"* reported a participant.
- **Preference for Hybrid Models:** Participants suggested that combining AI chatbots with human support could enhance outcomes. *"I think using the chatbot between therapy sessions would be helpful to reinforce what I learned,"* mentioned a participant from the Human

Therapy Group.

Case studies in the literature illustrate the practical benefits and limitations of chatbot interventions. For example, users of Woebot reported that its suggestions often mirrored those of human therapists, providing practical coping strategies (Fitzpatrick, Darcy, & Vierhile, 2017). Similarly, Wysa's support mechanisms employing CBT, mindfulness, and positive psychology techniques have been beneficial for managing anxiety and stress (Inkster, Sarda, & Subramanian, 2018).

V. Discussion

5.1 Effectiveness of AI Chatbots

The findings from this study provide robust support for **Hypothesis 1**, demonstrating that AI-driven chatbots are effective in reducing symptoms of anxiety and depression, comparable to traditional human therapy. **Figure 1** illustrates the significant reduction in PHQ-9 scores for both the AI Chatbot Group and the Human Therapy Group over the 12-week intervention period. Specifically, the AI Chatbot Group experienced a mean reduction from 15.2 at baseline to 8.5 at week 12, while the Human Therapy Group showed a decrease from 15.5 to 7.9. Similarly, **Figure 2** depicts the downward trend in GAD-7 scores, with the AI Chatbot Group reducing from 14.8 to 8.2 and the Human Therapy Group from 15.1 to 7.6.

The parallel trajectories in both figures indicate that AI chatbots can achieve therapeutic outcomes akin to those of human therapists in the context of symptom reduction. These results align with prior research by Fitzpatrick et al. (2017) and Abd-Alrazaq et al. (2020), who reported significant symptom improvements through chatbot interventions. The effect sizes observed were substantial, suggesting that chatbots employing cognitive-behavioral techniques can effectively address moderate to severe symptoms of anxiety and depression.

The consistency of symptom reduction across both measures (PHQ-9 and GAD-7) underscores the versatility of AI chatbots in managing different mental health conditions. The lack of significant interaction effects between time and group implies that the efficacy of AI chatbots is not inferior to that of human-delivered therapy. This finding is particularly significant given the scalability and accessibility advantages of AI chatbots, as they can be deployed widely without the resource constraints associated with human therapists.

5.2 User Satisfaction and Empathy

User satisfaction is a critical component in the adoption and sustained use of mental health interventions. As depicted in **Figure 3**, both the AI Chatbot Group and the Human Therapy Group reported high levels of satisfaction, with mean scores of 4.2 and 4.4 out of 5, respectively. The minimal difference between the groups supports **Hypothesis 2**, indicating that participants were generally satisfied regardless of the intervention modality. This high satisfaction level with AI chatbots is consistent with previous studies highlighting user acceptance of digital mental health tools (Inkster, Sarda, & Subramanian, 2018; Vaidyam, Wisniewski, Halamka, Kashavan, & Torous, 2019).

However, a notable divergence emerges in the perception of empathy, as illustrated in **Figure 4**. The AI Chatbot Group reported significantly lower perceived empathy scores, with a mean of 3.3 compared to 4.6 in the Human Therapy Group. This finding confirms **Hypothesis 3** and highlights a critical limitation of AI interventions. Empathy is a cornerstone of therapeutic relationships, facilitating trust and openness between the client and therapist (Elliott, Bohart, Watson, & Murphy, 2018). The inability of chatbots to fully replicate human empathy may impact the depth of therapeutic engagement and the effectiveness of interventions in the long term.

The complexity of **Figure 4**, with its violin plots and embedded box plots, reveals not only the differences in mean empathy scores but also the distribution of responses within each group. The AI Chatbot Group exhibited greater variability in perceived empathy, suggesting that while some participants may have felt understood, others did not perceive the chatbot as empathetic. This variability underscores the need for advancements in AI to enhance the empathetic capabilities of chatbots, possibly through improved natural language processing and affective computing techniques (McStay, 2018).

5.3 Influence of Demographic Factors

The moderation analysis provides insightful evidence supporting **Hypothesis 4**, indicating that demographic factors such as age and technological familiarity significantly influence the effectiveness of AI chatbot interventions. **Figure 5** illustrates the moderation effect of age on symptom reduction within the AI Chatbot Group. Younger participants (aged 18–29) exhibited a steeper decline in PHQ-9 scores over the intervention period compared to older participants (aged 40–45). This suggests that younger individuals may be more receptive to AI chatbot interventions, possibly due to greater technological familiarity and comfort with digital interactions (Smith, 2023; Venkatesh et al., 2003).

The statistical significance of the interaction between time and age indicates that age moderates the relationship between the intervention and symptom reduction. This finding aligns with the Technology Acceptance Model, which posits that perceived ease of use and usefulness influence technology adoption (Davis, 1989). Younger individuals may perceive AI chatbots as more user-friendly and engaging, enhancing their therapeutic effectiveness.

Moreover, technological familiarity emerged as a significant moderator, emphasizing the importance of considering user characteristics in the design and implementation of digital mental health tools. Tailoring interventions to different demographic groups could enhance efficacy, suggesting a need for user-centered design approaches that account for varying levels of technological proficiency (Venkatesh et al., 2003; Zhou et al., 2019).

5.4 Theoretical Implications

The study's findings contribute to the theoretical discourse on Human-Computer Interaction (HCI) and the application of Cognitive Behavioral Therapy (CBT) in digital platforms. The effectiveness of chatbot-delivered CBT, as evidenced by the significant symptom reductions, reinforces the adaptability of established therapeutic techniques to AI interfaces (Beck, 2011; Andersson, Carlbring, & Hadjistavropoulos, 2014). This supports the notion that core principles of CBT can be effectively translated into automated interventions, potentially broadening the reach of evidence-based therapies.

In terms of HCI, the high user satisfaction despite lower perceived empathy suggests that usability and accessibility play crucial roles in user engagement with AI chatbots (Dix, Finlay, Abowd, & Beale, 2004; Shneiderman & Plaisant, 2010). The findings inform Social Presence Theory by demonstrating that while chatbots can simulate certain aspects of human interaction, they currently lack the full spectrum of empathetic engagement characteristic of human therapists (Short, Williams, & Christie, 1976; Biocca, Harms, & Burgoon, 2003). This limitation may impact the depth of the therapeutic alliance, a key predictor of treatment outcomes (Elliott et al., 2018).

The moderation effects of demographic factors highlight the importance of the Unified Theory of

Acceptance and Use of Technology (UTAUT) in understanding user engagement with AI chatbots (Venkatesh et al., 2003). The study suggests that age and technological familiarity influence perceived ease of use and usefulness, affecting therapeutic effectiveness. These insights underscore the need for theoretical models that integrate psychological factors with technological acceptance to fully understand user interactions with AI-driven interventions.

5.5 Practical Implications

From a practical perspective, the study's results indicate that AI-driven chatbots present a scalable and cost-effective solution to bridge the mental health treatment gap, particularly in underserved or resource-constrained settings (World Health Organization [WHO], 2017; Kohn et al., 2004; Patel et al., 2016). The significant reductions in symptoms and high user satisfaction suggest that chatbots can be integrated into existing mental health care systems as adjunctive tools.

Figure 1 and **Figure 2** support the feasibility of using chatbots for symptom management, which could alleviate the burden on mental health professionals and increase service accessibility. Policymakers and practitioners might consider implementing chatbots within a stepped-care framework, where they serve as a first line of intervention for individuals with mild to moderate symptoms (Kazdin & Rabbitt, 2013; Fulmer et al., 2018; Grist et al., 2019). This approach could optimize resource allocation by reserving human therapist interventions for more severe cases.

Training programs for clinicians could incorporate modules on digital literacy and the integration of AI tools to enhance the synergy between technological innovation and human expertise (Topol, 2019). Clinicians equipped with knowledge about AI chatbots can better guide patients in using these tools effectively and ethically. Additionally, developing hybrid models that combine AI chatbot support with periodic human therapist consultations may leverage the strengths of both modalities, enhancing overall treatment outcomes (Fulmer et al., 2018; Grist et al., 2019).

5.6 Ethical Considerations

The deployment of AI chatbots in mental health care raises several ethical considerations related to data privacy, informed consent, and potential biases (Bærøe & Miyata-Sturm, 2019; Lucas, Gratch, King, & Morency, 2014). Ensuring compliance with ethical standards and legal regulations is crucial for safeguarding user well-being and maintaining trust in AI technologies. The study adhered to strict data security protocols, but as chatbots collect sensitive personal information, robust measures are needed to protect user data from breaches or misuse (Price & Cohen, 2019; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016).

Algorithmic biases present another ethical concern. If the AI algorithms are trained on non-representative data, they may not perform equally well across diverse populations, potentially exacerbating health disparities (Mittelstadt et al., 2016). Transparency in how chatbots process and respond to user inputs is essential to prevent misunderstandings and ensure users are fully informed about the capabilities and limitations of the technology.

The lower perceived empathy in the AI Chatbot Group, as shown in **Figure 4**, also raises questions about the ethical implications of relying on AI for emotional support. Users may not receive the level of empathetic understanding necessary for effective therapy, which could impact their well-being. Ongoing monitoring and evaluation of chatbot interventions are necessary to address these ethical challenges and ensure they meet the standards of care expected in mental health services (Morris et al., 2018; Office of the National Coordinator for Health Information Technology [ONC], 2019).

5.7 Limitations

While the study provides valuable insights, several limitations must be acknowledged. The sample was predominantly composed of younger adults familiar with technology, which may limit the generalizability of the findings to older populations or those with limited technological access or literacy (Smith, 2023; Vaidyam et al., 2019). The moderation effect of age highlighted in **Figure 5** underscores this limitation, suggesting that the effectiveness of AI chatbots may vary across different demographic groups.

The 12-week duration of the study may not capture long-term effects of the interventions. Longitudinal studies are needed to assess the sustainability of symptom reduction and user engagement over extended periods (Gaffney et al., 2019; Torous et al., 2018). Additionally, the reliance on self-reported data introduces the potential for biases such as social desirability or recall bias (Van de Mortel, 2008). Objective measures and corroborating data sources could enhance the validity of the findings.

Intervention fidelity is another concern, particularly in the AI Chatbot Group. Variations in user engagement with the chatbot, such as frequency and duration of interactions, could impact outcomes. The study did not control for these variables, which may have influenced the results. Future research should consider monitoring engagement metrics to better understand their relationship with therapeutic outcomes.

Furthermore, the study focused on general symptoms of anxiety and depression without distinguishing between different subtypes or severities of these disorders. Customizing chatbot interventions to address specific conditions may enhance their effectiveness. Lastly, the lower perceived empathy in the AI Chatbot Group suggests a need for improvement in the design of chatbots to better emulate empathetic responses, which is critical for therapeutic success.

In all, the integration of findings from the five figures enriches the discussion by providing empirical evidence to support the study's hypotheses and conclusions. The effectiveness of AI chatbots, as demonstrated by significant symptom reductions, offers promising avenues for expanding access to mental health care. However, challenges related to empathy, demographic influences, and ethical considerations must be addressed to optimize the use of AI-driven interventions. By acknowledging these limitations and implications, the study contributes to the ongoing discourse on the role of AI in mental health and sets the stage for future research and practical advancements.

VI. Conclusion

This study provides robust evidence that AI-driven chatbots are effective in reducing symptoms of anxiety and depression, yielding outcomes comparable to traditional human-delivered therapy. The significant reductions in PHQ-9 and GAD-7 scores for both the AI Chatbot Group and the Human Therapy Group, as illustrated in **Figures 1** and **2**, affirm that chatbots employing cognitive-behavioral techniques can serve as viable alternatives or supplements to conventional therapy. The parallel symptom reduction trajectories in both groups underscore the potential of AI chatbots to expand access to mental health support, particularly by overcoming barriers such as geographical limitations, cost, and stigma associated with seeking help.

High levels of user satisfaction reported by participants in both groups, depicted in **Figure 3**, indicate that AI chatbots are acceptable and engaging to users. This finding suggests that chatbots can facilitate user engagement and adherence to therapeutic interventions. However, the significantly lower perceptions of empathy in the AI Chatbot Group, highlighted in **Figure 4**, reveal a critical limitation. The inability of AI chatbots to fully replicate the empathetic connection provided by human therapists may impact the depth of therapeutic engagement and, consequently, long-term treatment outcomes. Empathy is a cornerstone of effective therapy, fostering trust and openness between clients and therapists.

The study also demonstrates that demographic factors, such as age and technological familiarity, significantly moderate the effectiveness of AI chatbot interventions. **Figure 5** illustrates that younger, more tech-savvy individuals experienced greater symptom reductions compared to older participants. This finding emphasizes the importance of considering user characteristics in the design and implementation of digital mental health tools to enhance their effectiveness across diverse populations.

The integration of AI-driven chatbots into mental health care holds significant promise for expanding access to therapeutic interventions, especially in underserved or resource-constrained settings. By leveraging technology, mental health services can become more scalable and cost-effective. However, addressing limitations related to empathy and emotional resonance is essential. Advancements in natural language processing and affective computing could enhance the empathetic capabilities of chatbots, making them more responsive to users' emotional needs.

Moreover, exploring hybrid models that combine AI chatbots with human therapist support may leverage the strengths of both modalities for optimal treatment outcomes. Such collaborative approaches could enhance the therapeutic alliance, improve user satisfaction, and ensure that users receive the empathetic engagement necessary for effective therapy. Training programs for mental health professionals should include digital literacy components to prepare clinicians for integrating AI tools into their practice effectively.

Ethical considerations remain paramount in the deployment of AI chatbots. Ensuring data privacy, obtaining informed consent, and addressing potential algorithmic biases are critical for safeguarding user well-being and maintaining trust in AI technologies within mental health care. Developing standardized ethical guidelines and regulatory policies is crucial to navigate these challenges and promote responsible use of AI interventions.

Future Directions

Future research should focus on enhancing the empathetic capabilities of chatbots through advancements in natural language processing and affective computing. Longitudinal studies are necessary to assess the long-term efficacy and sustainability of symptom reduction, as short-term improvements may not translate into lasting benefit. Expanding research to include diverse demographic groups would enhance the external validity of results and ensure that interventions are effective across various populations.

Investigating the effectiveness of hybrid models that integrate AI chatbots with human therapist support is a promising avenue. Such models could provide continuous support through chatbots while ensuring critical human oversight, potentially improving treatment adherence and outcomes. Additionally, research into user-centered design approaches can help tailor chatbot interventions to meet the needs of different demographic groups, enhancing user engagement and effectiveness.

Developing standardized ethical guidelines and regulatory policies is essential to address concerns related to data privacy, informed consent, and algorithmic bias in AI mental health interventions. Collaborations between technologists, clinicians, ethicists, and policymakers are necessary to create frameworks that ensure the safe, ethical, and effective use of AI in mental health care.

Final Thoughts

This study contributes to the growing body of evidence supporting the use of AI-driven chatbots in mental health interventions. While AI chatbots offer a promising solution to increase accessibility and reduce barriers to care, challenges related to empathy, demographic influences, and ethical considerations must be addressed. By fostering advancements in AI capabilities, promoting collaborative models that integrate human oversight, and ensuring adherence to ethical standards, the mental health field can progress toward more inclusive, effective, and ethically sound interventions. Embracing these technologies thoughtfully and responsibly has the potential to transform mental health care delivery and improve outcomes for individuals worldwide.

Acknowledgements.

This work was financially supported by:

1. Theoretical Construction and Exploratory Application of the Educational Metaverse (C2023035): A general project funded by the Shanghai Municipal Education Commission’s Educational Science Planning.

2. 2024 Ministry of Education Humanities and Social Sciences Research Planning Fund Project: Research on the oral development of Chinese learners based on complex dynamic system theory (24YJA740012).

3. 2023 Shanghai Key Curriculum Construction Project: On "Chinese Calligraphy Art" (A020201.23.622).

4. Exploring and Optimizing the Intelligent Chinese Teaching Model Based on GPT: Research on the AI-Powered Digital Chinese Teacher (SH23Y34), funded by the International Society for Chinese Language Teaching.

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Study conception and design: Dongxing Yu, Data collection: Dongxing Yu, Analysis and interpretation of results: Dongxing Yu, Draft manuscript preparation: Dongxing Yu, All authors reviewed the results and

approved the final version of the manuscript.