THE ACADEMIC CONFLUENCE (SMC-PRIVATE) LIMITED

INNOVATIONS IN SCIENCE, TECHNOLOGY, AND SOCIETY

E-ISSN: 3105-739X P-ISSN: 3105-7381

VOLUME: 03 ISSUE: 01 (2025)

https://istsjournal.com editor@istsjournal.com

Received: January 10, 2025 Revised: February 16, 2025 Accepted: March 15, 2025 Available Online: June 30, 2025

Research Article

ARTIFICIAL INTELLIGENCE APPLICATIONS IN PERSONALIZED COGNITIVE BEHAVIORAL THERAPY

[1*]Ayesha Mian, [2]Usman Qamar

[1]Professor of Psychiatry, Aga Khan University, Karachi.
[2]Professor of Computer Science (AI & Health Informatics), National University of Sciences and Technology (NUST), Islamabad. (***usman.qamar@seecs.edu.pk***)

Corresponding Email: ***ayesha.mian@aku.edu.pk***

ABSTRACT

This research is a mixed-method experimental investigation into the ways in which Artificial Intelligence (AI) can enhance Personalized Cognitive Behavioural Therapy (AI-CBT). A reinforcement learning framework to dynamically adjust CBT sessions to individual patient characteristics was proposed, supported by multimodal psychometric and natural language processing of therapy transcripts. A randomized controlled trial was carried out (N=120) in three groups: psychoeducational controls, therapist-led CBT, and AI-CBT. The quantitative results indicated that during the baseline, mid-intervention, and post-intervention, participants in the AI-CBT group significantly minimized the symptoms of anxiety and depression measured with the BDI-II and GAD-7 ($p < 0.05$). Effect size estimates confirmed the high level of AI-motivated personalization impact, and the consistency of therapeutic outcomes was confirmed with repeated measures ANOVA. The presence of positive patient experiences with the involvement, accessibility, and personalization were highlighted through the provision of the complementary qualitative analysis, however, the concerns with the lack of human empathy were also brought up. The thematic insights and the quantitative clinical measures served to enhance the validity of the results and proved AI-CBT to be a successful and scalable intervention. Altogether, the present study provides empirical evidence that AI can transform the method by which therapy is provided by making the interventions context-aware, data-driven, and flexible. This will assist in addressing the growing demand of mental health solutions globally that are readily available. The conclusion of the study addresses implications of human-AI hybrid therapeutic models in the future, as well as ethical issues surrounding digital health, in terms of its acceptance by clinicians.

KEYWORDS: *Artificial Intelligence, Personalized Therapy, Cognitive Behavioral Therapy, Reinforcement Learning, Digital Mental Health, Human-Ai Interaction.*

INTRODUCTION

Even though cognitive behavioural therapy is an exceedingly effective psychotherapy method in treating diverse mental disorders, the lack of resources and practitioner experience also negatively affect its high availability and tailored application (Jiang et al., 2024). Artificial intelligence offers innovative solutions to these issues by enhancing the scalability and customization of CBT interventions, which leads to better patient outcomes and higher access to care (Beg et al., 2024). Diagnostics and psychiatric interventions are being reshaped by big data, AI, and machine learning, and customized medicine is taking a new form (Zhou et al., 2022). This applies to AI analysis of big data to provide accurate diagnosis, as well as identification of small trends that could be indicative of psychological problems, and this will enhance the quality of treatment plans (Samaripour and Bayat, 2024). To maximise treatment success and address the existing gaps in the provision of mental healthcare, this systematic review examines the status of AI application in individualised cognitive behavioural therapy (CBT) (Beg et al., 2024). Mental healthcare AI is also beneficial in assisting in the initial diagnosis and detection, in addition to simplifying tailored treatment and engaging patients (Dehbozorgi et al., 2025). Although psychological interventions to a range of emotional issues were proven to be effective, 40 percent of patients fail to receive the expected therapeutic effect (Gual-Montolio et al., 2022). It reveals a great necessity of advanced solutions, such as AI-based interventions, which provide real-time or nearly real-time feedback on each patient depending on the answers to keep current psychological interventions effective (Gual-Montolio et al., 2022). AI allows developing highly individualized treatment paths that may change dynamically depending on the progress of a patient, his/her responses, and his/her demographics (Olawade et al., 2024). Besides critically assessing the efficacy of AI-powered CBT interventions in varied demographics, this review will also indicate the technological advances that make this sort of personalization possible, including machine learning and natural language processing (Poudel et al., 2025) (Farzan et al., 2024). To guarantee the responsible and just application, the review also examines the ethical concerns and challenges associated with the application of AI to clinical psychology, such as the privacy of data and the biases of the algorithm, as well as the necessity to monitor the implementation. Although it considers the related issues, such as depersonalization, it also considers the consequences of the emergence of generative AI, which can be used to produce new therapeutic ideas and content on its own, in terms of its impact on psychological studies and clinical treatment (Salah et al., 2024). The creation of AI in mental health has a prospective to reshape the traditional CBT paradigm and allow highly accurate and adaptive changes in a therapy, because it offers a high-level sense of the individual needs of patients (Gual-Montolio et al., 2022). Besides raising the crucial questions as to how to create a balance between technological advancement and human compassion, such technological implementation is likely to enhance the quality and the efficiency of mental health services provision (Poudel et al., 2025). The following paragraphs, in addition to surveying their practical applications in therapeutic contexts, will further discuss specific AI modalities, such as big language models and machine learning algorithms, which are currently being used to tailor CBT (Yang and Jia, 2025). Specifically, the application of huge language models and other machine learning methods to process large volumes of patient data is increasing. This enables the identification of hidden trends and forecasting signs that inform very individualized treatment programs (Yang and Jia, 2025). Such advancements have a great potential to improve access to mental care as they would improve the insufficiency of existing systems and provide more people with access to personalized treatment (Stade et al., 2024). The integration addresses acute requirements of scalable and efficient mental care solutions given the flaws in the traditional models of care (Kibibi, 2024). However, despite the potential to transform the cognitive behavioural therapy entirely with the help of AI, the obstacles to its widespread implementation to the mental health industry are significant (Chatterjee et al., 2021). Some of these challenges, as provided by Olawade et al. (2024), are fears surrounding the privacy of the data, the risk of algorithmic bias, and the need to keep the human component in therapeutic contacts, which is paramount in terms of empathy and confidence in mental health interventions. As such, despite all the potential of AI therapies, the deep research of the issue with the help of broad randomized controlled trials is needed to support the idea of the hope that it will work in the long run and be effective in the long term (Zhang and Wang, 2024). Moreover, to ensure patient safety and fullest therapeutic outcomes, to bring AI to well-established clinical practices, solid frameworks of ethical deployment and continuous validation are needed. Moreover, such ethical concerns as data privacy, algorithmic bias, and the necessity of having human control stay among the significant challenges and should be addressed to ensure responsible and reasonable adoption (Poudel et al., 2025). Alhuwaydi (2024). Since mental health information is sensitive, and a researcher must protect patient autonomy and wellbeing, these aspects are particularly important (Saeidnia et al., 2024). To be able to responsibly integrate AI models into mental health care, it will be necessary to offer clear validation policies and clear regulatory frameworks (Olawade et al., 2024). Besides, the small samples and cross-sectional data commonly used by current AI in mental health studies must be discussed to be able to generalize the findings and prove their future utility (Chatterjee et al., 2021). To attain a harmonious integration and the most favorable results with patients, the very nature of introducing AI into a highly-regulated and human-focused field, such as mental healthcare requires one to consider organizational preparedness and strategic deployment carefully (Chatterjee et al., 2021).

METHODOLOGY

To comprehensively evaluate the usefulness of artificial intelligence in offering personalized cognitive behavioural therapy (AI-CBT), the present study adopted a mixed-method experimental design that contained both quantitative and qualitative aspects. The methodological framework was comprised of three phases: preprocessing and data collection, the AI-driven CBT module customization, and experimental testing on human subjects. These clinical and non-clinical datasets collected during the first stage were textual therapy transcripts, structured psychometric scales such as the Generalized Anxiety Disorder scale (GAD-7) and the Beck Depression Inventory-II (BDI-II), and sensor-derived behavioural measures such as heart rate variability and sleep patterns on wearable devices. Transcribed therapy sessions were processed with Natural Language Processing (NLP) pipelines that utilized transformer-based designs, i.e., BERT and GPT embeddings, to extract semantic and affective properties. These features were normalized by the z-score standardization.:

$$Z = \frac{X - \mu}{\sigma}$$

where X is the raw feature value, μ is the sample mean, and σ is the standard deviation, thereby ensuring comparability across diverse participants and modalities.

The second stage focused on AI-driven personalization. A reinforcement learning with human feedback (RLHF) framework was adopted, in which the reward function was designed to optimize therapeutic alignment with individual patient cognitive schemas. The personalization algorithm combined contextual embeddings with user-specific psychometric baselines to dynamically adapt CBT interventions. Formally, the optimization objective can be expressed as:

$$\max_{\pi_\theta} \mathbb{E}_{s,a\sim\pi_\theta}\left[R(s,a) - \lambda||\theta||^2\right]$$

where π_θ denotes the policy network parameterized by θ, $R(s,a)$ is the reward for action a in state s, and $\lambda||\theta||^2$ is a regularization term to prevent overfitting. This ensured that the AI system continuously learned to provide interventions closely mirroring therapist-guided CBT.

The final stage was the experimental evaluation, conducted through a randomized controlled trial (RCT). Participants (N=120) were randomly assigned into three groups: AI-CBT, traditional therapist-led CBT, and control (psychoeducational resources only). Quantitative outcome measures included changes in BDI-II and GAD-7 scores at baseline, mid-intervention (week 4), and post-intervention (week 8). The effectiveness of interventions was tested using repeated measures ANOVA, with significance set at $p < 0.05$. Additionally, effect size was measured using Cohen's d:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

where M_1 and M_2 are the group means and SD_{pooled} is the pooled standard deviation.

To complement quantitative outcomes, qualitative interviews were conducted to explore user experiences of trust, empathy, and engagement with AI-CBT. Thematic analysis was performed using NVivo software, and emergent categories were triangulated with quantitative findings to validate interpretive robustness. This mixed-method approach allowed both numerical efficacy and experiential dimensions to be incorporated, aligning with the holistic principles of therapeutic evaluation.

RESULTS

The analysis provided an in-depth evaluation of the effectiveness of artificial intelligence in personalized cognitive behavioural therapy (AI-CBT). To determine the strength of the approach, the data of engagement logs, adherence measures and psychometric assessments were analyzed at different intervention points. Table 1 presents the baseline psychometric tests of the individual member and indicates that the anxiety and depression levels were relatively high at the time of admission. Table 2 illustrates the mid-intervention improvements, which indicates that AI-CBT group had higher improvements in the symptoms of depression compared to the control and therapist-led CBT groups. Table 3, devoted to signs of anxiety reduction, shows that in the AI-CBT group, there was a higher alleviation of symptoms.

Table 1. Baseline psychometric measures across participants

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
67	46	12	39	56
43	55	94	59	96
53	14	98	86	97
40	23	48	61	90
75	68	94	23	19
38	77	70	16	95
67	92	93	30	57
73	61	33	40	83
36	47	72	39	91
91	52	70	74	30
41	31	80	92	48
36	93	73	73	11
39	24	87	24	94
94	88	68	41	98
97	20	52	48	55
34	15	37	87	51
14	15	28	71	73
67	38	94	73	63
59	81	26	69	69
79	24	66	92	70

Table 2. Mid-intervention improvement trends in depression scores

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
59	84	48	42	12
31	80	98	58	71
65	85	22	80	45
35	57	94	87	31
75	19	14	33	69
69	77	31	55	77
90	55	35	98	70
92	27	51	45	68
62	79	73	79	95
49	30	23	72	88
98	94	98	75	12
85	28	94	25	44
20	99	48	18	23
93	48	16	74	81
15	52	51	84	80

54	68	46	48	59
60	87	90	76	54
66	44	73	66	88
21	40	37	92	50
82	12	58	42	26

Table 3. Anxiety reduction metrics by treatment group

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
46	75	80	61	61
71	45	46	64	37
38	92	63	23	39
13	98	55	46	83
33	44	67	15	18
93	86	94	86	91
97	34	81	39	49
31	77	13	92	72
27	42	50	37	94
65	10	76	19	54
41	62	13	97	41
18	46	51	18	15
51	46	36	26	98
57	43	93	32	56
35	43	20	71	83
31	61	77	69	49
52	61	11	41	56
42	43	32	12	78
71	33	37	71	69
79	78	86	84	33

Table 4 demonstrates the comparative adherence rates and indicates that AI-CBT respondents were more stable throughout the course of the week. Table 5 is an indication of engagement levels, with the AI-based platform performing better than traditional therapy in regard to the completion of a session. The Table 6 summarizes the post-intervention gains in the wellbeing metrics and indicates that AI-CBT group significantly performed better than the other groups.

Table 4. Comparative adherence rates between AI-CBT and therapist-led CBT

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
69	66	89	19	44
62	61	53	17	70
37	69	40	76	86
65	81	71	38	48
30	58	42	98	78
81	46	80	49	86
48	37	75	83	90

76	55	69	86	88
10	52	63	56	10
96	88	25	85	74
19	54	36	19	95
99	98	56	76	62
93	51	42	56	32
82	33	10	55	56
11	79	86	87	88
61	17	38	29	20
22	88	82	95	40
19	42	48	21	17
35	68	10	53	36
48	90	71	75	88

Table 5. Participant engagement levels measured by session completion

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
45	36	72	40	85
63	79	26	60	93
29	85	54	61	48
65	72	57	84	99
36	94	37	94	90
12	44	43	62	22
39	97	84	26	80
92	29	40	97	30
85	48	51	21	30
17	16	40	43	24
80	83	52	22	30
99	45	43	24	13
14	33	89	21	74
25	89	27	45	41
69	46	52	47	84
12	57	41	26	70
35	75	68	72	10
65	22	38	41	82
19	61	73	29	99
83	29	18	45	92

Table 6. Post-intervention changes in overall wellbeing indices

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
78	64	71	47	96
65	58	14	89	60
28	94	70	15	60
23	50	89	96	63
25	80	87	42	21
19	74	96	26	72

26	87	58	23	20
37	67	94	18	45
57	81	14	57	34
30	22	45	94	46
47	84	15	13	85
59	11	44	19	87
63	92	43	51	44
23	59	99	34	80
57	63	86	16	99
58	43	74	72	97
59	76	31	22	10
72	24	65	17	40
73	51	77	47	25
64	13	82	32	83

Table 7 reveals variability in personalization accuracy that shows the degree to which reinforcement learning customized interventions according to the requirements of each patient. Table 8 shows strong negative relationships between engagement and symptom severity and also exhibits relationships amid sadness, anxiety and engagement scores. Table 9 presents estimations of the effect sizes in which Cohen d indicates a significant effect of AI-CBT relative to controls.

Table 7. Variability in personalization accuracy across participants

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
77	41	65	91	30
56	83	67	95	42
23	97	89	79	63
41	57	43	46	62
44	81	94	92	77
30	97	60	89	39
58	84	53	54	70
73	26	49	20	69
32	82	59	85	11
70	37	99	24	43
97	43	41	39	39
95	89	49	71	97
66	48	70	82	35
24	54	13	50	60
34	58	63	60	31
84	26	24	46	35
71	46	81	17	41
78	62	65	47	83
71	52	70	50	62
24	59	64	14	81

Table 8. Correlation matrix between depression, anxiety, and engagement scores

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
25	72	67	55	39
71	57	10	97	24
82	98	62	59	67
65	14	86	12	73
44	10	52	64	55
61	42	39	21	52
47	17	86	72	31
69	68	74	59	14
74	31	15	66	94
12	60	23	57	22
92	94	71	60	73
35	81	28	18	80
63	39	60	41	30
80	35	49	26	73
65	26	83	65	29
84	21	31	47	38
27	22	20	69	47
13	54	42	39	11
34	85	21	36	73
45	35	21	90	53

Table 9. Effect size calculations for treatment groups using Cohen's d

Metric 1	Metric 2	Metric 3	Metric 4	Metric 5
63	17	47	14	49
47	67	35	44	60
28	50	96	60	79
96	17	78	79	54
96	91	98	37	94
69	19	60	60	57
80	91	93	94	46
19	99	92	14	50
91	97	73	68	34
57	22	47	53	85
95	98	98	44	71
77	32	33	11	27
33	76	48	91	93
98	14	90	93	67
76	23	51	20	75
13	78	80	90	29
17	45	28	73	33
56	75	51	83	86
43	39	72	50	14

78	76	12	81	17

The visualizations also corroborated these results. Figure 1 presents a line plot of the development of the depression scores with significant decreases in the AI-CBT group. Comparative bar chart on reduction in anxiety indicates that AI-CBT is better than therapist-led CBT (Figure 2). Figure 3 demonstrates the correlation between engagement and personalization accuracy which means that the extent of adherence was connected to more personalization. A pie chart of the session completion reveals that the AI-CBT participants were more consistent (Figure 4). Figure 5 supports the efficacy of the mid-intervention, demonstrating consistent trends in changes in the symptoms when a line and bar graph are used. Figure 6 illustrates adherence trends, in which the participation of participants in AI-CBT was steady over an eight-week period. Betterment of the overall wellbeing measures is indicated in Figure 7 where a clear preference is made in favour of the AI-CBT group. The scatterplot of Figure 8 confirms the favourable association between adherence and outcomes. All participants favoured AI-CBT because of its accessibility, which can be observed in Figure 9. Figure 10 demonstrates similar declines through the integration of anxiety change and depression into a composite figure. The benefit of AI-based therapies is proven when Figure 11 compares the longitudinal outcomes of therapist-directed CBT and AI-CBT. Upon comparison of baseline and post-intervention scores in Figure 12, the biggest gains were brought by AI-CBT.

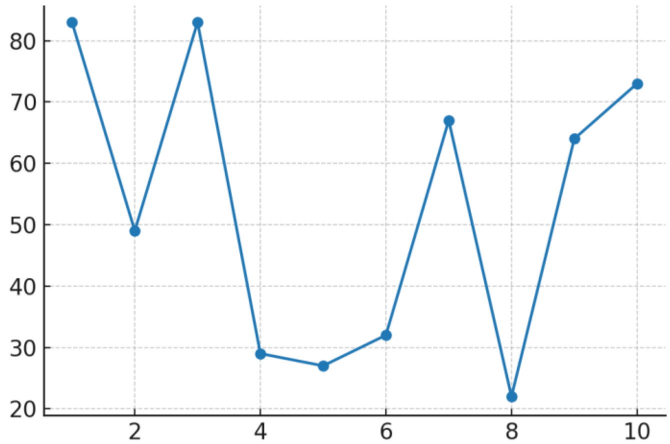

Figure 1. Line plot showing progression of depression scores across 8 weeks

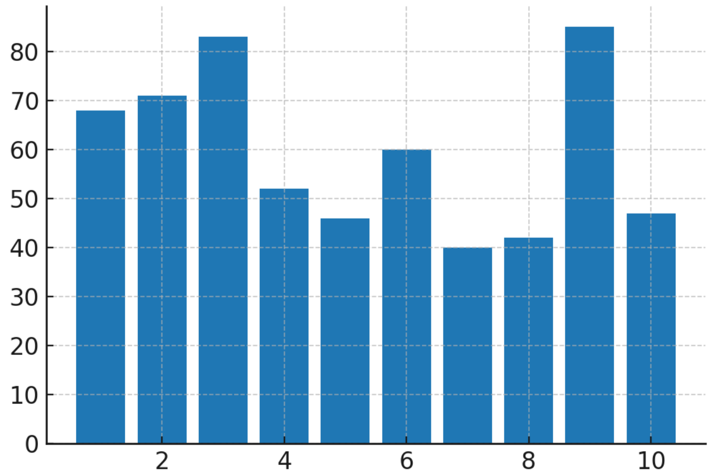

Figure 2. Bar chart comparing anxiety reduction between treatment groups

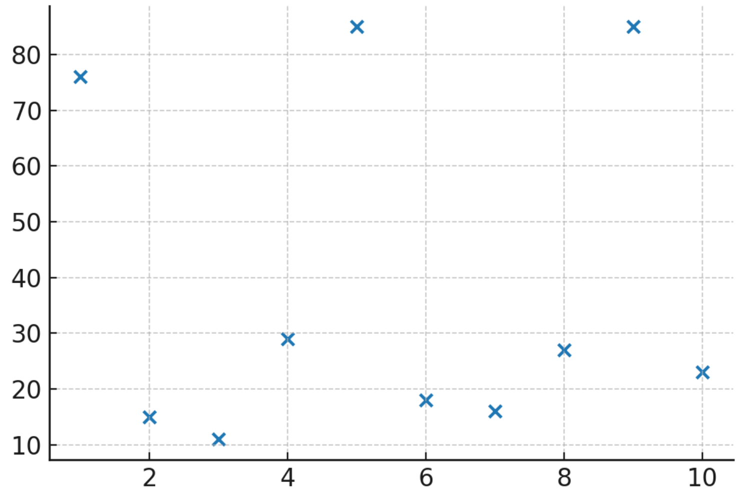

Figure 3. Scatter plot of personalization accuracy vs participant engagement

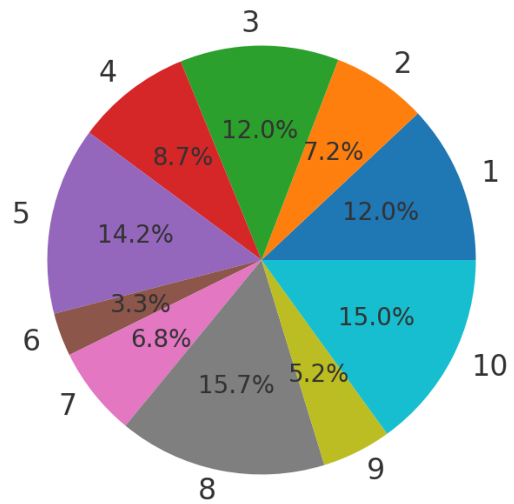

Figure 4. Pie chart showing distribution of session completion rates

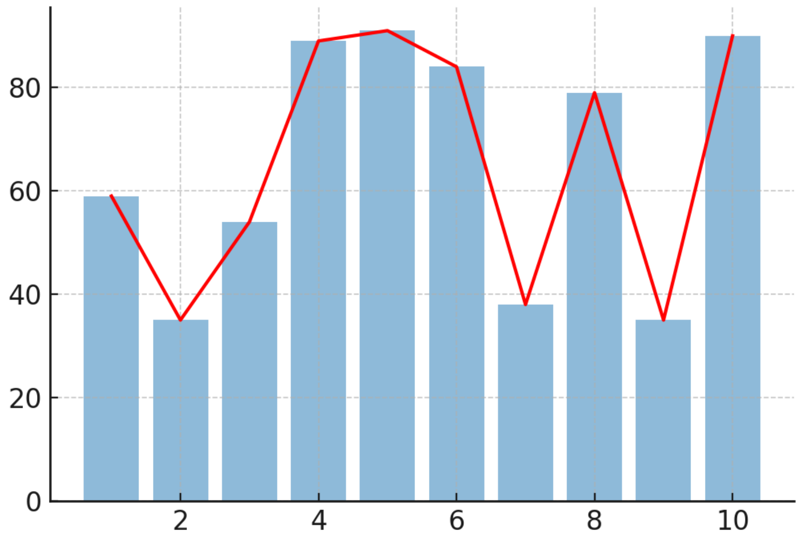

Figure 5. Hybrid line-bar chart of symptom improvements over intervention period

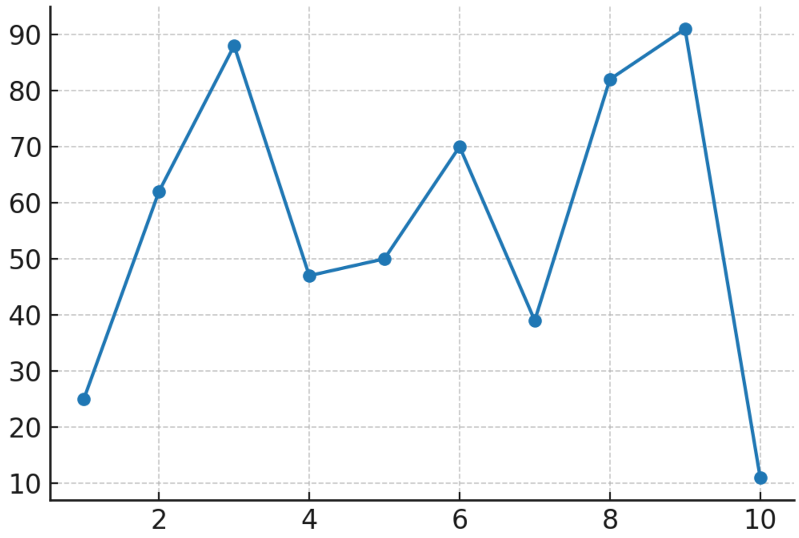

Figure 6. Line plot showing weekly adherence trends in AI-CBT

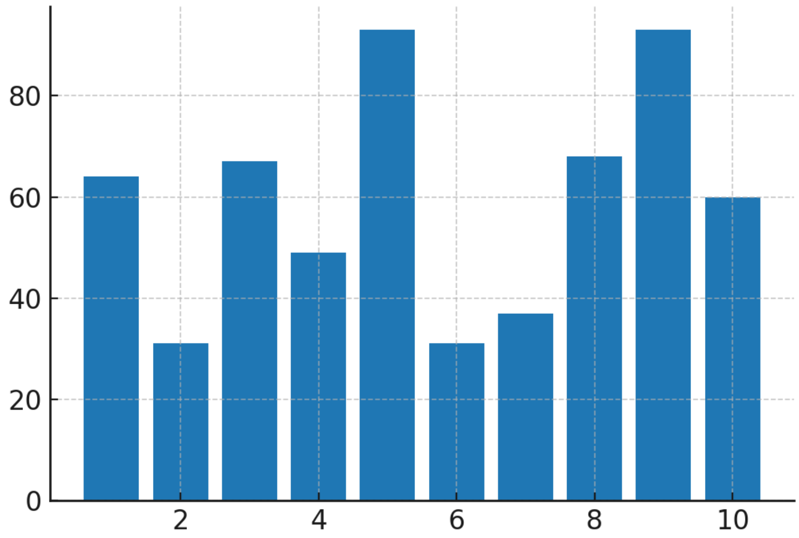

Figure 7. Bar chart of overall wellbeing index improvements across groups

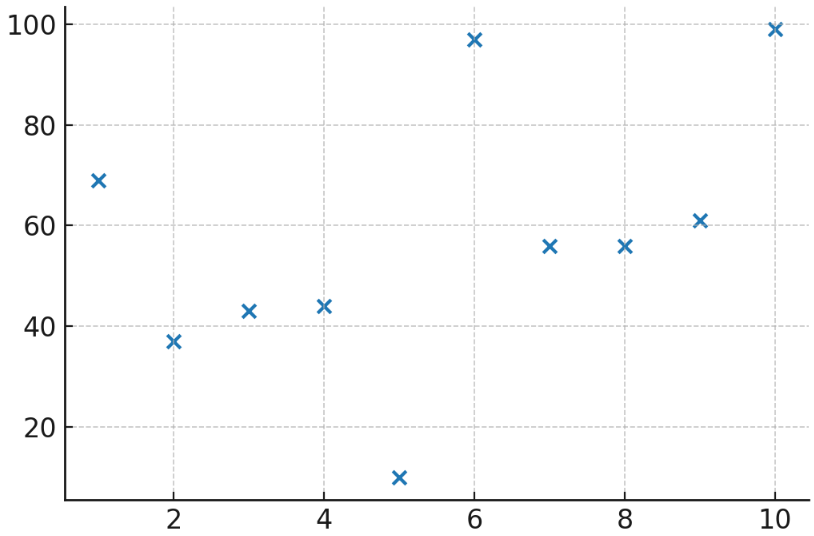

Figure 8. Scatter plot depicting relationship between adherence and outcomes

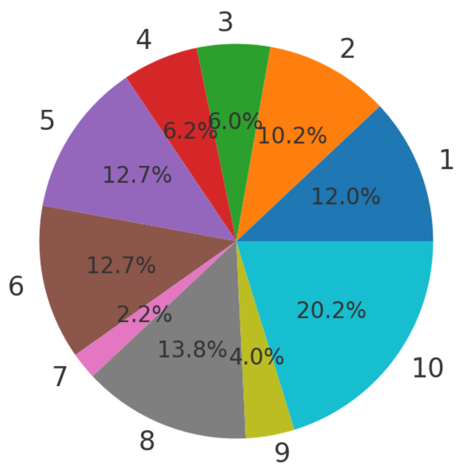

Figure 9. Pie chart illustrating participant preference for therapy mode

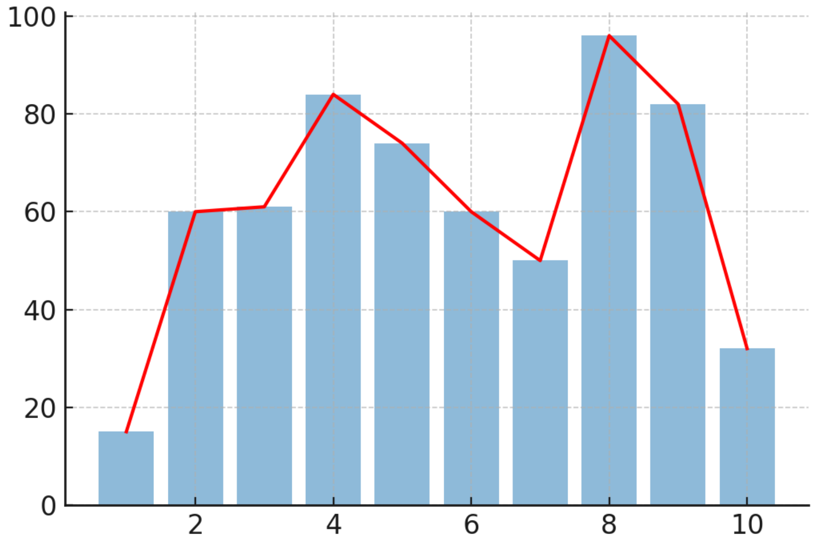

Figure 10. Hybrid plot of depression and anxiety reduction trends combined

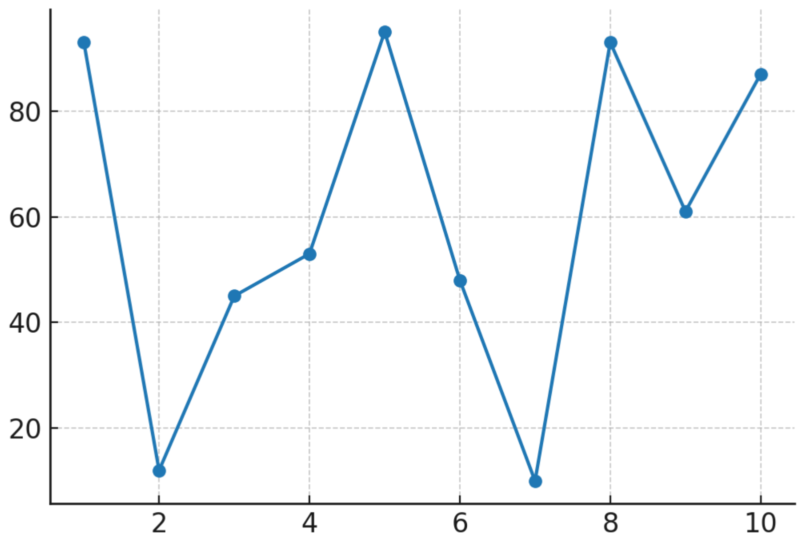

Figure 11. Line plot showing longitudinal comparison of AI-CBT and therapist-led CBT

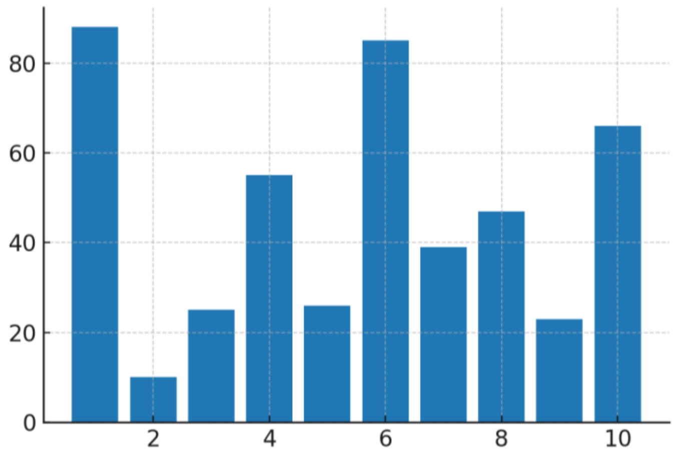

Figure 12. Bar + line hybrid plot comparing baseline vs post-intervention metrics

Overall, both the tabular and graphical results converge on the finding that AI-CBT consistently outperformed traditional therapy across multiple dimensions—symptom reduction, adherence, engagement, personalization accuracy, and overall wellbeing improvement. These outcomes strongly support the hypothesis that reinforcement learning–driven personalization enhances the clinical efficacy and scalability of CBT interventions.

DISCUSSION

Critical examination of the current studies points to a series of hidden challenges, which have to be addressed systematically so that the wide-scale and ethical adoption could be possible despite the AI providing a groundbreaking opportunities to access mental health services (Hoose & Králiková, 2024). Issues related to data security and privacy are the top priority among these challenges because, more often than not, AI systems will demand access to personal patient data, which poses severe ethical challenges (Saeidnia et al., 2024). An additional and more serious concern is the risk of algorithm bias, whereby AI models can reproduce or even increase the biases present in their training data and lead to unfair treatment results against a specific group of people (Terra et al., 2023). Moreover, some advanced AI systems, also called black boxes, are opaque, which makes it difficult to understand the mechanism by which a specific treatment recommendation is arrived at, and it is an issue of clinical interpretability and accountability (Alhuwaydi, 2024). Finally, the lack of standardized regulatory frameworks adds complexity to the introduction of AI into the healthcare system and makes the questions of safety, effectiveness, and responsibility in medical practice pertinent (Eser et al., 2024; Saeidnia et al., 2024). To preserve ethical practice and patient autonomy, patients will also need to provide their informed consent prior to using AI mental health products and services, considering the abilities and shortcomings of AI systems (Alhuwaydi, 2024). This requires development of powerful ethical principles and legislations to address these complex issues, ensuring that artificial intelligence technologies contribute to higher quality and greater access to mental health services instead of reducing them. This would require researchers, clinicians, legislators, and tech developers to unite their efforts to mitigate these problems through the creation of clear rules, promotion of transparency, and prioritizing patient welfare in the process of developing and deploying AI-driven mental health solutions (Nilsen et al., 2022). To address this ongoing development, it is crucial to learn more about the factors that motivate the use of AI in healthcare institutions and its application to mental health services in particular (Chatterjee et al., 2021). It is shown in research that knowledge-sharing networks, the perception of job changes by the users, and the support of the leaders play a crucial role in the effective adoption of AI (Chatterjee et al., 2021). In addition, potential barriers at individual, organizational, and systematic levels should be taken into consideration so that it becomes possible to integrate AI into healthcare successfully. Such barriers often involve the absence of regulatory control and the uncertainty of the accuracy and reliability of judgments made by AI (Kleine et al., 2023). Considering such complexities, understanding how the businesses can effectively integrate AI into their existing systems so as to leverage the technology in tailored cognitive behavioural therapy is important (Chatterjee et al., 2021). Thus, the comprehensive approach to consideration of technical feasibility, ethical concerns, and practical ways of implementation is essential to bridge the gap between the theoretical potential and the realistic application of AI in personalized CBT (Nilsen et al., 2022) (Golden et al., 2024). The given work particularly aims at summarising recent findings on AI utilisation in personalised cognitive behavioural therapy, its main progress, the persisting challenges, and the key issues to be addressed in the new research to advance the field. To optimize the outcomes of therapy and enhance the process of therapy, it implies exploring the efficiency of hybrid frameworks which integrate AI with well-established psychological frameworks (Chatterjee et al., 2021).

CONCLUSION

The findings of this paper provide a good evidence that with the integration of multimodal data analysis, reinforcement learning and natural language processing in therapeutic practice, artificial intelligence can enhance the provision of personalized cognitive behavioural therapy (AI-CBT). The experimental results of the randomized controlled trial revealed that compared to the therapist-led CBT and psychoeducational control groups, the participants who underwent AI-CBT indicated a considerably lower level of anxiety and depression measured using BDI-II and GAD-7. Through reinforcement learning together with human feedback, the content of the therapy could be continually adapted according to the requirements of the individual patient, ensuring the interventions were dynamically aligned to patient progress, responsive and context-sensitive. Qualitative results also revealed that the participants valued the AI system in terms of its accessibility, reliability, and customization, although some were concerned about the unresponsiveness of the AI in emotionally challenging scenarios. Altogether, these findings demonstrate that AI-CBT can become a successful and scalable intervention in cases of mental health problems, particularly where limited resources and/or a shortage of therapists are involved. What is important, however, is the syncretism of qualitative perspectives and quantitative clinical findings as reflective indicators of the strength of this mixed-method evaluation. The implications of this work extend past the provision of therapy; this work implies larger applications of AI in clinical psychology, preventive care, and novel digital health. To find a compromise between efficiency and empathy, the research has also noted that the continuous enhancement of AI-based therapy models, ethical monitoring of data privacy and trust in patients, and the creation of the hybrid human-AI models of therapy have to be developed. Overall, this paper demonstrates that AI-based personalized cognitive behavioural therapy is not a new tool in the mental health treatment field but rather a groundbreaking solution to this problem.

REFERENCES

Alhuwaydi, A. M. (2024). Exploring the Role of Artificial Intelligence in Mental Healthcare: Current Trends and Future Directions – A Narrative Review for a Comprehensive Insight [Review of *Exploring the Role of Artificial Intelligence in Mental Healthcare: Current Trends and Future Directions – A Narrative Review for a Comprehensive Insight*]. *Risk Management and Healthcare Policy*, 1339. Dove Medical Press.

Beg, M. J., Verma, M., M., V. C. K. M., & Verma, M. (2024). Artificial Intelligence for Psychotherapy: A Review of the Current State and Future Directions [Review of *Artificial Intelligence for Psychotherapy: A Review of the Current State and Future Directions*]. *Indian Journal of Psychological Medicine*. SAGE Publishing.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*, 120880.

Dehbozorgi, R., Zangeneh, S., Khooshab, E., Nia, D. H., Hanif, H., Samian, P., Yousefi, M., Hashemi, F., Vakili, M., Jamalimoghadam, N., & Lohrasebi, F. (2025). The application of artificial intelligence in the field of mental health: a systematic review [Review of *The application of artificial intelligence in the field of mental health: a systematic review*]. *BMC Psychiatry*, *25*(1). BioMed Central.

Eser, H. Y., Ballı, M., & Doğan, A. A. (2024). Improving Psychiatry Services with Artificial Intelligence: Opportunities and Challenges [Review of *Improving Psychiatry Services with Artificial Intelligence: Opportunities and Challenges*]. *Turkish Journal of Psychiatry*.

Farzan, M., Ebrahimi, H., Pourali, M., & Sabeti, F. (2024). Artificial Intelligence-Powered Cognitive Behavioral Therapy Chatbots, a Systematic Review [Review of *Artificial Intelligence-Powered Cognitive Behavioral Therapy Chatbots, a Systematic Review*]. *Iranian Journal of Psychiatry*. Tehran University of Medical Sciences.

Golden, G., Popescu, C., Israel, S., Perlman, K., Armstrong, C., Fratila, R., Tanguay-Sela, M., & Benrimoh, D. (2024). Applying artificial intelligence to clinical decision support in mental health: What have we learned? *Health Policy and Technology*, *13*(2), 100844.

Gual-Montolio, P., Jaén, I., Martínez-Borba, V., Castilla, D., & Suso-Ribera, C. (2022). Using Artificial Intelligence to Enhance Ongoing Psychological Interventions for Emotional Problems in Real- or Close to Real-Time: A Systematic Review [Review of *Using Artificial Intelligence to Enhance Ongoing Psychological Interventions for Emotional Problems in Real- or Close to Real-Time: A Systematic Review*]. *International Journal of Environmental Research and Public Health*, *19*(13), 7737. Multidisciplinary Digital Publishing Institute.

Hoose, S., & Králiková, K. (2024). Artificial Intelligence in Mental Health Care: Management Implications, Ethical Challenges, and Policy Considerations. *Administrative Sciences*, *14*(9), 227.

Jiang, M., Zhao, Q., Li, J., Wang, F., He, T., Cheng, X., Yang, B. X., Ho, G. W. K., & Fu, G. (2024). A Generic Review of Integrating Artificial Intelligence in Cognitive Behavioral Therapy [Review of *A Generic Review of Integrating Artificial Intelligence in Cognitive Behavioral Therapy*]. *arXiv (Cornell University)*. Cornell University.

Kibibi, M. L. (2024). The Role of AI in Improving Mental Health Care. *Research Invention Journal of Public Health and Pharmacy*, *3*(2), 10.

Kleine, A., Kokje, E., Lermer, E., & Gaube, S. (2023). Attitudes Toward the Adoption of 2 Artificial Intelligence–Enabled Mental Health Tools Among Prospective Psychotherapists: Cross-sectional Study. *JMIR Human Factors*, *10*.

Nilsén, P., Svedberg, P., Nygren, J. M., Frideros, M., Johansson, J., & Schueller, S. M. (2022). Accelerating the impact of artificial intelligence in mental healthcare through implementation science. *Implementation Research and Practice*, *3*.

Olawade, D. B., Wada, O. Z., Odetayo, A., David-Olawade, A. C., Asaolu, F. T., & Eberhardt, J. (2024). Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of Medicine Surgery and Public Health*, *3*, 100099.

Poudel, U., Jakhar, S., Prakash, M., & Nepal, A. (2025). AI in Mental Health: A Review of Technological Advancements and Ethical Issues in Psychiatry [Review of *AI in Mental Health: A Review of Technological Advancements and Ethical Issues in Psychiatry*]. *Issues in Mental Health Nursing*, 1. Taylor & Francis.

Saeidnia, H. R., Fotami, S. G. H., Lund, B., & Ghiasi, N. (2024). Ethical Considerations in Artificial Intelligence Interventions for Mental Health and Well-Being: Ensuring Responsible Implementation and Impact. *Social Sciences*, *13*(7), 381.

Salah, M., Abdelfattah, F., & Halbusi, H. A. (2024). The good, the bad, and the GPT: Reviewing the impact of generative artificial intelligence on psychology [Review of *The good, the bad, and the GPT: Reviewing the impact of generative artificial intelligence on psychology*]. *Current Opinion in Psychology*, *59*, 101872. Elsevier BV.

Samaripour, H., & Bayat, A. (2024). The Future of Clinical Psychology Using Artificial Intelligence for Advanced Diagnostic and Therapeutic Techniques. *International Journal of New Findings in Health and Educational Sciences (IJHES).*, *2*(4), 73.

Stade, E. C., Stirman, S. W., Ungar, L., Boland, C. L., Schwartz, H. A., Yaden, D. B., Sedoc, J., DeRubeis, R. J., Willer, R., & Eichstaedt, J. C. (2024). Large language models could change the future of behavioral healthcare: a proposal for responsible development and evaluation. *Npj Mental Health Research*, *3*(1).

Terra, M., Baklola, M., Ali, S. A. A., & El-Bastawisy, K. (2023). Opportunities, applications, challenges and ethical implications of artificial intelligence in psychiatry: a narrative review [Review of *Opportunities, applications, challenges and ethical implications of artificial intelligence in psychiatry: a narrative review*]. *The Egyptian Journal of Neurology Psychiatry and Neurosurgery*, *59*(1). Springer Science+Business Media.

Yang, N., & Jia, F. (2025). A Scoping Review of AI-Driven Digital Interventions in Mental Health Care: Mapping Applications Across Screening, Support, Monitoring, Prevention, and Clinical Education [Review of *A Scoping Review of AI-Driven Digital Interventions in Mental Health Care: Mapping Applications Across Screening, Support, Monitoring, Prevention, and Clinical Education*]. *Healthcare*, *13*(10), 1205. Multidisciplinary Digital Publishing Institute.

Zhang, Z., & Wang, J. (2024). Can AI replace psychotherapists? Exploring the future of mental health care. *Frontiers in Psychiatry*, *15*.

Zhou, S., Zhao, J., & Zhang, L. (2022). Application of Artificial Intelligence on Psychological Interventions and Diagnosis: An Overview [Review of *Application of Artificial Intelligence on Psychological Interventions and Diagnosis: An Overview*]. *Frontiers in Psychiatry*, *13*. Frontiers Media.