# Improving Treatment Outcomes and Patient Engagement in Talking Therapies

Limbic
Research team
London, UK
research@limbic.ai

January 5, 2024

## Summary

The importance of supporting mental well-being is increasingly critical, but patient engagement in psychological talking therapy remains a challenge. To address this issue, we developed an AI-enabled therapy support tool designed to offer therapeutic support during mental health treatment. Here, we conducted a real-world study of 3,961 patients to test the effectiveness of the tool in improving patient engagement and clinical outcomes. The tool was piloted with patients undergoing Cognitive Behavioural Therapy (CBT) treatment in the National Health Service (NHS) Talking Therapies services in the United Kingdom. Our findings indicate that patients who used the tool achieved significantly better treatment outcomes, showcased by higher rates of reliable improvement (94.3% vs. 69.8% in the control group) and reliable recovery (71.4% vs. 50.7% in the control group). Interestingly, the results also indicated that the AI tool enabled faster recovery, i.e. fewer therapy sessions were required to achieve recovery. These results suggest that the use of AI-enabled therapy support tools in talking therapy can lead to increased patient engagement, better treatment outcomes and reduced cost of service delivery. This study is a critical step illustrating the potential of AI tools to improve efficacy and efficiency of psychological talking therapies, generating substantial benefit to both patients and healthcare services.

# 1 Introduction

The need to support mental well-being has become increasingly critical, as mental health conditions are one of the leading causes of disability and disease burden worldwide (World Health Organisation, 2022). Prior to the COVID-19 pandemic, the most prevalent mental health disorders, such as anxiety disorders and depression, were estimated to affect 29% of the world's population in their lifetime Steel et al. [2014]. It has been estimated that the pandemic has increased the prevalence of depression by 27.6% and anxiety disorders by 25.6% globally Santomauro et al. [2021].

Psychological talking therapies, such as Cognitive Behavioural Therapy (CBT) can reduce the burden of mental health challenges and have been found to be highly effective for many mental illnesses Ontario et al. [2017], Hofmann et al. [2014]. However, human-led talking therapy is resource intensive, leading to supply-demand imbalances in many healthcare systems which result in long wait times and negative outcomes for the patients. Moreover, despite the general benefit of talking therapies, patients often fail to fully engage in therapy, with many dropping out or missing sessions. This has a negative impact on both patients and mental health services that are already under a lot of strain. For example, it can lead to a worsening of mental health symptoms and re-referrals to mental health services Verbist et al. [2022]. There is a clear need for approaches that can enhance engagement and retention in mental health treatment and ultimately make talking therapy treatment more effective and more efficient.

Digital technologies, such as mobile and web-hosted applications, have been proposed as potential solutions to this need Rudd and Beidas [2020], Taylor et al. [2020]. Evaluations of mobile apps designed to support or deliver elements of mental health treatment have shown that these tools can deliver benefits in the form of improved user experience, better patient engagement in care, user motivation, easier tracking of progress, and improved therapeutic alliance Chandrashekar [2018], Koh et al. [2022], Henson et al. [2019]. Moreover, there are examples demonstrating improved therapeutic recovery and alleviation of symptoms of mental illness for patients who have used digital health interventions compared to the standard of care without digital interventions Hull et al. [2020], Denecke et al. [2022], Firth et al. [2017a,b]. However, the major problem that still applies to most digital mental health products is poor long-term engagement and lack of personalisation Borghouts et al. [2021]. Moreover, most digital mental health products are designed as stand-alone tools that do not integrate with and support human-delivered therapy.

To this end, we developed a novel AI-enabled therapy support mobile application, *Limbic Care*, which can support individuals during their therapy. The key focus of this tool is incorporating Artificial Intelligence (AI) to ensure that it can provide a flexible and personalised experience for patients. For example, it can offer a truly naturalistic and dynamic conversation tailored to a patient's specific responses. This more naturalistic engagement with the tool holds the promise to overcome the widely experienced engagement problems reported in other mental digital health solutions and help support the patients in between sessions.

We hypothesised that this AI-enabled therapy support tool could improve engagement and through this treatment success as the patients have a more convenient method to engage with therapy between their sessions. Firstly, the tool provides a more flexible way for patients to complete homework exercises outside of sessions which are a core ingredient for success in cognitive behavioral therapy. Secondly, it offers a greater degree of privacy and discretion than traditional paper and pen methods. Thirdly, the naturalistic interaction with the app allows patients to discuss their feelings and emotions in a convenient way outside the therapy sessions, while receiving support on a level that resembles interactions with a therapist. Therefore, we anticipated an increase in engagement metrics for individuals who were using the therapy support tool during their therapy and this leading to improvements in their clinical outcomes.

The use of AI solutions in healthcare is still an emerging area of research Wilson and Marasoiu [2022], with limited studies conducted in clinical settings. Therefore, we conducted a pilot study to assess the effectiveness of the AI-enabled therapy support tool in a clinical context. We conducted an observational study within NHS Talking Therapies Services in the UK, comparing engagement and clinical outcomes between patients who used the novel AI-enabled therapy support tool and those who did not. The results of this study show that the AI-enabled therapy support tool had a positive impact on the engagement and clinical outcomes for individuals in a real-world setting.

# 2 Method

Here we evaluate the effectiveness of an innovative AI-enabled therapy support tool (Limbic Care, developed by Limbic Ltd.). The tool was implemented as part of a pilot project within the National Health Service (NHS) Talking Therapies services in the UK.

## 2.1 Therapy Support Tool

The AI-enabled therapy support tool is a mobile application designed to offer therapeutic support to patients aged 18 and above who are in psychological talking therapy under the supervision of a trained clinician. The application features a conversational chatbot and facilitates the completion of therapist-assigned homework exercises and interventions as an integral component of the therapeutic process (see Figure 1). The primary aim of the mobile app is to encourage and empower patients to engage in therapeutic interventions (delivered via the app) between their psychological talking therapy sessions.

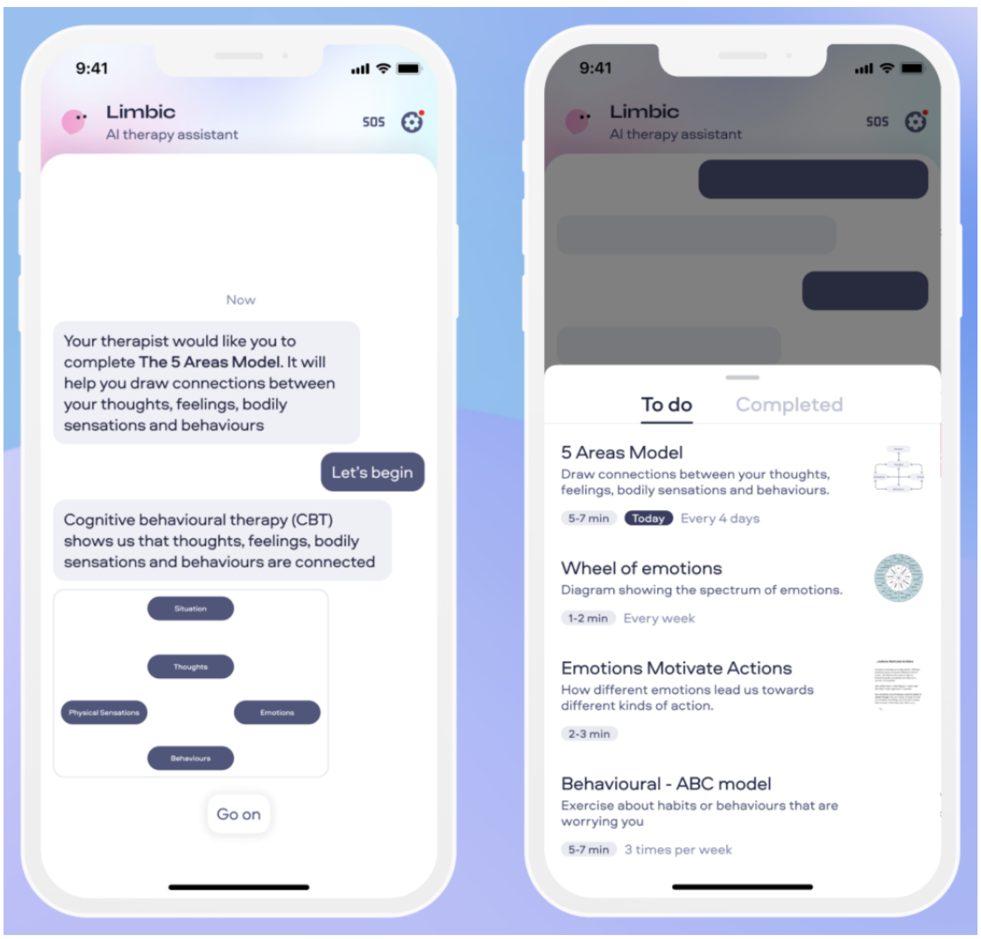


Figure 1: An example of the AI-enabled therapy support tool user interface showing the conversational interface (left) and the therapeutic intervention to-do list (right).

## 2.2 Study design

This is an pilot study, with an observational real-world design, to investigate the impact of the AI-enabled therapy support tool on engagement with therapy and improvement in clinical outcomes.

The analysis was conducted using data from 3,961 patients who referred to nine NHS Talking Therapies services across England between June 2022 and March 2023. NHS Talking Therapies services cover adults presenting with varying severity of common mental health conditions such as depression and anxiety disorders. Our study specifically focused on patients diagnosed with depression and anxiety disorders, such as generalised anxiety disorder (GAD), post-traumatic stress disorder (PTSD) and social phobia, undergoing Cognitive Behavioral Therapy (CBT) treatment. Among these patients, 35 individuals used the AI-enabled therapy support tool for activities such as homework completion, and emotion tracking before and after behavioural activation exercises. This group was compared to a matched control group of 3,926 patients who did not use the therapy support tool during treatment.

To ensure that the groups were matched, the control group only included patients who had the same diagnosis and treatment pathway as the group that used the AI-enabled therapy support tool. Thus, we only included patients who received a diagnosis of depression, GAD, PTSD or social phobia and were undergoing CBT treatment rather than counselling or other treatments. The distribution of patients across treatment steps was similar between the group using the AI-enabled therapy support tool and the control group - the statistical test showed a non-significant difference ($\chi^2$ (1) = 1.37, $p = 0.242$). Moreover, both groups were equated in terms of the services where they received treatment and the timeframe during which the treatment happened (June 2022 to March 2023). While there was no random allocation to the treatment group, we ensured to match the groups as well as possible based on these variables.

Patients who used the AI-enabled therapy support tool referred to the services through a self-referral tool, Limbic Access. Patients' progress was tracked across their treatment (average of 6 sessions across the cohort, range of 1 to 27 sessions) to understand the utility of the AI-enabled therapy support tool.

The primary objective of this study was to determine whether the AI-enabled therapy support tool could outperform standard-of-care practices in two crucial domains:

1. Engaging patients in their treatment to encourage increased exposure to therapeutic techniques. Engagement in psychological therapy has been identified as a significant predictor of treatment outcomes Harrison et al. [2019]

2. Improving treatment outcomes, such as reliable improvement and reliable recovery

#### 2.2.1 Ethics statement

As determined by the NHS and in accordance with NICE principles Ross [2002], clinical audit studies within the NHS Talking Therapies framework do not require additional patient consent or ethical approval Ross [2002]. When registering to use the AI-enabled therapy support tool, patients provided written informed consent as part of a privacy policy agreement, allowing the service to use anonymised patient data for audit purposes and to support research.

### 2.3 Outcome measures

The outcome measures reported in this study are routinely assessed during mental healthcare provision by the NHS Talking Therapies services. Dropout rates and do-not-attend rates were used as indicators of treatment engagement, whereas reliable improvement and reliable recovery rates were used as measures of treatment success.

#### 2.3.1 Dropout rate

We were interested in evaluating whether the use of the AI-enabled therapy support tool would reduce the likelihood of patients dropping out of the service during treatment. Dropouts were defined as those patients who cancelled an appointment and did not re-book a new appointment. This is measured as a percentage of patients dropping out from treatment.

#### 2.3.2 Number of do-not-attend sessions

We were interested in evaluating whether the use of the AI-enabled therapy support tool would reduce the number of sessions where patients did not attend their sessions without informing the service. The number of do-not-attend (DNA) rate sessions is measured as the number of sessions that were reported as DNA by the services.

### 2.3.3 Percentage of attended sessions

Both dropouts and DNAs lead to a reduction in the total number of attended sessions. This scenario is undesirable as it allocates resources inefficiently, diverting them from patients who could genuinely benefit from the sessions. Consequently, services seek to maximise the percentage of attended sessions to optimise resource allocation. Therefore, we calculated the percentage of attended sessions as a measure of the total impact of patient engagement on services: Percentage attended sessions = Attended sessions / (Attended sessions + DNAs). Notably, dropouts indirectly affect this metric by reducing the overall number of attended sessions.

### 2.3.4 Reliable improvement

We were interested in evaluating whether the use of the AI-enabled therapy support tool would enable a higher rate of reliable improvement in the NHS Talking Therapies services. An individual has achieved reliable improvement when there has been a significant improvement in their condition after the course of treatment, measured by the difference between their first and last scores on clinically validated questionnaires tailored to their specific condition. For example, Patient Health Questionnaire (PHQ-9) Kroenke et al. [2001] is used to measure depression symptom severity and Generalised Anxiety Disorder Assessment (GAD-7) Spitzer et al. [2006] to measure anxiety symptom severity. We measure the improvement rate as the percentage of patients who achieved reliable improvement.

### 2.3.5 Reliable recovery

We were interested in evaluating whether the use of the AI-enabled therapy support tool would enable a higher rate of reliable recovery in the NHS Talking Therapies services. An individual has achieved reliable recovery when they meet the criteria for reliable improvement and if they have moved to recovery. Recovery is defined as moving from a clinical case at the start of the treatment to a below clinical case at the end of the treatment, measured by scores from the clinical questionnaires. We measure the reliable rate as the percentage of patients who achieved reliable recovery.

### 2.3.6 Number of sessions required to achieve reliable recovery

While the overall recovery rate is of the highest importance to healthcare services, the efficiency with which this recovery is achieved is also critical. While additional therapy sessions have been shown to increase the likelihood of recovery Gyani et al. [2013], each session is costly and drains service resources with an average cost of > £100 per therapy session in NHS talking therapies Griffiths and Steen [2013]. Achieving recovery with fewer treatment sessions will create large financial and resource benefits for the service.

Therefore, we were interested in investigating whether the AI-enabled therapy support tool would impact the number of treatment sessions required to achieve reliable recovery. For this purpose, we calculated the reliable recovery rates for both groups as a function of the number of attended sessions. Hereby, we increased the threshold for the number of attended sessions iteratively and calculated the average recovery rate for all patients who attended fewer sessions than the set threshold.

## 2.4 Analysis

To compare the group that used the AI-enabled therapy support tool to the group that did not (control group), we compared the outcome measures between the services and used a Chi-squared test to measure whether there was a difference between the two groups. For continuous variables, independent sample t-tests were used.

# 3 Results

## 3.1 Dropout rate

Among the patients using the AI-enabled therapy support tool, 17.1% dropped out during treatment, in contrast to 24.5% in the control group. Statistical analysis did not reveal a significant difference between the groups ($\chi^2$ (1) = 0.205, $p$ = 0.651). Nevertheless, initial evidence suggests a positive relationship between dropouts and the use of the AI-enabled therapy support tool indicating potential benefits of the AI-enabled therapy support tool on dropout rates.

## 3.2 Number of do-not-attend sessions

In the AI-enabled therapy support tool group, the number of average DNA sessions was 0.37, compared to the average of 0.53 DNAs in the control group. Similarly to dropout rates, the statistical analysis did not show a significant difference between the two groups ($t(3956)$=-1.43, $p = 0.162$), however, there is a trend that the group using the tool has a lower number of DNAs compared to the control group.

## 3.3 Percentage of attended sessions

While the observed trends of dropouts and DNAs did not result in significant differences, they trended in the same direction. Importantly, mental health services focus on minimising DNAs and dropouts to optimise their resource allocation, particularly clinician time, and both of these events lead to a reduction in the percentage of attended sessions. Therefore, we investigated the effect of the AI-enabled therapy support tool on the percentage of attended sessions. In the AI-enabled therapy support tool group, 94.6% of sessions were attended, whereas in the control group, only 90.6% of sessions were attended. This difference between the groups was significant ($t(3956)$=-2.46, $p = .019$) indicating that the usage of the AI-enabled therapy support tool leads to a higher utilisation of therapy sessions provided by the healthcare service.

## 3.4 Reliable improvement

In the group that used the AI-enabled therapy support tool, 94.3% of patients achieved reliable improvement, compared to 69.8% of patients in the control group (see Figure 2A). The percentage of individuals who achieved reliable improvement was significantly higher for individuals who used the AI-enabled therapy support tool compared to the group that did not use the tool ($\chi^2$ (1) = 8.77, $p = 0.0031$).

## 3.5 Reliable recovery

In the group that used the AI-enabled therapy support tool, 71.4% of patients achieved reliable recovery, compared to 50.7% of patients in the control group (see Figure 2B). The percentage of individuals who achieved reliable recovery was significantly higher for individuals who used the AI-enabled therapy support tool compared to the group that did not use the tool ($\chi^2$ (1) = 5.18, $p = 0.0228$).

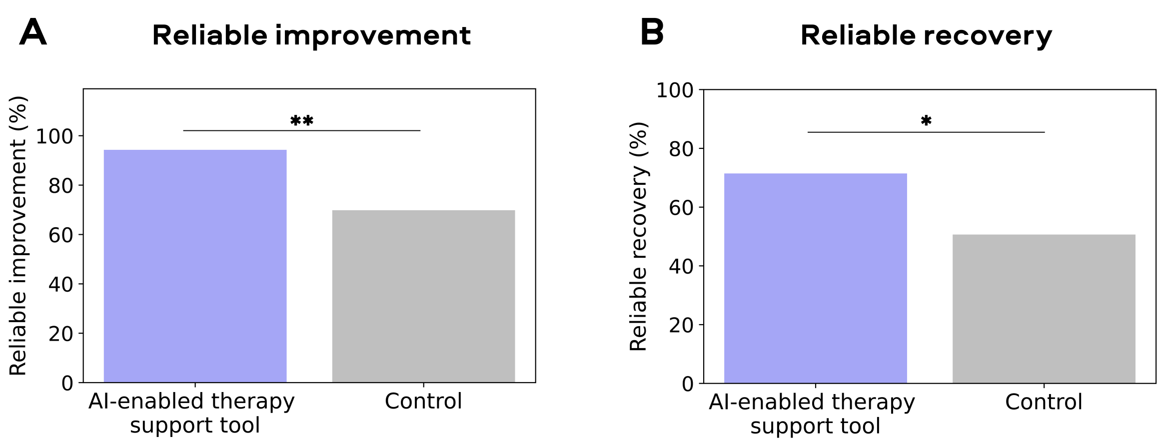


Figure 2: The reliable improvement rate (A) and reliable recovery rate (B) for patients who used the novel AI-enabled therapy support tool (purple) and the control group (grey) who did not use the tool. *$p < 0.05$, **$p < 0.01$

### 3.6 Number of sessions required to achieve reliable recovery

Besides the overall recovery rates, we were also interested in the number of sessions required to achieve recovery. Hereby, we investigated whether the usage of the AI-enable therapy support tool would facilitate faster recovery, i.e. increase the recovery rates with fewer sessions required.

Indeed, the rate of improvement per session was higher in the group that utilized the AI-enable therapy support tool (see Figure 3). This means that the recovery rate rises more steeply in the experimental group. In other words, the AI-enabled tool leads to comparable recovery rates to the control groups with fewer therapy sessions required.

In Figure 3, it is clearly visible that with less than 5 therapy sessions the group using the AI-enabled therapy support tool surpasses the recovery rates of the control group after the complete course of therapy (indicated by the grey dotted line). On average, this part of the experimental group had received 3.5 therapy sessions and had achieved a reliable recovery rate of 66.6% which is higher than the overall reliable recovery rate in the control group (50.7%) after a complete course of treatment which consists of an average of 5.8 sessions in this group.

This suggests that the AI-enabled therapy support tool enables recovery rates that are at least as high as in the standard of care (i.e. the control group) but with 39.7 % fewer therapy sessions required. Therefore, these results indicate that the usage of the AI-enabled therapy support tool can dramatically reduce the cost of delivering therapy while equating treatment outcomes.

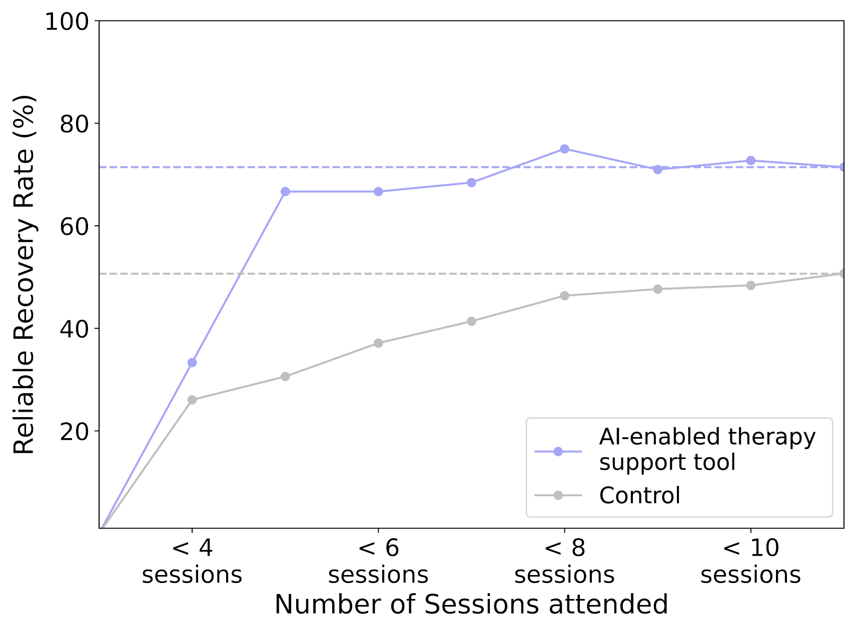


Figure 3: Reliable recovery rate as a function of the number of attended sessions. The dotted line represents the overall average of reliable recovery rates for each group.

# 4 Discussion

In this study, we investigated the effects of a novel AI-enabled therapy support tool on patient engagement and clinical outcomes in the NHS Talking Therapies services in the United Kingdom. The group that used the AI-enabled therapy support tool, Limbic Care, showed significant improvement in engagement and treatment outcomes compared to the control group. Specifically, patients using the AI-enabled therapy support tool were significantly more likely to attend more sessions, and achieve reliable improvement and reliable recovery than patients who did not have access to this technology. We observed a remarkable increase of 35 percentage points in the reliable improvement and a 40.8 percent increase in reliable recovery. Moreover, this increase in overall recovery rates was also associated with a faster benefit from therapy, i.e. less therapy sessions were required to achieve high recovery rates. These initial findings are promising, indicating that the integration of the AI-enabled therapy support tool with standard talking therapy holds substantial potential for improving the quality of mental health treatment.

These findings are important from two perspectives. Firstly, improved recovery rates directly benefit the patients indicating a higher quality of care. Secondly, the improved outcomes could be achieved more efficiently through the AI-enabled therapy support tool, meaning that fewer therapy sessions are required to achieve recovery. Therefore, a cost-effective solution like Limbic Care, which helps to boost recovery rates, will support the healthcare services to meet their targets related to quality of care. This is especially true when also considering that this tool did not only increase recovery rates, but also reduced dropout rates and do-not-attend rates, which create costs for the service providers. Therefore, our results indicate that the usage of Limbic Care might be a highly promising approach to improve the quality of care while at the same time reducing costs, a solution that is urgently needed in an environment where services are stretched and quality of care suffers.

As with any study, certain limitations warrant consideration. The study's observational nature introduces the possibility of confounding factors influencing the observed results. Specifically, the lack of randomized allocation to the study arms, could have let to selection bias or other confounds that were not equated between the study arms. Therefore, future studies should provide further support for the observed findings. Nonetheless, we aimed to match the groups as well as possible, to rule out the most obvious confounding factors. Both the control and treatment groups underwent CBT therapy during similar time periods within the same services. Moreover, both groups were closely matched in terms of diagnostic categories and treatment pathways. While the potential for differences between the groups remains, our comprehensive analysis covered the most apparent factors, mitigating this potential limitation.

As the next step, we intend to conduct future research with a larger sample to confirm the effectiveness of the AI-enabled support tool. We anticipate implementing controlled experimental designs, such as a randomised controlled trial, to explore causal relationships in a more robust manner. This could help us to understand further the mechanisms of how this AI-enabled therapy support tool can bring value to patients and mental health providers.

In conclusion, the findings of this study demonstrate the potential of AI-enabled therapy support tools in revolutionising mental health treatment. The early successes observed in this pilot suggest that Limbic Care holds substantial promise in not only enhancing patient outcomes but also supporting healthcare providers in a resource-efficient manner. As the landscape of mental healthcare continues to evolve, embracing innovative technological solutions like AI-driven support tools could play a pivotal role in shaping the future of treatment delivery.

# References


J. Borghouts, E. Eikey, G. Mark, C. De Leon, S. M. Schueller, M. Schneider, N. Stadnick, K. Zheng, D. Mukamel, and D. H. Sorkin. Barriers to and facilitators of user engagement with digital mental health interventions: systematic review. *Journal of medical Internet research*, 23(3):e24387, 2021.

P. Chandrashekar. Do mental health mobile apps work: evidence and recommendations for designing high-efficacy mental health mobile apps. *Mhealth*, 4, 2018.

K. Denecke, N. Schmid, and S. Nüssli. Implementation of cognitive behavioral therapy in e–mental health apps: Literature review. *Journal of medical Internet research*, 24(3):e27791, 2022.

J. Firth, J. Torous, J. Nicholas, R. Carney, A. Pratap, S. Rosenbaum, and J. Sarris. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. *World Psychiatry*, 16(3):287–298, 2017a.

J. Firth, J. Torous, J. Nicholas, R. Carney, S. Rosenbaum, and J. Sarris. Can smartphone mental health interventions reduce symptoms of anxiety? a meta-analysis of randomized controlled trials. *Journal of affective disorders*, 218:15–22, 2017b.

S. Griffiths and S. Steen. Improving access to psychological therapies (iapt) programme: Scrutinising iapt cost estimates to support effective commissioning. *The Journal of Psychological Therapies in Primary Care*, 2(2):142–156, 2013.

A. Gyani, R. Shafran, R. Layard, and D. M. Clark. Enhancing recovery rates: lessons from year one of iapt. *Behaviour research and therapy*, 51(9):597–606, 2013.

P. Harrison, G. E. Hardy, and M. Barkham. The relationship between expected engagement and talking therapy outcome. *Clinical Psychology & Psychotherapy*, 26(4):492–501, 2019.

P. Henson, H. Wisniewski, C. Hollis, M. Keshavan, and J. Torous. Digital mental health apps and the therapeutic alliance: initial review. *BJPsych open*, 5(1):e15, 2019.

S. G. Hofmann, J. Q. Wu, and H. Boettcher. Effect of cognitive-behavioral therapy for anxiety disorders on quality of life: a meta-analysis. *Journal of consulting and clinical psychology*, 82(3):375, 2014.

T. D. Hull, M. Malgaroli, P. S. Connolly, S. Feuerstein, and N. M. Simon. Two-way messaging therapy for depression and anxiety: longitudinal response trajectories. *BMC psychiatry*, 20(1):1–12, 2020.

J. Koh, G. Y. Tng, and A. Hartanto. Potential and pitfalls of mobile mental health apps in traditional treatment: An umbrella review. *Journal of Personalized Medicine*, 12(9):1376, 2022.

K. Kroenke, R. L. Spitzer, and J. B. Williams. The phq-9: validity of a brief depression severity measure. *Journal of general internal medicine*, 16(9):606–613, 2001.

H. Q. Ontario et al. Psychotherapy for major depressive disorder and generalized anxiety disorder: a health technology assessment. *Ontario health technology assessment series*, 17(15):1, 2017.

S. Ross. Principles for best practice in clinical audit, 2002.

B. N. Rudd and R. S. Beidas. Digital mental health: the answer to the global mental health crisis? *JMIR Mental Health*, 7(6):e18472, 2020.

D. F. Santomauro, A. M. M. Herrera, J. Shadid, P. Zheng, C. Ashbaugh, D. M. Pigott, C. Abbafati, C. Adolph, J. O. Amlag, A. Y. Aravkin, et al. Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the covid-19 pandemic. *The Lancet*, 398(10312):1700–1712, 2021.

R. L. Spitzer, K. Kroenke, J. B. Williams, and B. Löwe. A brief measure for assessing generalized anxiety disorder: the gad-7. *Archives of internal medicine*, 166(10):1092–1097, 2006.

Z. Steel, C. Marnane, C. Iranpour, T. Chey, J. W. Jackson, V. Patel, and D. Silove. The global prevalence of common mental disorders: a systematic review and meta-analysis 1980–2013. *International journal of epidemiology*, 43(2):476–493, 2014.

C. B. Taylor, E. E. Fitzsimmons-Craft, and A. K. Graham. Digital technology can revolutionize mental health services delivery: The covid-19 crisis as a catalyst for change. *International Journal of Eating Disorders*, 53(7):1155–1157, 2020.

I. Verbist, D. Huey, and H. Bennett. Predicting treatment outcomes in improving access to psychological therapy (iapt) services. *Mental Health Review Journal*, 27(1):114–131, 2022.

L. Wilson and M. Marasoiu. The development and use of chatbots in public health: Scoping review. *JMIR human factors*, 9(4):e35882, 2022.