

**ENHANCING TREATMENT EFFICACY AND USER ENGAGEMENT IN MENTAL HEALTH CARE: INTEGRATING AI INTO TRADITIONAL THERAPEUTIC PRACTICES AND ADDRESSING ETHICAL CONSIDERATIONS**

Dr. Kashifa Yasmeen<sup>1</sup>, Dr. Shahid Nadeem<sup>2</sup>, Hassan Imran (Corresponding Author)<sup>3</sup>, Amna Bibi<sup>4</sup> Tayyeba Ahmad<sup>5</sup>, Muhammad Mansoor Abbas<sup>6</sup>, Asif Ali Jauhar<sup>7</sup>

<sup>1</sup> Assistant Professor, Department of Applied Psychology, University of Sahiwal, Pakistan, Email: [kashifa@uosahiwal.edu](mailto:kashifa@uosahiwal.edu)

<sup>2</sup> Professor, Department of Management Science, University of Central Punjab Lahore, Pakistan, Email: [shahid.nadeem@ucp.edu.pk](mailto:shahid.nadeem@ucp.edu.pk)

<sup>3</sup> PhD Scholar, Department of Psychology, Riphah International University Faisalabad Campus Pakistan, Email: [hassanimran332@gmail.com](mailto:hassanimran332@gmail.com)

<sup>4</sup> MS Scholar, Department of Psychology, The University of Lahore, Main Campus, Pakistan, Email: [amnabibil197@gmail.com](mailto:amnabibil197@gmail.com)

<sup>5</sup> Lecturer, Department of Psychology NUML University Faisalabad Campus, Pakistan. Email: [tayyeba.ahmad@numl.edu.pk](mailto:tayyeba.ahmad@numl.edu.pk)

<sup>6</sup> PhD Scholar, Department of Psychology, Riphah International University Faisalabad Campus Pakistan, Email: [msrao264@gmail.com](mailto:msrao264@gmail.com)

<sup>7</sup> PhD Scholar, Department of Psychology, Riphah International University Faisalabad Campus Pakistan, Email: [asifalijohar786786@gamil.com](mailto:asifalijohar786786@gamil.com)

**Abstract**

This study examines the integration of artificial intelligence (AI) into mental health care, focusing on its impact on treatment efficacy, user engagement, and ethical considerations. As mental health issues rise globally, AI tools such as chatbots and predictive analytics are emerging to complement traditional therapeutic practices by offering personalized support and real-time monitoring. The study employs a mixed-methods approach, utilizing quantitative assessments with a sample of 100 practitioners and 200 patients, combined with qualitative insights from semi-structured interviews. Data were collected through validated tools like the PHQ-9 and GAD-7 to measure treatment outcomes, and thematic analysis explored ethical concerns, including privacy and the authenticity of AI-driven therapeutic relationships. Results indicated significant improvements in depression and anxiety symptoms, with user engagement serving as a key mediator in enhancing treatment efficacy. Structural equation modeling (SEM) further highlighted the importance of engagement in translating AI interventions into meaningful clinical outcomes. However, the study is limited by its reliance on self-reported data and a geographically specific sample. These findings suggest that while AI has the potential to improve mental health outcomes, its success largely depends on fostering high levels of user engagement. Future research should explore diverse populations and investigate the long-term effects of AI in mental health care, focusing on how different AI tools perform across various mental health conditions. By understanding these dynamics, mental health

practitioners can better integrate AI into their practices, ensuring ethical considerations are met while optimizing treatment outcomes. Keywords: AI, mental health, user engagement, treatment

**Keywords:** Artificial Intelligence, Mental Health, AI Enhanced Therapy, User Engagement, Treatment Efficacy, Mental Health Efficacy, Ethical Considerations.

## **Introduction**

The integration of artificial intelligence (AI) into traditional therapeutic practices represents a transformative shift in mental health care, offering the potential to enhance treatment efficacy, improve user engagement, and address ethical considerations. AI tools, such as chatbots and virtual assistants, are increasingly being utilized to supplement traditional therapies, providing patients with immediate support and personalized resources (Fitzpatrick et al., 2017). These technologies can facilitate continuous monitoring of emotional states, enabling therapists to better tailor interventions based on real-time data (Bickmore et al., 2010). Furthermore, AI can enhance user engagement by providing accessible, on-demand support, which is particularly crucial for individuals who may hesitate to seek in-person therapy (Kumar et al., 2020). However, the implementation of AI in mental health raises significant ethical concerns, including issues of privacy, data security, and the authenticity of the therapeutic relationship (Binns, 2018). As AI systems collect and analyze sensitive emotional data, maintaining confidentiality and ensuring informed consent become paramount (Vayena et al., 2018). This complex landscape necessitates a careful examination of how AI can complement traditional therapeutic practices while navigating the associated challenges.

## **Enhancing Treatment Efficacy**

AI's capacity to enhance treatment efficacy is rooted in its ability to analyze vast amounts of data quickly and accurately. Machine learning algorithms can identify patterns in a patient's responses over time, enabling therapists to detect changes in emotional states that may not be immediately apparent (Wang et al., 2020). This data-driven approach can lead to more personalized treatment plans, as therapists can tailor interventions based on specific insights derived from AI analyses. Moreover, AI can facilitate evidence-based practices by integrating research findings into therapeutic approaches, allowing clinicians to apply the most effective techniques for each patient's unique situation (Scherer et al., 2019). By bridging the gap between research and practice, AI has the potential to improve clinical outcomes significantly.

## **Improving User Engagement**

User engagement is crucial for effective therapy, and AI technologies can play a vital role in fostering this engagement. Digital platforms powered by AI can offer users interactive features, such as gamified therapy modules or personalized progress tracking, which can motivate individuals to actively participate in their mental health journey (Hollis et al., 2017). Additionally, AI-driven chatbots can provide 24/7 support, making mental health resources accessible outside traditional office hours (Fitzpatrick et al., 2017). This immediacy can be particularly beneficial for individuals experiencing crises or those who might otherwise delay seeking help. The ability to engage with AI tools at their convenience can empower users to take charge of their mental health and enhance their commitment to therapeutic processes.

## **Addressing Ethical Considerations**

Despite the potential benefits of integrating AI into therapeutic practices, ethical considerations must be prioritized. Issues of privacy and data security are paramount, especially as AI systems

handle sensitive information about users' mental health. Ensuring that data is stored securely and used responsibly is critical to maintaining user trust (Vayena et al., 2018). Furthermore, the authenticity of AI interactions raises questions about the nature of therapeutic relationships. While AI can simulate empathy and support, it lacks genuine human understanding, which can be essential for effective therapy (Binns, 2018). As such, ethical frameworks must be established to guide the responsible use of AI in mental health, ensuring that technology complements rather than replaces the human elements of care.

### **Future Directions**

Looking ahead, the integration of AI into traditional therapeutic practices presents both opportunities and challenges that warrant ongoing research and dialogue. Future studies should focus on longitudinal assessments of AI's impact on treatment outcomes, user engagement, and the ethical landscape of mental health care (Kumar et al., 2020). Additionally, interdisciplinary collaboration between mental health professionals, ethicists, and technologists is essential to develop best practices that prioritize patient welfare while harnessing the capabilities of AI. As the field continues to evolve, a balanced approach that emphasizes both technological innovation and the core principles of therapeutic care will be vital for optimizing mental health interventions in the digital age.

### **Background and Context**

The integration of artificial intelligence (AI) into mental health care is a growing field that aims to enhance traditional therapeutic practices. As mental health issues become more prevalent, there is an increasing demand for accessible and effective treatment options. AI technologies, such as chatbots and predictive analytics, offer innovative solutions that can complement human therapists, providing personalized support and facilitating real-time monitoring of patients' emotional states. However, this integration also raises significant ethical concerns regarding privacy, data security, and the authenticity of therapeutic relationships.

#### **Statement of the Problem**

Despite the potential benefits of AI in enhancing therapeutic practices, there is limited understanding of how these technologies impact treatment efficacy, user engagement, and ethical considerations in mental health care. Furthermore, the lack of comprehensive frameworks for integrating AI into existing therapeutic models poses challenges for practitioners and patients alike, necessitating a critical examination of these dynamics.

### **Significance of the Study**

This study aims to bridge the gap between technological innovation and mental health care practices. By investigating the intersection of AI and therapy, the findings will provide valuable insights for practitioners, policymakers, and researchers, promoting the responsible and effective use of AI in improving mental health outcomes.

### **Scope and Delimitations**

The study will focus on the integration of AI in therapeutic practices within adult mental health care. It will examine various AI tools, including chatbots and predictive analytics, while excluding the application of AI in non-therapeutic settings or among populations with specific needs (e.g., children, severe mental illness).

#### **Theoretical Framework**

**Unified Theory of Acceptance and Use of Technology (UTAUT).** Developed by Venkatesh et al. (2003), UTAUT consolidates several models to understand user acceptance of technology. It

identifies key constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions as significant factors influencing technology adoption. This framework can provide a comprehensive understanding of how these elements interact in the context of integrating AI tools into therapeutic practices.

### **Research Objectives**

1. To quantitatively assess the impact of AI tools on treatment outcomes in mental health therapy, focusing on specific disorders (e.g., anxiety, depression).
2. To analyze how AI-enhanced interventions influence user engagement metrics, including adherence rates and frequency of interaction with therapeutic tools.
3. To investigate the ethical challenges posed by AI in mental health care, particularly regarding data privacy, informed consent, and algorithmic bias.
4. To propose a structured framework for effectively integrating AI technologies into existing therapeutic practices, ensuring alignment with clinical guidelines and patient needs.

### **Research Questions**

1. What measurable improvements in treatment outcomes can be attributed to the use of AI tools compared to traditional therapeutic methods?
2. How do AI-enhanced therapeutic tools affect patient engagement levels, including session frequency and duration, compared to conventional therapy?
3. What specific ethical concerns do mental health professionals identify regarding the implementation of AI technologies, and what strategies can mitigate these issues?
4. What best practices can be identified for integrating AI into traditional therapeutic frameworks that enhance efficacy while maintaining ethical standards?

### **Literature Review**

The integration of artificial intelligence (AI) into mental health care has gained traction in recent years, prompting significant research on its potential to enhance treatment efficacy. Studies indicate that AI technologies, such as machine learning algorithms and natural language processing, can improve diagnostic accuracy and personalize treatment plans. For instance, AI-driven predictive analytics have shown promise in identifying at-risk individuals and tailoring interventions based on individual characteristics and historical data (Bach et al., 2021). This shift toward personalized care aligns with the growing emphasis on precision medicine in mental health, which seeks to provide more effective, individualized treatments based on patient data. User engagement is another critical area where AI can play a transformative role. Traditional therapeutic practices often struggle with patient adherence and engagement, leading to suboptimal outcomes. Research has shown that AI tools, such as chatbots and mobile health applications, can enhance patient interaction by providing real-time feedback and support outside of therapy sessions (Fitzpatrick et al., 2017). These tools not only facilitate continuous communication between therapists and patients but also empower individuals to take an active role in their treatment. By leveraging gamification and personalized content, AI applications have been shown to significantly increase user engagement and motivation, ultimately improving adherence to therapeutic protocols.

However, the integration of AI in mental health care raises significant ethical considerations that must be addressed. Concerns regarding data privacy, informed consent, and algorithmic bias are paramount, as AI systems often rely on large datasets that may contain sensitive personal information (O’Neil, 2016). Ethical frameworks are needed to ensure that AI tools are used responsibly and transparently, safeguarding patient autonomy and privacy. Recent literature emphasizes the importance of developing guidelines that address these ethical challenges while

promoting the responsible use of AI technologies in clinical settings (Davenport & Kalakota, 2019). To effectively incorporate AI into traditional therapeutic practices, a structured integration framework is essential. Studies suggest that a collaborative approach involving mental health professionals, technologists, and ethicists can facilitate the seamless adoption of AI tools (Bickmore et al., 2020). Such frameworks should prioritize training for clinicians, ensuring they are equipped to use AI tools effectively while remaining sensitive to the ethical implications. By fostering a multidisciplinary dialogue, the mental health field can harness the benefits of AI while mitigating risks, ultimately leading to improved patient outcomes and enhanced therapeutic practices.

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Research indicates that AI-enhanced interventions often yield positive outcomes in terms of treatment efficacy. For instance, meta-analyses have shown that digital therapeutics utilizing AI can reduce symptoms of depression and anxiety more effectively than traditional therapies alone (Krebs et al., 2021). Furthermore, AI applications can facilitate data-driven insights, allowing practitioners to tailor their approaches based on individual patient needs, thus enhancing overall treatment effectiveness (Harrison et al., 2022). Such evidence underscores the potential of AI to revolutionize therapeutic practices by providing more personalized and responsive care. User engagement is a critical factor in the success of mental health interventions. Studies suggest that AI tools can significantly improve user adherence and participation rates by offering interactive and accessible support (Moreno et al., 2021). For example, platforms utilizing conversational agents have reported higher user satisfaction and engagement levels due to their user-friendly interfaces and round-the-clock availability (Bickmore et al., 2019). By fostering a more engaging therapeutic experience, AI can help bridge the gap between traditional practices and the needs of modern patients.

However, the integration of AI in mental health care also raises significant ethical considerations. Issues such as data privacy, algorithmic bias, and informed consent are paramount. Research has highlighted concerns regarding the potential for AI systems to perpetuate biases present in training data, which could adversely affect marginalized populations (Obermeyer et al., 2019). Ethical frameworks emphasizing beneficence, autonomy, and justice are essential in guiding the development and implementation of AI technologies in therapeutic settings, ensuring that they serve to enhance rather than hinder patient care (Hoffman et al., 2020). Despite the promising findings, gaps in the literature remain. For instance, there is a lack of longitudinal studies that assess the long-term efficacy of AI-enhanced therapies compared to traditional methods.

Additionally, research exploring diverse populations and cultural contexts is limited, which may hinder the generalizability of current findings (Bennett et al., 2021). Addressing these gaps will be crucial for the continued advancement and acceptance of AI in mental health care.

Integrating AI into traditional therapeutic practices has the potential to significantly enhance treatment efficacy, improve user engagement, and address critical ethical issues. By utilizing a theoretical framework that incorporates the Technology Acceptance Model (TAM) and the Health Belief Model (HBM), researchers can further explore the factors influencing the adoption of AI in therapy and the implications for user participation. The ongoing exploration of these dynamics will be essential for maximizing the benefits of AI while minimizing potential risks in mental health care (Lund et al., 2021).

## **Methodology**

### **Research Design**

This study employs a mixed-methods research design, combining quantitative and qualitative approaches to provide a comprehensive understanding of the integration of AI into traditional therapeutic practices. By using both numerical data and narrative insights, this design allows for a more nuanced exploration of the efficacy, engagement, and ethical implications of AI-enhanced therapies.

### **Research Approach**

The research will utilize a pragmatic approach, focusing on practical outcomes and the applicability of findings to real-world settings. This approach is well-suited for investigating the integration of AI technologies in mental health, as it emphasizes the importance of both measurable outcomes and user experiences.

### **Population and Sample**

The target population for this study included mental health practitioners and patients currently using or exposed to AI-enhanced therapeutic interventions. A purposive sampling method will be employed to select approximately 100 practitioners and 200 patients from various mental health facilities, ensuring a diverse representation across demographics, including age, gender, and socioeconomic status.

### **Data Collection Methods**

Data was collected through a combination of surveys and semi-structured interviews. The surveys assessed treatment efficacy and user engagement metrics, utilizing validated scales such as the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder Scale (GAD-7). Semi-structured interviews provided deeper insights into the experiences and perceptions of both practitioners and patients regarding the use of AI in therapy.

### **Data Analysis Procedures**

Quantitative data was analyzed using statistical software (SPSS) to conduct descriptive and inferential statistics. The analysis included comparing pre- and post-intervention scores to evaluate treatment efficacy. Qualitative data from the interviews was transcribed and analyzed thematically, allowing for the identification of common themes related to user engagement and ethical considerations.

### Ethical Considerations

Ethical approval was obtained from an institutional review board (IRB) before the study commenced. Informed consent was secured from all participants, ensuring they understood the purpose of the research and their right to withdraw at any time. Confidentiality was maintained by anonymizing participant data and securely storing information.

### Limitations of the Methodology

Several limitations were acknowledged. The reliance on self-reported data may have introduced bias, as participants might have overestimated their engagement or treatment outcomes. Additionally, the study's focus on a specific geographic area limited the generalizability of findings to broader populations. Finally, the rapidly evolving nature of AI technology meant that results might quickly become outdated as new tools and practices emerged.

### Results

Table 1 Demographic Characteristics of Participants

Characteristic	Practitioners ( <i>n</i> =100)	Patients ( <i>n</i> =200)
Age (Mean ± SD)	40.5 ± 8.2	34.2 ± 12.1
Gender		
Male	40 (40%)	80 (40%)
Female	60 (60%)	120 (60%)
Ethnicity		
Caucasian	50 (50%)	100 (50%)
African American	20 (20%)	40 (20%)
Hispanic	15 (15%)	30 (15%)
Other	15 (15%)	30 (15%)
Experience (Years)	15.3 ± 7.5	-

The study sample includes 100 practitioners and 200 patients. Practitioners have a mean age of 40.5 years (SD = 8.2) and an average of 15.3 years of experience, indicating a mature and experienced professional cohort. Patients are younger, with a mean age of 34.2 years (SD = 12.1). Gender distribution is balanced, with 40% males and 60% females in both groups. Ethnic diversity is notable, with 50% Caucasian, 20% African American, and 15% Hispanic participants. This diverse demographic allows for a comprehensive examination of the integration of AI in mental health care across various backgrounds.

Table 2 Treatment Efficacy

Measure	Pre-Intervention (Mean ± SD)	Post-Intervention (Mean ± SD)	F-value	p-value	Partial $\eta^2$
PHQ-9	12.4 ± 4.5	6.7 ± 3.8	37.89	<0.001	0.38
GAD-7	10.2 ± 4.0	5.1 ± 3.2	34.76	<0.001	0.36

Table 2 treatment efficacy results revealed significant improvements in both depression and anxiety symptoms following the intervention. The PHQ-9 scores showed a substantial decline from a mean of 12.4 (SD = 4.5) pre-intervention to 6.7 (SD = 3.8) post-intervention, with an F-value of 37.89 and a p-value of <0.001, indicating a strong statistical significance and a large effect size (partial  $\eta^2 = 0.38$ ). Similarly, GAD-7 scores decreased from a mean of 10.2 (SD = 4.0) to 5.1 (SD = 3.2), supported by an F-value of 34.76 and a p-value of <0.001, also reflecting a significant impact with a substantial effect size (partial  $\eta^2 = 0.36$ ). These findings underscore the effectiveness of the AI-enhanced therapeutic intervention in significantly alleviating both depression and anxiety symptoms among participants.

**Table 3 Hierarchical Regression Analysis for User Satisfaction**

Predictor	$\beta$	SE	t-value	p-value
Demographics				
Age	-0.15	0.05	-3.00	0.003
Gender (Female = 1)	0.10	0.10	1.00	0.317
Step 2: Frequency of Use				
Frequency of Use	0.45	0.08	5.63	<0.001
Step 3: Perceived Effectiveness				
	0.30	0.07	4.29	<0.001

Table 3 The hierarchical regression analysis revealed significant predictors of user satisfaction with the AI-enhanced intervention. Age negatively influenced satisfaction ( $\beta = -0.15$ ,  $p = 0.003$ ), indicating older participants were less satisfied. Gender was not a significant predictor ( $\beta = 0.10$ ,  $p = 0.317$ ). Importantly, frequency of use ( $\beta = 0.45$ ,  $p < 0.001$ ) and perceived effectiveness ( $\beta = 0.30$ ,  $p < 0.001$ ) were strong positive predictors, suggesting that higher engagement and greater perceived effectiveness significantly enhance user satisfaction.

**Table 4 Correlation Analysis**

Variable	1	2	3	4
PHQ-9 Change	-			
GAD-7 Change	0.85**	-		
Frequency of Use	0.60**	0.55**	-	
Satisfaction Rating	0.70**	0.65**	0.80**	-

**$p < 0.001$ ,  $p < 0.01$ ,  $p < 0.05$**

The correlation analysis highlights significant relationships among the key variables. Changes in PHQ-9 scores (depression) were strongly correlated with changes in GAD-7 scores (anxiety) ( $r = 0.85$ ,  $p < 0.01$ ), indicating that improvements in depression are associated with reductions in anxiety. Additionally, both PHQ-9 change and GAD-7 change were positively correlated with frequency of use ( $r = 0.60$ ,  $p < 0.01$ ;  $r = 0.55$ ,  $p < 0.01$ , respectively), suggesting that increased engagement with the AI tools correlates with better mental health outcomes. Furthermore, satisfaction ratings exhibited strong positive correlations with both PHQ-9 change and GAD-7 change ( $r = 0.70$ ,  $p < 0.01$ ;  $r = 0.65$ ,  $p < 0.01$ ), as well as with frequency of use ( $r = 0.80$ ,  $p < 0.01$ ). These findings underscore the interconnectedness of treatment outcomes, user engagement, and satisfaction with AI interventions.



**Table 5 Mediation Analysis Results**

Path	Estimate	SE	95% CI
AI Intervention → User Engagement (a)	0.45	0.08	[0.30, 0.60]
User Engagement → Treatment Efficacy (b)	0.50	0.10	[0.30, 0.70]
Total Effect (c)	0.75	0.09	[0.57, 0.93]
Indirect Effect (ab)	0.225	0.05	[0.15, 0.35]

The mediation analysis results indicated significant relationships among the variables involved. The path from the *AI intervention to user engagement* (a) was estimated at 0.45 (SE = 0.08), with a 95% confidence interval (CI) of [0.30, 0.60], suggesting a positive impact of the intervention on engagement. User engagement subsequently influenced *treatment efficacy* (b), with an estimate of 0.50 (SE = 0.10) and a 95% CI of [0.30, 0.70], further supporting the notion that higher engagement levels enhanced treatment outcomes. The *total effect* (c) was significant at 0.75 (SE = 0.09), with a 95% CI of [0.57, 0.93], indicating a robust overall impact. Additionally, the *indirect effect* (ab) was estimated at 0.225 (SE = 0.05), with a 95% CI of [0.15, 0.35], highlighting that user engagement mediated the relationship between the AI intervention and treatment efficacy. These findings underscored the importance of user engagement in facilitating the positive effects of AI interventions on mental health outcomes.

**Table 6 ANCOVA Results for Treatment Efficacy**

Measure	F-value	p-value	Partial $\eta^2$
PHQ-9	29.67	<0.001	0.34
GAD-7	25.43	<0.001	0.32

The Multivariate Analysis of Covariance (MANCOVA) results demonstrated significant effects of the AI-enhanced intervention on both depression and anxiety measures. For the PHQ-9, the analysis yielded an F-value of 29.67 with a p-value of <0.001 and a partial  $\eta^2$  of 0.34, indicating a large effect size and substantial improvement in depressive symptoms. Similarly, the GAD-7 scores showed a significant F-value of 25.43 ( $p < 0.001$ ) and a partial  $\eta^2$  of 0.32, reflecting a strong effect on anxiety symptoms. These findings highlight the effectiveness of the intervention in significantly reducing both depression and anxiety among participants.

**Table 7 Cluster Analysis Results**

Cluster	Frequency of Use (Mean $\pm$ SD)	Satisfaction Rating (Mean $\pm$ SD)	<i>n</i>
1	1.5 $\pm$ 0.5	3.0 $\pm$ 0.6	50
2	4.5 $\pm$ 0.5	4.5 $\pm$ 0.5	100
3	6.0 $\pm$ 1.0	4.9 $\pm$ 0.3	50

The cluster analysis revealed distinct patterns in frequency of use and satisfaction ratings among participants. In **Cluster 1**, which included 50 participants, the mean frequency of use was low at 1.5 (SD = 0.5), accompanied by a relatively low satisfaction rating of 3.0 (SD = 0.6), indicating that infrequent engagement with the AI tools correlates with diminished satisfaction. **Cluster 2**, comprising 100 participants, showed a moderate frequency of use (Mean = 4.5, SD = 0.5) alongside a higher satisfaction rating of 4.5 (SD = 0.5), suggesting that regular engagement leads to improved satisfaction. Finally, **Cluster 3** reported the highest frequency of use at 6.0 (SD = 1.0) and the highest satisfaction rating of 4.9 (SD = 0.3) among its 50 participants, reinforcing the idea that greater engagement significantly enhances satisfaction. Overall, these findings highlight a clear positive relationship between the frequency of AI tool usage and user satisfaction, underscoring the importance of active participation in the therapeutic experience.

**Table 8 Logistic Regression Results for Treatment Response**

Predictor	$\beta$	SE	Odds Ratio (OR)	p-value
Frequency of Use	0.55	0.20	1.73	0.002
Perceived Effectiveness	0.70	0.25	2.01	0.005
Engagement Cluster (High vs. Low)	1.25	0.30	3.49	<0.001

Table 8, the logistic regression analysis identified several significant predictors of positive outcomes related to the AI-enhanced intervention. **Frequency of use** emerged as a strong predictor, with a coefficient ( $\beta$ ) of 0.55 (SE = 0.20), indicating an odds ratio (OR) of 1.73 ( $p = 0.002$ ). This suggests that for each unit increase in frequency of use, the likelihood of positive outcomes increases by 73%. Similarly, **perceived effectiveness** was a significant predictor, with a  $\beta$  of 0.70 (SE = 0.25) and an OR of 2.01 ( $p = 0.005$ ), indicating that higher perceptions of effectiveness more than double the odds of achieving positive outcomes. Finally, participants in the **high engagement cluster** compared to the low engagement cluster showed a substantial effect, with a  $\beta$  of 1.25 (SE = 0.30) and an OR of 3.49 ( $p < 0.001$ ), highlighting that high engagement significantly enhances the probability of favorable results. Overall, these findings emphasize the critical roles of both user engagement and perceived effectiveness in achieving successful outcomes with AI interventions.

**Table 9 Bayesian Model Results**

Parameter	Estimate	95% CI
Intercept	3.50	[2.80, 4.20]
Treatment Type (AI)	-2.40	[-3.10, -1.70]
User Engagement	-1.20	[-1.80, -0.70]
Variance (Patients)	0.70	[0.50, 1.00]

Table 9, the Bayesian hierarchical modeling results provide valuable insights into the effects of treatment type and user engagement on outcomes. The *intercept* is estimated at 3.50, with a 95% confidence interval (CI) of [2.80, 4.20], indicating a baseline effect on the outcomes. The model reveals that the *treatment type* (AI) has a negative estimate of -2.40 (95% CI: [-3.10, -1.70]), suggesting that the AI intervention is associated with significantly improved outcomes compared to traditional methods. Additionally, *user engagement* shows a negative estimate of -1.20 (95% CI: [-1.80, -0.70]), indicating that higher engagement levels are linked to better results. The *variance among patients* is estimated at 0.70 (95% CI: [0.50, 1.00]), reflecting individual differences in treatment response. Overall, these findings reinforce the effectiveness of AI interventions and highlight the importance of user engagement in optimizing therapeutic outcomes.

**Table 10 SEM Results**

Path	Estimate	SE	CR	p-value
Treatment Efficacy → User Engagement	0.45	0.09	5.00	<0.001
User Engagement → PHQ-9 Change	-0.40	0.10	-4.00	<0.001
User Engagement → GAD-7 Change	-0.35	0.09	-3.89	<0.001

Table 10, the Structural Equation Modeling (SEM) analysis reveals significant pathways influencing treatment outcomes. The path from **treatment efficacy to user engagement** has an estimate of 0.45 (SE = 0.09), with a critical ratio (CR) of 5.00 and a p-value of <0.001, indicating a strong positive relationship. This suggests that increased efficacy of the AI intervention is associated with higher levels of user engagement. Furthermore, user engagement negatively impacts changes in PHQ-9 scores, with an estimate of -0.40 (SE = 0.10) and a CR of -4.00 (p < 0.001), indicating that greater engagement leads to a significant reduction in depressive symptoms. Similarly, user engagement also negatively influences changes in GAD-7 scores, with an estimate of -0.35 (SE = 0.09) and a CR of -3.89 (p < 0.001), signifying that enhanced engagement correlates with reduced anxiety levels. Overall, these results highlight the critical role of user engagement as a mediator between treatment efficacy and mental health outcomes.

## Discussion

The results of this study demonstrated that the AI-enhanced intervention significantly improved both depression (PHQ-9) and anxiety (GAD-7) symptoms, aligning with the hypotheses that increased frequency of use and perceived effectiveness positively impacted treatment outcomes. The findings indicate that user engagement acts as a crucial mediator between the AI intervention and treatment efficacy, suggesting that higher engagement not only enhances user satisfaction but also leads to better mental health outcomes. Specifically, the strong negative correlation between user engagement and both PHQ-9 and GAD-7 changes highlights the effectiveness of the intervention in reducing symptoms when users are actively engaged. Furthermore, the mediation analysis underscored the importance of user engagement in translating the benefits of the AI intervention into meaningful clinical outcomes. The indirect effect observed indicates that while the AI intervention was effective on its own, the extent to which users engaged with the platform played a pivotal role in achieving those improvements. This finding emphasizes the necessity for mental health practitioners to actively promote user engagement strategies to optimize treatment effects.

Moreover, the structural equation modeling (SEM) results provided robust evidence of the pathways through which treatment efficacy and user engagement influence mental health outcomes. The significant paths connecting treatment efficacy to user engagement and

subsequently to changes in PHQ-9 and GAD-7 scores suggest a clear framework for understanding how AI interventions can be enhanced. Practitioners can leverage these insights to develop targeted interventions that not only focus on the AI tools' effectiveness but also actively cultivate user engagement, ultimately leading to improved mental health results. These results are consistent with existing literature that emphasizes the importance of user engagement in therapeutic interventions. Previous studies have shown that active participation in treatment is associated with improved mental health outcomes (Kazantzis et al., 2010). Additionally, the significant role of perceived effectiveness corroborates findings from research on digital health interventions, which highlight that users who believe in the effectiveness of the tools are more likely to engage and benefit from them (Donker et al., 2013).

### **Implications of Findings**

The study's findings suggest that integrating AI into therapeutic practices can significantly enhance treatment efficacy, particularly when user engagement is prioritized. Mental health practitioners might consider strategies to increase user engagement, such as providing personalized feedback and fostering a sense of community among users. This approach could lead to more effective and sustainable mental health interventions.

### **Limitations of the Study**

Despite its contributions, the study has several limitations. The sample was predominantly from a specific demographic, which may limit the generalizability of the findings. Additionally, the reliance on self-reported measures for engagement and satisfaction may introduce bias. Longitudinal studies are needed to assess the long-term effects of AI interventions on mental health.

### **Practical Applications**

Mental health practitioners can apply these findings by incorporating AI tools that enhance user engagement, such as interactive features or gamified elements that encourage regular use. Training programs for practitioners on how to effectively integrate AI tools into their practice could also facilitate better outcomes.

### **Recommendations**

Future research should explore diverse populations to enhance the generalizability of results. Additionally, investigating the mechanisms through which user engagement influences treatment efficacy could provide deeper insights. Studies could also examine the impact of different types of AI interventions and their effectiveness across various mental health conditions.

### **Conclusion**

This research highlights the transformative potential of integrating AI-enhanced interventions into mental health care. The findings demonstrated that such interventions significantly reduce symptoms of depression and anxiety, emphasizing the critical role of user engagement in this process. By illustrating the strong relationship between treatment efficacy, user engagement, and mental health outcomes, the study underscores the necessity for mental health practitioners to prioritize strategies that enhance user interaction with AI tools. The evidence suggests that as users engage more with these interventions, their perceived effectiveness increases, which in turn contributes to greater symptom relief. Moreover, the implications of this study extend beyond academic contributions; they offer practical applications for mental health professionals. By fostering an environment that encourages regular use and active participation, practitioners can

maximize the benefits of AI interventions, leading to more effective therapeutic outcomes. While the research has its limitations, including a specific demographic focus, it sets a foundation for future studies to explore diverse populations and further investigate the mechanisms of engagement. Ultimately, this research advocates for a collaborative approach in mental health care, where technology and user participation work in tandem to enhance the efficacy of treatment strategies.

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