Benefits and Harms of Large Language Models in Digital Mental Health

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Abstract

The past decade has been transformative for mental health research and practice. The ability to harness large repositories of data, whether from electronic health records (EHR), mobile devices, or social media, has revealed a potential for valuable insights into patient experiences, promising early, proactive interventions, as well as personalized treatment plans. Recent developments in generative artificial intelligence, particularly large language models (LLMs), show promise in leading digital mental health to uncharted territory. Patients are arriving at doctors' appointments with information sourced from chatbots, state-of-the-art LLMs are being incorporated in medical software and EHR systems, and chatbots from an ever-increasing number of startups promise to serve as AI companions, friends, and partners. This article presents contemporary perspectives on the opportunities and risks posed by LLMs in the design, development, and implementation of digital mental health tools. We adopt an ecological framework and draw on the affordances offered by LLMs to discuss four application areas—care-seeking behaviors from individuals in need of care, community care provision, institutional and medical care provision, and larger care ecologies at the societal level. We engage in a thoughtful consideration of whether and how LLM-based technologies could or should be employed for enhancing mental health. The benefits and harms our article surfaces could serve to help shape future research, advocacy, and regulatory efforts focused on creating more responsible, userfriendly, equitable, and secure LLM-based tools for mental health treatment and intervention.

1 Introduction

"When I use ChatGPT to talk things through and vent about how I feel, it goes on to tell me to get help and that I'm not alone. But why does it feel as if it's mocking me? It feels as if it's having a laugh at my expense." – A paraphrased social media post

In November 2022 [1], OpenAI released ChatGPT. ChatGPT followed the mold of past chatbots by providing a simple interface for people to easily interact with a conversational agent. However, unlike past publicly accessible chatbots, ChatGPT was powered by OpenAI's proprietary language generation model, often called Large Language Models (LLMs). OpenAI's LLM (named GPT, for Generative Pre-trained

Transformers [2]) was created through a large-scale collection of text from the Internet combined with manual review through a process often called Reinforcement Learning From Human Feedback (RLHF) [3]. ChatGPT's underlying language and simple interface astonished users with answers that were surprisingly coherent and wide-ranging. Since then, conversations across academic, medical, industry, and policy domains have begun to discuss how LLMs could offer new possibilities for diagnosis, treatment, and patient care in mental health.

Over the past decade, there has been increased conversation around the growing potential for digital technologies, artificial intelligence (AI), and machine learning to contribute value to mental health research and practice. Research has demonstrated some of this potential. For example, methods from natural language processing (such as sentiment analysis) have been used to assess people's emotional states from their text, speech, or social media language [4, 5]. These studies have consistently shown that computational or predictive analyses of digital data can accurately detect mood [6], mental health states [7], and even the risk of potential harm [8] and suicide [9]. Collectively, the implications of this research include the potential for valuable insights into daily patient experiences, a paving of the way for early and proactive interventions, and the design of personalized treatment plans. However, as people further rely on online tools to seek care for their mental health, researchers and activists have sounded the alarm about the potential for harm if digital mental health interventions are staged without the awareness or consent of people experiencing distress [10, 11]. Scholars have also expressed concern that the use of predictive analytics in mental health could compromise patient and clinician agency [12], exacerbate systemic disparities encoded in the training data of AI models [10, 13], and propagate insights poor in clinical grounding or construct validity [14]. The challenges in implementing an AI-informed mental health care model have further invited criticism and skepticism around the role of AI in this field [15], even as researchers have increasingly sought to draw upon both computational and psychiatric expertise and paradigms to advocate for an "(AI) model-based psychiatry" [16]. With the rapid introduction of LLMs in new parts of everyday life, initiatives in digital mental health are likely to be similarly disrupted, opening doors to new opportunities for mental healthcare, while also setting the stage for new and previously unconsidered harms.

This discussion of benefits and harms can already be seen unfolding in popular discourse around LLMs and mental health. For instance, ChatGPT was not created as a mental health support tool—however, people in distress have started to use ChatGPT for mental health support and non-judgmental guidance, as the opening quote to this Introduction shows. As discussed in online communities (such as Reddit [17]), users have turned to ChatGPT in moments of suicidal ideation, and expressed their belief that ChatGPT saved their life in moments of despair. Other users have described their approach to carefully training LLM-based chatbots to behave as therapists from different theoretical orientations, such as prompting chatbots to take on the role of an Acceptance and Commitment (ACT) therapist. Several mental healthcare organizations and companies [18–20] have also begun to research the integration of LLMs into the design of their services. This increased use of LLMs in service delivery has been met with excitement [21], but also with justified skepticism, given potential racial or gender biases [22, 23] and unexpected outputs [24] from LLM-based chatbots. For example, in June 2023, the National Eating Disorder Association was forced to shut down a chatbot created to provide clinically validated information after the chatbot provided harmful and dangerous advice to users, including diet and weight loss advice [24, 25]. Unbeknownst to the administrative staff at NEDA, the chatbot company that provided its services to NEDA had "rolled out an AI component to its chatbots" [24]. The chatbot was introduced soon after several pivotal events, including an attempt by NEDA helpline volunteers to unionize and the closing of the NEDA helpline, raising awareness of the potential that nascent technology may be used to replace human staff [25]. The harms of irresponsible uses of LLMbased technologies can even be lethal—according to a report from the Belgian news outlet La Libre (via Belga News Agency) [26], a Belgian man is said to have tragically ended his own life after engaging in conversations with an AI chatbot, for six weeks, discussing climate change.



Figure 1: An ecological conceptualization of the use of large language models in digital mental health, based on the Social Ecological Model [34].

Many of the arguments that highlight the potential harms of LLMs are warranted. LLMs are trained on an Internet that is largely devoid of fact-checking. As a result, LLMs often reproduce convincing misinformation [27], and in the context of the COVID-19 pandemic, were found to be capable of generating highly persuasive, difficult to discern health misinformation about COVID-19's precautionary and prevention measures [28]. Some have described LLMs as being similar to super-powerful auto-completion tools, as it can be hard to systematically control for specific outputs [29]. This can be problematic in a mental health context, where the success of interventions can be highly dependent on the nature of a provider's response [30–32]. LLMs have been described as a "blurry JPEG image" [33] of the rest of the Internet, similarly containing both substantial utility as well as the potential for harm to users. Today, just as in digital mental health spaces, there are widespread debates around the consequences of LLMs for truthful public discourse on one hand, and productivity and efficiency on the other.

This article is situated against the backdrop of this larger debate. We present a state-of-the-art informed perspective on contexts where LLMs can potentially be beneficial, and where there may be significant risk of harm. We conclude with directions and recommendations that can help amplify benefits while also minimizing harms.

2 Theoretical Frameworks

Drawing on Insel's [35] four key areas where LLMs could influence mental health, we conceptualize benefits and harms in the use of LLMs for administering tele-mental healthcare, for supporting crisis response, for providing clinical decision support in psychiatric settings, and for psychotherapy. To organize our discussion, we adopt the Social Ecological Model widely used in the public health field [34] and map each of Insel's potential application contexts into a four-tier framework. This ecological analysis allows us to understand the complex interplay between individuals and the broader social and environmental contexts they are embedded in—contexts that influence and shape people's mental health as well as contexts in which LLM-based technologies could exist.

Figure 1 shows this organization of the potential uses of LLMs in mental health. The innermost layer focuses on the individual seeking mental healthcare and considers personal factors such as values, beliefs, knowledge, skills, and experiences in how an individual might appropriate LLMs to seek help and support to overcome their distress. The next layer is the caregiver layer, where LLMs might be appropriated by supporters, counsellors, crisis volunteers, and others to respond to an individual in crisis. The third layer centers around institutional efforts and initiatives in caregiving, where we discuss the role that LLMs can

play in enabling decision-making within health systems. At the final layer, we discuss potential futures where LLMs could transform telehealth paradigms.

In addition, to systematically identify and discuss the factors that can support or hinder caregiving at each level resulting from LLMs, we adopt the concept of affordances [36]. Affordances refer to the potential actions or uses that an object, environment, or system offers to individuals based on their perceived characteristics or features [37]. To understand the benefits and harms of LLMs in digital mental health, we begin by describing the various affordances of LLMs that are relevant for the above four-tiered ecological framework. First, LLMs enable natural language understanding—users can input text-based queries, prompts, or commands in natural language, and the model interprets and responds to them coherently. Second, by offering end users the ability to engage in open dialogue, and by parsing the semantics of the user input, LLMs allow users to interact with conversational agents in a natural environment [38]. These affordances are relevant to the use of LLMs in psychotherapy. Next, LLMs are extremely powerful information retrieval systems and are able to parse very large repositories of data efficiently—users can thus request information on a wide range of topics by asking questions or requesting explanations and the model can provide answers, summaries, or context on various subjects. This affordance is relevant to the use of LLMs in crisis response. Third, LLMs can provide *predictions* of outcomes of interest by learning from its underlying data—users can seek answers, recommendations, and suggestions from the LLM for various scenarios and use cases, making this affordance relevant to clinical decision support. Finally, LLMs also allow efficient text summarization—users can request concise summaries of longer texts, making it easier to grasp the main points of an article, document, or report. Complementarily, LLMs can be used for content generation and machine translation tasks. Together, these features can be highly valuable for envisioning new models of telehealth.

3 For Careseekers: Psychotherapy Chatbot

Perhaps one of the most widely spoken of applications of LLMs in mental health centers around their use for psychotherapy; Insel discusses the potential for LLMs, particularly GPT-4, to serve as autonomous therapists [35]. In fact, LLM-powered chatbots like Replika are already claiming to be an "AI comparison, [...] always ready to chat when [a person] needs an empathetic friend" [39]. However, for decades, the idea of using a machine to serve as a therapy bot has met with significant heated debate and controversy, specifically around their value to individuals in distress. For example, the Rogerian therapy chatbot ELIZA was first created by Joseph Weizenbaum as a commentary on the irreplaceability of human interaction in mental health support [40]. After careseekers in distress found ELIZA to provide useful support, some mental health professionals argued that chatbots may be able to scale up basic forms of mental health support [41]. Weizenbaum was shocked by this enthusiasm, and responded that "no humane therapy of any kind" can or should be done via a chatbot computer program [42], grounding his argument in Rogers's own ideas around person-centered therapy. These debates continue today, and this section synthesizes the salient points in these conversations.

3.1 Potential Benefits

Improving the Reach of Therapeutic Care. Mental health conversational agents have historically been rule-based, meaning they would engage with users based on predetermined scripts [43]. This limitation made it challenging for conversational agents to deliver human-like interactions, as they could not engage in open-ended conversations that were tailored to users' emotional requirements. LLMs (grounded in generative AI) have demonstrated impressive performance in participating in realistic human-like conversations in a coherent manner, following practically any type of prompt from the end user [44].

A subsequent benefit offered by this type of naturalistic LLM-powered chatbots in psychotherapy is accessibility. Chatbots are available around the clock, providing users with a convenient and immediate source of support. This can be especially valuable for individuals who have difficulty accessing traditional in-person therapy due to geographical or scheduling constraints [45], those living in underserved areas, such as mental health professional shortage areas [46, 47], or those who might be otherwise marginalized in conventional mental health care [48, 49]—over half of U.S. counties lack a single psychiatrist [46], and a recent survey revealed that 60% of mental health professionals have had no available slots for new patients following the COVID-19 pandemic [50]. Research has demonstrated that online and self-guided single-session interventions can reduce depressive symptoms [51, 52]. The naturalistic and accessible interface associated with LLM-powered chatbots may allow for a new modality to deliver efficacious and self-guided psychotherapy interventions.

Improving Therapeutic Quality through Personalization and Evidence-based Adaptation.

LLM-based chatbots are trained on large amounts of historical data, to the order of many terabytes of data [53]. Current and future LLMs could be further fine-tuned to be better at providing support based on whether past support responses (from humans or the chatbot) were evaluated by humans as being efficacious. This might include the specific emotional patterns, style, or tonality of response that align best with the needs and expectations of a given client or patient. Researchers have demonstrated that natural language processing techniques that harness the power of LLMs can empower and equip supporters with writing suggestions during practice training sessions. For example, Hsu et al. [54] create the CARE system for mock chats, which uses LLMs to offer suggestions to online peer supporters as they undergo training. Participants found recommendations from the CARE system to be helpful, particularly when faced with uncertainty around how best to respond during the mock training session. Learnings from LLM-based systems can be directly applied when supporters are helping people in distress without the aid of any computational system. Similarly, Sharma et al. [55] developed HAILEY, an AI-powered agent that offers real-time guidance to enhance the empathetic responses of peer supporters as they assist those in need of support. The research found that peer supporters can effectively incorporate AI feedback with this system, benefiting from both direct and indirect AI assistance, without developing an excessive reliance on AI. In contrast, supporters reported enhanced self-efficacy after receiving AI feedback, underscoring the promise of LLMs as teaching aids for supporters. LLMs can further allow for an enhanced ability to use data for actionable and evidencebased insights into the nature of support, including how to adapt support for the individual and their context.

Destigmatizing the Seeking of Care. LLM-based chatbots can be built to draw on evidence-based psychotherapy techniques to deliver helpful support exercises for a user, with potentially less stigma than traditional psychotherapy. Recent empirical research has demonstrated that language models can be utilized to help individuals work to reframe negative thoughts and beliefs through in-context learning [56], if trained on relevant data. For example, Ziems et al. [57] draw upon six theoretically grounded reframing strategies to demonstrate that language models can be used to identify and reframe various types of cognitive distortions. Similarly, Sharma et al. [56] utilize a dataset consisting of potential thoughts and corresponding reframed thoughts (validated by practitioners) to train an LLM that generates reframed thoughts for new contexts. This work demonstrates the promise of LLMs in providing CBT-based exercises that are personalized to a user's context, which may lower the barriers to seeking treatment or support, often stemming from stigma, shame, or structural factors, as has been argued for AI as well [58, 59]. LLM-based chatbots may thus motivate more people to reach out for mental health needs, and help normalize the process of seeking care through self-disclosure and processing of thoughts, whether with other humans or chatbots. Such

¹This system is publicly testable at bit.ly/changing-thoughts.

normalization of care-seeking has been identified to be very important to fight the prevailing societal stigma surrounding mental illness [60].

3.2 Potential Harms

Black [61] has noted how those working at the intersection of AI and care are quick to explain that "a chatbot will never equal, let alone surpass, the abilities of a human therapist or counselor." However, a growing number of commercial initiatives are building LLM-informed psychotherapy chatbots, with a belief that "mental health chatbots [can be] instantly and all but universally available at a fraction of the cost of a therapist" [61]. Given the pace of development, while there may be benefits for those in distress, a careful consideration of harms is crucial.

An Erosion of the Therapeutic Alliance. The therapeutic alliance, characterized by trust, mutual respect, and emotional connection, is a key predictor of psychotherapy outcomes. The emotional connection built between psychotherapists and their clients plays a pivotal role in developing this alliance [62]. Patients are more likely to engage actively in psychotherapy sessions and work towards making behavior changes when they perceive a sense of genuine care and understanding from their therapist [63].

Chatbots may be trained on billions of documents that describe rich emotional experiences, but they lack the capacity for genuine emotional connection. Psychotherapists are trained to not only understand a client's emotional state, but to also empathize with a client's feelings through their own lived emotional experiences. Psychotherapists discern the nuances of complex emotional experiences, including co-occuring sadness, anger, and fear, and respond in a compassionate manner. They can also pick up on non-verbal cues – body language, facial expressions, tone of voice, and even pauses in speech are all non-verbal (or textual) cues that psychotherapists interpret [64]. LLM powered chatbots, in contrast, are limited in their capacity to understand or interpret the broader context of the client's experiences, as expressed through these non-verbal cues. This limitation makes it more difficult for a connection to be built between chatbot and user.

The emotional connection between therapist and client is also foundational to building trust and rapport, particularly when clients are assured that their expressions of distress and vulnerability are confidential [65, 66]. This trust is essential for successful psychotherapy, as it encourages open and honest communication. Psychotherapy excels in an environment when patients are comfortable sharing their deepest concerns, fostering a therapeutic alliance [67]. To date, it is unclear if chatbots can build the type of trust and rapport that is essential to successful therapy, particularly given the potential for digital mental health data to be leaked, sold, or even legally used for targeted advertising [68, 69]. LLM chatbots risk taking away the human element of psychotherapy. Existing studies have demonstrated that users express negative reactions to unhelpful and risky chatbot responses [70], which is dangerous – first experiences with mental healthcare can quickly set the tone for future engagements (or disengagements) with mental healthcare [71].

A Lack of Appropriate Safeguards for Patient Safety. The excitement for LLM-based therapy bots needs to be tempered with the reality and safety issues they pose to clients and patients. Generative AI-based conversational agents have been found to be unable to recognize, and respond appropriately to, signs of distress [70]. Most commercial chatbots for mental health claim psychology-trained workers to carefully write and evaluate the dialogue for these bots [61]. However, in the interest of safety, chatbots can be constrained by predefined scripts [24] and may struggle to adapt to the intricate and evolving emotional states of clients. Research has also shown that while chatbots can offer structured interventions that can be easily scaled up (such as self-guided exercises from CBT), sustained user engagement often requires the involvement of human psychotherapists [72]. It is also important to note that many mental health issues involve complex and multifaceted emotional experiences. Patients dealing with trauma, grief, or deep-seated

emotional struggles often require nuanced, empathetic support that goes beyond providing information or structured interventions [73]. Human therapists can adapt and respond to the evolving needs of their clients, maintaining their motivation and commitment to therapy, and tailor their responses and interventions to the unique needs of each individual [74]. LLM chatbots may lack capacity for such personalized adaption of therapeutic techniques in response to unique patient needs.

4 For Care Providers: Crisis Response

The introduction of the 988 crisis response number in July 2022 was a significant step forward in the field of mental health [75, 76]. This new service provides individuals in crisis with immediate access to mental health support, as an alternative to calling 911 for police or fire department assistance. However, one challenge that remains is the scarcity of a trained workforce to respond effectively to mental health crises, often resulting in calls being transferred to 911 and risking additional harm to callers [77]. Between 2015 to 2020, 23% of people who were killed by police in the U.S. were experiencing mental health crises at the time [78]. Insel [35] highlights the potential of LLMs in addressing this issue, emphasizing their dual role in potentially detecting the severity of a crisis and supporting 988 in providing real-time assistance. Below, we explore the benefits and harms of using LLMs in this context.

4.1 Potential Benefits

Matching Users to Contextually Relevant Volunteers. Meta-reviews of existing crisis line services have revealed a lack of effectiveness, especially of distal outcomes, such as reduction in symptoms or feelings of distress in callers in a followup period after the call [79]. Empirical studies of helplines have investigated the reasons driving this phenomenon, finding that they stem from dissatisfied callers and responders inability to attend to callers' diverse needs [80]. LLMs could strengthen infrastructures like 988 by helping to effectively route people in distress to helpline volunteers based on an assessment of their needs. Through their proficiency in natural language understanding, LLMs could be utilized to analyze the language of distress to match people to the types of context-specific support and specialized volunteers that they may need. This rapid assessment can help ensure that individuals in immediate need receive the contextually relevant forms of support they need promptly. In turn, this could reduce the burden on crisis responders by prioritizing high-risk cases. These possibilities have already been demonstrated in prior research – Althoff et al. [81] used data from an SMS texting-based counseling service where people in crisis engaged in therapeutic conversations with counselors, to build computational approaches that described which types of language of volunteers elicited better conversational outcomes.

Culturally-Sensitive Vetted Guidance. LLM technologies can be harnessed to bolster the expertise of crisis responders and volunteers through real-time linguistic framing and support. This potential is supported by recent research that has trained language models towards semantic, issue-based, and lexical reframing of opinions, arguments, as well as unhelpful thoughts [82, 83]. Additionally, LLMs could help by surfacing guidance and recommendations to specific crisis situations which have been previously vetted (by human experts), to be helpful in mitigating crisis; Sharma and De Choudhury [84] highlighted this potential through models that learn from positive support seeking and support provisioning engagements on online forums. LLMs could help to suggest appropriate interventions, coping strategies, and de-escalation techniques based on the information provided by the caller and matching this to similar crisis intervention scenarios in historical data. This real-time assistance can be invaluable in calming the situation and ensuring the safety of the individual in crisis. Further, we discussed in the previous section that LLMs can be programmed to respond in linguistically diverse ways; in a crisis scenario, culturally resonating support can have significant

impact on the caller's mental health outcomes. Prior research has shown how language barriers can hinder effective crisis intervention [80]; thus by empowering crisis volunteers with language tailored to the identity and culture of the caller, LLMs could help promote greater inclusivity on helplines, including 988 as well as those in more resource-constrained settings.

4.2 Potential Harms

A Lack of Contextual Understanding. Although AI-powered crisis response has been advocated to be particularly helpful during rapidly evolving ad well as protracted societal crises like mass shootings [85] and the COVID-19 pandemic [86] due to their ability to be deployed quickly and at scale, crisis response is an extremely high-stakes domain, and thus risk and harms could have debilitating impacts on stakeholders involved, especially the callers. First, multiple factors influence what precipitates a crisis as well as what strategies could help mitigate it [87]. Such factors could exist outside the realm of the training data used to build the LLMs, often perhaps in messy offline contexts—contexts in which LLMs may have little to no insight. Further, the "black box" nature of such AIs make identifying contextual gaps inscrutable [88]. While a human crisis responder could be well-equipped, trained, or use their awareness of the situation to probe those unobserved factors behind the crisis, LLMs may provide inappropriate or hallucinated responses or those without sufficient empathy, potentially leading to an ineffective, harmful, or non-consensual crisis response that perhaps even worsens the caller's emotional state. Even with prompt engineering, it can be hard to control what an LLM may say to an individual in crisis—the harmful outputs produced by the AI-assisted NEDA chatbot, as introduced in the Introduction, demonstrates how harmful directly exposing crisis response service users to LLMs may be.

The Complexities of Data Use and Consent. Ultimately, an LLM is only as good as its training data [29]. Scholars have repeatedly discussed how by learning from large datasets on the internet, LLMs could "overrepresent hegemonic viewpoints and encode biases" [29], creating ethically contentious outcomes potentially extending or even exacerbating inequities in care [89]. However, beyond diversity, the scale and scope of the training data also matters, especially in an application domain like crisis response. The successful use of LLMs in crisis responses hinges on being able to train them on copious amounts of data spanning caller-volunteer conversations. Normally, these conversations are seldom recorded or transcribed beyond service optimization purposes, both to protect confidentiality of the data, as well as to ensure callers find the crisis resource to allow more disinhibited exchange with the volunteer [90]. It is known that knowledge of being tracked or monitored could create a "Hawthorne effect" [91] leading to people being less truthful of their thoughts and feelings, and perhaps feeling silenced and fearful of the consequences of surveillance. Since privacy is often "contextual" [92], in a crisis setting, callers might be concerned about how their data is collected, stored, and perhaps most importantly, who does what with this data. An emerging crisis may also present challenges to a caller's capacity to recognize these potential harms and to make the most rational decision for themselves. The best example of this might be the Crisis Text Line scandal from 2022, where the efforts of the organization to collect and share conversational data with a for-profit spinoff without user consent alarmed many [93]. Thus efforts to collect conversational data going forward, to train LLMs, may undermine the goals of adequate assessment of a caller's experience and deploying the most appropriate intervention. Sourcing training data without adequate informed consent or participatory involvement of the data producers (e.g., the people in distress seeking help) may further complicate their use in LLMs, by reducing their agency in controlling "what data is captured, how it is used, or who it benefits" [94] and by rendering their data labor invisible [95].

5 For Institutions: Clinical Decision Support

In his article, Tom Insel argued that LLMs can provide clinicians with comprehensive and up-to-date information, aiding in the decision-making process [35]. We examine the benefits and potential harms of incorporating LLMs into clinical decision support.

5.1 Potential Benefits

Unlocking Vast Medical Knowledge. One of the most significant advantages of using LLMs in clinical decision support is the ability to access a wealth of information. These models can learn from vast amounts of medical literature, offering clinicians insights on various conditions, treatments, and potential side effects, including that is latest in the medical field. Side effects of psychiatric medications in particular are often very nuanced and demonstrate patient heterogeneity in effects [96, 97]. LLMs can not only surface how similar patients have responded to specific treatments but also can help inform health professionals about previously unknown potential side effects by learning from complex drug interactions spanning thousands of clinical trials [98] and online discussions around interactions [99]. This knowledge can assist healthcare professionals in making well-informed decisions. The knowledge ingested by LLMs can also be utilized toward predictive analytic approaches, in order to augment decision support about patient outcomes, hospital readmission risk, and disease progression—all of which have been shown to be outcome predictable using machine learning techniques [100–102]. LLMs could both improve the precision of these predictions and aid in proactive patient management and resource allocation.

Providing Individually-Tailored Recommendations. LLMs can provide tailored recommendations based on the patient's unique circumstances that is gleaned from their historical electronic health records, clinical notes, or hospital discharge summaries, which together can significantly impact patient care and improve patient outcomes [103]. LLMs can easily and quickly ingest diverse types of conventional health (EHR) and health-adjacent data (e.g., smartphone or wearable use, social media activities) of patients to develop such personalized models [104], and utilize it for differential diagnosis [105]. When it comes to personalized treatment, differential diagnosis is perhaps one of the biggest strengths offered by LLMs [105]. With this knowledge, clinicians may be empowered to reduce the risk of misdiagnosis [106]; misdiagnosis hurts the efficacy of therapeutic and pharmacologic treatments down the road, and can enable individuals to function better in their personal and professional lives, maintain relationships, and achieve their life goals. LLMs can importantly democratize the medical knowledge encoded in interactions amongst health professionals by providing information not only to clinicians but also to patients and their families [107]. Informed patients can engage in shared decision-making with providers, fostering a collaborative approach to healthcare and improving health literacy [108].

5.2 Potential Harms

Perpetuating Misinformation and Contextually Uninformed Decisions. Relying solely on LLMs for clinical decision support without verification from human experts can lead to the dissemination of misinformation, potentially harming patients' health and well-being [109]. Jin and Chandra et al [110] recently showed that while GPT-4 like LLMs are largely adept at providing accurate responses to a variety of health queries, for some types of queries they produce incorrect information. In fact, Zhou et al. showed that GPT models (a type of LLM built by Open AI) could be prompt engineered relatively easily to reproduce medically incorrect information [28]. Due to the complex and sensitive nature of mental health issues, clinical decision-making demands nuanced, context-specific understanding and personalized care. LLMs, while

powerful, lack the ability to grasp the intricacies of an individual's mental state and history, especially factors ans aspects that may not be apparent in its training data such as from EHRs [111]. Given the lack of "objective" medical measures of mental illness, clinicians utilize a variety of collateral information in their decision-making [112], for instance, through interactions with the patients' family members or relying on non-clinical insights. LLMs are likely to miss opportunities to learn from such collateral information that tend to be heavily individual-specific and unique. By relying on specific types of biased training data stemming from the lived experience of specific (majority) populations, LLMs might overlook the subtleties in language related to mental health, such as expressions tied to traumatic experiences or coping mechanisms, which shape a person's own conceptualization of their mental health [113, 114]. As Harrigian et al [115] noted, when these nuances are not considered during the training of predictive models (here, LLMs), there is a risk of these signals generating numerous false alarms in decision-making when applied to different populations. This may be exacerbated by temporal artifacts as also noted by Harrigian et al [115]. That is, when there are group-level differences in temporal alignment of the data between model training and deployment, it can exert an impact on predictive performance of LLMs dedicated for psychiatric decision-making.

Moreover, existing commercial LLMs have been demonstrated to not generalize well to non-English health contexts [110], producing to poor quality, non-comprehensive, and hallucinated information [116], thus disadvantaging non-English speaking patients. In psychiatry, where accurate diagnosis and timely, culturally-sensitive treatment is paramount for success of care paradigms [10], relying solely on automated systems can be particularly perilous, that can lead to poor response to treatment or prolonged duration of untreated mental illness.

Suggesting Clinically Unverified or Incorrect Treatments. The above problems can be exacerbated when considering individuals with serious mental illnesses, such as schizophrenia or bipolar disorder. These conditions often require highly individualized care and diagnosis, as symptoms can manifest differently from person to person. Misinformation from an LLM could lead to inappropriate treatment plans, exacerbating the suffering of already vulnerable individuals. LLMs learn from web and social media data, which is often considered a strength, but such data (e.g., Reddit health conversations) has also been shown to include scientifically unsupported, clinically unverified, sometimes dangerous treatments [117, 118]. Uncritical use of such data for model training may result in such medically unverified strategies to trickle into an LLM's decision-making [119]. Furthermore, researchers have shown that in supervised classification tasks, LLMs often fail to outperform existing fine-tuned traditional machine learning models [120]. In resourcescare settings where access to mental health professionals and services is limited [47], these systems may be one of the few available resources for support [119], making false positives or false negatives in clinical decisions make the potential for harm even more significant. False negatives in predicting adverse mental health events may leave marginalized individuals without the support they need. False positives, on the other hand, may exacerbate stigma, perpetuate bias, harassment and marginalization, and importantly, diminish trust in care systems [121].

Ethical Issues in Automated Decision-Making. The use of LLMs for clinical decision-making in mental health also raises ethical and legal questions, particularly in matters of liability [122, 123]. If a clinical decision goes awry based on recommendations from an LLM, who bears responsibility? When clinicians rely on LLMs for diagnosis, treatment, or advice without proper verification, they could be held accountable for any resulting harm to patients. Legal questions may emerge regarding their duty of care, professional negligence, and the informed use of technology [124]. Unlike traditional human healthcare providers, LLMs lack the capacity for judgment and accountability [29, 125], which makes determining liability in cases of misinformation or harm resulting from improper decisions challenging. Liability in LLM-based clinical decision-making in mental health—"a field where classifications of diseases as well

as definitions of what is and what is not a disease are in a state of constant flux" [126] – may further be complicated by the often unpredictable and context-dependent nature of mental disorders. Administrative models have been demonstrated to be accurate in predicting suicidal behaviors at only 50% rate [127], with scholars often considering this task "unpredictable" [128] or suicide events to be "random" [129]. Even if LLMs promise better performance in such prediction tasks, as has been the case with other types of AI [130], liability issues complicate realizing their practical clinical value.

6 For Society: Telehealth 2.0

Finally, Insel envisions generative AI to revolutionize telehealth services [35] through what he calls "Telehealth 2.0". LLMs in telehealth may offer a variety of opportunities and challenges.

6.1 Potential Benefits

Enhancing Efficiency of Care-Delivery. Perhaps the most promising opportunity pertains to the efficiency and automation provided by LLMs in the context of telehealth. One of the significant benefits of LLMs in mental health can be the automation of various tasks. Since LLMs can be used to transcribe and summarize large volumes of text data, such as stemming from therapy sessions, it can help to reduce the administrative burden on clinicians and healthcare workers [131]. This, in turn, could allow clinicians to focus more on providing quality patient care. Automation may also lead to more consistent and thorough documentation of patient interactions, which can be invaluable in maintaining continuity of care [132]. In fact, by identifying patterns, trends, and insights in patient-clinician interactions, the chances of patient concerns being overlooked can be reduced – an issue widely recognized in traditional healthcare models, and particularly among racial and gender minorities [133–136]. It can instill confidence in the patient that their voices and concerns are more likely to be heard.

Enriching Counselor/Provider Training with Cultural Competence. Next, LLMs can play a valuable role in counselor/provider training in the context of telehealth. LLMs can be employed to curate and compile extensive resources, including textbooks, research papers, case studies, and guidelines relevant to counseling. These can serve as a comprehensive knowledge base for trainees [137]. LLMs can also generate realistic case scenarios, reflecting various mental health issues, patient backgrounds, and cultural contexts. Trainees can engage with these scenarios to practice their counseling skills [138]. Notably, LLMs can analyze and provide feedback on the trainee's counseling sessions. As shown in Sharma et al's work [55, 139], by processing the dialogue and the dynamics of the conversation, AI systems can offer insights on communication effectiveness, active listening, and therapeutic rapport. This feedback can be invaluable for trainees to identify areas for improvement. Moreover, such a scalable approach can ensure that a broader group of individuals is equipped to respond effectively to those in need. Furthermore, as discussed by Pendse et al [10], one of the biggest impediments to accessing care lies in a poor alignment between a patient's cultural understandings of their experience of mental health, and that of the counsellor/provider's. LLMs can assist in cultural competency training by providing trainees with information about various cultures, their values, and belief systems.

6.2 Potential Harms

Dehumanizing Mental Health Treatment Paradigms. Automation by learning from vast datasets has been touted to be a inimitable strength of LLMs [140]. However, while automation can be efficient, it

may also lead to a depersonalized healthcare experience and by rendering human labor (of healthcare workers) increasingly obsolescent. Mental health care is not only about diagnosing and treating the underlying illnesses but also about providing emotional support, empathy, and comfort to patients [141]. These human aspects of care in an LLM-informed telehealth model may not be fully replicated by machines [142]. Moreover, the success of many pharmacological and therapeutic approaches to mental health treatment hinges upon trust and respect between patients and providers [143]. A dehumanized healthcare experience punctuated by AI may erode this trust, as patients might feel that their care is being delivered by algorithms that lack a comprehensive understanding of their individual needs. Careless automation of telehealth paradigms may also lead to disinvestment in care work and to a shift away from patients' values and preferences – interfering with the goals of a patient-centered model of care [144]. By removing humans from the care delivery loop, increased LLM or generative AI based automation may dissuade individuals from pursuing the healthcare profession altogether or demotivate healthcare workers from persisting in a profession where their jobs may be at risk of displacement. The obsolescence of healthcare workers could have economic and social implications, including job losses, economic dislocation, and potential labor market disruptions.

Threats to Data Privacy. The most prominent risk perhaps centers around that the analysis of sensitive patient data by LLMs – an approach that can threaten privacy [125]. This is especially critical if the utility of LLMs is viewed to be centered around gleaning meaning from electronic health records, which contain patient health information (PHI) [145]. It has been noted in recent research that LLMs can accidentally divulge private information if prompted in specific ways [27]. This is because, in learning from vast data, these models learn relationships between personally identifiable information or PII (e.g., names, addresses etc.) and other linguistic elements. These attributes of LLMs can make them vulnerable to data breaches [146] to unauthorized parties or to bad actors employing them for contexts beyond the intended use.

Demographic and Representational Biases. Language models have, for some years, been shown to replicate human-like as well as systemic biases, whether around gender [147–149] or racial sterotypes [150– 152]. In a telehealth context, if used to provide recommendations, such as to clinicians or trainees based on historical patient-clinician interactions or therapy sessions, LLMs can inadvertently introduce biases based on any underlying skewness in the training data. If not carefully monitored, this can lead to unfair or inaccurate representations of patient-provider interactions. For instance, if the training data skews the representativeness of one demographic group versus another, LLM-based suggestions in telehealth could lead to or exacerbate gender, racial, or ethnic inequities. This concern is not merely theoretical; commercially accessible LLMs have exhibited racial and gender biases in non-medical contexts, and these very models have been found to propagate stereotypes related to race within the field of medicine [23]. Biases may also arise from LLMs learning stigmatizing representations of language in training data [153], and propagating those through inappropriate language or portraying mental health issues in a negative light. It is already known that stigmatizing language often surfaces in EHR patient notes [154]. If used for knowledge summarization in a telehealth context, LLMs may thus over-pathologize common emotions or behaviors, causing undue alarm. Stigma already hinders support-seeking in mental health, and this is known to prolong the duration of untreated mental illness [155]. Additional concerns of harm stem from LLMs creating informational or perspective "echo chambers", where LLMs inadvertently perpetuate pre-existing beliefs and biases held by providers or patients, as they exist in biased training data. For example, it is already known that screening tools in psychiatry may be biased in ways that tend to over-diagnose Black patients with schizophrenia [156]. LLMs may pathologize these biases by learning from such data. An over-reliance on LLMs for summarizing EHR information or providing training materials could result in not challenging end users sufficiently to consider a variety of approaches to providing mental healthcare, rather than an LLM-recommended approach.

7 Conclusion, Recommendations, and Future Directions

Long before LLMs were put in the hands of the lay internet user through ChatGPT, Bender and Koller [157] noted that it will be crucial to acknowledge the limitations of LLMs and place their strengths within a broader perspective. This approach can serve to moderate exaggerated expectations, which can lead both the general public and researchers astray in terms of the capabilities of these technologies. At the same time, these understandings have the potential to stimulate fresh research pathways that are not solely reliant on the utilization of ever bigger language models in every possible domain of societal interest. Throughout this article, we discussed the many dimensions of the debate centered around the use of LLMs in digital mental health applications. We offer some reflections and specific considerations for future research.

7.1 Reflections and Lessons Learned

What is apparent from our above discussion is that, however fine-tuned and tailored LLMs may be to data stemming from real-world mental health contexts, LLM-powered chatbots or decision-support tools cannot serve as a replacement for human psychotherapists or health workers. Neither can a machine alone be a surrogate to a real person during moments of distress. The significance of the human therapist may be further underscored by the fact that the appeal of chatbots in therapy may vary among different age groups. For digital natives, who are more accustomed to interacting with technology, the appeal of a machine therapist might be greater that of previous generations; but across age groups, preferences for a human therapist is likely to remain strong. Thus, what are the boundaries of the role of LLMs in digital mental health, for who, and what responsibilities do developers and healthcare providers have in ensuring their ethical use? A realistic "safety-first" approach might be to use them as surrogates, rather than as standalone AI therapists.

For such a safety-first approach, it will be essential to strike a balance between harnessing the potential of LLMs and ensuring that human experts remain integral to the decision-making process in psychiatry and mental health, particularly when dealing with the most vulnerable and resource-scarce populations. An approach, such as a human-in-the-loop or more preferably, an AI-in-the-loop system, may help to combine the cognitive strengths of healthcare providers with the analytical capabilities of LLMs. Horvitz's [158] conceptualization of "mixed initiative" systems might be particularly pertinent to mental health applications where, based on the situation, users can take the lead when they have a specific goal or intention, while also allowing AI to take the initiative when it can provide value or assist the user. In critical uses surrounding clinical decision-support or crisis response, mixed initiatives between the human and the AI (LLM) can enable them to work together as partners, with the system actively seeking input from the user and the user having the ability to request information, clarification, or assistance from the LLM component. To this end, it will be essential to establish clear protocols for verifying the underlying LLM's recommendations of clinical decisions or crisis intervention strategies, ensuring human experts remain responsible for final decisions and that providers maintain their ethical and legal obligations to prioritize patient safety and wellbeing. In psychotherapy or telehealth, human oversight will ensure that there are appropriate safeguards in place that prepare for potential harms when the underlying "stochastic parrots" [29], provide inappropriate, incorrect, or misinformed outcomes, because of the non-deterministic nature of these technologies.

In addition, if LLMs are to be utilized in this high stakes domain, thoughtful investments to create or gather realistic training data will also be needed, that do not compromise the very mission and values that underlie psychotherapeutic practices or crisis intervention. For instance, creating keystone datasets has been advocated to help advance psychological research using LLMs [159]. Consent, awareness, and literacy regarding how specific data (e.g., EHRs, crisis helpline call logs, or psychotherapy chat transcripts) is used in specific LLMs, how, and by whom will be equally important considerations in ensuring governance of these systems. On that note, for any type of mental health-relevant data that can be made available for LLM training, utmost care will need to be employed to prevent unauthorized access or data breaches, which could

lead to severe harm, including identity theft or emotional distress for individuals in distress or in crisis. Within the telehealth context, in employing LLMs to summarize patient-provider interactions or therapy sessions to support clinical care or to train counsellors, it will be paramount to protect PHI and PII in EHR data, ensuring not only compliance with data protection regulations, but also to maintain patient trust their personal information is secure and will not be misused.

Broadly speaking, there is a pressing requirement for increased empirical research and advocacy efforts aimed at helping mental health service users and practitioners differentiate the quality, usability, and efficacy of LLMs, as well as identifying the suitable use cases, scenarios, and target populations that stand to gain from their application.

7.2 Recommendations

Building on these reflections, we suggest technical, ethical, and human-centered recommendations to ensure that the use of LLMs in mental health settings carefully balances effectiveness and responsibility.

Developers of LLM-based mental health tools should shoulder the responsibility in keeping applications safe for end users of these tools. This can be implemented through self-accountability frameworks, such as, by reporting to the public, or through outcomes of red teaming efforts. Additional accountability can come from companies describing what types of training data was used to build the models, how they were evaluated following training, what performance metrics were used to assess performance, and the extent to which performance was tests in various contexts and scenarios. Several efforts in these lines have been proposed in the algorithmic fairness and accountability literature, such as Datasheets for describing the capabilities and limits of datasets used for building AI models [160], Model Cards for bringing transparency to how complex models work [161], and disclosures of ethics practices to demonstrate how model builders remain accountable for the outcomes of AI [162]. Some stakeholders have argued that this can be achieved if the creators of domain-specific LLMs open source their models [163], others advocating for a regulatory solution [164]. And yet, some have critiqued both approaches because of the risk of open LLMs being exploited by malicious actors or regulation resulting in concentrating power in the hands of a few that stifles innovation and competition [165]. Nevertheless, what this debate underscores is a need for continuous monitoring and evaluation mechanisms to ensure responsible usage and adherence to ethical guidelines within a high stakes domain like mental health.

There has been some policy movement around developing standards and tools to help ensure that AI technologies are safe, secure, and trustworthy; e.g., US President Joe Biden's 2023 executive order on AI [166] or the Group of Seven (G7) announcement of a new code of conduct and international guiding principles on AI [167]. However, scholars have argued that a one-size-fits-all regulatory model for generative AI will be unsuitable for specific health applications [168], and an adaptable approach to oversight will be needed that can evolve with the rapidly and ever-evolving capabilities of this technology. This adaptive approach will need to go hand in hand with continuous monitoring, external auditing, and benchmarked evaluation of these systems to ensure responsible usage and adherence to ethical guidelines.

Autonomous bodies to enforce oversight would also need to be created in the digital mental health field to establish what types of standards might be suitable for the four types of uses of LLMs in mental health. For instance, what standards would ensure safety if LLMs were to be integrated into the 988 system or within psychotherapy contexts? Pharmacological treatments undergo a clearance process with the FDA and scholars have long advocated for a need to consider similar regulatory processes for digital mental health as well. After many years of research, Empatica is one of the few digital mental health technologies that has received clearance from the FDA for medical use [169, 170]. This conversation may be extended to LLM-based mental health technologies too, to ensure that a reasonable level of safety is promised in any application that reaches mental health support seekers.

Furthermore, it will be essential for legal, infrastructure, privacy, and security teams to review organizational policies and procedures to guarantee adherence to state and federal laws and regulations, particularly in the context of personal health information exchange protocols, accountability, liability, service reimbursement, and clinical workflows. Concurrently, there is a demand for the creation of educational curricula and methods to instruct people with lived experience of mental illness, mental health professionals and caregivers, and health system administrators in fundamentals of generative AI, its practical application, and its role in enhancing how care is extended.

In the book *The Soul of Care* [171], Arthur Kleinman describes how "the work of the doctor has moved away from hands-on practice to high-technology diagnosis and treatment," which has distanced doctors from engaging with the human experiences of their patients. Medical enterprises, digital healthcare services, and healthcare institutions have initiated the integration of LLMs into their core operations [168]. In this piece, we emphasize the need to attend to immediate challenges in the use of this paradigm-shifting technology, given its rapid clinical roll-out [168]. As Arthur Kleinman discusses, the importance of emotionally engaged human doctors in the practice of care can never be replaced, and future LLM-augmented medical technologies must be cognizant of the importance of human connection in care.

Acknowledgments and Disclosures

This work was supported by NIMH grants R01MH117172 (PI: De Choudhury) and P50MH115838 (Co-I: De Choudhury), and a grant from the American Foundation for Suicide Prevention (PI: De Choudhury). This content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Mental Health or AFSP. We thank the members of the Social Dynamics and Well-Being Lab at Georgia Tech for helping to shape early discussions on the topic.

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