

A Generic Review of Integrating Artificial Intelligence in Cognitive Behavioral Therapy

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Abstract

Cognitive Behavioral Therapy (CBT) is a well-established intervention for mitigating psychological issues by modifying maladaptive cognitive and behavioral patterns. However, delivery of CBT is often constrained by resource limitations and barriers to access. Advancements in artificial intelligence (AI) have provided technical support for the digital transformation of CBT. Particularly, the emergence of pre-training models (PTMs) and large language models (LLMs) holds immense potential to support, augment, optimize and automate CBT delivery. This paper reviews the literature on integrating AI into CBT interventions. We begin with an overview of CBT. Then, we introduce the integration of AI into CBT across various stages: pre-treatment, therapeutic process, and post-treatment. Next, we summarized the datasets relevant to some CBT-related tasks. Finally, we discuss the benefits and current limitations of applying AI to CBT. We suggest key areas for future research, highlighting the need for further exploration and validation of the long-term efficacy and clinical utility of AI-enhanced CBT. The transformative potential of AI in reshaping the practice of CBT heralds a new era of more accessible, efficient, and personalized mental health interventions.

Keywords: Artificial intelligence, Mental health, Cognitive behavioral therapy, Large language model, Machine learning, Deep learning

1 Introduction

Mental health issues have become increasingly prevalent, especially in the post-pandemic era [Penninx et al \(2022\)](#). Psychological distress brought on by COVID-19 has added to the existing mental health crisis, leading to higher rates of depression, anxiety, and suicidal ideation. Consequently, there is an urgent need for effective and accessible mental health interventions. Cognitive Behavioral Therapy (CBT) is widely recognized as one of the most important psychological interventions for addressing a range of mental health issues [Foreman and Pollard \(2016\)](#); [David et al \(2018\)](#). As the gold standard for treating depression and anxiety, CBT has been integrated into healthcare systems worldwide. Its primary goal is to identify and restructure patients' maladaptive cognitive frameworks to help them develop coping skills, address behavioral issues, and alleviate symptoms. However, the delivery of CBT, as it is traditionally conducted individually and face-to-face by a therapist, faces barriers in real life, including social stigma and limited access to qualified therapists, particularly in underserved areas. Only 27% of those receiving psychological therapy actually access standardized care [Bandelow et al \(2017\)](#). To address these challenges, technological advancements have led to the development of Computer-Based Cognitive Behavioral Therapy (CCBT) and Internet-Based Cognitive Behavioral Therapy (ICBT) [Webb et al \(2017\)](#). These variations use computer software and the Internet as a medium to deliver CBT interventions based on established theories and techniques. Several established online CBT platforms, such as MoodGYM [Australian National University \(2024\)](#) and 30-Day Self-Service Psychological Expert [China Cognitive Behavioral therapy professional organization \(2024\)](#), have emerged. These online platforms have partially alleviated some of the issues related to the shortage of mental health professionals and poor accessibility [Christ et al \(2020\)](#). However, they still face challenges, such as limited interactivity and high dropout rates. In addition, they offer interventions that address only general cognitive issues rather than individual specific needs. Given this challenge, there is an urgent need for more flexible and adaptive forms of CBT to better meet the diverse needs of different patient populations.

In recent years, rapid advancements in artificial intelligence (AI) technology have led various industries to explore its innovative applications. AI's exceptional capabilities in data analysis, pattern recognition, and automation offer vast potential in the delivery of mental health services, providing new tools and methods for assessment, diagnosis, and treatment of mental health conditions [Lee et al \(2021\)](#); [Margaroli et al \(2023\)](#); [Demszky et al \(2023a\)](#). For instance, deep learning (DL) models can automate mental health assessments and diagnostic processes, alleviating the workload of professionals while enhancing the accuracy and efficiency of diagnoses [Vuyyuru et al \(2023\)](#). Furthermore, AI can also aid in detecting and understanding patients' unique

emotional expressions, thereby offering recommendations for personalized psychological interventions and support [Assunção et al \(2022\)](#). Given the shortage of skilled mental health professionals, innovative AI approaches have been developed to guide peer-to-peer mental health support [Sharma et al \(2023a\)](#). Additionally, AI-based psychological counseling support systems, such as those utilizing large language models (LLMs), have also been developed to assist junior counselors in providing online psychological support [Fu et al \(2023\)](#). These studies demonstrate that AI not only expands the boundaries of traditional mental health services, but also brings new opportunities for improving their accessibility and utility globally [Graham et al \(2019\)](#); [Demszky et al \(2023b\)](#). In the realm of CBT, the integration of AI has led to revolutionary advancements, particularly with the rise of LLMs. Notable research in this area includes the development of CBT-specific prompts and tailored datasets, leading to models like CBT-LLM, which are specifically designed for CBT delivery [Na \(2024\)](#). Other efforts have resulted in conversational counseling agents based on LLMs, such as utilizing GPT-2 in CBT to generate human-like textual narratives to provide psychological support [Rajagopal et al \(2021\)](#), providing psychological counseling using CBT techniques [Lee et al \(2024\)](#), and delivering dialogue modules focused on Socratic questioning using LLMs like OsakaED and GPT-4 [Izumi et al \(2024\)](#). These advancements have made cognitive behavioral interventions more personalized and precise, better addressing the needs of diverse patients.

Given the abundance of research emerging in this field, several review articles have summarized innovative developments in CBT. However, the existing reviews focused mainly on CBT applications [Huguet et al \(2016\)](#); [Denecke et al \(2022\)](#) and the development of ChatGPT in redesigning CBT for different age groups and genders [Chandra et al \(2023\)](#). There is a lack of comprehensive review summarizing the application of AI's role across various stages of CBT delivery. To address this, we provide a detailed literature review of AI's role in enhancing CBT in this paper.

2 Background

Cognitive behavioral therapy (CBT) stands as a structured, time-limited psychological treatment that focuses on the interplay between cognitive processes, emotional responses, and behavioral patterns. This therapeutic approach operates on the premise that thoughts, emotions, and behaviors are interconnected, and aims to enhance psychological well-being by addressing maladaptive cognitive patterns and behaviors [Beck and Beck \(2011\)](#). The theoretical foundation of CBT encompasses both cognitive and behavioral aspects. Regarding the origins of CBT, there are varying views in the academic community. However, it is generally accepted that the popularization of the “cognition” began with Ellis’s Rational Emotive Therapy (RET) in the 1950s, followed by Beck’s Cognitive Therapy (CT) in the 1960s. Since then, CBT has continuously integrated various behavioral therapies and theories, evolving into the widely used psychological treatment seen today.

CBT interventions typically target three domains: cognition, behavior, and emotion [McGinn and Sanderson \(2001\)](#). In the cognitive domain, CBT focuses on individuals’ cognitive processes, including thoughts, beliefs, and interpretations. This

involves aiding clients in identifying and understanding negative or distorted thought patterns, such as negative automatic thoughts and cognitive distortions (CD) (e.g., jumping to conclusions, all-or-nothing thinking and mental filtering). Techniques like cognitive restructuring (CR) are used to adjust these patterns, fostering a more objective and positive perspective toward oneself and the world. In the behavioral domain, CBT addresses individuals' maladaptive behavioral patterns and habits. Therapists collaborate with clients to explore their unhealthy behaviors, such as social withdrawal, avoidance, and substance or alcohol misuse. Techniques such as behavioral experiments, graded exposure, and behavioral activation (BA) are then employed. Further, CBT acknowledges the interplay between the body and the mind. Physiological responses such as tension, fear, and anxiety can impact cognition and behavior. Thus, CBT also focuses on regulating physiological responses through techniques such as deep breathing, progressive muscle relaxation, and physical activity to enhance emotional regulation and psychological well-being. For the emotional domain, CBT targets clients' emotional awareness and ways to manage them by aiding clients to recognize negative emotions as they arise, accurately identify them, and utilize appropriate cognitive and behavioral strategies to support better emotional well-being. The three domains are intertwined, and CBT typically tailors a range of techniques and strategies based on the individual's specific circumstances and needs, aiding in problem-solving, improving mental health, and building resilience [Dobson and Dozois \(2021\)](#).

CBT has been employed to address a variety of mental health issues, including anxiety disorder [Olatunji et al \(2010\)](#), depression [Tymofiyeva et al \(2019\)](#), schizophrenia [Turkington et al \(2004\)](#), attention deficit and hyperactivity disorder [Pan et al \(2019\)](#), insomnia [Benard and Lukandu \(2018\)](#), eating disorders [Linardon et al \(2017\)](#), bipolar disorder [Driessen and Hollon \(2010\)](#), substance use disorders [McHugh et al \(2010\)](#), and obsessive-compulsive disorder [Moody et al \(2017\)](#). Beyond mental health, CBT has been explored as a tool for managing chronic health conditions like low back pain [Piette et al \(2016\)](#); [Heapy et al \(2017\)](#), asthma [Parry et al \(2012\)](#), and tinnitus [Parry et al \(2012\)](#). Prior to initiating CBT, therapists typically conduct assessments to determine symptom severity and treatment goals. These assessments may involve dialogue between therapist and client or self-administered tools like the Beck Depression Inventory (BDI-II) or the Beck Anxiety Inventory (BAI) [Bech et al \(1996\)](#); [Beck et al \(1988\)](#); [Foa et al \(1993\)](#). Based on this assessment, therapists work with the clients to establish treatment goals and offer personalized cognitive and behavioral strategies tailored to their needs.

3 Artificial intelligence in CBT

Integrating AI into CBT presents a myriad of potential applications, promising to enhance the effectiveness and utility of therapy. To provide a summary of the extant literature on the integration of AI into CBT across the delivery process, we conducted a literature review by performing searches on the ArXiv and Google Scholar database without date restrictions. Search terms considered in this review were selected based on two elements, CBT (e.g., cognitive behavioral therapy, cognitive distortions,

cognitive restructuring, and exposure therapy) and technology (e.g., artificial intelligence, machine learning, deep learning, natural language processing, large language model, chatbot, and virtual reality). Articles that enhance, support, or implement CBT through AI technology will be selected. Results were categorized based on the stage at which AI was integrated in the CBT delivery process and were synthesized. In this section, we present the synthesized findings describing the role of AI in different stages of the CBT treatment process, as illustrated in Figure 1.

To be clear, this article only covers the stages of CBT that current AI technology has addressed. Due to the complexity of CBT treatment, some details and specific treatment stages have not yet been covered by AI, and thus are not discussed here. Future research and technological advancements may further expand AI's role in CBT delivery, encompassing more stages of the treatment process.

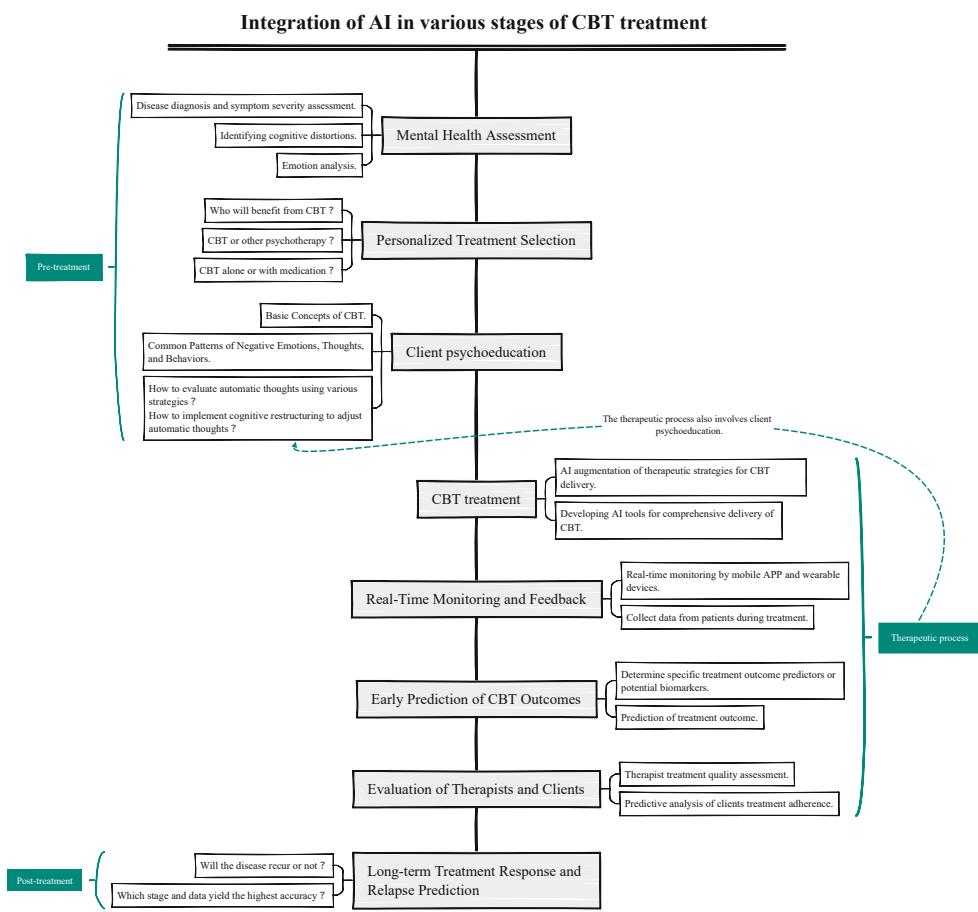


Fig. 1: The role of AI in various stages of CBT treatment.

3.1 Integration of AI in the Pre-Treatment Stage

A comprehensive assessment is a foundational step in all psychological treatments, including CBT. This initial assessment involves gathering information on the client's history, current issues, and therapeutic goals through structured or semi-structured interviews, questionnaires, and standardized scales. In CBT, particular emphasis is placed on assessing the client's cognitive and behavioral patterns, as well as their emotional responses. The insights from this detailed assessment guides therapists in crafting tailored CBT treatment plans that effectively address the client's concerns, thereby maximizing therapeutic outcomes. Traditional CBT assessment methods, while thorough, often rely heavily on manual processes, which can be subjective and time-consuming. The reliance on the therapist's clinical skills and professional acumen can also limit diagnostic accuracy and treatment efficiency. In contrast, AI technology, with its advanced data processing and analysis capabilities, offers a powerful alternative. AI can rapidly analyze vast amounts of client data to identify patterns and correlations, thereby assisting therapists in assessing patient symptoms more accurately and swiftly, and in identifying adverse emotions and cognitive distortions.

3.1.1 Mental health assessment

Disease diagnosis and symptom severity assessment

AI is increasingly employed for the diagnosis and assessment of common mental illnesses such as depression and anxiety. [Wanderley Espinola et al \(2022\)](#) proposed a methodology to support the diagnosis of mental disorders in psychiatric emergency context using vocal acoustic analysis and machine learning, targeting disorders like major depressive disorder, schizophrenia, bipolar disorder, and generalized anxiety disorder. [Siddiqua et al \(2023\)](#) employed a survey questionnaire distributed among Bangladeshi students with a total of 684 responses were obtained, and utilized ten machine learning models and two deep learning models to predict three levels of depression severity (normal, moderate, and extreme) with remarkable accuracy. [Vuyyuru et al \(2023\)](#) introduced the Trans-CNN, which effectively integrates the strengths of Transformer and Convolutional Neural Network (CNN) architectures. This model demonstrates superior performance in identifying depressive disorders compared to traditional CBT methods and standalone Transformer or CNN models by analyzing textual data such as patient narratives, treatment records, and diagnostic reports.

Despite these advancements, the existing research is centered around AI models focused on the diagnosis and assessment of singular psychological disorders, with limited research dedicated to the development of comprehensive models capable of simultaneously diagnosing multiple co-occurring psychological conditions.

Identifying cognitive distortions

CBT postulates an individual's emotions and behaviors are influenced by their perception and interpretation of events. Cognitive distortions refer to erroneous or irrational patterns of thinking that can lead to negative emotions and maladaptive behaviors. During the initial assessment phase of CBT, therapists collaborate with clients to explore these cognitive patterns and reactions to specific events, aiming to assist the

client in identifying and understanding potential cognitive distortions, which were categorized into ten types by Burns theory [Burns and Beck \(1999\)](#). They include: all-or-nothing thinking, over generalization, mental filter, disqualifying the positive, jumping to conclusions, magnification and minimization, emotional reasoning, should statements, labeling and mislabeling, and blaming oneself or others.

Currently, AI technology facilitates the identification of cognitive distortions primarily through text classification techniques. Researchers utilize various textual data as inputs to build models and algorithms that automatically identify and categorize these cognitive distortions. However, due to the lack of publicly available structured datasets specifically designed for detecting cognitive distortions, researchers often turn to alternative data sources such as social media data [Alhaj et al \(2022\)](#); [Wang et al \(2023b\)](#), personal blogs [Simms et al \(2017\)](#), and everyday narratives [Xing et al \(2017\)](#); [Shickel et al \(2020\)](#); [Mostafa et al \(2021\)](#). [Shreevastava and Foltz \(2021\)](#) compared five classification algorithms for detecting cognitive distortions using a therapist Q&A dataset obtained from Kaggle. [Tauscher et al \(2023\)](#) applied NLP methods to identify cognitive distortions from text messages exchanged between patients with severe mental illnesses and their clinical therapists. Challenges in this task include dealing with short texts that lack contextual information and imbalanced data where certain distortion types are underrepresented, leading to poorer classification performance. To address these issues, researchers have proposed various solutions. [Alhaj et al \(2022\)](#) suggest enriching short textual representations to improve cognitive distortions' classification of the Arabic context over Twitter. It also utilizes a transformer-based topic modeling algorithm (BERTopic) that employs a pre-trained language model (AraBERT). [Ding et al \(2022\)](#) tackled data imbalance with approaches like data augmentation and domain-specific models, demonstrating the effectiveness of the pre-trained language model MentalBERT. Recent advances have expanded the scope of cognitive distortion detection to include multimodal datasets. This cross-modal research approach provides a more holistic perspective, enabling a more comprehensive detection of cognitive distortions. For instance, [Singh et al \(2023\)](#) proposed a multitask framework that integrates text, audio, and visual data to detect cognitive distortions, achieving significant performance improvements over existing state-of-the-art models.

Recently, LLMs have also shown promise in complex psychological tasks such as identifying cognitive distortions [Qi et al \(2023\)](#); [Nazarova \(2023\)](#); [Chen et al \(2023\)](#); [Lim et al \(2024\)](#). [Qi et al \(2023\)](#) conduct experiments to compare LLMs and supervised learning in cognitive distortion identification and suicide risk classification. The experimental results indicate that LLMs struggle with accurately identifying complex cognitive distortions in Chinese social media data, suggesting that deep learning algorithms remain the preferred solution for complex psychological tasks like cognitive distortion identification. [Nazarova \(2023\)](#) developed TeaBot, an AI tool fine-tuned on GPT-3, and employs CBT techniques to aid users in identifying and challenging distorted thoughts. [Chen et al \(2023\)](#) introduced the Diagnosis of Thought (DoT) framework, which strategically prompts the LLMs to produce diagnosis rationales pertinent for cognitive distortions detection. Although the DoT method demonstrates its capability in classifying cognitive distortions, it also exhibits a notable flaw, namely,

the model tends to over-diagnose cognitive distortions even when the user's statements are benign. Lim et al (2024) addressed this by introducing the ERD framework, involving extraction, reasoning, and debate among multiple LLM agents to classify cognitive distortions from user utterances. This approach significantly mitigates the issue of overdiagnosing cognitive distortions in the DoT method.

Emotion analysis

Emotion analysis is essential for understanding individuals' emotional states. This understanding enables therapists or conversational agents to offer more empathetic support and feedback in CBT interventions, thereby strengthening the therapeutic alliance and enhancing the interactive experience Brave et al (2005); Provoost et al (2019). Furthermore, emotional states also serve as indicators of intrinsic goals, observable behaviors, and treatment efficacy. During the therapeutic process, individuals are more likely to benefit from treatment when they can effectively manage their emotions Mehta et al (2021). Therefore, during the initial assessment phase, therapists explore the clients' emotional responses and assist them acquire healthier emotion regulation strategies. AI-assisted emotion analysis has become increasingly prevalent in mental health Tanana et al (2021); Assunção et al (2022); Khare et al (2023). Provoost et al (2019) employed an emotion mining algorithm to assess the overall sentiment and five specific emotions expressed in texts written by patients during Internet-based cognitive behavioral therapy (ICBT), finding moderate agreement between the algorithm and human judgment in evaluating the overall sentiment, while the agreement was low for specific emotions. Patel et al (2019) proposed an intelligent social therapeutic chatbot. This chatbot defined several basic emotion labels, and based on these emotion labels, three deep learning algorithms were employed to extract emotions from user chat data. Kozłowski et al (2023) introduced Terabot, a conversational system that enhanced sentiment and emotion recognition by integrating CBT techniques and replacing BERT with RoBERTa in a neural language model framework. However, Striegl et al (2023) pointed out that some emotion recognition methods Fitzpatrick et al (2017); Provoost et al (2019) categorize emotions into discrete classes, failing to capture the continuum and diversity of emotions accurately. To address this, they proposed a deep learning-based dimensional text emotion recognition system within the context of CBT using the ALBERT pre-trained model Lan et al (2019), fine-tuned on emotion-annotated data for dimensional score prediction.

In recent years, ChatGPT, as a prominent example of conversational AI, shows potential in assisting individuals with emotion understanding and management. Rathje et al (2023) initially assessed GPT's capability for overall sentiment analysis (positivity, negativity, or neutrality) in English and Arabic texts. They found that GPT demonstrates effective multilingual sentiment analysis, achieving performance levels comparable to top-performing machine learning models from previous years. Furthermore, they examined GPT's ability to accurately discern more nuanced discrete emotions such as anger, joy, fear, and sadness. The results demonstrated a high level of consistency between GPT's performance and human judgement. Elyoseph et al (2023) also underscored GPT's superiority over humans in emotional cognition, as highlighted in their study.

Despite AI's capabilities in emotion detection and understanding, there remains a perception that individuals may perceive AI-driven support as lacking genuine emotional resonance compared to human interaction [Yin et al \(2024\)](#). Thus, future research should focus on making AI responses more conversational and human-like to address this perception. Additionally, to ensure rigor and utility in real clinical settings, human cross-validation is required.

3.1.2 Personalized treatment selection: identifying CBT beneficiaries

Within the realm of precision medicine, aligning clients with the most suitable treatment is a critical and significant objective [Ozomaro et al \(2013\)](#). This involves selecting an effective treatment plan before commencing therapy, thereby avoiding the risks associated with ineffective treatments. CBT is a well-established psychotherapy approach to address mental health issues, however, its effectiveness varies among individuals experiencing different mental health conditions. This variability highlights the need to identify which clients are likely to respond favorably to CBT and to assess its effectiveness in treating specific mental health conditions. Researchers are increasingly exploring the potential of AI models to predict which clients may benefit from CBT and to determine the most appropriate treatment for each person [Ball et al \(2014\)](#); [Reggente et al \(2018\)](#); [Vieira et al \(2022\)](#). Studies suggest that AI can analyze extensive clinical data to forecast which patients are more likely to respond positively to CBT. This capability can assist clinicians in selecting suitable candidates for CBT, thereby optimizing resource allocation. For example, [Reggente et al \(2018\)](#) used machine learning with cross-validation to investigate the potential of functional connectivity patterns to predict obsessive-compulsive disorder (OCD) symptom severity in individuals after treatment. The findings have important clinical implications, particularly in the development of personalized medicine approaches aimed at identifying OCD patients who would derive the greatest benefit from intensive CBT. Similarly, [Vieira et al \(2022\)](#) conducted a comprehensive review and quantitative synthesis of previous studies utilizing machine learning to predict the outcomes of CBT treatment in various diagnostic categories. They concluded that, on an individual level, the accuracy of predicting CBT benefit was approximately 74.0%.

Besides CBT, other types of psychological interventions, such as Psychodynamic Therapy (PDT) and person-centered counseling for depression may be equally effective. Moreover, not all clients may require high-intensity CBT interventions. Some individuals might benefit from low-intensity interventions. Traditionally, the trial-and-error method in psychotherapy can be both time-consuming and costly, with the risk of clients undergoing multiple ineffective treatments before finding the one that works best for them. This not only delays effective care but also increases the overall cost of treatment. Therefore, determining the most suitable treatment for specific individuals before the delivery of therapy is crucial. Addressing this gap, [Delgadillo and Gonzalez Salas Duhne \(2020\)](#) and [Schwartz et al \(2021\)](#) had applied machine learning algorithms to recommend optimal treatment approaches based on patients' pre-treatment characteristics. This method can contribute to substantial cost savings in mental health care, making high-quality psychotherapy more accessible and affordable.

Additionally, there is a growing interest in whether combining CBT with medication or other treatments can enhance outcomes. Several researchers have explored this possibility [Gunlicks-Stoessel et al \(2020\)](#); [Pei et al \(2022\)](#); [Stephenson et al \(2023\)](#). For example, [Gunlicks-Stoessel et al \(2020\)](#) found that combining CBT with medication is equally effective and more long-lasting than medication alone. Furthermore, they noted that the combination of medication and CBT could increase response rates and prolong the duration of effectiveness, especially when CBT is administered to clients responsive to pharmacotherapy.

These research underscores the potential of AI in refining the selection of psychological treatments and highlights the importance of personalized approaches in enhancing therapeutic outcomes.

3.1.3 Client psychoeducation

In CBT, client education is a crucial step both before and throughout the therapy process, as shown in Figure 1. Before commencing therapy, psychoeducation involves introducing the fundamental principles and techniques of CBT, aiding them in understanding common patterns of negative emotions, thoughts, and behaviors and coping strategies [McGinn and Sanderson \(2001\)](#). In the treatment process, psychoeducation is reflected in teaching clients how to identify and assess automatic thoughts, how to perform cognitive restructuring, and how to find alternative explanations for automatic thoughts, thereby adjusting these automatic thoughts. By conveying that individuals can acquire and master skills to address psychological issues, psychoeducation enhances clients' sense of self-efficacy and can even contribute to symptom reduction on its own [Cuijpers \(1998\)](#).

Psychoeducation can be delivered through various formats, including written materials, videos, audio recordings, as well as organizing specialized lectures and seminars. The advent of mobile applications has introduced novel avenues for delivering psychological education and support, capitalizing on their convenience and adaptability. Psychological education has been seamlessly integrated into several mobile applications, some of which have demonstrated efficacy in treating various mental disorders, including stress [Rose et al \(2013\)](#), anxiety and depression [Harrison et al \(2011\)](#), eating disorders [Cardi et al \(2013\)](#), post-traumatic stress disorder [Reger et al \(2013\)](#), and obsessive-compulsive disorder [Whiteside et al \(2014\)](#). For instance, [Whiteside et al \(2014\)](#) developed the smartphone application "Mayo Clinic Anxiety Coach", designed to deliver CBT for anxiety disorders, including OCD. This application comprises a psychological education module that instructs users on the utilization of the application, conceptualization of anxiety, descriptions of various anxiety disorders, explanations of CBT, and guidance on assessing alternative forms of therapy. Similarly, [Martínez-Miranda et al \(2019\)](#) developed a mobile-based embodied conversational agent (ECA) for the prevention and detection of suicidal behavior. The ECA introduces users to a segment of psychoeducational video in which a combination of cartoon-like images in motion are accompanied by a narrator explaining the basic elements of CBT. Users can access the video at any time through the application's main menu. The advantages of delivering psychological education through mobile applications are self-evident:

information becomes portable, and patients can access it easily. Heng (2021) integrated CBT within immersive gaming experiences to assist individuals suffering from generalized anxiety disorder (GAD). In this approach, CBT elements are seamlessly interwoven with the diegetic components of the game, providing psychoeducation in an engaging and entertaining manner.

AI-powered models facilitate personalized psychoeducation by tailoring modules to each patient's understanding and preferences. For example, Bhaumik et al. Bhaumik et al (2023) introduced MindWatch, a system harnessing AI-driven language models for early symptom detection and personalized psychological education. Within the psychological education module, they utilized the foundational Llama 2 model within the Amazon SageMaker Studio environment to deliver tailored education to individuals experiencing mental health issues. Numerous chatbots incorporate modules for psychoeducation as well. For instance, Jang et al (2021) developed Todaki, a chatbot for managing Attention Deficit Hyperactivity Disorder (ADHD). This chatbot offers tailored psychoeducation and brief CBT sessions, enabling individuals with ADHD to acquire self-help skills for managing their condition effectively. Similarly, Su et al (2022) created XIAO AN, an AI-assisted psychotherapy robot utilizing multimodal signal recognition and natural interaction technology. XIAO AN monitors emotions and offers brief, comprehensive psychological therapy based primarily on CBT, integrating psychological education modules.

Through these approaches, integrating CBT principles into various technological platforms has facilitated the dissemination of psychological education, empowering individuals to better understand and manage their mental health.

3.2 Integration of AI in CBT therapeutic process

CBT intervention encompasses the implementation of various strategies, including cognitive restructuring, behavioral activation, and exposure therapy, etc. These strategies are intrinsically connected to cognition, emotions, and behavior. During CBT treatment, psychotherapists select appropriate strategies based on the patients' symptoms and needs to provide targeted treatment. In section 3.2.1, we will delve into how AI technology can enhance each CBT strategy. Following this, Section 3.2.2 will focus on how researchers are developing chatbots to integrate multiple CBT strategies, offering comprehensive mental health support to users. Next, Section 3.2.3 introduces how wearable devices or smartphone applications equipped with AI technology can now be used to monitor patients' psychological states during CBT treatment. Finally, Section 3.2.4 introduces some researchers utilize AI to make early predictions about the outcomes of CBT treatments.

3.2.1 AI Augmentation of Therapeutic Strategies for CBT delivery

Cognitive restructuring (CR)

Cognitive restructuring (CR) is a fundamental component of CBT, characterized as a structured, goal-oriented, and collaborative intervention. It involves the patient and therapist working together to identify and correct irrational thoughts, evaluations, and beliefs by generating more adaptive alternative cognitive patterns Clark

(2013). Thereby alleviating negative emotions, improving mental health, and promoting healthier behaviors and coping strategies. To some extent, it is considered analogous to Cognitive Reappraisal Shurick et al (2012); Zhan et al (2024). Recent advancements have leveraged AI models to conduct CR effectively. The majority of these efforts aim to provide evidence that AI language models can effectively engender reframed thinking in response to negative emotional situations, as well as to compare the efficacy of different models in CR. For instance, de Toledo Rodriguez et al (2021) collected a small-scale CBT dataset via the crowd-sourcing platform Prolific. They validated Google's T5 transformer and BERT model for their ability to transform initial negative cognition into more positive or realistic alternatives. Human evaluation revealed that T5-generated reconstructions resembled original human-written responses more closely, while BERT showed a relatively lower performance but higher positive sentiment. Maddela et al (2023) introduced PATTERNREFRAME, a novel dataset that incorporates personas and classical unhelpful thought patterns, extending the reframing task to include the identification and generation of thoughts corresponding to a given persona and unhelpful pattern. They evaluated various language models using prompt-based and fine-tuning methods for their efficacy in identifying and reframing these thoughts. Unlike de Toledo Rodriguez et al (2021) and Maddela et al (2023), who conceptualize CR tasks as a sentence rewriting task, Xiao et al (2024) emphasize client empowerment over reliance on therapist-driven solutions. They propose, Helping and Empowering through Adaptive Language in Mental Enhancement (HealMe), a model utilizing Large Language Models (LLMs) for CR through three steps: distinguishing between situations and thoughts for a rational perspective, generating alternative perspectives through brainstorming to alleviate negative thinking, and providing suggestions that recognize the client's efforts and promote positive action.

Previous research primarily focused on the perspective of holistic CR, attempting to address how language models can be utilized to generate CR. However, Sharma et al (2023c,b) have begun to delve deeper into exploring various dimensions of CR, and examining people's preferences for particular types of restructuring. To be more specific, Sharma et al (2023c) investigated how negative thinking can be restructured, how language models can be utilized to facilitate such restructuring, and which types of restructuring individuals experiencing negative thoughts prefer. They introduced a framework comprising seven linguistic attributes for reconstructing thoughts and trained a retrieval-enhanced in-context learning model to generate reconstructed thoughts. Additionally, they conducted a randomized field study on the Mental Health America (MHA) website. In another work, Sharma et al (2023b) designed and evaluated a CR tool based on human language model interaction. This system leverages language models to assist individuals in various steps of CR, including identifying cognitive traps within thoughts and selecting more actionable, empathetic, or personalized reconstruction suggestions when reconstructing negative thoughts. Furthermore, they demonstrated that language models can not only be utilized for generating reassessments but also aid individuals in enhancing their own reassessment abilities. Wang et al (2024b) argue that while Sharma et al (2023c,b) explored the enhancement of reframed thoughts within a single attribute in one generation, their efforts were

limited in addressing multiple features. Consequently, they developed ReframeGPT, leveraging GPT-3 as an inference engine to generate and iteratively refine reframed thoughts across various features, aiming to achieve high-quality reframing. [Li et al \(2024\)](#) focused on aligning GPT-4's reconstructive thinking with human performance, enhancing model performance in CR tasks by understanding the differences between human and AI-generated reconstructions.

Identifying a patient's automatic thoughts and emotions is crucial for effective CR. In traditional face-to-face CBT sessions, therapists refine identified automatic thoughts through methods such as Socratic questioning. However, when delivering CR in iCBT, accurately capturing thoughts and emotions poses challenges. Hence, [Furukawa et al \(2023\)](#) trained the T5 model to predict emotions associated with each automatic thought. They then compared these predictions with judgments from relevant experts, demonstrating the accuracy of T5 predictions. The application of T5 in iCBT platforms holds promise for achieving more efficient CR. [Shidara et al \(2022\)](#) and [Jiang et al \(2024\)](#) also have both underscored the significance of automatically identifying patients' cognitive distortions and emotions in CR. In response to this, corresponding efforts have been made. Particularly, [Jiang et al \(2024\)](#), drawing on the ABCD model in CBT, employed the pre-trained model ERNIE 3.0 to construct a hierarchical text classification model for extracting automatic thoughts and emotions from user statements. Furthermore, they also validated the efficacy of LLMs in this task.

Behavioral activation (BA)

Behavioral activation (BA) is a essential therapeutic strategy in CBT, focusing on addressing observable behaviors for intervention [Petersen et al \(2016\)](#). In BA, therapists collaborate with clients to formulate specific goals and plans, encourage the modification of negative behavior patterns, gradually increase the frequency and diversity of positive activities, and help clients regain a sense of pleasure and meaningful engagement in daily life. [Lewinsohn \(1974\)](#) and [Jacobson et al \(1996\)](#) demonstrated that behavioral activation achieves outcomes comparable to full CBT and is comparable to pharmacotherapy [Dimidjian et al \(2006\)](#). Individuals with mental disease may have problems with reduced daily activities, loss of interest, avoidance behavior and social avoidance. To facilitate the application of BA, researchers have developed innovative interventions.

Innovative interventions have been developed to facilitate BA application. [Dahne et al \(2019\)](#) developed a Spanish-language behavioral activation self-help mobile application called ¡Aptícate!. Within this app, the user identifies individualized values and associated activities across five life areas, including relationships, daily responsibilities, recreation, career and education, and health. Evaluation results also demonstrated the feasibility and preliminary effectiveness of this app. [Rohani et al \(2020\)](#) developed a mobile health system called MUBS (Mobile-based Behavioral Activation System) to support patients with depression through behavioral activation therapy. The system implements a unique content-based probabilistic recommendation algorithm to motivate patients to engage in positive behaviors by providing activity directories and personalized rewards, helping them build awareness of behavioral activation.

While these studies primarily focus on evaluating the efficacy of BA or developing applications to assist, prompt and motivate patients to actively engage in various activities, without explicitly linking AI to BA. Against this background, [Madhu et al \(2022\)](#) and [Rathnayaka et al \(2022\)](#) explore how AI technology can be utilized to enhance the effectiveness of behavioral activation. [Madhu et al \(2022\)](#) proposed a novel approach for activity recognition utilizing AI. They employed multi-modal data (combining speech and text) and utilized a BERT model for emotion recognition, along with logistic regression for sentiment detection. Subsequently, an activity classification model was employed wherein emotion and sentiment were integrated with keywords to accurately identify the appropriate activity for behavioral activation. This method achieved accuracies exceeding 80% in emotion recognition, sentiment detection, and activity recognition tasks. [Rathnayaka et al \(2022\)](#) designed and developed a chatbot named Bunji using AI technology to provide emotional support, personalized behavior activation, and remote health monitoring. Participatory evaluation in a pilot study environment also demonstrated the practicality and effectiveness of the chatbot.

Exposure therapy (ET)

Exposure therapy, a common technique in CBT, involves gradually exposing patients to anxiety-provoking or phobias-provoking situations to help them adapt and reduce their fear responses [Abramowitz \(2013\)](#). It is used to treat various psychological disorders, including specific phobias, panic disorder, post-traumatic stress disorder (PTSD), obsessive-compulsive disorder (OCD), and social anxiety disorder. In recent years, virtual reality (VR) technology has emerged as a potent adjunct to traditional exposure therapy [Jameel \(2020\)](#), leading to the development of Virtual Reality Exposure Therapy (VRET), validated by research for its effectiveness within CBT [Scozzari and Gamberini \(2011\)](#); [Maples-Keller et al \(2017\)](#); [Ørskov et al \(2022\)](#).

While VRET may not yield superior results in terms of therapeutic efficacy compared to traditional exposure therapy within the CBT framework, it presents unique advantages like enhanced patient comfort, safety, real-time customization of exposure content, and simulation of personalized real-life scenarios. The integration of VR with CBT has led to the development of interactive applications and serious games to augment therapeutic interventions. [Heng \(2021\)](#) developed ReWIND, an RPG-styled serious game based on the ABCDE model of CBT. The design intention of ReWIND is to immerse players diagnosed with symptoms of Generalized Anxiety Disorder (GAD) in various anxiety-inducing situations within a virtual environment and provide them with constructive psychological interventions. The game aims to deliver psychological education to players in an engaging and interactive manner. Similarly, [Giordano et al \(2022\)](#) emphasize that CBT is the most successful protocol in gambling disorder (GD) treatment, and they developed a serious virtual game called Alter Game, based on VRET, aimed at preventing relapse in patients with gambling disorder. Additionally, [Michelle et al \(2014\)](#) proposed an Android application named CBT Assistant, where patients can choose, set, and customize their own exposure fear ladders based on a generic template for graded exposure therapy. This feature distinguishes CBT Assistant from other CBT applications. The fusion of VRET with AI technology further enhances its efficacy in addressing mental health challenges. [Åhs et al \(2020\)](#)

proposed and discussed the idea of utilizing Explainable Artificial Intelligence (XAI) to enhance CBT treatment for speech anxiety in VR settings. [Rahman et al \(2022\)](#) explore a range of machine learning models' performance on the task of arousal prediction using publicly available datasets. They propose a pipeline to address the model selection issue with various parameter configurations in the context of VRET.

Homework

A CBT session typically lasts 45-60 minutes, which is often insufficient for many patients. Homework assignments bridge the gap between sessions, allowing patients to apply learned skills and enabling therapists to assess skill acquisition and maintenance [Beck \(1979\)](#); [LeBeau et al \(2013\)](#). In the professional literature, homework assignments are frequently delineated as precise, structured therapeutic tasks upon during sessions, intended for completion between sessions. This process entails collaborative delineation of therapeutic objectives for the homework, determining pertinent activities or data collection as components of the homework, strategizing the practical execution of the homework, and subsequently reviewing the homework during subsequent sessions [Kazantzis et al \(2010\)](#). Homework assignments may encompass a range of activities within each session, such as engaging with relevant materials, documenting thoughts and emotions, practicing specific skills or behaviors, or engaging in communication with others [Tang et al \(2017\)](#).

Research has found that clients who consistently complete homework derive greater benefits from interventions compared to those who complete little or no homework [Burns and Spangler \(2000\)](#), yet traditional paper-based CBT homework pose various impediments that can significantly undermine users' motivation to complete tasks as instructed. Non-compliance with homework is cited as one of the most common reasons for the failure of CBT treatments [Helbig and Fehm \(2004\)](#), persisting as a prevalent issue in clinical practice. The prevalence of digital devices and the internet has enabled the transformation of traditional homework into digital formats, thereby enhance CBT homework compliance. However, there is a lack of guidelines for designing mobile phone apps tailored for this purpose. Consequently, [Tang et al \(2017\)](#) proposes six essential features of an optimal mobile app aimed at maximizing CBT homework compliance, aiming to provide theoretical guidance for the development of such applications.

Innovative approaches, such as the integration of traditional diary writing with mobile technology and LLM, offer promising solutions to enhance homework compliance. For example, [Peretz et al \(2023\)](#) developed a machine learning model capable of recognizing the presence of homework assignments during therapy sessions based on natural language dialogue between therapists and clients in real-world settings, as well as determining the type of homework assigned. Such advancements hold significant promise in bolstering therapists' ability to assign and monitor homework tasks, ultimately fostering enhancements in therapeutic outcomes. [Nepal et al \(2024\)](#) integrated traditional diary writing with mobile technology and LLM to create a diary application with contextual awareness, named MindScape. Specifically, the application utilizes real-time analysis of behavioral data collected from smartphones and employs LLM to provide personalized, contextually relevant writing prompts. These prompts

are designed to guide users in reflection and contemplation, facilitating the recording of their thoughts within daily life contexts. This innovative approach not only fosters a habit of regular self-reflection but also addresses the challenge of homework compliance in CBT. During CBT for tinnitus alleviates the patients are typically assigned various homework tasks, including diary writing and self-monitoring. These homework assignments primarily consist of handwritten text data. However, analyzing this data can be extremely time-consuming for therapists, leading to decreased treatment efficiency. To address this issue, [Jeong et al \(2024\)](#) proposed utilizing LLMs like GPT-2 to analyze the homework data of patients undergoing CBT. Their goal is to predict the Tinnitus Handicap Inventory (THI) scores from the homework, which can, in turn, predict the outcomes of CBT treatment, thereby enabling the selection of more personalized and effective treatment plans. Additionally, they compared the performance of the latest language models, particularly Google's T5 and Flan-T5, in predicting THI scores. Finally, they looked ahead the application of this research to monitor and predict the effectiveness of CBT treatment in patients with depression.

In summary, AI augments various CBT strategies by leveraging natural language processing and machine learning techniques, improving effectiveness and engagement.

3.2.2 Developing AI tools for comprehensive delivery of CBT

While CBT strategies are often discussed individually, in clinical practice, they are typically combined to address the specific needs of clients. Recent advancements in AI have fostered the creation of digital tools that utilize the principles and techniques of CBT. These tools integrate multiple CBT strategies, thus providing a comprehensive approach to treatment. AI-powered chatbots, also referred to as conversational agents or relational agents exemplify such innovations, with chatbots being particularly notable. According to a review by Abd et al. [Abd-Alrazaq et al \(2019\)](#), out of 17 chatbots offering psychotherapy, 10 were based on CBT. They are capable of mimicking the communication styles of human therapists by engaging users in interactive dialogues that include both verbal and non-verbal exchanges. This allows them to offer efficient, personalized, and readily accessible CBT treatment, available 24/7. Pioneering chatbots like Woebot, Wysa, Tess, and Youper are emblematic of this trend. Their innovative approaches and effectiveness have garnered significant attention and recognition as effective psychological support systems based on CBT. In recent years, in response to diverse needs, researchers have developed many new AI tools based on CBT principles [Oliveira et al \(2021\)](#); [Rizea \(2022\)](#); [Rani et al \(2023\)](#); [Sabour et al \(2023\)](#); [Su et al \(2022\)](#); [Nwoye et al \(2024\)](#). As summarized in Table 1, we have outlined specific AI tools currently utilized in CBT interventions

Table 1: AI tools used in current CBT intervention

AI tools	Description
Woebot ¹	Woebot is a chatbot that offers CBT-based therapy for depression and anxiety. It engages users in daily conversations, tracks their emotions, and introduces CBT concepts through short videos or interactive word games. Using decision trees and natural language processing, Woebot responds empathetically and provides helpful suggestions. It can also detect concerning language and directs users to external resources if needed.
Wysa ²	Wysa is a therapy chatbot designed to support mental health issues like depression, anxiety, stress, and loneliness. It utilizes CBT, mindfulness, and positive psychology techniques. Instead of AI-generated responses, Wysa uses pre-crafted therapeutic conversations developed by clinicians for safe and effective interactions. Its adaptive AI understands complex user inputs and offers empathetic feedback and tailored CBT-based tools.
Youper ³	Youper is a chatbot that delivers CBT through three steps: a personalized mental health assessment, instant support via conversations, and symptom monitoring. It uses a decision tree to select responses, conducts real-time emotion analysis, and provides CBT interventions based on the user's emotional state.
Tess ⁴	Tess is a psychological AI chatbot providing brief conversations for mental health support, psychoeducation, and reminders. It uses clinician-prepared statements to deliver interventions based on user-reported moods. Tess adjusts its responses based on user feedback, favoring CBT-based interventions for positive reactions and offering alternatives for neutral or negative ones. The platform is customizable to align with specific treatments or user demographics.
BetterHelp ⁵	BetterHelp is an online therapy platform that uses AI to match patients with licensed therapists and offers various approaches like CBT and psychodynamic therapy.
Rumi ⁶ Oliveira et al (2021)	Rumi is a chatbot that uses Rumination-focused Cognitive Behavioral Therapy (RFCBT) to explore the relationship between thoughts, feelings, and actions, aiming to improve mental health and reduce depressive and anxious symptoms.
Cloud Bot Rizea (2022)	Cloud Bot is a chatbot that utilized NLP technology to function as a psychologist. It focuses on applying a cognitive restructuring CBT technique to address users' issues.

Table 1: AI tools used in current CBT intervention (continued)

AI tools	Description
Saarthi Rani et al (2023)	Saarthi is a chatbot using NLP and AI for delivering CBT and remote health monitoring to people with mental health issues. It offers real-time, evidence-based treatment that is accessible, affordable, and convenient, aiming to reduce anxiety and depression symptoms and enable long-term mental health monitoring.
SchizoBot Nwoye et al (2024)	SchizoBot is a chatbot using artificial neural networks to deliver CBT for managing schizophrenia, aiding clinicians and ensuring consistent therapy administration for patients.
XIAO AN Su et al (2022)	XIAO AN is a Chinese AI psychotherapy robot designed to monitor emotions and provide effective therapy, primarily using CBT principles. It has shown effectiveness in treating anxiety disorders in clinical trials without replacing therapists.
Emohaa Sabour et al (2023)	Emohaa is a Chinese conversational agent, which consists of two platforms: one is template-based (CBT-Bot) for structured conversations and exercises based on Cognitive Behavioral Therapy principles, while the other (ES-Bot) allows for open-ended discussions on emotional issues and provides emotional support.

By offering efficient, personalized, and readily accessible CBT treatment, these AI agents provide round-the-clock support to individuals undergoing therapy, which to some extent helps alleviate the pressure of insufficient medical resources. Nevertheless, it's worth noting that given the sensitivity of mental health support, it is crucial to assess the chatbots before presenting them to users.

3.2.3 Real-time monitoring and feedback

Traditional CBT often lacks real-time monitoring capabilities, relying solely on self-reported data from clients. However, the advent of mobile health technologies offers new possibilities for monitoring client health outside CBT sessions. According to research by [Yang et al \(2018\)](#), CBT is well-suited for mobile platform applications, which facilitate real-time monitoring of user states and provide valuable data to therapists. Consequently, numerous mobile applications have been developed to deliver CBT treatment and track users' psychological states in real-time. [Addepally and](#)

¹**Woebot:** <https://woebotehealth.com/>

²**Wysa:** <https://www.wysa.com/>

³**Youper:** <https://www.youper.ai/>

⁴**Tess:** <https://www.cass.ai/x2ai-home>

⁵**BetterHelp:** <https://www.betterhelp.com/>

⁶**Rumi:** <https://www.facebook.com/rumibot.bot/>

Purkayastha (2017) noted that loneliness can be a risk factor for depression. To address this issue, the MoodTrainer application was developed, which tracks users' locations and isolating behaviors in real-time and provides CBT interventions when it detects relevant behaviors. Also, Michelle et al (2014) introduced an Android application named CBT Assistant. This APP analyzes input data from individuals with social anxiety disorder (SAD) to identify stressors or situations triggering their mental health issues and assesses their severity. Additionally, some mobile applications are designed for specific CBT treatment scenarios, such as continuously tracking the sleep patterns of individuals with sleep disorders Schabus et al (2023) or providing cessation monitoring and CBT examples to smokers Alsharif and Philip (2015), thereby enhancing their success rates. These mobile applications leverage the capabilities of mobile devices to collect real-time data and provide personalized interventions and support to individuals undergoing CBT treatment.

In recent years, wearable devices and smartphone applications equipped with AI technology are emerging as a trend for monitoring patients' psychological states. During CBT process, AI algorithms can monitor stress levels, physical activity, speech changes, and other indicators to detect variations in a patient's psychological state. These algorithms can send timely alerts to both patients and healthcare providers. Garcia-Ceja et al (2015) embedded accelerometer sensors into smartphones to detect stress levels using classification algorithms like naive bayes and decision trees, achieving 71% accuracy. Additionally, the long-term collection and analysis of large datasets can help therapists and patients gain a deeper understanding of the patient's mental health patterns. With the assistance of AI, therapists can access more comprehensive information, enabling them to discern trends in mental health, identify triggers, and evaluate treatment efficacy. These insights are crucial for making informed therapeutic decisions and designing personalized interventions. Goodwin et al (2019) collected physiological and movement data from wrist-worn biosensors in 20 adolescents diagnosed with ASD. They developed prediction models utilizing ridge-regularized logistic regression. These models demonstrate high accuracy in forecasting instances of aggressive behavior towards others occurring within the subsequent minute. Such advancements lay the groundwork for proactive behavioral interventions and timely adaptive intervention systems in the future.

Despite the growing use of AI-equipped wearable devices and mobile applications for monitoring psychological states and data collection, there is relatively limited research specifically focused on their application to CBT, particularly considering the unique demands of real-time interaction inherent in this therapeutic approach.

3.2.4 Early prediction of treatment outcomes

Even among those for whom CBT proves effective, there may be a subset with limited benefits, potentially leading to a misallocation of both client time and limited healthcare resources. Hence, predicting treatment outcomes early in the therapeutic journey assumes critical importance, particularly to prevent the misallocation of client time and healthcare resources. Recent advancements in AI and large-scale data analysis have enabled the development of models capable of forecasting individual responses to CBT with high accuracy. Hahn et al (2015) applied a novel machine learning approach

to predict individual-level response to CBT using fMRI data in patients diagnosed with panic disorder and agoraphobia (PD/AG). Similarly, [Tolmeijer et al \(2018\)](#) utilize the machine learning methods to predict how people will respond when offered CBT for psychosis. Their two-step methodology involved first identifying potentially predictive regions and then developing a model based on these regions to make individual-level predictions. In a large-scale study, [Kaldo et al \(2021\)](#) analyzed data from over 6000 patients undergoing Internet-delivered CBT (ICBT). They evaluated the accuracy of various machine learning algorithms in predicting treatment outcomes and explored the integration of these algorithms into an Adaptive Treatment Strategy. [Isacsson et al \(2023\)](#) further examined the clinical utility of machine learning in predicting ICBT outcomes. They investigated the optimal timing within the treatment process for the model's predictive accuracy to support adaptive treatment strategies, proposing an optimal predictive model and offering specific recommendations based on their comprehensive analysis. Despite advancements, traditional predictive models often exhibit limited accuracy, particularly in assessing the effectiveness of treating adolescent social anxiety. Under this background, [Zheng et al \(2022\)](#) addressed this by employing deep learning techniques to construct a predictive model for the correlation between CBT and adolescent social anxiety, showcasing significantly improved predictive accuracy and reduced complexity compared to traditional models. [Prasad et al \(2023\)](#) seeks to develop a state-of-the-art deep-learning framework for predicting clinical outcomes in ICBT by leveraging large-scale, high-dimensional time-series data of client-reported mental health symptoms and platform interaction data.

Numerous researchers have also explored the use of specific treatment outcome predictors and potential biomarkers associated with particular diseases. For instance, [Wei et al \(2023\)](#) utilized the Hamilton Depression Rating Scale (HDRS) score as the primary outcome measure to investigate symptom changes in subjects undergoing CBT. Employing machine learning algorithms, they developed a support vector regression model, ultimately identifying left dorsolateral prefrontal cortex (DLPFC) Regional Homogeneity (ReHo) as a neuroimaging biomarker for the therapeutic effects of CBT in depression. Many previous studies have relied on highly selective samples to predict the outcomes of CBT. However, few have utilized routine available socio-demographic and clinical data to accomplish this task. Therefore, [Hilbert et al \(2020, 2021\)](#) applied machine learning methods to clinical and socio-demographic data to predict the mental health treatment outcomes of individual patients. Their findings suggest that using routine data alone can feasibly predict treatment outcomes for mental disorders, with accuracy significantly surpassing chance levels.

These studies collectively highlight the promise of integrating advanced AI methodologies with clinical practice to enhance the early prediction of CBT treatment outcomes, offering potential pathways for more tailored and effective therapeutic interventions.

3.2.5 Evaluation of therapists and clients in CBT treatment

The application of AI in CBT extends beyond the diagnosis and assessment of disorders, it also encompasses crucial evaluations of therapists and clients by analyzing conversation data during therapy sessions.

Therapist treatment quality assessment

Given the prevalence of mental health issues, ensuring the quality of psychotherapy is crucial to addressing the growing mental health demands and the complexities of the social environment. Traditionally, quality assessment is performed by human evaluators who listen to therapy recordings and review therapy notes to assess specific therapeutic skills. However, this approach is costly and time-consuming, resulting in limited feasibility and hindering widespread implementation in practical settings. To address these challenges, some researchers and technology developers have begun exploring the use of automated techniques to monitor the quality of psychotherapy. AI offers automated solutions for assessing therapy sessions and monitoring treatment fidelity of CBT sessions [Chen et al \(2022a\)](#). For example, [Ewbank et al \(2020\)](#) used a large-scale dataset containing session transcripts from more than 14000 patients receiving internet-enabled CBT (IECBT) to train a deep learning model to automatically categorize therapist utterances according to the role that they play in therapy, generating a quantifiable measure of treatment delivered. The closer the content provided by the therapist aligns with standard CBT protocols, the more positively it correlates with significant symptom improvement in patients. Conversely, the quantity of content unrelated to therapy shows a negative association. This method allows for the indirect assessment of the efficacy of CBT psychotherapy provided by the therapist. However, [Flemotomos et al \(2021\)](#) emphasize that, for CBT, the most commonly utilized coding scheme is the Cognitive Therapy Rating Scale (CTRS), which defines a set of 11 session-level codes reflecting skills and techniques specific to the intervention. Consequently, they introduced a model for quality assessment of psychotherapy sessions based on adapted BERT representations of therapy language use. Their analysis focused on the binary classification of CBT sessions concerning the overall CTRS score. [Chen et al \(2022b\)](#) also utilized CTRS scores to assess the quality of CBT sessions. However, unlike [Flemotomos et al \(2021\)](#), they proposed a hierarchical framework for automatically evaluating the quality of transcribed CBT interactions. [Ardulov et al \(2022\)](#) proposed an approach that explicitly focuses on control-affine dynamical system models. They attempted to extract local dynamic modes from short windows of conversation and learn to correlate the observed dynamics with CBT competence. Furthermore, some studies aim to identify areas where the therapist excels and areas where improvement is needed by analyzing recordings of therapy sessions, comparing therapists' language and behavior against standards of specific therapeutic models [Stirman et al \(2021\)](#); [Flemotomos et al \(2022\)](#); [Zhang et al \(2023\)](#); [Wang et al \(2024a\)](#). This process aids therapists in enhancing their professional skills, thereby improving the overall quality of therapy. Particularly, [Wang et al \(2024a\)](#) developed PATIENT- Ψ , a novel patient simulation framework for CBT training. Specifically, they constructed diverse patient profiles and corresponding cognitive models based on CBT principles, and used a large language model to act as a simulated therapy patient. This role-playing therapeutic scenario helps mental health trainees practice CBT skills.

Predictive analysis of clients treatment adherence

Treatment adherence refers to the extent to which clients actively engage in and comply with the advice and instructions provided by healthcare professionals, thereby adhering to the treatment regimen, and it directly impacts the effectiveness and outcomes of the treatment [DiMatteo et al \(2002\)](#). Therefore, client adherence evaluation is essential components of effective healthcare delivery. Particularly, against the backdrop of ICBT, there has been a reduction in face-to-face interactions between healthcare professionals and clients, which may lead to low client engagement and high dropout rates. AI models can analyze client behavior and responses during therapy sessions to evaluate their understanding, engagement, and adherence to treatment content. [Côté-Allard et al \(2022\)](#) presents a minimally data-sensitive approach, based on a self-attention deep neural network, to perform adherence forecasting of clients undergoing G-ICBT. This study leverages between 7 to 42 days of user-interaction data (login/logout) from the eMeistring platform. This analysis can identify individuals who may be at risk of early dropout from intervention. With this information, clinicians can implement meaningful and targeted interventions such as reminders, scheduling direct interactions, or modifying the treatment approach to prevent premature termination.

3.3 Integration of AI in Post-treatment Stage

3.3.1 Long-term treatment response and relapse prediction

Since current CBT interventions typically have relatively short durations, leading to inadequate durability of effects for some patients post-treatment, with a considerable proportion experiencing relapse after treatment cessation. Hence, predicting individual long-term clinical responses and relapse risks remains a significant challenge. AI presents a promising avenue for predicting relapse risks and enhancing the durability of CBT's effects in patients undergoing CBT. [Måansson et al \(2015\)](#) proposed the first study using the multivariate SVM-fMRI method to successfully predict long-term treatment response of ICBT for social anxiety disorder, achieving a predictive accuracy reached 92% (95% confidence interval 73.2–97.6). [Lorimer et al \(2021\)](#) utilized machine learning techniques, specifically the XGBoost algorithm, to analyze follow-up data of patients undergoing Low-Intensity Cognitive Behavioral Therapy (LiCBT). They developed a dynamic prediction tool capable of identifying cases with higher relapse risk at four distinct time points during the patients' treatment journey, with the ability to dynamically adjust prediction accuracy. This tool's capacity for early identification of high-relapse cases, combined with targeted relapse prevention measures, can significantly enhance the long-term efficacy of LiCBT in situations where psychological resources are limited.

In conclusion, the integration of AI in CBT holds promise for revolutionizing the delivery and efficacy of psychological interventions. By leveraging AI technologies throughout various stages of the treatment process, clinicians can enhance treatment outcomes, personalize interventions, and optimize resource allocation, ultimately improving mental health outcomes for individuals on a global scale.

4 Datasets

Datasets play a crucial role in driving research at the intersection of CBT and AI, providing foundational material for training, testing, and validating AI algorithms, and furnishing practitioners and researchers with the bedrock for constructing and evaluating CBT models. This section aims to review existing publicly datasets relevant to the application of CBT and AI. In the context of disease diagnosis and assessment tasks, numerous datasets have already been extensively reviewed in various comprehensive articles. Consequently, we will not elaborate on these datasets further in this paper. Moreover, it is worth noting that for the task of selecting personalized treatment strategies, there is a noticeable lack of publicly available datasets. This paper will not cover these datasets in detail. Instead, we focus on datasets for specific CBT-related tasks such as identifying and classifying cognitive distortions, conducting cognitive restructuring, and analyzing CBT conversation data. For clarity, datasets where descriptions are unclear or ambiguous in the literature will not be discussed in this paper.

Table 2 provides a comprehensive overview of datasets used for detecting and classifying cognitive distortions. As can be seen from this table, most of the cognitive distortion data sets are in English, and fewer are in Chinese. Moreover, these datasets present several notable challenges: First, low reliability. The labeling criteria vary significantly across different datasets, leading to inconsistencies. Moreover, the inherently subjective nature of labeling cognitive distortions further compromises reliability. Second, there is a pronounced issue of data imbalance, with certain classes of cognitive distortions lacking adequate representation. This imbalance hampers the model's ability to generalize well across all classes. Table 3 summarizes datasets relevant to cognitive restructuring. Additionally, Table 4 outlines datasets that involve CBT conversations. For these areas, high-quality, annotated datasets are particularly scarce for both cognitive restructuring and CBT conversation analysis.

Table 2: Cognitive Distortions Dataset. For a clean presentation, we have only shown the simplified version of the cognitive distortion dataset, see Appendix A for more details.

Study	Description
Wang et al (2023b)	Size of Dataset: A total of 1644 data entries across 11 types of cognitive distortions, and 2000 entries for normal cases. Language: Not reported. Data Modalities: Text.
Elsharawi and El Bolock (2024)	Size of Dataset: A total of 34370 samples across 14 types of cognitive distortions. Language: English. Data Modalities: Text.

Table 2: Cognitive Distortions Dataset (continued)

Study	Description
Shickel et al (2020)	Size of Dataset: Dataset CrowdDist contained 7,666 texts across all 15 distortions, with an average of 511 responses per distortion. Dataset MH contained two subsets: MH-C was annotated with 15 cognitive distortion labels with 1164 distorted texts, and the MH-D dataset was annotated with binary distorted/non-distorted labels, distorted for 1605 texts, not distorted for 194 texts. Language: English. Data Modalities: Text.
Lim et al (2024)	Size of Dataset: A total of 2530 samples across 10 types of cognitive distortions. Language: English. Data Modalities: Text.
Shreevastava and Foltz (2021)	Size of Dataset: A total of 3000 samples, 39.2% were marked as not distorted, while the remaining were identified to 10 type of distortions. Language: English. Data Modalities: Text.
de Toledo Rodriguez et al (2021)	Size of Dataset: A total of 200 samples across 14 types of cognitive distortions. Language: English. Data Modalities: Text.
Sharma et al (2023c)	Size of Dataset: A total of 1077 samples across 13 types of cognitive distortions. Language: English. Data Modalities: Text.
Maddela et al (2023)	Size of Dataset: About 10k samples across 10 types of cognitive distortions. Language: English. Data Modalities: Text.
Wang et al (2023a)	Size of Dataset: 7,500 cognitive distortion thoughts across 7 types of common cognitive distortions. Language: Chinese. Data Modalities: Text.
Qi et al (2023)	Size of Dataset: A total of 3407 posts across 12 types of cognitive distortions. Language: Chinese. Data Modalities: Text.

Table 2: Cognitive Distortions Dataset (continued)

Study	Description
Na (2024)	<p>Size of Dataset: A total of 22,327 samples across 10 types of cognitive distortions.</p> <p>Language: Chinese.</p> <p>Data Modalities: Text.</p>

Table 3: Cognitive Restructuring Dataset.

Study	Tasks	Dataset source	Description
Sharma et al (2023c)	Cognitive Reframing of Negative Thoughts through Human-Language Model Interaction.	Thought Records Dataset and Mental Health America (MHA) website.	<p>Size of Dataset: A total of 300 situations-thoughts pairs, reframed thoughts per situation.</p> <p>Component: situation; thought; reframe; thinking_traps_addressed.</p> <p>Language: Chinese.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes¹.</p>
Lin et al (2024)	Detection of Cognitive Distortion and cognitive restructuring.	The corpus labeling utilizes one specialized opensource dataset, the Chinese psychological Q&A dataset PsyQA Sun et al (2021).	<p>Size of Dataset: A total of 1900 sentences.</p> <p>Component: original text and reconstruction text.</p> <p>Language: Chinese.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes².</p>
Shidara et al (2022)	Identification and evaluation of automatic thoughts and cognitive restructuring.	Recruit participants.	<p>Size of Dataset: Not reported.</p> <p>Language: Japanese.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes. It can be obtained by sending an email.</p>

5 Discussion

The integration of AI into CBT has led to significant advances in pre-treatment assessment, the therapeutic process, and post-treatment follow-up. First, AI has improved

¹ Sharma et al (2023c): <https://github.com/behavioral-data/Cognitive-Reframing>

² Lin et al (2024):

<https://github.com/405200144/Dataset-of-Cognitive-Distortion-detection-and-Positive-Reconstruction>

¹ Lee et al (2023): <https://github.com/behavioral-data/Empathy-Mental-Health>

Table 4: CBT session dataset.

Study	Tasks	Dataset source	Description
Lee et al (2023)	Enhancing Empathetic Response of Large Language Models Based on Psychotherapy Models.	Crowdsourced Reddit posts of mental health from Sharma et al (2020).	Size of Dataset: Three levels of empathy strategies, and the number of pairs for each strategy was as follows: “emotion reaction”=1,047, “exploration”=481, and “interpretation”=1,436. Language: English. Data Modalities: Text. Open Source: Yes ¹ .
Na (2024)	Enhance the precision and efficacy of psychological support through LLMs	Get PsyQA Questions Sun et al (2021), which is derived from the Chinese online mental health support forum Yixinli, then utilizes CBT Prompt to generate CBT answers.	Size of Dataset: 22,327 entries, each comprising questions, descriptions, and CBT responses. Language: Chinese. Data Modalities: Text. Open Source: Yes. Follow the data copyright protocols and obtain it by email. Note: The questions in the dataset originate from online mental health forum, and the responses are generated by ChatGPT, not professionals.

efficiency by assisting with pre-treatment screening and diagnosis, reducing therapist workload, and enabling real-time adjustments to treatment plans through predictive capabilities. Second, AI has enabled more personalized CBT by analyzing rich patient data and identifying subtle patterns, enabling customized treatment plans that go beyond the traditional reliance on therapist expertise alone. Finally, AI-powered CBT platforms have increased the accessibility of mental health services by providing remote and cost-effective treatment options through online platforms and mobile applications that offer 24/7 support. However, there are several limitations to current AI applications in CBT. In pre-treatment assessment, while AI excels in diagnosing psychological disorders and assessing cognitive distortions and emotional states using textual data, it has fewer applications in analyzing video, audio, and behavioral data. The potential of multimodal data for comprehensive diagnosis remains largely untapped. During the therapeutic process, AI enhances individual CBT strategies but struggles to cover the complexity of interventions comprehensively. AI tools like chatbots and virtual therapy assistants vary in quality and lack standardized development, leading to inconsistencies. Moreover, there are inadequate metrics for evaluating feasibility, engagement, and satisfaction, complicating platform comparison and improvement. Most AI-driven wearable devices and mobile applications focus on general indicators like heart rate and activity levels, lacking specialized tools for monitoring CBT-specific indicators. In post-treatment, while AI aids in predicting long-term treatment responses and relapse risks, challenges include variability in prediction data and insufficient research on utilizing predictive results to formulate personalized intervention strategies.

The future of AI in CBT holds great potential. Autonomous learning and adaptive therapy systems can emulate human CBT therapists, engaging in multi-round interactions with patients and adjusting strategies based on real-time feedback. Group intelligence support and decision-making systems can improve both therapist guidance and patient outcomes by aggregating the experience of experienced practitioners and facilitating intelligent social support. Cognitive augmentation and assistive systems can develop personalized tools to enhance cognitive function, thereby increasing the effectiveness of CBT. Customized, personalized CBT models can adapt to users' specific data, such as social background, culture, education, and environment, to provide tailored responses and interventions that increase therapeutic effectiveness and user satisfaction. Despite the potential of AI, several challenges need to be addressed. Data security and privacy are paramount, requiring compliance with privacy regulations, anonymization of sensitive information, and advanced encryption techniques. Ethical and algorithmic bias must be mitigated by ensuring data diversity, involving multiple stakeholders in development, and continuously monitoring AI systems. Model explainability and transparency are essential for responsible AI decisions, requiring methods to improve interpretability and the use of rigorously tested models. Over-reliance on AI is a risk because the success of CBT depends on the therapist-patient relationship, which AI cannot replicate. AI should be a complementary tool, not a replacement. Evaluation of models in clinical practice is necessary to assess real-world effectiveness, acceptance, trust, and usability, taking into account training costs and impact on medical practice. In summary, while AI offers promising enhancements to CBT, it must be used responsibly and ethically, complementing the guidance of professional therapists. The ultimate goal is to use technology to support, not replace, human-centered mental health care.

6 Conclusion

In this paper, we have conducted a comprehensive literature review of the integration of AI technology into CBT . We explored the application of AI throughout the CBT process, highlighting its significant transformative impact and existing limitations. Subsequently, We have summarized publicly available datasets relevant to various CBT-related tasks to provide a foundation for future research. We suggested future research directions and acknowledged the practical challenges that AI faces in clinical settings. Overall, our review illuminates the multifaceted integration of AI in CBT, highlighting its potential while providing a nuanced understanding of its capabilities. We hope that the findings will guide future research, bring new perspectives to clinical practice, and contribute to the advancement of mental health care.

Acknowledgements. This work was supported by grants from the National Natural Science Foundation of China (grant numbers:72174152, 72304212 and 82071546), Wuhan University Innovation and Entrepreneurship Projects for College Students (No: 202410486100), Fundamental Research Funds for the Central Universities (grant numbers: 2042022kf1218; 2042022kf1037), and the Young Top-notch Talent Cultivation Program of Hubei Province. Guanghui Fu is supported by a Chinese Government Scholarship provided by the China Scholarship Council (CSC).

Declarations

- Competing Interests: The authors have no competing interests to declare that are relevant to the content of this article.

Appendix A Cognitive distortion dataset

In this section, we provide full detail of the dataset as described in Section 4.

Table A1: Cognitive Distortions Dataset.

Study	Tasks	Dataset source	Description
Wang et al (2023b)	Cognitive distortion classification.	Published research papers on cognitive distortions, examples from articles on the web that introduce cognitive distortions and social media posts.	<p>Size of Dataset: Before expansion: There were a total of 353 data entries for all cognitive distortions, and 1000 entries for normal cases. After expansion: There are now a total of 1644 data entries across 11 types of cognitive distortions, and 2000 entries for normal cases.</p> <p>Label: 12 labels, including 11 cognitive distortions and no cognitive distortions.</p> <p>Language: Not reported.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes. However, the article says it will share, but no link is given.</p>
Shickel et al (2020)	Detection and Classification of Cognitive Distortions.	Dataset CrowdDist, comes from the popular crowdsourcing platform Mechanical Turk(MTurk). Dataset MH, comes from TAO Connect, an online mental health therapy service.	<p>Size of Dataset: Dataset CrowdDist contained 7,666 text responses across all 15 distortions, with an average of 511 responses per distortion. Dataset MH contained two subsets: The MH-C dataset was annotated with 15 cognitive distortion labels with 1164 distorted texts, and the MHD dataset was annotated with binary distorted/non-distorted labels, distorted for 1605 texts, not distorted for 194 texts.</p> <p>Label: situation; thought; reframe; thinking_traps_addressed.</p> <p>Language: English.</p> <p>Data Modalities: Text.</p>

Table A1: Cognitive Distortions Dataset (continued)

Study	Tasks	Dataset source	Description
Elsharawi and El Bolock (2024)	Detection and Classification of Cognitive Distortions.	Facebook Empathetic Data, Twitter Data and Crowd-Sourcing.	<p>Size of Dataset: A total of 34370 samples.</p> <p>Label: 14 labels.</p> <p>Language: English.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes. However, the article says it will share, but no link is given.</p>
Lim et al (2024)	Detection and Classification of Cognitive Distortions.	Dataset Therapist Q&A comes from crowd-sourced data science repository, Kaggle.	<p>Size of Dataset: A total of 2530 samples.</p> <p>Label: 10 labels.</p> <p>Language: English.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes¹.</p>
Shreevastava and Foltz (2021)	Automatic Detection and Classification of Cognitive Distortions.	Dataset Therapist Q&A comes from crowd-sourced data science repository, Kaggle.	<p>Size of Dataset: A total of 3000 samples, 39.2% were marked as not distorted, while the remaining were identified to have some type of distortion.</p> <p>Label: 11 labels, including 10 cognitive distortions and no cognitive distortions.</p> <p>Language: English.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes. However, the article says it will share, but no link is given.</p>
de Toledo Rodriguez et al (2021)	Convert negative or distorted thoughts into more realistic alternatives.	A variety of sources such as CBT books, forums and public content aggregators.	<p>Size of Dataset: A total of 200 samples.</p> <p>Label: 14 labels.</p> <p>Language: English.</p> <p>Data Modalities: Text.</p> <p>Open Source: Yes².</p>

Table A1: Cognitive Distortions Dataset (continued)

Study	Tasks	Dataset source	Description
Sharma et al (2023c)	Cognitive Reframing of Negative Thoughts through Human-Language Model Interaction.	Thought Records Dataset and Mental Health America (MHA) website.	Size of Dataset: A total of 1077 samples. Label: 13 labels. Language: English. Data Modalities: Text. Open Source: Yes ³ .
Madela et al (2023)	Training models to generate, recognize, and reframe unhelpful thoughts.	Obtain a diversity of contexts, situations and thoughts from PERSONA-CHAT dataset Zhang et al (2018), and ask crowdworkers to rewrite them.	Size of Dataset: About 10k examples of thoughts containing unhelpful thought. Label: 10 labels. Language: English. Data Modalities: Text. Open Source: Yes ⁴ . However, this article says it will be shared and gives a github link, but it does not contain data.
Wang et al (2023a)	Cognitive Distortion Detection and investigate the association between cognitive distortions and mental health.	Carefully select and train volunteers to observe scenes and note possible cognitive distortions, then have experts evaluate the results.	Size of Dataset: 7,500 cognitive distortion thoughts. Label: 7 common cognitive distortions. Language: Chinese. Data Modalities: Text. Open Source: Yes ⁵ .

Table A1: Cognitive Distortions Dataset (continued)

Study	Tasks	Dataset source	Description
Qi et al (2023)	Classification of Cognitive Distortions.	Comments on a Sina Weibo post by the user "Zoufan".	<p>Size of Dataset: A total of 3407 posts. Label: 12 labels. Language: Chinese. Data Modalities: Text. Open Source: Yes⁶.</p>
Na (2024)	Enhance the precision and efficacy of psychological support through LLMs.	Get PsyQA Questions Sun et al (2021), which is derived from the Chinese online mental health support forum Yixinli, then utilizes CBT Prompt to generate CBTanswers.	<p>Size of Dataset: A total of 22,327 samples. Label: 10 labels. Language: Chinese. Data Modalities: Text. Open Source: Yes. Follow the data copyright protocols and obtain it by sending an email. Note: The questions in the dataset originate from online mental health forum, and the responses are generated by ChatGPT, not professionals.</p>

¹ Lim et al (2024): <https://www.kaggle.com/datasets/sagarikashreevastava/cognitive-distortion-detetction-dataset>

² de Toledo Rodriguez et al (2021): <https://github.com/itoledorodriguez/cbt-dataset>

³ Sharma et al (2023c): <https://github.com/behavioral-data/Cognitive-Reframing>

⁴ Maddela et al (2023):

https://github.com/facebookresearch/ParlAI/tree/main/projects/reframe_thoughts

⁵ Wang et al (2023a): <https://github.com/bcwangavailable/C2D2-Cognitive-Distortion>

⁶ Qi et al (2023): <https://github.com/HongzhiQ/SupervisedVsLLM-EfficacyEval>

Appendix B Abbreviation

In this section, as shown in Table B2, we summarize the full names and abbreviations of various specialized terms mentioned throughout the text. By providing this list of abbreviations, our aim is to assist readers in quickly referencing and understanding the meanings of these terms, thereby enhancing comprehension of the content and its context within the paper.

Table B2: Full name and abbreviation of terms

Abbreviation	Full Name
ADHD	Attention Deficit Hyperactivity Disorder
AG	Agoraphobia
AI	Artificial Intelligence
AR	Augmented Reality
BA	Behavioral Intervention
CBT	Cognitive Behavioral Therapy
CCBT	Computer-Based Cognitive Behavioral Therapy
CD	Cognitive Distortions
CNN	Convolutional Neural Network
CR	Cognitive Restructuring
CTRS	Cognitive Therapy Rating Scale
DLPFC	Dorsolateral Prefrontal Cortex
DoT	Diagnosis of Thought
ECA	Embodied Conversational Agent
ET	Exposure Therapy
GAD	Generalized Anxiety Disorder
GD	Gambling Disorder
GPT	Generative Pretrained Transformer
HDRS	Hamilton Depression Rating Scale
ICBT	Internet-Based Cognitive Behavioral Therapy
IECBT	Internet-enabled CBT
LiCBT	Low-Intensity Cognitive Behavioral Therapy
LLM	Large Language Model
MHA	Mental Health America
MUBS	Mobile-based Behavioral Activation System
NLP	Natural Language Processing
OCD	Obsessive-Compulsive Disorder
PD	Panic disorder
PDT	Psychodynamic Therapy
PTM	Pre-trained Language Model
PTSD	Post-Traumatic Stress Disorder
Q&A	Question and Answering
ReHo	Regional Homogeneity
RET	Rational Emotive Therapy
SAD	Social Anxiety Disorder
THI scores	Tinnitus Handicap Inventory scores
VR	Virtual Reality
VRET	Virtual Reality Exposure Therapy
XAI	Explainable Artificial Intelligence

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