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Integration of artificial intelligence in mental health therapy: an adaptive model for psychological interventions in the digital era

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Abstract

Background: The rise of mental health disorders has driven the need for accessible and adaptive psychological support through digital means. This study explores user perceptions of adaptive AI in mental health therapy, focusing on interaction quality and effectiveness.
Aim: This study aims to examine the relationship between the adaptive intelligence of AI systems and the quality of psychological interaction on the perceived effectiveness of interventions in AI-based digital therapy.
Method: Employing a descriptive correlational quantitative approach, data were collected from 30 users of mental health AI therapy applications such as Woebot and Wysa. The instrument used was a Likert-scale questionnaire (1–5), and the data were analyzed using descriptive statistics, Pearson correlation, and simple linear regression via SPSS version 26.
Result: The mean scores for all variables fell within a moderately positive range. However, no significant relationship was found between adaptive intelligence or interaction quality and intervention effectiveness ($r = -0.308$ and $r = -0.001$; $p > 0.05$). The regression model was also not significant ($R^2 = 0.096$; $p = 0.256$), indicating a low contribution of the independent variables to perceived effectiveness.
Conclusion: These findings provide valuable insights for the development of more personalized and empathetic AI systems in digital psychological services, and serve as a foundation for ethical and human-centered AI design and policy integration.

INTRODUCTION

The development of digital technology has brought significant changes to various aspects of human life, including mental health. This transformation encompasses not only how individuals access healthcare services but also how psychological support is delivered and adapted through technological means (Chen et al., 2022a; Hua et al., 2024; Topol, 2018). As the prevalence of mental health disorders particularly depression and anxiety increases, the need for accessible, rapid, and personalized mental health services has become increasingly urgent. According to the World Health Organization (WHO), more than 970 million people worldwide experience mental disorders or substance abuse, with depression and anxiety being the most common (WHO, 2022).

Barriers such as the limited number of mental health professionals, uneven geographic distribution, and persistent social stigma have made access to conventional mental health services highly constrained, particularly in developing countries (Andersson & Titov, 2014). In this context, Artificial Intelligence (AI) has emerged as a potential solution to expand the reach of psychological interventions (Topol, 2018). AI enables the development of systems capable of early detection of mental health issues, delivering preliminary interventions, and providing psychological support virtually (Bickmore & Picard, 2005; Fitzpatrick et al., 2017; Norman, 1998).

One notable application of AI in this field is the use of therapeutic chatbots that leverage Natural Language Processing (NLP) (Calvo et al., 2016; Doraiswamy et al., 2020; Inkster et al., 2018). This technology allows users to interact with the system as if conversing with a counselor or therapist. Chatbots such as Woebot and Wysa have been widely adopted and have shown effectiveness in helping users manage stress and anxiety through automated Cognitive Behavioral Therapy (CBT) approaches (Batra et al., 2017; Fitzpatrick et al., 2017; Tene & Polonetsky, 2013).

Despite their promise, a central challenge in integrating AI into mental health therapy lies in the system's ability to respond to the complex and contextual nature of human psychological dynamics (Lamo et al., 2022a; Suresh & Guttag, 2021). This has led to the emergence of adaptive models AI systems that can tailor intervention strategies based on users' input and emotional states in real-time (Golden et al., 2023). This approach is supported by the theory of Adaptive Artificial Intelligence, which emphasizes a system's capability to continuously learn from interactions and update its responses contextually (Microsoft, 2025; Schreiber, 2001).

Beyond technical capabilities, the effectiveness of AI in psychological therapy also heavily depends on users' perceptions of interaction quality and the empathy conveyed by the system. The Human-Computer Interaction (HCI) theory highlights the importance of interface design and user experience in fostering effective relationships between humans and digital systems (Claridad, n.d.; Norman, 1998; Zainab, 2025). In this regard, AI is expected not only to exhibit technical intelligence but also to interact in a sensitive and supportive manner.

However, there remains a lack of quantitative studies exploring user perceptions of the effectiveness of adaptive AI in mental health therapy (Baumel et al., 2019; Shelton et al., 2021). Most existing research tends to focus on technical aspects or system trials without directly addressing user experiences (Hollis et al., 2018). Therefore, this study aims to fill that gap by examining user perceptions of adaptive intelligence, interaction quality, and the effectiveness of AI-driven psychological interventions. By employing a descriptive quantitative approach, this research is expected to contribute to the development of AI systems that are more responsive, ethical, and human-centered within the digital mental health landscape.

LITERATURE REVIEW

Theoretical Framework

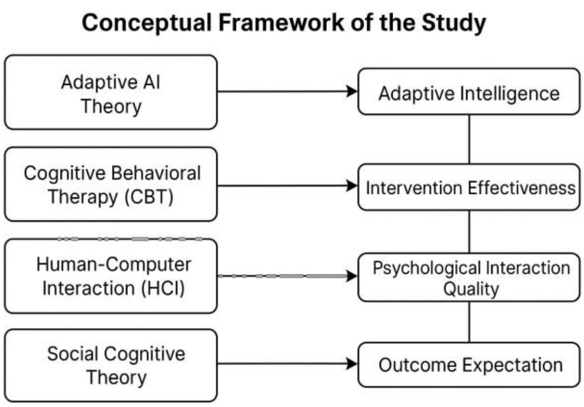
This study is grounded in several theoretical foundations that form the conceptual framework for understanding the integration of Artificial Intelligence (AI) in mental health therapy. First, the Theory of Adaptive Artificial Intelligence (Schreiber, 2001) underpins the development of AI systems capable of dynamically adapting to users' emotional responses. This theory emphasizes the importance of continuous learning from prior interactions to enhance the relevance and effectiveness of digital interventions.

Second, Cognitive Behavioral Therapy (CBT) serves as the basis for automated psychological interventions delivered via chatbot. CBT has been proven effective in addressing various mental health issues such as depression and anxiety and is well-suited for implementation through text-based digital interactions (Fitzpatrick et al., 2017; King, 2002).

Third, Human-Computer Interaction (HCI) is employed as a supporting theory to explain how users' perceptions of interface design, empathy, and usability influence emotional engagement and the successful use of digital services (Bickmore & Picard, 2005; Norman, 1998).

Lastly, Social Cognitive Theory by Bandura, (1986) is used to understand how self-efficacy beliefs formed during interactions with AI can mediate behavioral change and psychological improvement (Bandura, 1986). This theory reinforces the argument that positive digital interaction experiences can foster users' confidence in managing their mental health independently.

Figure 1. Conceptual Framework of the Study



Adaptive Intelligence in AI Systems

Adaptive intelligence refers to an AI system's capability to modify its responses and behaviors based on previous interactions, enabling it to become more personalized, responsive, and context-aware for each user (Hua et al., 2024; Lamo et al., 2022a; Rahsepar Meadi et al., 2025). In the context of mental health therapy, this adaptive capacity is critical, given the dynamic and deeply personal nature of users' psychological conditions

(Golden et al., 2023; Lamo et al., 2022b; Suresh & Guttag, 2021). The theory of Adaptive Artificial Intelligence (Microsoft, 2025; Schreiber, 2001) posits that adaptive systems enhance the effectiveness of digital interactions through continuous learning from user input.

According to Microsoft (2025), adaptive AI does not merely adjust output based on present input but also builds a long-term understanding of users' preferences and emotional patterns to improve service outcomes. Golden et al. (2023) demonstrated that AI systems with adaptive mechanisms can enhance user retention and provide more relevant therapeutic experiences than static systems. The ability of these systems to tailor responses to mood changes underscores the growing significance of adaptive models in digital mental health (Bickmore & Picard, 2005; He et al., 2023; Hua et al., 2024).

Furthermore, the implementation of adaptive AI in therapeutic chatbots has shown promise in improving both the accessibility and efficacy of mental health interventions (Khawaja & Bélisle-Pipon, 2023). AI-powered chatbots offer real-time psychological support, personalized interventions, and reduced access barriers to traditional mental health services (Inkster et al., 2018; Torous et al., 2021).

However, the application of AI in mental health must consider ethical dimensions, user privacy, and data security. While adaptive AI holds great potential, concerns surrounding user trust and the validity of interventions remain critical (Alang, 2019; Doraiswamy et al., 2020; Tene & Polonetsky, 2013).

Psychological Interaction Quality

Psychological interaction quality refers to how users perceive their interactions with AI systems in terms of empathy, emotional comfort, and communication clarity (Bickmore & Picard, 2005; Norman, 1998). According to Human-Computer Interaction (HCI) theory, the success of interactive systems is largely determined by users' perceptions of usability and the system's sensitivity to emotional needs (Calvo et al., 2016; Norman, 1998).

Inkster et al. (2018) examined the effectiveness of Wysa, an AI-based chatbot designed for emotional support, and found that perceived empathy, polite language, and response speed significantly influenced user engagement. In the digital therapy context, even simulated empathy plays a crucial role in the effectiveness of initial psychological support. Thus, interaction quality must be understood as both a technical and psychological construct.

Beyond technical aspects, psychological interaction quality involves components such as trust, a sense of safety, and the comfort to disclose personal issues. Other studies suggest that emotional connectedness facilitated by AI systems can strengthen initial therapeutic alliances, which in turn enhance the effectiveness of digital interventions (Bickmore & Picard, 2005; Fitzpatrick et al., 2017; Thakkar et al., 2024). Therefore, the success of AI in mental health therapy is strongly influenced by the extent to which users perceive their interaction as meaningful and empathetic rather than merely automated.

Effectiveness of AI Interventions

In the realm of digital mental health therapy, the effectiveness of interventions refers to the extent to which AI systems can deliver positive psychological outcomes, such as reduced stress symptoms, improved emotional regulation, and user satisfaction with the therapeutic experience (Andersson & Titov, 2014; Mohr et al., 2017). Effective interventions are characterized by sustained user engagement, perceived helpfulness of responses, and measurable improvements in mental well-being over time (Andersson & Titov, 2014; Fitzpatrick et al., 2017; Linardon et al., 2019a).

Several studies have demonstrated that AI can serve as an effective self-help tool, especially for mild to moderate conditions such as anxiety and situational depression. In an experimental study, Fitzpatrick et al., (2017), found that Woebot, a chatbot based on Cognitive Behavioral Therapy (CBT), significantly reduced symptoms of depression and anxiety within just two weeks. These therapeutic effects are largely attributed to the structured, automated nature of CBT, delivered through friendly and consistent conversations.

A recent study by Hua et al., (2024) revealed that AI systems employing Large Language Models (LLMs) like GPT can generate linguistically and emotionally relevant suggestions, even in cases of mild stress or crisis (Hua et al., 2024). However, such interventions are most effective when customized to the user's cultural and psychological context, including sensitivity to emotional expression and local social norms. Consequently, personalization and adaptiveness are essential to enhancing the success of AI systems in digital mental health services (Linardon et al., 2019b; Naslund et al., 2016; Schreiber, 2001).

Ethics, Privacy, and Technological Challenges

The integration of Artificial Intelligence (AI) into mental health services raises several significant ethical and privacy concerns. AI systems often access and process highly sensitive information, such as mental health status, emotional patterns, and individual psychological vulnerabilities. Various studies have highlighted that the lack of robust security standards, algorithmic transparency, and accountability mechanisms can increase the risk of data misuse and undermine public trust in AI-based digital services (Tene & Polonetsky, 2013).

To address these issues, Mandal et al. (2025) recommend the development of privacy-aware AI models that allow users to control their personal data through encryption and strict access protection systems.

On the other hand, while AI systems have been designed to simulate empathy through language and emotionally attuned responses, their capacity remains limited to surface-level interactions. Such simulations cannot yet replicate the depth and authenticity of emotional connections typically formed in face-to-face therapy. Topol (2018) asserts that AI should be positioned as a complementary tool a "co-therapist" that supports human professionals rather than a total replacement in psychological practice (Bickmore & Picard, 2005; Topol, 2018).

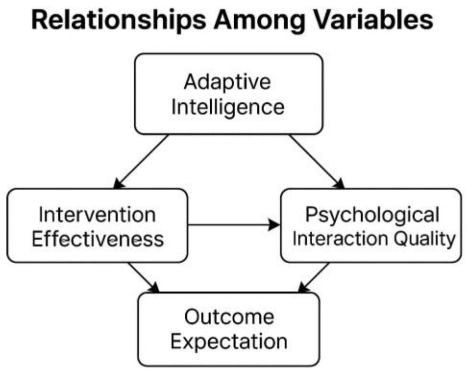
METHODS

Design

This study employed a quantitative approach using a correlational research design. The objective of this approach was to identify the relationship between the adaptive intelligence of AI systems, the quality of psychological interaction, and the effectiveness of interventions in the context of AI-assisted mental health therapy. A quantitative design was selected as it allows for objective measurement of user perceptions and enables statistical analysis of the relationships among variables.

The relationships among the variables examined in this study are illustrated in the following research model.

Figure 2. Relationships Among Variables



Participants

The participants of this study were 30 individuals aged between 18 and 45 years who had actively used Artificial Intelligence (AI)-based mental health applications such as Woebot, Wysa, or Replika for a minimum of two weeks. The sample consisted of 18 females and 12 males, with the majority being university students (60%) and early-career professionals (30%), while the remaining were freelance or unemployed. Most respondents held at least a bachelor's degree (70%), and their average duration of application usage ranged from 2 to 6 weeks. These demographic characteristics were included to ensure that participants had sufficient exposure to AI-driven therapy features and were capable of critically assessing their interaction experiences.

A total of 30 respondents were recruited for this study using purposive sampling. This sample size is considered adequate for preliminary statistical analysis in social and behavioral sciences. According to Roscoe (1975), sample sizes larger than 30 and fewer than 500 are appropriate for most quantitative studies involving correlation or regression analysis (Roscoe, 1975). Furthermore, Hair et al. (2010) support the sufficiency of a minimum of 30 participants for basic multivariate techniques when the model involves a limited number of variables. Therefore, the use of 30 participants in this study meets the minimum statistical requirements for the applied analytical methods (Hair et al., 2010).

Instruments

The research instrument used in this study was a closed-ended questionnaire designed using a 5-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). The instrument was developed based on three main constructs: adaptive intelligence of the AI system, quality of psychological interaction, and intervention effectiveness. Indicators for adaptive intelligence included the system's ability to personalize user experiences, adjust responses based on emotions, and learn from prior interactions. Indicators for psychological interaction quality included emotional comfort, perceived empathy from the system, and communication clarity. Meanwhile, intervention effectiveness was measured through indicators such as stress reduction, improved emotional regulation, and user satisfaction with AI-delivered services. The questionnaire underwent content validation by experts in digital psychology and AI technology and was tested for reliability using Cronbach's Alpha to ensure internal consistency of the items.

Data Analysis

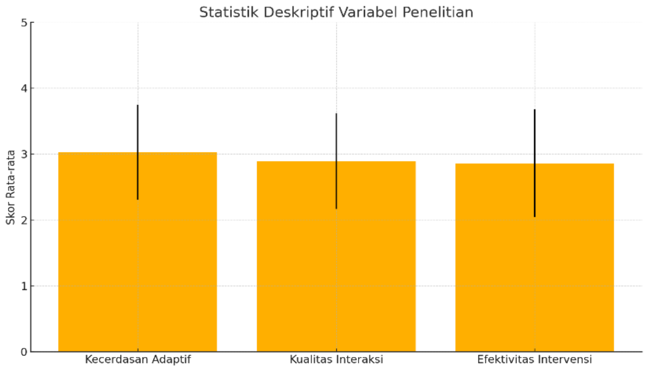
Data analysis was conducted in two stages. First, descriptive analysis was carried out to determine the mean, standard deviation, and data distribution for each variable. Second, inferential analysis was conducted using Pearson's correlation test and simple linear regression to examine the relationships between variables. All analyses were performed using SPSS version 26, with a significance level set at 0.05.

RESULTS AND DISCUSSION

Result

This study aimed to analyze the relationship between AI system adaptive intelligence, psychological interaction quality, and the effectiveness of AI-based psychological interventions in the digital era. Based on data collected from 30 respondents who had used AI applications for mental health therapy, the following statistical findings were obtained:

Figure 3. Descriptive Statistics of Research Variables



Adaptive Intelligence recorded the highest mean score (~3.03) with a moderate standard deviation, indicating a generally positive and consistent perception among users.

Psychological Interaction Quality followed with a slightly lower average score (mean = 2.89), suggesting that user experiences with AI interactions remain at a moderate level.

Intervention Effectiveness had a mean score of 2.86, indicating that perceptions of therapeutic outcomes from AI-based digital therapy were not particularly high, although they remained within the neutral to moderately positive range.

Overall, the mean scores for all three variables fall within the "moderately positive" category, suggesting that users perceive AI systems in digital therapy as reasonably adaptive, interactive, and therapeutically adequate.

Table 1. Pearson Correlation Results

Variable 1	Variable 2	Correlation Coefficient (r)	Significance (p)
Adaptive Intelligence	Intervention Effectiveness	-0.3079310414438527	0.09783401684581468
Interaction Quality	Intervention Effectiveness	-0.0013320018404228003	0.9944262978518216

Adaptive Intelligence exhibited a weak negative correlation with Intervention Effectiveness (r = -0.308), though this relationship was not statistically significant (p = 0.098 > 0.05).

Psychological Interaction Quality showed virtually no correlation with Intervention Effectiveness (r = -0.001), and the relationship was also not significant (p = 0.994).

These results suggest that user perceptions of AI adaptiveness and interaction quality do not statistically influence perceived intervention effectiveness. This may be attributed to external factors not captured within the current model or limitations in the operationalization of the measured variables.

Table 2. Simple Linear Regression Results

Predictor Variable	Coefficient (B)	Standard Error	t-statistic	p-value	R-squared	Significance Model (F-test p-value)
Adaptive Intelligence	0.355251455882319	0.20964010241072806	1.694577763496358	0.10166127652668341	0.09613285853698483	0.2555124591361258
Interaction Quality	0.04126366658273595	0.2084883832040567	0.19791830100360744	0.8445915751787059	0.09613285853698483	0.2555124591361258

Adaptive Intelligence showed a negative regression coefficient (B = -0.355; p = 0.102), indicating that higher perceived adaptiveness was associated with slightly lower perceived effectiveness. However, this relationship was not statistically significant.

Interaction Quality had a small positive coefficient (B = 0.041; p = 0.845), also not statistically significant, suggesting no meaningful contribution to perceived intervention effectiveness.

The R-squared value of 0.096 indicates that only 9.6% of the variance in intervention effectiveness could be explained by the two predictor variables.

The model's overall significance (F-test $p = 0.256 > 0.05$) confirms that the regression model is not statistically significant.

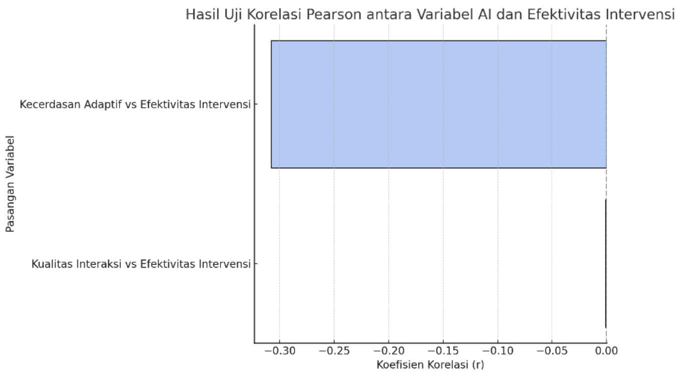
These findings indicate that perceptions of AI adaptiveness and interaction quality do not significantly predict the perceived effectiveness of digital psychological interventions. This points to the potential influence of other unexamined factors or the need for more deeply personalized and context-aware AI systems to achieve meaningful therapeutic effects.

In conclusion, while AI systems in digital therapy are generally perceived as moderately adaptive and interactive, these perceptions do not translate into significant improvements in users' perceived intervention outcomes. Further research is needed to explore additional psychological, contextual, or technical factors that may play a more substantial role in therapeutic effectiveness.

Discussion

This study aimed to analyze the relationship between the adaptive intelligence of Artificial Intelligence (AI) systems, the quality of psychological interaction, and the effectiveness of digital therapeutic interventions in the context of mental health. It responds to the increasing adoption of AI in psychological services, while focusing specifically on the extent to which AI can produce meaningful therapeutic outcomes. Based on quantitative data analysis, no significant relationships were found among the three variables. These findings contribute to the ongoing discourse on the effectiveness of AI systems in digital psychological services and reveal a notable gap between technological expectations and users' actual experiences.

Figure 4. Pearson Correlation Results



Adaptive Intelligence and Intervention Effectiveness

The Pearson correlation analysis showeAdaptive Intelligence and Intervention Effectivenessd a weak negative and statistically non-significant relationship between AI system adaptive intelligence and intervention effectiveness ($r = -0.308$; $p = 0.098$). This suggests that although users perceived AI as relatively adaptive in responding to their inputs, such adaptiveness did not translate into significantly improved therapeutic outcomes. These findings contrast with Golden et al. (2023), who asserted that adaptive AI systems hold strong potential for enhancing therapeutic personalization and clinical results. (Golden et al., 2023). A possible explanation lies in the current limitations of natural language processing (NLP) technologies, which may still fall short in capturing users' emotional nuance and contextual depth.

Furthermore, Schreiber's (2001) theory of Adaptive Artificial Intelligence emphasizes the importance of behavior-based feedback loops to improve intervention relevance. In the context of this study, the absence of a significant relationship may also be attributed to limited exposure or insufficient duration of system use among respondents.

Psychological Interaction Quality and Intervention Effectiveness

The correlation between psychological interaction quality and intervention effectiveness yielded r = -0.001 ($p = 0.994$), indicating no statistical relationship whatsoever. This outcome contradicts Human-Computer Interaction (HCI) theory Norman (1998) which posits that interaction quality plays a crucial role in shaping user experience, including in emotional contexts. In a study by Inkster et al. (2018), empathetic interaction and emotional support delivered by AI were shown to increase user satisfaction and perceived intervention effectiveness.

The discrepancy in this study may stem from users' perception that AI remains rigid in conveying empathy. Despite using natural language to simulate empathy, AI systems still struggle to foster genuine emotional connection, rendering the interaction insufficiently supportive in therapeutic contexts.

Regression Analysis: Simultaneous Contribution of Predictors

Simple linear regression analysis revealed that the model comprising adaptive intelligence and interaction quality as predictor variables explained only 9.6% of the variance in intervention effectiveness (R^2 = 0.096; p = 0.256). This indicates that most of the variance in perceived effectiveness of digital therapy is influenced by other factors not captured in this study. These may include users' psychological backgrounds, usage duration, socio-cultural context, and the complexity of individual mental health conditions.

This finding aligns with studies by Chen et al., (2022) and Jovanovic et al., (2021) who stated that AI is most effective as a companion tool, not as a full replacement for human psychological services. Therefore, AI should be positioned (Topol, 2018).

The results of this study directly address the research question regarding the relationship between adaptive intelligence, psychological interaction quality, and the perceived effectiveness of AI-driven mental health interventions. While the research anticipated a positive association among these variables, the findings revealed no statistically significant correlations. This suggests that although users perceive AI systems as moderately adaptive and interactive, such perceptions do not translate into meaningful therapeutic outcomes. Hence, the study contributes to the discourse by demonstrating that current adaptive AI systems may still fall short in delivering personalized psychological impact, thereby affirming the complexity of translating human-like interaction into effective digital therapy. These results emphasize the need for deeper emotional modeling and cultural sensitivity in AI design, as merely optimizing adaptive mechanisms is not yet sufficient to achieve therapeutic relevance.

Implication

Theoretically, this study underscores the importance of an interdisciplinary approach between technology and psychology in designing AI systems that are not only intelligent but also sensitive to users' emotional dynamics. It also demonstrates that existing applications of adaptive and HCI theories have not yet fully translated into users' lived experiences with AI systems.

From a practical standpoint, the findings emphasize the need for developing AI systems that integrate deeper emotional and contextual learning. Designers and developers of digital mental health technologies should prioritize features that can interpret affective expression, recognize psychological patterns, and provide interventions that are not only rational but also emotionally and culturally meaningful.

Limitation and Suggestion for Further Research

This study acknowledges several limitations that should be considered in interpreting the findings. First, the sample size was relatively small (n = 30), which may limit the generalizability of the results. Although the sample meets the minimum statistical requirements for preliminary analysis, larger and more diverse samples would allow for more robust and representative conclusions. Second, the reliance on self-reported data may introduce response bias, as participants' evaluations of AI systems are subjective and influenced by individual expectations or emotional states at the time of survey completion. In addition, the study only captured user perceptions after a minimum of two weeks of usage, which may not fully reflect long-term engagement or behavioral outcomes. Third, the study did not account for moderating factors such as users' psychological backgrounds, cultural context, or specific mental health conditions, which may significantly influence the effectiveness of AI-driven interventions.

Future research should address these limitations by employing longitudinal designs, increasing sample heterogeneity, and incorporating qualitative methods such as interviews or diary studies to gain deeper insights into users' emotional experiences with AI. Moreover, future studies should explore the integration of emotion-recognition algorithms, cultural adaptability features, and co-therapy models that combine AI with human therapist supervision. These directions can contribute to the development of more ethically grounded and clinically effective AI systems in the mental health domain.

CONCLUSIONS

This study aimed to examine the integration of Artificial Intelligence (AI) in mental health therapy through the adaptive model as an alternative psychological intervention in the digital era. Based on quantitative data analysis from 30 respondents who had used AI-based digital therapy applications, several key findings emerged. First, users' perceptions of the adaptive intelligence of AI systems were found to be moderate but did not exhibit a significant relationship with perceived intervention effectiveness. This indicates that the system's real-time responsiveness alone is insufficient to directly enhance therapeutic outcomes. Second, the quality of psychological interaction between users and AI also showed no significant relationship with the effectiveness of interventions. This suggests that while users may engage in interaction with AI, emotional aspects such as empathy and comfort are not yet strong enough to meaningfully influence therapeutic success. Third, results from the simple linear regression analysis revealed that the model containing adaptive intelligence and interaction quality explained only 9.6% of the variance in intervention effectiveness. This suggests that AI-based digital therapy effectiveness is likely influenced by other factors not covered in the current model.

These findings imply that while AI holds considerable potential to expand access to psychological services, the implementation of adaptive models and the enhancement of interaction quality require further development. AI should be positioned as a complementary tool (co-therapist) in mental health practice, rather than as a complete replacement for human professionals.

Moreover, this study highlights the critical need for the integration of technological and psychological approaches in designing AI systems that are more empathetic, adaptive, and context-aware capable of addressing the nuanced challenges of digital psychological interventions in a human-centered manner.

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AUTHOR CONTRIBUTIONS STATEMENT

UN conceptualized the study, led the methodology design, and supervised the overall research process. MB contributed to the theoretical framework development and provided critical revisions during the manuscript drafting. HR was responsible for data collection, statistical analysis, and initial interpretation of results. DA handled the literature review, visualization of the conceptual model, and refinement of the discussion and conclusion sections. All authors contributed equally to the writing, editing, and final approval of the manuscript.

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