

# Chapter 7

## Advancements in Psychotherapy and Treatment: The Use of AI Interventions for Psychopathologies

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### ABSTRACT

*This chapter explores the potential of Artificial Intelligence in mental health, with a special focus on psychopathologies. The researchers expand on AI's role in assisting clinicians' diagnosis, symptom tracking, predictive modelling, and therapy for psychiatric and neurodevelopmental disorders like Depression, Anxiety, Post-Traumatic Stress Disorder (PTSD), Substance Use Disorder, Autism Spectrum Disorder (ASD), and ADHD. Crucial interventions include wearables for anxiety, virtual reality exposure for PTSD, and robotic social companions for children with ASD. Despite*

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*these advancements, the use of AI chatbots as a replacement for therapy has been a subject of debate, largely due to issues around safety. The study highlights potential limitations, including risks in user interactions, limited therapeutic support, algorithmic biases, accessibility issues, and ethical concerns; advocating for “Human in the Loop” models where AI and clinicians work together, and calling for ethically designed AI systems that augment access without compromising on empathy, nuance and relational depth.*

## **THE SCALE OF THE MODERN MENTAL HEALTH CRISIS**

The World Health Organisation (2022) reports that more than a billion people, roughly one in every eight across the world, are living with unnoticed mental health conditions. These may present as symptoms of general anxiety, persistent dysthymia or depression, substance dependence, or trauma reactions impacting people’s daily lives.

While the general populace remains unaware, the world continues to face this emergent public health challenge, all the while lacking the needed support systems and accessible healthcare.

Despite the scale at which mental health affects our population, it continues to receive limited attention in healthcare systems across the world. The World Health Organisation's Mental Health Atlas (2020) reveals that most countries allocate less than 2% of their entire health budgets to mental health services. In some of the world's most economically disadvantaged regions, including parts of South Asia and sub-Saharan Africa, mental health spending drops to as little as \$0.25 per person annually, not nearly enough to offer even the most basic care (WHO, 2021).

The consequences of underinvestment are both clinical and economic, with the World Economic Forum projecting that mental health conditions will impose costs exceeding \$6 trillion annually on the global economy by 2030, surpassing the combined economic burden of cancer, diabetes, and respiratory diseases (World Economic Forum, 2011). However, this impact is measured not only in dollars, but through the real patients and clinicians being affected.

The COVID-19 pandemic highlighted how mental health affects everything from how we learn, relate to each other, work, or handle stress or change. No country can move forward, either economically or socially, while putting mental health on the back burner. Even in developed countries like the United States or the United Kingdom, between 35% and 50% of people are unable to access the mental health care they need (World Health Organization, 2021).

In low- and middle-income countries, this treatment gap reaches a high of 85%, according to the World Health Organisation (2022). The majority of people with

the greatest need never get the support they deserve, often due to a dearth of professionals, social stigma, a lack of funding, and inaccessible services, resulting in many suffering alone.

One of the most tragic outcomes of this treatment gap is suicide. Every year, over 800,000 people lose their lives to suicide, making it the second leading cause of death among those aged 15 to 29 (UNICEF, 2021). While women attempt suicide more often, men are more likely to die by suicide, due to the use of more lethal means and sociocultural pressures to suppress emotional vulnerability or avoid seeking help (World Health Organization, 2014; Canetto & Sakinofsky, 1998).

This crisis certainly did not begin with the COVID-19 pandemic; rather, the global mental health system had long been strained, under-resourced, and ill-equipped to meet growing demands. Longer wait times, burned-out clinicians, and a mental health crisis that has even children in middle school showing levels of stress far exceeding their age (National Academies of Sciences, Engineering, and Medicine, 2019; WHO, 2022).

The Lancet Commission on Global Mental Health and Sustainable Development in 2016 showcased sobering numbers, calculating that low- and middle-income countries needed over 1.18 million more mental health workers to cover basic services (Patel, 2018). These issues were pertinent in countries with greater allocation of resources as well. In the United Kingdom, around one-third of child and adolescent psychiatry consultant posts in the NHS sat empty, forcing young people to wait months for care (Royal College of Psychiatrists, 2022). While in the United States, over 150 million live in Mental Health Professional Shortage Areas, per the Kaiser Family Foundation (2023), making the reality hard to ignore. People do not hesitate to seek help, but there is simply no one to provide it.

What was already a struggling system collapsed under the weight of a global pandemic. Depression and anxiety went up sharply. A study in *The Lancet* (2021) discovered that, in just one year, cases of both rose by over 25% worldwide (Santomauro et al., 2021). At the same time, therapy appointments were suddenly cancelled as health systems struggled to keep going.

In-person support groups dissolved. Many school-based mental health programs were paused or cut down. During the peak of the crisis, the World Health Organisation (2020) reported that nearly 80% of outpatient mental health services were disrupted in several countries, leaving millions of people without the support they needed. Across the globe, uncertainty became part of daily life, and it was heavy and persistent.

Yet, new forms of support emerged almost organically. Telehealth adoption accelerated at breakneck speed, with therapists moving entire practices online in a matter of days. This shift worked well for many people, remote therapy sessions from home, the lack of commute, and fewer obstacles to getting help. When official

systems failed, communities filled the void. Grassroots support networks formed naturally while online peer support groups multiplied rapidly. Technology also began to play a role in offering support, as some tools could pick up early signs of distress from how a person spoke or wrote. Mobile apps started serving as tools for tracking mood fluctuations, sleep quality, and anxiety levels (Torous et al., 2021).

Traditional mental health systems are still stretched thin, but there's a growing sense of hope that technology, especially newer tools like artificial intelligence, could fill some of the gaps that have gone unaddressed for years.

AI has already reshaped numerous aspects of daily life, and its expansion into mental health care was perhaps inevitable. Take Woebot, a chatbot developed by researchers at Stanford that chats with people using techniques from cognitive behavioural therapy. It's designed to help with things like mood and anxiety, offering support through everyday conversations (Fitzpatrick et al., 2017). Other tools can study how someone writes or speaks to spot early signs of depression or distress (Cummins et al., 2018; Inkster et al., 2018).

One big advantage of AI is that it can reach many people at once. In remote or low-resource areas, where mental health support is hard to find, whether it's because of distance, money, or lack of services, even a simple app on a phone can make a difference. In countries like India and Nigeria, where more than 80% of people don't get the care they need (WHO, 2022), these tools could offer a small but important step toward getting help.

AI might take some weight off the shoulders of mental health professionals, like helping with routine work or offering support between therapy sessions. But that's only one side of the story. The truth is that many AI-based mental health tools are still in their early days. Some look promising on the surface, but most haven't been tested widely enough to know if they really work for people from different backgrounds, cultures, or age groups. What works for one person might not work for another, and we don't fully understand those differences yet.

In the end, AI might not be the answer, but it could still become part of it, especially in settings and places where access to care is limited or non-existent. If used thoughtfully and responsibly, it can expand the reach of mental health support. But it will need strong guardrails, human oversight, and ongoing evaluation to ensure it does more good than harm. As mental health needs grow globally, it's clear the system must evolve. That evolution may include technology, but it must also include people, policies, and values.

The manner in which artificial intelligence has revolutionised the progress of mental health research and intervention has been an increasingly fascinating trajectory for both the field of psychology and technology.

## First Historical Ventures

The idea of chatbots has existed for many decades, ever since the cognitive revolution in the field of psychology in the 1950s. ELIZA was one of the first chatbots developed in the 60s by Weizenbaum. It was an early natural language processing program, a field of AI that enables computers to understand and communicate using human language (Fanni et al., 2023). Eliza simulated a therapist's conversational approach, and primarily operated through pattern recognition and response generation, utilising simple keyword matching to reflect user statements as questions. While reliant on pre-scripted responses, ELIZA laid a foundation for all future mental health applications by showcasing the ability of AI to engage users in therapeutic dialogue (Weizenbaum, 1966). Over at Stanford in 1972, psychiatrist Kenneth Colby developed PARRY, which simulated a patient with schizophrenia. Utilising a natural language program, it was able to mirror the behaviour of someone with the same disorder. It became one of the first AI programs to pass the Turing Test, and PARRY highlighted AI's potential to embody specific mental health conditions (Colby et al., 1972). While these historical attempts existed, they lacked the conversational depth and dynamism needed to replicate human conversation.

## The Advent of Rule-Based Systems

The 1980s and 1990s witnessed the emergence of rule-based expert systems, which were able to assist with diagnostic decision-making and treatment planning (Alowais et al., 2023). Programs like MYCIN, which possessed psychological derivatives and early diagnostic support tools, were able to incorporate formalised clinical knowledge, diagnostic criteria, and treatment protocols into structured decision trees at a time when psychiatric diagnosis was becoming increasingly standardised due to the publication of the DSM-III in 1980 (van Melle, 1978, Kawa & Giordano, 2012).

Based on those established clinical guidelines, programs were able to incorporate differential diagnosis algorithms, various risk assessment protocols, and treatment recommendations (Moreno & Plant, 1993). However, the complexity of human psychology could not be easily captured by such rigid decision trees, as they were often lacking the nuances needed for true diagnosis and treatment plans (Sun et al., 2025).

The late 20th century witnessed the emergence of computerised cognitive-behavioural therapy (CBT) programs. These interactive software applications aim to provide evidence-based therapy interventions for prevalent mental health conditions. Although the initial efforts were somewhat rudimentary compared to today's AI-powered interventions, they signified a transition into utilising technology to enhance the accessibility of mental healthcare. As computing power advanced, AI's role in mental healthcare evolved exponentially.

## Recent Developments and Technological Assistance

However, like always, technology was able to offer a solution to these rudimentary efforts in the form of Generative AI and Large Language Models (LLM), transforming chatbots into dynamic and interactive systems. They were now often providing real-time, appropriate, and empathetic responses, able to understand the nuances of language and experience. This ability to foster feelings of understanding and support comes from extensive psychologically sensitive data, containing clues into conversational tones and empathy. This contextual understanding is the key reason behind the improved responses and the degree of support the user experiences (Zhao et al., 2024; Banh & Strobel, 2023), and a key step in making mental healthcare more streamlined and accessible.

From ELIZA's simple pattern matching to contemporary multimodal AI analysis systems, the historical trajectory of mental health and AI showcases both technological advancements as well as a fundamental evolution in how psychological phenomena are conceptualised and studied.

## RECENT TRENDS IN DIGITAL HEALTHCARE

AI can revolutionise mental healthcare through insights or solutions which are not easily accessed through conventional tools and methods (Nilsen et al., 2022). It holds the potential to broaden the availability and accessibility of healthcare and improve treatment outcomes while reducing stigma (Minerva & Giubilini, 2023) by providing personalised treatment options through accessible platforms (Olawade et al., 2024).

### Assisting Clinicians in Diagnosis

Whether through analysing speech, text, facial expressions, or health records, AI can transform how clinicians diagnose mental health conditions through the use of predictive modelling (Lee & Yoon, 2021). Sentiment analysis, where changes in people's emotions are explored through their online posts and diaries, could help professionals assess when a user started experiencing certain emotions (Uban et al., 2021).

Voice analysis could be used in telephonic appointments or through apps like Cogito, an AI platform used for telehealth services. This allows any alterations in speech patterns or pitch to be tracked and monitored, and reported to the therapist or clinician to serve as additional proof of anxiety or depression (Flanagan et al., 2021; Kuziemytsky et al., 2019). Kintsugi, another platform, frequently uses facial

and vocal analysis to inform the therapist about elevated distress levels during a session, providing practitioners with another useful tool (Kintsugi, 2022).

AI can also assist in recognising potential patients who might be at risk, through analysing their electronic health records (Davenport & Kalakota, 2019), allowing clinicians to pay greater attention to those patients during routine checks (Olawade et al., 2024). This is primarily because machine learning algorithms go through records and patient data, which would likely include full medical histories, clinical notes, and any tests, which could make it easier to identify any potential patterns (Iyortsuun et al., 2023).

## **Predictive Models and Wearable Devices**

In addition to algorithms, a notable trend in predictive modelling is the use of wearable technologies as well as mental health apps, as these can collect real-time data on the behaviour of users (Sabry et al., 2022). These devices are able to track sleep patterns, physical activities, and social interactions, and users can often track their moods and food habits, which could help in recognising any potential risk factors (Koutsouleris et al., 2022). In addition to predicting mental health risks, these tools could also predict how the user might respond to treatment modalities, whether it's psychotherapy, medication, or changing lifestyle (Ghaffar Nia et al., 2023). These allow tailored interventions and clinician-guided recovery, leading to more effective treatment, a reduced recovery time, and overall improved patient satisfaction (Dawoodbhoy et al., 2021). These same devices can also be used to monitor patients in treatment, making it easier to identify those at risk of relapse, through changes in sleep patterns, physical activity, etc, and alert therapists to follow-up (Zlatintsi et al., 2022).

## **Dynamic and Stigma-Free Therapy**

AI can also be particularly helpful in guiding and modifying treatment decisions during the therapeutic process. It might be easier to track and inform the clinician about how the user is feeling about the therapeutic process, allowing for modifications to be made (Kumar et al., 2022). The same principle can also be utilised in chatbots and mental health apps, with real-time modification to the kind of questions and approach being used based on the users' responses, minimising the amount of trial and error or unilaterally using the same modality and approach for everyone (Kaldo et al., 2021).

These chatbots and virtual therapists can increase the accessibility of mental health resources for those who might hesitate to approach traditional practitioners, and are able to offer round-the-clock support, which can be very helpful in provid-

ing immediate emotional support, not restricted by any geographical constraints (Omarov et al., 2023). However, it's important to note that these are rarely the only avenues of support, and most chatbots would have a system of connecting people to human therapists in moments of crisis, including elevated distress or self-harm risks (Olawade et al., 2024).

There are many global chatbots available, of which Wysa, originally developed in India and now one of the leading bots catering to a global audience, is a key one. It caters to a lot of mental health conditions, including depression, anxiety, stress, and loneliness and uses CBT, mindfulness, and positive psychology to provide emotional support (Wysa, 2023).

## **Easing Therapist Burden**

AI can especially be utilised to ease some of the burden on therapists by taking on certain administrative tasks, allowing therapists to focus more on the therapeutic tasks and improving overall outcomes (Al Kuwaiti et al., 2023). Talkspace is one such platform that takes on the worries of scheduling and billing, ensuring that therapists have enough bandwidth to focus on the therapy (Talkspace, 2018).

AI assessments can also ensure objective measurement of treatment and how it's progressing, as they can go beyond self-report measures, and utilise physiological data, behavioural observations, or even tonal changes, allowing therapists to make data-driven decisions regarding treatment plans and next steps (Garriga et al., 2022).

## **Self-Management of Issues**

In addition to therapy chatbots, modelling, and other treatment-focused programs, AI can also make self-management of mental health easier (Stawarz et al., 2019). Many apps provide grounding and self-care activities as well, one of which is SuperBetter. It encourages people to complete tasks alongside interactive content that would help their overall mental well-being, and a study conducted with 283 participants suggested that this could help manage depression (Roepke et al., 2015). However, these are primarily effective when they are not pushed as a replacement for face-to-face support, but only as an addition (Stawarz et al., 2019).

It's important that even with all these new and developing trends, all these advancements are only ever used in a responsible manner, for the betterment of patients and users with a commitment to adhere to ethical principles and guidelines (Olawade et al., 2024).

## KEY PSYCHOLOGICAL DISORDERS AND AI INTERVENTIONS

### Depression: Prevalence and Global Burden

Depression is one of the most prevalent mental health disorders worldwide. Usually characterised by a persistent low mood, lack of interest and negative thinking patterns (Chand & Arif, 2023), depression has a significant effect on one's physical health as well as daily functioning. People are known to lose more years to depression than any other condition (Smith, 2014). According to the World Health Organisation, 280 million people in the world suffer from depression globally (World Health Organization: WHO & World Health Organization: WHO, 2023). Yet, the majority of the people diagnosed with depression do not get adequate treatment due to factors like stigma, lack of awareness, and an insufficient supply of mental health professionals (Arnaez et al., 2019).

However, as awareness is moving in a positive direction worldwide, there has been an increase in the diagnosis of depression. A study indicated that the number of incident cases of depression worldwide increased from 172 million in 1990 to 25.8 million in 2017, representing an increase of 49.86% (Liu et al., 2019). Another meta-analysis study confirmed this and indicated that there has been a constant increase in the prevalence of depression globally over time, one that cannot be explained due to differences in study design or publication bias (Moreno-Agostino et al., 2020).

### Challenges in Diagnosis

The varied nature of depression, along with the lack of standardised definitions and concomitant comorbidities, all act as challenges for diagnosis. The absence of clarity on the threshold of severity and symptoms which should be mandatorily present in depression makes the diagnosis even more taxing (Fried et al., 2022). In South Asian countries, factors like stigma and lack of trained mental health professionals add to the challenge of diagnosis (Ogbo et al., 2018). Even though scientific advances have been made in the past regarding clinical research and brain neuroimaging techniques, most of the studies are carried out using group differences as data (Lee & Passarotti, 2022). This makes it incredibly difficult for clinicians to diagnose depression in individuals with atypical symptoms. Moreover, it's even more ambiguous to diagnose depression in children and adolescents since they might show different characteristic features of depression, often unknown to adults (Lee & Passarotti, 2022).

## Artificial Intelligence and Depression

Recent developments in Artificial Intelligence (AI) can facilitate the prevention, diagnosis, and treatment of depression. AI cannot replace therapy when it comes to diagnosis and treatment, but it can help clinicians make the process easier and more efficient. When it comes to diagnosis, AI can assist with clinician-generated data, which significantly improves predictive performance as compared to structured data with laboratory values (Zafar et al., 2024). Traditional diagnosis of depression involves self-report questionnaires, which can raise concerns about reliability, validity, and objectivity, even when performed under the supervision of trained clinicians. Richter et al. (2021) suggest that the psychiatric diagnostic process would benefit greatly from adding data-driven tools that can enhance diagnostic accuracy and specificity alongside the clinical interview and self-report questionnaires.

## Chatbots and Depression

Artificial Intelligence officially entered the arena of talk therapy through therapy chatbots. Various studies have proven the effectiveness of therapy chatbots for depression over a short period of time (Stein, 2025). Another meta-analysis has confirmed this finding and further highlights the promising role of AI-based chatbot interventions in alleviating depressive and anxiety symptoms among adults (Zhong et al., 2024). H. Liu et al. (2022) conducted a comparison study between AI therapy chatbots and bibliotherapy as a self-help treatment for depression. Bibliotherapy can be described as the process of using literature, information and support to improve one's mental health (Monroy-Fraustro et al., 2021). The study revealed better effectiveness of the therapist chatbot over 16 weeks. This highlights the potential of AI therapy chatbots for depression, even for long-term treatment. The same study also established the superiority of AI therapy chatbots for forming a therapeutic alliance between the chatbot and the client. This particular finding contradicts the popular belief about the incapability of AI in forming a therapeutic relationship with clients.

These chatbots are hypothesised to be more effective than mental health smartphone applications owing to refinement in the latest generative AI and Large Language Models (LLMs). A disorder like depression affects anyone regardless of their socioeconomic status. Hence, for the economically and socially marginalised as well as geographically disadvantaged populations, therapy chatbots might be the only option for easily accessible and affordable interventions when it comes to depression (Stein, 2025). However, it's too far-fetched to believe that AI therapists will completely replace human therapy.

Although rule-based AI chatbots like Woebot and Wysa have improved depression symptoms over a short period of time, users still report frustration with responses

that seem generic, empty, constrained, and repetitive (Siddals et al., 2024). However, Large Language Models (LLMs) are trained on large amounts of data, and have been surpassing human performance in different fields (Siddals et al., 2024). With ChatGPT's user base growing to 100 million weekly active users, generative chatbots present a significant opportunity for digital mental health. Certain meta-analysis studies have also reflected on the positive experiences of users in generative chatbots when it comes to making people feel heard, dealing with relationship issues or reducing psychiatric distress (Siddals et al., 2024).

A study explored that some users utilised chatbots in conjunction with therapy, while some used them because they couldn't access therapy or didn't get the help they were seeking. Upon comparing it with therapy, the reactions received were mixed. Some users claimed that it could dive deeper into specific issues that a human therapist could not help them with. Moreover, people felt less lonely and were motivated to seek therapy after having conversations with chatbots. On the other hand, some users reported that it felt like they were talking to a void and were upset by the chatbot's inability to grasp a picture of their life (Siddals et al., 2024)

In recent times, several chatbots have emerged as an avenue for treatment, specifically for depression. One of the generative AI chatbots that has recently emerged is Therabot. It is made by the University of Southern California (USC) - Institute for Creative Technologies (ICT) to support mental health and emotional well-being, especially for individuals dealing with depression, anxiety, or emotional distress (*First Therapy Chatbot Trial Yields Mental Health Benefits*, 2025). In a study, Therabot was tested on its efficacy for major depressive disorder, and users showed a significant reduction in symptoms post-intervention. This proves that fine-tuned generative AI chatbots have the potential to deal with users who have major clinical symptoms, along with providing effective engagement and therapeutic alliance (Heinz et al., 2025)

Another generative AI chatbot that has been specifically made for mental health concerns is called Healo. Although it originated in India, Healo now serves a global audience (ANI Press Release & Business Standard, 2024). Designed by engineers and psychologists, it has a dataset of over 100000+, which makes it capable of dealing with users facing extreme mental health concerns like depression (MBDesk, 2024). Moreover, unlike any other generative AI chatbot, Healo does offer to match its users to human therapists. This supports the belief that AI-human collaborative therapy can combine AI's scalability with the essential human qualities of empathy, adaptability, and clinical judgment (Husnain et al., 2024)

## Limitations of Artificial Intelligence Chatbots for Depression

However, newer technology brings about new challenges that have not yet been tackled. As of now, clinical generative AI is limited to the implementation of evidence-based therapies (such as CBT) for clinical issues (Stade et al., 2024). Most models stick to scripted responses, which can feel monotonous and devoid of empathy (De Freitas & Cohen, 2024). Lastly, certain chatbots can be potentially harmful, exhibiting manipulative, gaslighting, and narcissistic behaviours if left untrained (Lin et al., 2024). For example, generative AI chatbots like ChatGPT have been known to agree with users, no matter what they say. This leads the users to believe that they are special and powerful and are the only ones who can see things beyond reality. Eventually, it can cause cases of delusional psychosis as termed by Dr. Joseph Pierre, a psychiatrist at the University of California (Dupré, 2025)

While AI chatbots offer accessible, stigma-free, and immediate support for people experiencing depression, their true potential lies in assisting, not replacing human care, making them valuable tools when integrated thoughtfully into a larger mental health support system.

## Anxiety Disorders

Anxiety disorders (ADs) are a group of mental health conditions that include generalised anxiety disorder (GAD), social anxiety disorder (SAD), panic disorder, and various phobia-related disorders. These disorders are among the most common mental illnesses globally, affecting approximately 284 million people worldwide (Abd-alrazaq et al., 2023a). Individuals with anxiety disorders often experience both psychological and physiological symptoms such as increased heart rate, excessive sweating, trembling, gastrointestinal issues, and muscle tension, all of which can significantly impair daily functioning and quality of life (Pavlopoulos et al., 2023).

Generalised anxiety disorder (GAD), one of the most prevalent forms, is characterised by persistent and excessive worry that is difficult to control. Diagnosis of GAD often involves the use of standardised screening tools such as the GAD-7, based on criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5). According to the DSM-5, an individual must experience inappropriate anxiety that is excessive in intensity and duration—persisting for at least six months—accompanied by symptoms such as restlessness, fatigue, difficulty concentrating, irritability, muscle tension, and sleep disturbances. Understanding and accurately diagnosing anxiety disorders is crucial for effective treatment and improving the overall well-being of affected individuals (Zafar et al., 2024).

## Artificial Intelligence and Anxiety

Artificial intelligence (AI) tools are a promising adjunct in the diagnosis and treatment of anxiety disorders (ADs), offering scalable, data-driven, and personalised approaches to support mental health care. Among the diagnostic innovations, wearable AI technologies stand out for their ability to capture physiological indicators associated with anxiety episodes, such as elevated heart rate, perspiration, and muscle tension. These devices have shown considerable accuracy; for instance, wearable AI has been reported to correctly classify individuals with and without anxiety in 81% of cases, with slightly better performance in detecting those without anxiety (92%) than those with anxiety (79%). Interestingly, while earlier studies indicated that the performance of these devices might depend on the type of algorithm used, recent evidence suggests that algorithm type does not significantly moderate accuracy. However, wearable AI should not be used in isolation, as physiological signals like heart rate variability, commonly linked to anxiety, can be influenced by multiple external factors. Thus, combining data from wearable devices with contextual information such as self-reported symptoms or clinical interviews enhances reliability and diagnostic precision (Abd-alrazaq et al., 2023a; Abd-alrazaq et al., 2023b).

### Use of AI in Therapy for Anxiety

The most impactful applications of AI in anxiety disorders lie in treatment and ongoing management. By reducing the burden of high caseloads on healthcare professionals, AI-driven systems improve access to timely care (Pavlopoulos et al., 2023). Furthermore, AI-powered chatbots and virtual assistants have shown effectiveness in delivering emotional support, psychoeducation, and coping strategies for managing anxiety symptoms. These systems use natural language processing (NLP) algorithms to understand user input and respond appropriately, often mimicking therapeutic conversations. They can also track mood changes, symptom patterns, and behaviour over time, allowing for a data-informed approach to personalised care (Zafar et al., 2024).

Among notable applications is Tess, an AI chatbot that conducts brief therapeutic conversations tailored to the emotional content shared by users. Tess uses a combination of cognitive-behavioural therapy (CBT), emotion-focused therapy, solution-focused brief therapy, and motivational interviewing to deliver relevant support strategies. For instance, when a user reports feeling anxious, Tess may suggest a relaxation technique or offer supportive psychoeducation. Tess enhances user experience by integrating emojis and casual language, fostering comfort and relatability (Fulmer et al., 2018).

Similarly, Youper represents a highly interactive AI tool that delivers entirely automated, evidence-based interventions through a chat interface. It is built around the common elements framework, which categorises treatment mechanisms into three core areas: attention change, cognitive change, and context engagement. These interventions are carefully structured, incorporating various formats such as open-text prompts, graphical interfaces, audio content, and written guidance, tailored to the user's progress and current mental state. Youper's use of just-in-time interventions ensures that therapeutic support is delivered precisely when users need it, making it particularly effective for real-time emotion regulation. Each conversation with Youper begins by identifying the user's emotional state and intensity, followed by guided skill practice in emotion regulation. These skills may include mindfulness, gratitude journaling, cognitive restructuring, or behavioural activation, drawn from empirically supported psychotherapies (Mehta et al., 2021).

In addition, AI-driven CBT platforms are transforming mental health care by offering structured therapy programs that users can complete at their own pace. These digital therapies include modules on cognitive restructuring, exposure techniques, and relaxation training, providing both interactive exercises and feedback mechanisms. Research supports their effectiveness in reducing symptoms of anxiety, and they are especially beneficial in settings with limited access to therapists (Farzan et al., 2025). Another frontier in AI-based treatment is virtual reality (VR) therapy, which uses immersive simulations to expose individuals to anxiety-inducing situations in a controlled environment. These experiences help patients build coping mechanisms through repeated, guided exposure. AI algorithms can enhance these treatments by dynamically adjusting the VR environment based on real-time data, such as emotional responses or physiological signals captured by wearable sensors. This leads to a more personalised and adaptive treatment experience, increasing efficacy and user engagement (Donnelly et al., 2021). Finally, mobile applications integrating AI, such as mindLAMP and BiAffect, offer another layer of mental health support. These apps collect diverse data streams—including behavioural patterns, smartphone usage, and passive sensing—to monitor emotional states and predict the likelihood of anxiety recurrence or recovery (Zafar et al., 2024).

## User Profile

A patient suffering from untreated social anxiety since adolescence relied on avoidance strategies to manage her symptoms, which included tachycardia, sweating, and fear of social judgment. Her condition worsened upon entering a professional environment with unavoidable social interactions. Traditional psychotherapy was unsuccessful due to difficulty establishing therapeutic rapport and feelings of shame. She turned to ChatGPT for psychoeducation and self-guided therapy. Through

AI-assisted relaxation techniques and exposure exercises, she experienced reduced anxiety and improved coping in social situations. The anonymous and accessible nature of the chatbot allowed her to express emotions without embarrassment. As symptoms stabilised, she sought expert validation through a virtual psychiatric service. The clinician confirmed the AI's guidance was aligned with medical standards and supported a dual approach of continued AI use alongside professional therapy, highlighting AI's potential in reducing barriers to care and supporting self-management of social anxiety when integrated cautiously with expert oversight (Grosshans et al., 2024).

## Future Directions for Anxiety Management

Future research in AI-driven anxiety management should explore personalised, interactive tools like Sonora, which uses audio diffusion models and LLMs to generate navigable soundscapes for relaxation. Preliminary findings suggest high engagement and reduced state anxiety, particularly in individuals with moderate to high trait anxiety. Further studies could refine personalisation features and assess long-term therapeutic impact (Torre et al., 2025). Integrating passive wearable actigraphy data to predict symptom deterioration presents a promising avenue for early intervention. Research should investigate how combining real-time behavioural data with AI-generated interventions can prevent relapse and provide tailored support for individuals with anxiety disorders (Jacobson et al., 2020).

## Understanding PTSD

Post-traumatic stress disorder, or PTSD, is a chronic psychiatric condition associated with significant levels of distress and dysfunction (Chandna et al., 2023). It is believed to develop after directly experiencing, witnessing, or being repeatedly exposed to a particularly traumatic event, which could be death, combat, sexual assault or serious injury (American Psychiatric Association, 2013). It can be considered a stressor-related disorder leading to an overactivation of the fear circuitry, accompanied by cognitive and affective dysregulation, avoidance of the stressor, reexperiencing the event, and hyperarousal (Bryant, 2019). While historically associated with combat veterans, PTSD can occur in anybody who has experienced a traumatic event (Murphy & Busuttill, 2014). According to World Health Organisation mental health surveys, PTSD has a lifetime prevalence ranging from 8% to 24%, although the rates seem higher in developed than developing countries, probably due to the stringent nature of diagnostic criteria (Bryant, 2019).

Simply experiencing a traumatic event is not enough to lead to PTSD, as some show considerable resilience in the face of these events. Biological, psychological,

and even situational factors can influence who develops PTSD (Rothbaum & Rauch, 2020). However, a third of people facing a traumatic event do end up showing clinical symptoms (Cusack et al., 2016).

## Exposure as Treatment and the Use of VR

Cusack et al. (2016) suggest that trauma-focused CBT, cognitive processing therapy, EMDR, and exposure therapy are frontline treatment options for PTSD. The latter activates the fear structure due to repeated exposure to the stimulus, allowing users to achieve habituation and eventual extinction of the fear response (Kothgassner et al., 2019). The actual exposure is key as imaginal exposure comes with patients struggling to visualise the traumatic event (Rizzo & Shilling, 2017). However, in-vivo exposure also comes with the challenge of allowing a graded increase in stimuli.

The advent of technology has offered some solutions. Virtual reality technology allows clinicians to create a virtual environment that is interactive and emotionally engaging, while mimicking the same stress and anxiety reactions that would emerge in real-life situations (Kothgassner et al., 2019). Its multi-sensory cues hold the potential to offer exposure repeatedly, in ways that might be difficult to find in everyday surroundings, especially if people have more unique triggers (Miloff et al., 2016).

## Advantages of Using Virtual Reality

The privacy that VR can offer reduces the hesitation that people might feel with traditional therapy methods, a constraint frequently affecting military personnel (Kothgassner et al., 2019), due to the levels of stigma they experience and associate with seeking treatment. This greatly influences help-seeking behaviour and reduces the impact of the treatment due to dropout rates and low engagement (Britt et al., 2015).

These allow users to experience support in a safe and controlled environment and experience the same reactions they would in naturalistic conditions (Dibbets, 2019). High costs in the past might have restricted the use of VR, but the recent affordability allows a larger populace to gain access. A noteworthy point is that VR, whether guided by AI or a human, cannot be used as a stand-alone tool. It needs to be accompanied by a trained therapist involved and double-checking on the treatment process to ensure that someone is there to step in if the user gets overwhelmed or if the technology malfunctions (Dibbets, 2019).

## Evidence-Based Psychotherapy (EBP) for PTSD

Evidence-based and trauma-focused psychotherapy is the frontline of interventions designed for PTSD (Veterans Administration/Department of Defense Clinical Practice Guideline Working Group, 2023). However, access is limited based on logistical and financial constraints, as people need awareness of the existence of these modalities for PTSD, appreciate their efficacy, and find a treatment provider who is affordable and readily available. Even with EBPs being considered best practice and an active effort being made to increase training and awareness in clinicians, people typically are not aware of or do not avail these methods (Lenton-Brym et al., 2025). Furthermore, the financial burden of accessing EBP is only exacerbated due to PTSD being commonly associated with increased absenteeism, leading to occupational impairment and financial burden (Williams & Williams, 2020).

Reducing these barriers is of critical importance, as is standardising treatment, as some treatment providers often deviate from the protocols and may exhibit differing competence in administration (Marques et al., 2019). However, recent advancements such as machine learning (ML) and generative AI are able to use artificial intelligence to improve therapeutic access and engagement (Lenton-Brym et al., 2025). Virtual agents like Ellie, for example, have demonstrated the capability to detect early signs of post-traumatic stress disorder (PTSD) and depression in war veterans, helping clinicians identify individuals in need of urgent intervention (Pavlopoulos et al., 2023)..

### Where AI can play a part

**Treatment Fidelity.** A major issue in standardised treatment is fidelity, how well the treatment matches protocols. Firstly, there might be differences in training the clinicians, leading to a difference in the effectiveness of providers. Secondly, these treatments include encouraging clients to confront their traumatic memories, which some clinicians might struggle with due to the risk of causing undue stress. Treatment fidelity is currently assessed by recording the sessions, which are then reviewed by trained experts, an unnecessarily long and cumbersome process (Lenton-Brym et al., 2025).

This could be mitigated by using AI to review, provide feedback, and even train clinicians in providing PTSD treatment, particularly cognitive processing therapy (CPT). Ahmadi et al (2021) highlight that some research groups have been able to develop ML algorithms to automate this process, and these models frequently match human reviewers. Using these models, some of which have more than 80% accuracy, would lead to a more effective system with immediate feedback on fidelity, thus improving the training process as well.

Currently, to obtain CPT competence, clinicians have to complete foundational workshops and frequent consultations with experts, a long process with practical and financial limitations (Monson et al., 2018). Using ML could allow trainees to simply complete online training and administer CPT to simulated and real patients, with immediate feedback provided by the AI through the use of an on-screen panel. This would allow clinicians, organisations, and even patients to have greater confidence in their intervention delivery (Lenton-Brym et al., 2025).

**Treatment Engagement.** Another key factor in treatment effectiveness is treatment completion, which includes the time and effort dedicated to psychotherapy tasks and reduced levels of dropout. Low engagement for PTSD treatment, due to the stigma and distressing nature of treatment (Kline et al., 2018), can often lead to reduced therapy outcomes (Sripada et al., 2020).

ML could be used to try and test out the theoretical causes and potential outcomes of psychotherapeutic approaches and potential drop-out rates. While it has not been used specifically for trauma-focused therapy, ML can help in understanding how client characteristics can influence the therapeutic alliance (Rubel et al., 2020), and the extent to which the client would be open to understanding their problem and seeking solutions (Penedo et al., 2023), which if expanded to CPT, could increase engagement rates. In addition, ML can also help in providing clinicians with treatment recommendations, identifying who could benefit from face-to-face or computerised interaction, and clients who receive these recommendations are more likely to finish the treatment and experience better outcomes (Duhne et al., 2022).

## Limitations for PTSD Treatment

However, using AI is not an instant fix; clinician oversight would always be needed. These predictive models might fail when presented with novel situations out of their trained datasets (Chekroud et al., 2024). Perhaps the key fact to remember is that these can only be adapted and utilised insofar as clinicians and clients are open and willing to make use of them (Lenton-Brym et al., 2025). It is noteworthy that older audiences might be more hesitant towards such technological modalities, and it might be the younger population that is more accepting of the idea of VR due to their higher digital literacy (Rizzo & Shilling, 2017).

## Substance Use Disorders: Understanding Addiction

As Dr. Gabor Maté puts it in *In the Realm of Hungry Ghosts*, “Addiction is not a choice anybody makes, it’s a response to emotional pain.” A common narrative is that people who use substances are just chasing pleasure or being irresponsible. However, it’s not about the pleasure; it is about trying to find some relief. People are

primarily attempting to escape something painful, even if they can't fully explain their struggles.

Substance Use Disorders (SUDs) are not just about “bad choices” or a lack of willpower. They reflect real, long-term changes in the brain structure and chemistry. Most addictive substances mess with the brain's reward system by triggering a flood of dopamine, one of the major chemicals responsible for motivation, pleasure, and reinforcement. That short-lived high can leave the brain wanting more, again and again. Over time, this cycle can take a serious toll on someone's emotional health, relationships, career, and overall well-being, and in many cases, it can become life-threatening (Koob & Volkow, 2016; National Institute on Drug Abuse, 2020).

## Mental Health and Addiction

SUDs don't look the same for everyone. For some people, it's something they dip into occasionally, while for others, it completely takes over their lives. Often, it's tangled up with other comorbid mental health conditions like depression, anxiety, or personality disorders. Individuals with mood, anxiety, or personality disorders are roughly twice as likely to also suffer from a substance use disorder compared to the general population (National Institute on Drug Abuse [NIDA], 2020), making recovery increasingly complex.

Alcohol is now a part of everyday life for most people. It is legal, easy to access, and often tied to celebration or stress relief. Due to this, we forget about the potential harm it can cause. The reality is hard to ignore: alcohol is linked to close to 3 million deaths around the world every year, and it plays a role in over 200 different health conditions, including mental health (WHO, 2023).

Long-term alcohol use has been connected to higher rates of depression, anxiety, sleep issues, and even suicidal thoughts (Boden & Fergusson, 2011). For some, it usually starts with just trying to take the edge off a tough day. But over time, this coping strategy can turn into something harder to manage. Instead of helping, it ends up feeding the very feelings people were trying to escape, leading to a self-fulfilling cycle.

Research from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) (Grant et al., 2004) highlights relapse as a major hurdle, especially for people managing both substance use and mental health challenges. However, studies don't always agree on how to define relapse. There is also a need for more consistent ways of assessing it, ideally once someone has gone through detox and with better reporting on how other psychiatric symptoms can play a role.

Relapse doesn't just happen out of the blue. In many cases, it is tied to multiple other issues like unresolved emotional struggles, ongoing stress, or simply not having the required support. They're some of the strongest reasons why people return to

substance use, as research has shown time and again (Marlatt & Witkiewitz, 2005; NIDA, 2018). This is precisely why treatment has to go deeper than just the diagnosis. People need care that reflects their reality, something that responds to what they're going through, not just the label in their file.

At the same time, the situation around deaths by overdose is becoming more alarming by the year. In 2022, over 109,000 people in the U.S. died from overdoses, a 54% jump since 2019 (CDC, 2023). Fentanyl plays a big role here, far more powerful than heroin and often mixed into other drugs like cocaine or meth without people knowing, making it even deadier, with potentially devastating consequences. As Dr. Nora Volkow, Director of the National Institute on Drug Abuse (NIDA), notes, "The recreational drugs today are much more dangerous than what was available on the market 10 years ago" (Volkow, 2023).

Concurrently, stronger and more widely available cannabis products are creating their own concerns. In 2022, daily cannabis use among young adults hit an all-time high according to NIDA's Monitoring the Future survey (NIDA, 2023). As cannabis products become stronger, the risks have grown too. Higher THC levels have been linked to serious effects like psychosis, repeated bouts of intense vomiting, and in some cases, thoughts of self-harm (Volkow et al., 2021).

The reality of street drugs is more unpredictable than ever. Depending on your location, what's sold can include anything from cannabis to MDMA to cocaine, and these are often mixed with other substances without people realising it. That means someone could end up consuming something far stronger or more dangerous than expected.

Still, not everything is bleak. Across the board, psychologists, researchers, and public health advocates are working to build better systems of support. Positive reinforcement programs, better community-based care, and efforts to reduce the stigma around getting help are shifting the landscape (APA Monitor on Psychology, 2023). Helping people recover shouldn't depend on where they live or whether they can afford care; everyone deserves a real chance at recovery.

## The Role of Technology in Recovery

One area that's gaining momentum is the use of AI and digital tools to support people in recovery. For example, chatbot-based motivational interviewing (MI) is showing real promise. In a 2024 study by Pham et al., a chatbot trained in MI techniques was able to hold supportive conversations where 98% of its responses followed proper MI guidelines. People using it reported feeling more confident about cutting back or quitting altogether. A 2023 review by Abd-Alrazaq et al. in the *Journal of Medical Internet Research* looked at 18 similar tools and found that when chatbots are grounded in proven methods like MI and CBT, they can help

people shift harmful habits, especially in moments when human support isn't immediately available. This works because these approaches offer structure, empathy, and actionable coping strategies that users can apply in real-time, helping them feel less alone and more in control during difficult moments.

Another simple but powerful tool is urge tracking, using apps to note cravings, emotional states, and environments in real-time. It helps people notice patterns like certain moods or places that tend to trigger substance use and makes those insights easier to talk through in therapy. A 2023 study by Bjerke et al. published in *JMIR mHealth and uHealth* found that apps like *Craving-Manager* not only helped people become more self-aware but also made therapy conversations more focused and helpful. In another 2022 study by Stone et al. published in *Addiction Research & Theory*, researchers showed that real-time data collection, known as ecological momentary assessment, could even predict relapse.

Plenty of apps are putting this research into practice. *Sober Grid*, developed with support from Harvard and the University of Pennsylvania, mixes peer support with AI to flag when someone might be at risk of relapse. It's being used in programs backed by SAMHSA. One example of how technology is starting to support people in recovery is *reSET-O*, the first app cleared by the FDA specifically for opioid use disorder. It's built around cognitive behavioural therapy and offers daily check-ins and guided modules to help people stay on track with their treatment (Campbell et al., 2022).

There are other tools that focus on helping people navigate risky moments. *Addict Free* uses location and time-based patterns to flag when someone might be in a situation that could trigger use and then offers practical suggestions to help them stay grounded (Zhou et al., 2019). Apps like *DTOX* are also making it easier for people to log their cravings and emotional states as they occur and share that information directly with their therapist. This kind of real-time insight has been shown to improve how connected and supported people feel in their recovery (University of Colorado, 2023).

What makes these tools valuable is how they offer support in the quieter moments that usually get missed, like when someone isn't in a session, but the cravings creep in or when motivation starts to wear thin, and there's no one around to talk to. For someone who doesn't have steady access to care for multiple reasons, whether because of distance, time, or cost, having something reliable on their phone can help them feel less alone. When these tools are combined with consistent therapy and human connection, they make recovery feel more manageable, real, and less isolating.

## Autism Spectrum Disorders and ADHD

The role of artificial intelligence (AI) and robotic therapeutic tools for the treatment of neurodevelopmental disorders, specifically Autism Spectrum Disorder (ASD) and Attention Deficit Hyperactivity Disorder (ADHD), has provided new therapeutic choices, especially in the arenas of social communication and attention enhancement (Scassellati et al., 2018). These tools are often not used as individual diagnostic and treatment tools; instead, they serve as kinds of assistive adjuncts to regular clinical care, especially for psychiatrists, therapists, and caregivers (Rucker & Webster, 2011).

### Improving Social Communication in Autism

Autism Spectrum Disorder consists of challenges in social interaction and communication, with restricted and repetitive patterns of behaviour. Robotic therapy tools like NAO and Kaspar have been created to assist children with ASD in practising and improving social communication skills (Scassellati et al., 2012). Children with ASD view robots as less socially complex and more predictable than human beings, making robots an ideal companion for learning and practising social behaviours (Scassellati et al., 2018). Milo, the humanoid robot, has been utilised in structured therapy sessions to teach the recognition of facial expressions, turn-taking, and emotional understanding (Kim et al., 2013). In a study by Srinivasan et al. (2015), children with ASD were found to interact much more with humanoid robots than with interventions led by human beings in the promotion of joint attention.

The structured, repetitive, and non-judging nature of robots helps create a low-anxiety atmosphere for social learning, which, for children on the spectrum, is often a very necessary environment. It is on this basis that robot-mediated interventions can be individualised and monitored in real time by AI systems that adapt their responses to the child's interaction pattern (Feil-Seifer & Matarić, 2011).

AI models trained on behaviour datasets, such as speech analysis, facial expressions, and eye-tracking patterns, are often used to promote early detection of ASD (Duda et al., 2016). For example, recognition-pattern algorithms assess attention and activity levels using either wearable sensors or video observation for ADHD (Liang et al., 2019). However, AI serves as a decision support system for psychiatrists, instead of replacing clinical evaluation altogether.

### Gamified Attention-Training Applications for ADHD

ADHD is defined by persistent patterns of inattention, hyperactivity, and impulsivity (American Psychiatric Association, 2013). Children with ADHD often

struggle to maintain focus in traditional therapeutic environments due to rigid session structures, and the nature of clinical settings contains limited movement or sensory engagement, interrupting their need for physical stimulation (Pelham et al., 2005). To address this, gamified digital therapeutics have recently gained traction as an engaging and evidence-based mode of behavioural intervention (Vindigni, 2023).

EndeavorRx, the first computer video game to be FDA-approved as a treatment for ADHD, uses adaptive algorithms that continually modify cognitive control and attention challenges (Kollins et al., 2020). Children playing the game showed very significant enhancement in objective measures of attention, specifically sustained attention and working memory (Kollins et al., 2020), and it allows mental health professionals to track in-app progress, adapt behavioural strategies in therapy sessions, reducing resistance to engagement (Pelham et al., 2005).

Other applications, such as Focus Pocus, use real-time neurofeedback and gamification of attention training and impulse control, personalised to the child, often under the supervision of a clinician using an AI-assisted dashboard (Johnstone et al., 2012). On the same line, Cogmed employs working memory structured tasks based on difficulty levels of the child's performance to make it challenging yet achievable (Klingberg et al., 2005). By using real-time data, these programs can change task difficulty to maintain cognitive engagement, delivering a scalable, home-based, and minimally intrusive intervention (Dovis et al., 2015).

These interventions do not replace medication or psychotherapy but represent a very effective adjunct, especially in multi-modal treatment plans involving behavioural therapy and parent training. Behavioural therapy includes reinforcing desired behaviours through token economies or observational learning (Fabiano et al., 2009). Gamified apps complement such routines at home in a non-threatening environment.

## Ethical Considerations for Neurodivergence

Though AI and robotic therapies have great promise, many limitations exist concerning child and adolescent mental health. A predominant concern is the over-reliance on quantitative measures. AI systems rely heavily on measurable behaviours (eye contact duration, response time, speech prosody) that risk not capturing the complex emotional and contextual behavioural acts associated with neurodevelopmental disorders (Williams et al., 2021). Furthermore, clinicians and caregivers may overinterpret these data, leading to potential misdirections in treatment or reinforcement of a mechanistic perspective toward mental health (Uhlhaas & Torous, 2019).

From an ethical perspective, employing AI technologies with children needs an even sharper focus. Data privacy, informed consent, and the dependency question must be closely considered. These children have unique vulnerabilities; the long-term

implications of their extensive interaction with machines, specifically humanoid robots, on emotional maturation and social generalisation are still little understood. Children may form strong attachments to these robots, potentially affecting their ability to form social relationships (van Straten et al., 2024). Furthermore, AI-enabled interventions are limited to well-resourced settings, and such inequity could accentuate existing health disparities. Hence, rigorous clinical validation, context-sensitive applied measures, and regulatory oversight must be ensured to guarantee safety, efficacy, and inclusivity as therapeutic aids.

While robotic social training and gamified attention-enhancement platforms have been empirically shown to improve core functional domains for children with neurodevelopmental disorders, it is relevant to mention that these tools act mainly as assistive complements, never as replacements, to regular therapy, demanding ethical awareness and clinical discretion.

## **Stress Monitoring and Burnout**

Stress and burnout are critical public health issues impacting the modern workplace setup and the overall well-being of employees. Burnout is referred to as a psychological syndrome consisting of emotional exhaustion, depersonalisation, and reduced sense of personal accomplishment (Maslach & Leiter, 2016). Moreover, high levels of stress are related to reduced productivity, increased absenteeism, and compromised holistic functioning for people working in healthcare, education, and corporate professions (Maslach & Leiter, 2016). In response to these concerns, artificial intelligence (AI) tools are emerging to offer effective interventions in stress tracking, resilience-enhancing, and self-guided therapy by providing a scalable and real-time means of support to various populations.

### **Apps That Use AI**

One of the most direct applications of AI in stress prevention is stress monitoring through smartphones or wearables (Egger et al., 2023). These collect biometric and behavioural data, including heart rate variability (HRV), sleep quality, voice modulation, and usage patterns, to recognise varying stress and emotional levels. Happify involves machine learning algorithms to monitor the moods of the user on the basis of self-reports and digital behaviours, and provides daily activities to make the stress bearable (Orji & Moffatt, 2018). Mindstrong Health uses smartphone usage data like typing speed and scrolling behaviour, along with passive data collection, to monitor cognitive changes related to chronic stress and burnout (Insel, 2017).

Passive monitoring of data can detect early signs of emotional distress even before the user has any conscious awareness of their symptoms (Onnela & Rauch, 2016).

Other apps also contain AI-generated insights offering tailored recommendations for appropriate coping mechanisms (Miner et al., 2017). These tools are an early intervention available discreetly and conveniently for those at risk for burnout, enabling them to reflect on emotions for self-regulation and keep their mental wellness in check.

AI-based mental health chatbots are becoming popular mediums to encourage stress relief and overall wellness within individuals. These bots are trained on various therapeutic concepts like Cognitive Behavioural Therapy (CBT), Acceptance and Commitment Therapy (ACT), and Positive Psychology to provide behavioural insights in an empathetic manner. For example, Woebot involves structured conversations aimed at restructuring negative thought patterns and strengthening resilience through psycho-education, gratitude journaling, breathing practices, and mindfulness practices. Their users experienced considerably fewer symptoms of depression and anxiety over two weeks compared to the control group (Fitzpatrick et al., 2017). Due to their constant availability, these chatbots compensate for the barriers of cost, stigma, and accessibility concerning professional mental health assistance.

## Guided Journaling and Reflective Interventions

Guided journaling, supported by psychological research to reduce rumination while clarifying feelings and increasing resilience, is also among the AI tools used. Apps such as Reflectly and Jour run Natural Language Processing (NLP) algorithms to analyse journal entries and provide personalised prompts reliant on mood, cognitive distortions, and repetitive themes (Angenius & Ghajargar, 2023). These exacerbate metacognitive thinking and use these techniques to help users keep track of their emotional patterns throughout time.

Guided journaling interventions are proven to benefit individuals experiencing emotional overload or decision fatigue through structured reflection and grounding. Expressive writing helps in lowering cortisol levels and attenuating stress reactions in high-demand professions (Pennebaker & Chung, 2013). With the integration of AI, the journaling platform may begin to highlight alarming patterns, such as hopelessness, increased anxiety language, with suggestions for next steps or escalation to human care, thereby supporting early interventions when the risk of burnout is evident (Torous et al., 2020).

## Applications in Workplace Mental Health

Every workplace has become a mediator where a lot of AI-based mental health interventions and strategies are coming into use, especially post-pandemic, which fast-tracked both remote work and the decline of mental health. Employers have been increasingly opting for wellness platforms like Ginger, Modern Health, and Unmind, AI-enabled programs, to give employees personalised stress assessments, digital therapy, and resilience-building techniques. These often include mood tracking, guided meditation, and speaking in real-time with AI coaches or licensed therapists, fulfilling the need to reduce distance (Firth et al., 2017).

On the other hand, piloting AI-enhanced employee assistance programs (EAPs) is offered for confidential self-assessments and AI triage systems to redirect users to the right resources, be it a digital CBT module, peer support, or clinical escalation. Such platforms enhance mental health support accessibility while ensuring anonymity and flexibility, two main engagement factors for employees (Zou, 2024).

Attridge (2019) suggests that AI-based stress-reduction programmes improve emotional regulation, job satisfaction, and productivity while reducing absenteeism and turnover. In addition, ongoing monitoring allows intervention to be conducted proactively, rather than solely reacting once a problem arises or a crisis emerges.

## AI AS A THERAPY ASSISTANT, NOT A REPLACEMENT

Over the past decade, as mental health concerns around the world reached crisis point, driven by the pandemic, loneliness, and financial pressures, the shortcomings of conventional mental healthcare models have increasingly become apparent. In this context, AI-based tools have appeared as low-cost, scalable solutions that can fill gaps in service (Fitzpatrick et al., 2017; Inkster et al., 2018). AI websites are available anytime without causing burnout to working professionals, resulting in valuable and accessible information for people who cannot afford to visit clinics for mental health (Naslund et al., 2017). These websites encourage users to remain anonymous, which helps in lowering the stigma and allows users to share sensitive information more freely (Lucas et al., 2014)

AI chatbots are considered a catalyst for improving efficiency, affordability, convenience and accessibility (Brown & Halpern, 2021). Computer-based chatbots are programmed to mimic therapeutic dialogue based on diverse therapeutic principles, and also help in providing support and psychoeducation to people suffering from mild-to-moderate emotional issues. Machine learning computer programmes have also indicated benefits in analysing speech patterns, text, and even facial expressions to assist clinicians during client sessions (Cummins et al., 2018; Inkster et al., 2018).

Doctors receive assistance from AI programs in terms of tracking patient progress, enhancing diagnostic accuracy, maintaining accurate client notes, and tailoring treatment plans, highlighting an increase in patient outcomes and an efficient process (Topol, 2019). This ability to process and recall vast amounts of information with greater accuracy than human therapists can support more personalised and precise mental health interventions.

However, issues come into play when AI is not just touted as a tool but rather as a possible substitute for human therapists. AI may significantly enhance mental healthcare by lessening the burden on clinicians, but it cannot be confused with a replacement for human therapists; that's where the "human-in-the-loop" framework comes into play.

## **Human-in-the-Loop Models**

The HITL models focus on cooperation between clinicians and AI systems such that AI accomplishes supportive duties like synthesising session summaries, tracking mood changes, or analysing linguistic trends, while human therapists maintain final authority for clinical decision making (Topol, 2019). This strategy enables therapists to attend to high-level therapeutic work with less administrative and cognitive burden. A study found that the quality of dialogue improves considerably when AI dashboards present empathetic responses alongside peer supporters, without compromising user autonomy (Bricout et al., 2022). HITL models maintain relational integrity in psychotherapy and enhance efficacy and accessibility (Blease et al., 2020) by incorporating AI into the treatment process. Such a model accords with global mental health organisations' ethical guidelines, which emphasise the use of AI to augment care and not replace it.

## **Role of Non-Replicable Pillars in Human Therapy**

Chatbots and AI programs might mimic empathy and offer contextually relevant responses, yet they do not possess conscious emotional experience, ethical intuition, and the capacity to establish true human relationships, which is a necessity for a successful psychotherapeutic relationship (Wampold, 2015; Blease et al., 2020). Human therapy involves real connection, by not only providing the cognitive insight, but sharing mutual emotional experience of how the client may feel (Wampold, 2015). The therapeutic relationship involves emotional connection, shared goals, and shared treatment plan, which are the strongest predictors of outcome across modalities (Norcross & Lambert, 2019). Human therapists depend on clinical judgment and ethical intuition to deal with highly complicated or risky situations, like suicidality, disclosures of trauma, or personality disorders. AI, based on pre-defined

algorithms and pattern detection, is incapable of properly interpreting nonverbal communication, real-time manipulations, or engaging in subtle moral reasoning (Blease et al., 2020). Although AI chatbots may provide structured support, users end up leaving the chat when the conversation becomes too mechanical or lacks emotional connection (Inkster et al., 2018). Therefore, while it's possible for AI to mimic therapy, it cannot match the relational depth of human beings.

## **Role in Underserved Regions Where Therapists Are Unavailable**

AI chatbot-based systems provide low-cost, on-demand services that do not need a trained clinician present. Mental health services can be expanded to underserved areas through online interventions (Naslund et al., 2017). These tools may provide evidence-based strategies, bringing about greater equity in access and breaking down stigma and cost barriers. Individuals are reluctant to get help because of shame or cultural prohibitions, but are more willing to reveal sensitive matters to non-human entities (Lucas et al., 2014). AI can act as an accessible first line of care; ideally, it should act as a stepping-stone towards human care, rather than a permanent replacement, especially for those with complex or chronic conditions (Fitzpatrick et al., 2017; Blease et al., 2020).

## **Risks in User Interaction**

The responses generated by AI platforms can often have issues with accuracy and trustworthiness, greatly influencing user interaction. If the chatbot is drawing from a flawed database, the responses produced could be flawed or contain inaccurate information (Boucher et al., 2021).

Platforms using generative AI constantly hold the potential to say the wrong thing, which could be due to a lack of empathy in responses, a lack of nuance, or even misleading information provided by the users (Denecke & Househ, 2021). An alternative to avoiding the pitfalls of generative conversations could be human oversight over the conversations, but this is often difficult to carry out feasibly due to practical constraints (Coghlan et al., 2023).

## **Limited Therapeutic Support**

While chatbots may be great in certain situations, if the users desire to gain a new level of self-understanding or build a rapport to encourage vulnerability, they will fall short. Expecting human-like interaction and then not receiving it can make

people feel worse at a moment when they hope to gain support, which is why clinician oversight is imperative (Sedlakova & Trachsel, 2022).

Misunderstandings with chatbots are a common feature of conversations, especially when long, complex messages are sent, often with metaphors or colloquialisms, leading to stilted or restricted responses. This situation is further worsened in different languages, as many nuances of the language might get missed, leading to very technical or academic responses (Boucher et al., 2021). Due to the inherent nature of communication, many non-verbal cues can be missed, which might have hinted at key psychological or physiological insights (Khawaja & Bélisle-Pipon, 2023), further emphasising why these tools cannot be seen as a replacement for therapy.

It can also be difficult for chatbots to keep track of everything mentioned or discussed over multiple user sessions or reference back to something mentioned previously to promote psychological insight, something therapists and medical professionals frequently do (Denecke & Househ, 2021).

## Potential Bias in Datasets

As mentioned, these AI-driven chatbots are frequently trained on large datasets from multiple sources. They might only reflect the experiences of the majority, losing out on knowledge regarding the experiences of minority communities (Coghlan et al., 2023). They may be likely to miss out on linguistic, cultural, ethnic, or racial nuances in the presentation of symptoms and experiences, as well as the suggestions and treatments that it offers. Even practitioner-matching apps might fail to adequately match the correct therapist or medical professional to those with protected characteristics, increasing the pervasive bias in healthcare (Husain et al., 2022). Furthermore, due to potentially biased datasets, it is also possible that the chatbot or app may end up perpetuating harmful stereotypes and assumptions (Denecke & Househ, 2021). As it is often those populations who have difficulty accessing traditional mental health support or adequate healthcare, this bias would further isolate them or make them hesitant to access support (Khawaja & Bélisle-Pipon, 2023).

## Ethical Design

Privacy, confidentiality and informed consent are essential in mental health care. Patients need to be explicitly informed if they are being interacted with by a human or an AI (Birhane et al., 2022). AI can mitigate symptoms in the short term, but continuous use of AI affects emotional health, social interaction or dependency on treatment (Joerin et al., 2020). Therefore, ethical design must ensure that AI complements human care, rather than displacing it.

## Lack of True Accessibility

While these tools aim to increase accessibility, especially for vulnerable populations, their user interfaces may make it difficult for the geriatric population or those with learning difficulties or neurodegenerative conditions to use (Rodríguez-Martínez et al., 2023). The information about conditions or coping strategies may often be presented in increasingly technical terms or presuming a certain level of knowledge in the user, making comprehension difficult, especially with a rural or economically weaker population. There may also be greater hesitation in accessing these tools in certain developing or underdeveloped nations, both due to financial constraints and the fact that they are not designed for these societies (Burr et al., 2020).

The effectiveness of digital tools is inextricably linked to the amount of digital literacy a person possesses, which holds for both clinicians and patients and their general beliefs about the use of technology. This can lead to significant generational and cultural differences, with younger generations from more urbanised settings more likely to make use of these tools (Boucher et al., 2021).

## Limited Oversight and Regulations

The lack of existing guidelines and regulatory bodies can enable companies to take advantage of the lack of security for the privacy of users. Their data could be sold to third-party organisations and bodies, violating the inherent need for confidentiality in healthcare, as they are not held to the same standards of professional conduct as professionals, which can be extremely problematic, especially for the tools which track biological and physiological symptoms (Husain et al., 2022). The lack of involvement from regulatory bodies also means that many tools are not up to medical standards and do not necessarily reach the people who might need support the most due to limited outreach and access to information (Wies et al., 2021).

While apps claim to anonymise their data, this can often be de-anonymised through data triangulation. Due to the lack of regulations regarding the storage of data, this could be hacked into and leaked by cyber-criminals, publicising medical records and further exacerbating the stigma associated with accessing mental health support or certain medical conditions, especially in cases like substance use and PTSD (Coghlan et al., 2023). These privacy issues also might lead to mistrust in users, not just in the tool itself but the medical professional who suggested it, damaging the working relationship and worsening health outcomes (Wies et al., 2021).

## CONCLUSION AND FUTURE DIRECTIONS

As global mental health systems continue to face significant strain from rising demands and insufficient resources, the integration of artificial intelligence (AI) into mental healthcare presents both a promising opportunity and a complex challenge. Traditional approaches, while deeply valuable, fall short in terms of accessibility, scalability, and timely intervention, especially in underserved or stigmatised populations. Against this backdrop, AI has emerged as a transformative force, offering innovative tools that support diagnosis, enhance treatment, reduce therapist burden, and empower individuals to manage their mental health with greater autonomy.

Today, AI is being used to assist clinicians through diagnostic support systems, predictive modelling, and wearable technologies. These tools offer clinicians additional data points and insights, allowing for more personalised and timely interventions. Wearable devices can detect physiological indicators of anxiety, and AI algorithms can process this data in real time, potentially alerting users or healthcare providers to early signs of distress. While not diagnostic tools on their own, these wearables, when used in conjunction with clinical assessments, can enhance early detection and intervention.

AI's role extends beyond diagnostics into treatment and self-management. Tools such as Healo, Wysa, Youper, Tess, and Woebot provide users with therapeutic content and engagement strategies drawn from evidence-based practices, including CBT, ACT, positive psychology, emotion-focused therapy, and solution-focused brief therapy. Importantly, these technologies are not only assisting those with anxiety or depression, but also individuals dealing with PTSD, ADHD, autism spectrum disorders, substance use disorders, and burnout. In doing so, AI tools are contributing to a more inclusive, responsive, and flexible mental healthcare system. They offer dynamic, stigma-free interventions that can be personalised, scaled, and adapted to various needs, something the traditional system has long struggled to achieve.

Rather than seeing AI as a replacement, it should be positioned as a supplement to human care, especially useful for initial engagement, symptom tracking, or as a bridge between therapy sessions. For individuals with complex or chronic mental health issues, AI must act as a stepping-stone toward comprehensive care rather than an endpoint. The ethical framework for AI in mental health, as advocated by global mental health organisations, supports this approach. These guidelines emphasise augmentation over replacement and call for continuous human oversight, transparency, and accountability in the deployment of AI tools. Such a model not only safeguards against potential harm but also aligns with the broader goals of ethical, person-centred care.

Moving forward, the integration of AI in mental healthcare must be guided by ethical design, interdisciplinary collaboration, and ongoing empirical research. Fu-

ture efforts should focus on improving personalisation, safeguarding user privacy, ensuring equitable access, and developing robust regulatory frameworks. There is also a need for longitudinal studies to assess the long-term efficacy, engagement, and safety of AI interventions in diverse populations. In conclusion, AI holds remarkable potential to enhance mental healthcare delivery, increase access, and support both patients and clinicians in meaningful ways. However, its role should remain that of a powerful ally, never a stand-in, for human empathy, judgment, and connection. By embracing a balanced, ethically informed model of care that combines technological innovation with the irreplaceable value of human interaction, we can build a more resilient, inclusive, and responsive mental health system for the future.

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## KEY TERMS AND DEFINITIONS

**Bibliotherapy:** The use of literature to improve one’s emotional and mental well-being.

**Delusional Psychosis:** This is a mental state where one experiences delusions, which are false, fixed beliefs and also experiences psychosis, which is a broader condition where one isn’t in contact with reality

**Digital Wellbeing:** It is a multidimensional concept that encompasses psychological, emotional, and social aspects of technology use.

**ELIZA:** An early natural language programme which explored communication between humans and computers using pattern matching and simulating conversations

**Generative AI:** Those artificial intelligence models which carry out independent and dynamic conversations with information drawn from large datasets. Thus, capable of more authentic and engaging conversations.

**Human in the Loop (HITL) models:** A co-operative model between AI and clinicians where AI engages in supportive clinical tasks while humans maintain the final say in clinical decision-making processes

**Large Language Models:** AI models that are built and run on large datasets, drawing from the same in order to understand, generate, and mimic human language.

**Predictive Modelling:** Refers to AI utilising past data and theoretical knowledge to predict future chances of developing a mental health condition or relapsing.

**Scripted AI:** Those artificial intelligence models which carry out conversations through pre-written responses and follow a defined structure.

**Telehealth:** Telehealth is used to describe using modern communication technologies, phones, videocalls, etc, in order to deliver medical and mental health services remotely.

**Virtual Reality (VR) Therapy:** A technology-assisted treatment that uses immersive, computer-generated environments to expose individuals to anxiety-inducing scenarios in a controlled and safe setting.

**Wearable AI Technology:** Electronic devices worn on the body that continuously monitor physiological signals such as heart rate, sweating, and muscle tension, when combined with artificial intelligence, can identify or help track the mental health of the individual.