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BRIEF REPORT

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Using machine learning to increase access to and engagement with trauma-focused interventions for posttraumatic stress disorder

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Abstract

Background: Post-traumatic stress disorder (PTSD) poses a global public health challenge. Evidence-based psychotherapies (EBPs) for PTSD reduce symptoms and improve functioning (Forbes et al., Guilford Press, 2020, 3). However, a number of barriers to access and engagement with these interventions prevail. As a result, the use of EBPs in community settings remains disappointingly low (Charney et al., *Psychological Trauma: Theory, Research, Practice, and Policy*, 11, 2019, 793; Richards et al., *Community Mental Health Journal*, 53, 2017, 215), and not all patients who receive an EBP for PTSD benefit optimally (Asmundson et al., *Cognitive Behaviour Therapy*, 48, 2019, 1). Advancements in artificial intelligence (AI) have introduced new possibilities for increasinfg access to and quality of mental health interventions.

Aims: The present paper reviews key barriers to accessing and engaging in EBPs for PTSD, discusses current applications of AI in PTSD treatment and provides recommendations for future AI integrations aimed at reducing barriers to access and engagement.

Discussion: We propose that AI may be utilized to (1) assess treatment fidelity; (2) elucidate novel predictors of treatment dropout and outcomes; and (3) facilitate patient engagement with the tasks of therapy, including therapy practice. Potential avenues for technological advancements are also considered.

KEYWORDS
access, fidelity, psychotherapy artificial intelligence, PTSD, treatment

BACKGROUND

Posttraumatic stress disorder (PTSD) poses a significant public health challenge that is associated with a tremendous global economic burden (McGowan, 2019; Watson, 2019). Multiple treatment guidelines recommend trauma-focused, evidence-based psychotherapy (EBP) for PTSD as the frontline class of interventions (Forbes et al., 2020; Veterans Administration/Department of Defense Clinical Practice Guidelines Working Group, 2023). However, access and engagement barriers limit the reach of these EBPs. As a result, only a small proportion of affected individuals receive EBPs, with an even smaller proportion completing a dose of treatment sufficient to achieve maximal gains (Shiner et al., 2020). Recent advancements in artificial intelligence (AI), including machine learning (ML) and generative AI, offer novel solutions for improving access to and engagement with EBPs for PTSD. Machine learning (ML) is the subarea of artificial intelligence concerned with using statistics to extract patterns from large amounts of data. ML algorithms are most commonly 'trained' on human-created examples of the task to be learned. For instance, if the task is to identify what emotion a speaker is expressing, a training example would consist of a video of a speaker paired with the correct emotion, usually as judged by a human observer or indicated by the speaker themselves during training data collection. The goal of the ML algorithm is to generalize from the specific examples seen at training time to be able to predict the correct emotion for a new, previously unseen video at test time. Conversely, generative AI focuses on the creation of novel content based on patterns and characteristics observed within a pre-existing dataset.

The present paper: (1) discusses barriers to accessing and engaging in EBPs for PTSD; (2) reviews the ways in which ML is already being used to overcome these barriers in the broader mental health field; and (3) suggests four potential avenues for the application of ML and generative AI in the domain of EBPs. We use Cognitive Processing Therapy (CPT; Resick et al., 2016) to illustrate these avenues, because our team has been implementing ML with a large CPT dataset and considering the best use of AI to facilitate CPT access and quality delivery. CPT is a 12-session intervention designed to help patients identify and challenge unhelpful beliefs that arose following a traumatic incident. CPT is one of several well-validated EBPs for PTSD, and it is considered a gold-standard intervention for the disorder (Asmundson et al., 2019).

BARRIERS TO EBP FOR PTSD

Logistical and financial limits to EBP access

Access to EBPs for PTSD is limited by financial and logistical factors. In order to receive an EBP for PTSD, an individual must: (1) be aware of the existence of EBPs for PTSD; (2) understand their relative efficacy (e.g. in comparison to other therapies); and (3) locate a trained provider who is available to begin treatment without significant delay. Despite the release of best-practice guidelines for the treatment of PTSD (Forbes et al., 2020; Veterans Administration/Department of Defense Clinical Practice Guideline Working Group, 2023) and significant organizational changes designed to increase training and implementation of EBPs for PTSD (e.g. within veterans' associations and public hospitals; see Rosen et al., 2016 for a review), there is little evidence that average consumers of mental health services outside these settings are knowledgeable about, or routinely seek, EBPs.

Access to qualified providers in these EBPs for PTSD is limited, and the cost of receiving them can be prohibitive. For example, outside of publicly funded settings (access to which is often limited to military personnel and veterans) in North America, the cost of a single course of treatment is a minimum of $1500–$3500 USD, depending on the education and experience of the provider. This problem is magnified when one considers that PTSD often gives rise to significant occupational impairment and workplace absenteeism, introducing additional financial burden among individuals with the disorder (Lee et al., 2020; Williams & Williams, 2020). Minimizing logistical and financial barriers to EBPs for PTSD access therefore remains a critical imperative.

Quality delivery

Even after gaining access to EBPs, individuals continue to experience significant variability in the quality of services they receive. Outcomes of EBPs for PTSD are maximized when delivered with fidelity (i.e. the extent to which the intervention is delivered with adherence to the relevant treatment manual and in a competent manner; Farmer et al., 2017; Keefe et al., 2022; Marques et al., 2019). However, research has shown that treatment providers often demonstrate variable treatment competence and tend to deviate from protocol adherence over time (Marques et al., 2019). Treatment fidelity may be particularly compromised in the delivery of EBPs for PTSD, as several of these treatments involve encouraging patients to directly confront or discuss trauma memories—a practice that some clinicians may fear is harmful or unduly distressing.

Treatment fidelity may be improved via routine monitoring and feedback provision to clinicians. However, current approaches to fidelity assessment are prohibitively costly and time-consuming (Finley et al., 2015; Maguen et al., 2018). In the current approach, treatment sessions are audio- or video-recorded and listened to by trained human raters who score these recordings on various facets of treatment fidelity. Creating and maintaining a pool of raters with inter-rater reliability is labour intensive. Given the demands of this process, fidelity assessment is rarely completed outside the context of randomized controlled efficacy trials or implementation studies. Moreover, even within clinical trials, feedback may not be given to study clinicians, or may be provided after a significant time delay, resulting in diminished practical utility (Monson et al., 2018).

The lack of practical, cost-effective quality assurance measures represents a broad issue in the provision of mental health services. Introducing novel approaches to assessing treatment adherence and competence is critical to ensure that patients experience the best possible outcomes.

Engagement with treatment

Perhaps in part due to poor treatment quality, many patients struggle with treatment adherence and engagement after barriers to access are successfully overcome. Treatment engagement can be operationally defined in terms of treatment completion (vs. dropout) and in terms of time and effort devoted towards the tasks of psychotherapy (e.g. homework completion). Low engagement in therapy has been associated with suboptimal therapy outcomes (Sripada et al., 2020). With respect to treatment dropout, the incidence of dropout from EBPs for PTSD is unfortunately high (e.g. 29% for CPT; Kline et al., 2018) and is often related to patients finding the intervention to be too distressing or not feeling motivated by the therapy rationale or specific therapy tasks (Alpert et al., 2020; Hundt et al., 2020). Concerningly, a significant proportion of patients who prematurely terminate therapy do not improve (Holmes et al., 2019).

Research examining predictors of treatment dropout has largely focused on demographic variables and has yielded inconsistent findings (Alpert et al., 2020; Cooper et al., 2018; Sloan et al., 2018). It has been proposed that focusing on therapist and patient behaviours that emerge early in therapy and predict treatment dropout may be a more fruitful endeavour, because doing so would provide opportunities for clinicians to modify their approach and help shape patient behaviour to reduce the likelihood of subsequent dropout (Alpert et al., 2020; Cooper et al., 2018). Existing research in this area suggests that difficulties in the therapeutic relationship (Ormhaug & Jensen, 2018; Yasinski et al., 2018), as well as higher levels of patient emotional avoidance (Alpert et al., 2020; Yasinski et al., 2018), overgeneralized beliefs and physiological reactivity in early treatment sessions (Alpert et al., 2020), predict higher dropout rates. Astute clinicians may readily incorporate these findings in clinical practice by remaining on the lookout for such behaviours and intervening accordingly (e.g. identifying and normalizing physiological reactivity, addressing maladaptive cognitions about emotional distress that are treatment-interfering). However, tools designed to help clinicians identify these warning signs of dropout, and help them decide how and when to intervene, are sorely needed.

It is also imperative to consider barriers to patient engagement in the tasks of psychotherapy. Treatment homework is a core component of most cognitive behavioural therapy (CBT) protocols, including CPT. For example, out-of-session practice assignments are given after every session in CPT, and most of these assignments are intended to be completed on a daily basis. CPT homework completion is associated with greater pre-to post-treatment improvements in PTSD symptoms (Stirman et al., 2018). However, since avoiding painful emotions and trauma reminders are hallmark symptoms of PTSD, engaging patients in CPT homework is often challenging (Stirman et al., 2018). Limited research has examined patients' perspectives regarding barriers to homework engagement in CPT. In the broader CBT literature, one study found that patients cited anxiety surrounding improper homework completion, difficulty translating emotional experiences into written words, low motivation and feeling unable to manage emotional distress evoked by homework completion as reasons for low engagement with homework (Barnes et al., 2013). If patients are to optimally benefit from EBPs for PTSD, further understanding and addressing barriers to homework engagement are necessary avenues for clinical research.

ARTIFICIAL INTELLIGENCE IN PSYCHOTHERAPY

Over the past decade, developments in artificial intelligence (AI) and machine learning (ML) have rapidly progressed and are increasingly being used in the mental health arena (Aafjes-van Doorn et al., 2020; Graham et al., 2019). Applications of this technology have been widespread and include using ML to identify and diagnose mental disorders, predict the longitudinal progression of mental health problems and provide support for affected individuals (see reviews by Shatte et al., 2019; Tai et al., 2019). However, efforts to apply AI to enhance psychotherapy provision have been more limited (Aafjes-van Doorn et al., 2020). We argue that AI and ML have untapped potential to facilitate access to, and engagement in, PTSD interventions. In the following sections, we offer three potential applications of AI and ML in PTSD psychotherapy research and practice.

Recommendation 1: Using ML to train professionals and provide ongoing fidelity assessment

The current issues of limited EBP access and insufficient quality assurance monitoring may be mitigated with the development of AI designed to teach and provide ongoing feedback to clinicians on their provision of evidence-based treatment for PTSD, including CPT implementation. Several research groups have developed ML algorithms to automate the process of assessing treatment fidelity in psychotherapy. A systematic review found that these models yield fair to excellent levels of human-to-computer agreement (Ahmadi et al., 2021), with some models correctly predicting fidelity with greater than 80% accuracy (Creed et al., 2022; Xiao et al., 2016).

The preponderance of research in this area has involved the development of algorithms based on behavioural coding measures designed to assess adherence to motivational interviewing (see Ahmadi et al., 2021 for a review). To our knowledge, only one research group (Creed et al., 2022) has reported data on an ML model designed to assess fidelity in CBT. This study was conducted with a sample of individuals experiencing a range of mental health problems as part of the Beck Community Initiative (Creed et al., 2016). Thus far, there have been no documented efforts to automate the assessment of fidelity in CPT or other trauma-focused interventions specifically. Developing such models reflects a critical avenue for ML research in CPT and other trauma-focused psychotherapy research.

We envision two possible applications of such technology. First, we suggest the development of a system that uses ML to provide immediate fidelity feedback to EBPs for PTSD, allowing for training of CPT clinicians at a less restrictive scale. Rather than the current approach of acquiring CPT competency through the completion of a foundational workshop and subsequent consultation (e.g. weekly groups with an expert CPT consultant; Monson et al., 2018), we envision a process in which trainees would complete an initial online training and then proceed to administer CPT to real or simulated patients while receiving automated fidelity feedback derived from ML algorithms. This feedback could be provided to clinicians immediately following sessions (e.g. an on-screen panel displayed to the clinician after exiting a treatment session, providing analytics on their fidelity to the intervention). Utilizing AI in this manner could enable organizations to have increased confidence in the delivery of the intervention, increase clinician confidence in intervention delivery and empower patient to better understand what treatment they are getting and at what level of quality. In fact, such an approach is now being offered by Lyssn (www.Lyssn.io).

In addition to providing immediate fidelity feedback, the technological advancements afforded by ML will also provide new ways to think about assessing and improving the quality of EBP provision. For example, multimodal processing, which combines text, audio and optionally video data, has been shown to provide stronger ML performance on tasks such as sentiment analysis and emotion recognition (Sourav & Ouyang, 2021; Tsai et al., 2019), compared to approaches that focus on only one modality. With the increasing popularity of remote therapy, video and audio recordings of both clinician and patient become more readily available, facilitating the use of multimodal algorithms to better identify high-level therapist speech acts, such as asking questions, as well as to make fine-grained distinctions among them, such as distinguishing Socratic questions from simple clarification or information seeking. With this approach, ML solutions may be used to provide objective feedback on additional indicators of therapy quality, such as the number of questions asked by the therapist in each section, the affective quality of the therapist's utterances, and speaker-turn duration.

Recommendation 2: Identifying novel predictors of therapy outcomes and dropout

To overcome barriers to treatment engagement, ML may also be used to elucidate and test theoretical predictors of psychotherapy outcome and dropout. Outside the context of trauma-focused therapy, research in this area is already underway. For example, ML has been used to identify patient characteristics that moderate the effects of therapeutic alliance (Rubel et al., 2020; Zilcha-Mano et al., 2018) and *problem coping experience* (i.e. the extent to which patients work on understanding the sources of their problems and seek solutions; Penedo et al., 2022, 2023) on treatment outcomes in psychotherapy.

Although these factors may inform initial treatment selection, they offer little by way of informing clinicians about indicators of likely dropout or treatment nonresponse after treatment has begun. To our knowledge, only one study (Nixon et al., 2021) has used ML to determine whether CPT nonresponders could be identified early in the intervention. Their results indicated that treatment responders could be readily identified by session 4 using predictive algorithms; however, differentiating between treatment nonresponders and delayed responders proved more difficult. Such data could be used to develop digital decision support and feedback systems that can guide clinician decision-making to reduce dropout and improve outcomes. For example, Duhne et al. (2022) used ML to develop such a system, providing clinicians with treatment approach recommendations (i.e. using a predictive algorithm to determine who is more likely to benefit from face-to-face vs. a computerized intervention). The authors reported that patients who received the AI-generated recommendations were less likely to drop out of treatment and experienced improved treatment outcomes.

Building on this approach, we propose that ML could be used to test additional predictors of treatment response and dropout that have not yet been examined, including factors that are amenable to modification. Unmodifiable factors like pre-treatment age, gender or type of trauma provide no opportunity as targets for improving patient outcomes. Conversely, factors such as emotionality (specific prominent emotions and reactivity), physiological arousal, dissociation and working alliance provide potential points of intervention to maximize treatment response. Once identified, this research may be extended to create feedback systems that can provide data to clinicians following initial treatment sessions, highlighting any modifiable risks for dropout or treatment nonresponse.

Multimodal ML systems can be developed to track patient engagement, emotional state, body language and frequency and length of utterances during each therapy session. Regression models trained on such data can quantify the strength of correlations between specific behaviours and dropout or treatment nonresponse. For example, ML models can track microexpressions in the face that may be correlated with therapy outcomes or an early indication of dropout. Additionally, changes in patient behaviour may be difficult for a clinician to mentally track over the course of a therapy session, let alone across multiple sessions spanning several weeks. A report generated by an ML system can assist the clinician in recognizing long-term changes in patient behaviour that they may wish to address or mitigate. In addition to this approach, generative AI may also be incorporated to offer clinicians concrete suggestions for reducing the risk of patient dropout or nonresponse.

Recommendation 3: Increasing engagement via therapy support tools

As previously highlighted, homework is a critical component in achieving successful treatment outcomes. Meta-analyses have demonstrated that therapeutic interventions with homework assignments yield significantly greater treatment effects than interventions without them (Kazantzis et al., 2000, 2010). Furthermore, research across various conditions highlights the strong correlation between homework adherence and improved treatment outcomes (Cooper et al., 2017; Kazantzis et al., 2010; Mausbach et al., 2010).

Offering patients feedback on therapy homework is imperative for enhancing homework engagement and quality (Murdoch & Connor-Greene, 2000; Núñez et al., 2015). In educational disciplines, AI has been demonstrated as an effective tool for providing students with tailored homework feedback, leading to marked improvements in outcomes (Berrezueta-Guzman et al., 2021; Johnson et al., 2009; Kelly et al., 2013). Research in this area has also highlighted the superiority of instantaneous (vs. delayed) feedback in enhancing performance (Kehrer et al., 2013). Whereas instantaneous homework feedback is typically unrealistic in clinical practice given limits on clinician availability and workload, AI may be leveraged to deliver this crucial feedback with unprecedented speed and consistency.

Although homework completion plays an important role within PTSD treatment, individuals often fail to complete homework due to a range of individual (e.g. avoidance, forgetting and difficulty with homework completion) and environmental (e.g. scheduling, lack of time or reinforcement) factors (Kazantzis & Shinkfield, 2007; Reger et al., 2013). Accordingly, ML may be used to help individuals and therapists identify and target patient-specific factors that interfere with homework completion both preemptively and throughout the duration of treatment, and generative AI may be used to provide rewarding feedback when such homework is completed and offer coping strategies to help deal with avoidance. Moreover, generative AI may provide individuals with guidance and real-time feedback that helps to minimize homework-related uncertainty and self-efficacy. Ultimately, AI may be used to dynamically tailor the type and amount of homework assigned to individuals at specific time points, which may help to minimize treatment dropout, maximize homework engagement and optimize its therapeutic benefit.

Within the context of CPT, homework feedback may be particularly beneficial with respect to helping patients when they first learn to differentiate between thoughts and feelings (e.g. identifying and offering correction when patients misidentify thoughts as feelings or vice versa), when they begin to identify 'stuck points' or erroneous beliefs that have emerged from the trauma (Resick et al., 2016) and when they learn to challenge these beliefs (e.g. if a patient has identified 'evidence' to refute a stuck point that in fact reflects another erroneous belief). Homework tools could utilize generative AI to provide verbal feedback, offer Socratic questions to help patients arrive at helpful responses or offer potential alternative interpretations of trauma-related events when patients feel stuck. AI may also be used to adjust therapy tasks according to a patient's skill level and to provide positive reinforcement for successful engagement with homework. For example, within CPT, a patient who is routinely struggling with more sophisticated worksheets may be encouraged to return to earlier, more simplistic worksheets and patients who have spent ample time on worksheet completion could be immediately and consistently reinforced for their efforts. These tools may help improve patient motivation by building momentum and keeping them engaged with tasks that are appropriate for their skill level.

Although the ability of ML models to handle sophisticated concepts such as distinguishing thoughts from feelings and identifying stuck points is currently unknown, the recent success of large language models (LLMs), such as GPT-4 and LLaMa 2, at tasks requiring the understanding of natural human language suggests this may be a fruitful direction for ML research. LLMs are particularly good at learning the appropriate styles of questions to ask when they are fine-tuned with appropriate data. Therefore, if sufficient examples are presented for Socratic questions, the LLM can learn to generate these types of questions. To this end, we envision the development of a customized chatbot, which could be framed as a patient's personal partner in progressing through the therapy. The chatbot would be able to provide advice or make suggestions that the patient might otherwise resist if it came instead from a human clinician. While a recent scoping review provided evidence of overall positive attitudes towards mental health chatbots among patient populations (Abd-Alrazaq et al., 2021), other research has demonstrated more heterogeneous attitudes, with particular concern raised about the potential impact of AI integration on patients' relationships with their health care providers (Faverio & Tyson, 2023). Integrating patients in the early stages of AI development appears critical for maximizing the subsequent acceptability of such technologies (Lambert et al., 2023).

Moreover, it is important to note that the ethics of generative AI in the context of psychotherapy must be carefully considered. Recently, AI chatbots have been critiqued and removed from the public domain following the provision of problematic advice and emotional insensitivity (Coghlan et al., 2023; McCarthy, 2023). Furthermore, generative AI models have been known to perpetuate systematic bias against marginalized communities, as they are commonly trained on large datasets that include discriminatory content and biased representations. For example, if most patients in a dataset are white males, the output from generative AI will be more likely to describe patients with these characteristics. Accordingly, to minimize risks and ensure that therapy tools that rely on generative AI are beneficial across diverse populations (e.g. marginalized individuals), it is essential that model building, evaluation and implementation be conducted in a manner that assesses and mitigates potential biases (Timmons et al., 2023). It is therefore critical to involve patient groups (e.g. minoritized individuals) and researchers from diverse backgrounds in the development and implementation of these AI-based technologies (de Hond et al., 2022; Xu et al., 2021). Furthermore, models should be developed using datasets that are representative of these populations (see Dankwa-Mullan et al., 2021), in accordance with existing ethical frameworks (e.g. see Coghlan et al., 2023's five-principle framework). The applicability of generated models to marginalized communities should also be explicitly tested and validated prior to their implementation (e.g. see Habicht et al., 2024). Finally, it is essential to continually evaluate these technologies for potential biases and fairness following their implementation (Taber et al., 2023). Towards this end, a therapy partner chatbot should be tested with a group of clinicians and iteratively be improved using strategies such as the Reinforcement Learning from Human Feedback algorithm (Ouyang et al., 2022). Clinicians can work with ML researchers to develop models to automatically detect emotional insensitivity and other undesired responses from the generative AI chatbot, which can then provide filters to prevent such responses from being conveyed to the patient.

CONCLUSION

This paper examined barriers to accessing and engaging with EBPs for PTSD. We explored the current landscape of ML and generative AI applications within the mental health domain and offered our recommendations for the effective integration of these technologies into EBPs for PTSD. PTSD presents an urgent public health challenge, compounded by a substantial economic burden. Despite the established efficacy of EBPs such as CPT, their widespread implementation is impeded by various logistical and financial constraints. Furthermore, ensuring consistent, high-quality delivery of EBPs remains a complex endeavour due to the inherent difficulties in assessing and maintaining treatment fidelity. Also, low patient engagement in therapy tasks, such as homework assignments, contributes to elevated dropout rates. The present paper explores how ML and generative AI can be used to potentially address these obstacles.

It is important to underscore potential challenges and limitations to the proposed applications of ML and generative AI to trauma-focused treatment. First, ML algorithms must be trained on vast datasets, which can be costly or otherwise challenging to access. Second, models that are developed on accessible datasets may demonstrate impressive predictive capacity within the datasets on which they are trained, but more modest ability when extrapolated to novel data and situations (Chekroud et al., 2024). Third, it is possible that clinician, patient and organizational acceptance of the integration of ML and generative AI into EBPs may be limited. The willingness to embrace these tools for various purposes, including clinician training, quality assurance and treatment adherence, will significantly impact the effectiveness of their use. Moreover, patient willingness to adopt these tools in EBPs is also crucial for the implementation of this new technology. A simultaneous focus on solutions that are driven top-down and bottom-up holds the promise of rendering EBPs more accessible, augmenting their quality and ultimately enhancing their effectiveness. However, further consumer-sensitive and collaborative research is needed to synthesize various stakeholders' perspectives, concerns and practical considerations to build AI that can make a significant impact on the delivery of EBPs in the real world. Fourth, serious data security issues may arise from the integration of ML and generative AI into psychotherapy, especially given that within-session data contains highly sensitive and private material. Fifth, the incorporation of these technologies within trauma-focused treatment requires significant attention to ethical considerations. For instance, it will be essential to develop clinical guidelines that provide clinicians with ethical guidance and instruction on incorporating these technologies within their practice.

Despite these concerns, ML and generative AI have potential to transform clinician training, treatment fidelity maintenance and adherence to treatment protocols, thereby elevating the overall quality of care. Additionally, harnessing AI-powered tools to bolster patient engagement, particularly through real-time feedback and support between therapy sessions. These enhancements aim to enrich the overall treatment experience for patients.

AUTHOR CONTRIBUTIONS

Ariella P. Lenton-Brym: Writing – review and editing; writing – original draft; project administration. **Alexis Collins:** Writing – original draft; project administration. **Jeanine Lane:** Writing – review and editing. **Carlos Busso:** Writing – review and editing. **Jessica Ouyang:** Writing – review and editing; writing – original draft. **Skye Fitzpatrick:** Writing – review and editing. **Janice R. Kuo:** Writing – review and editing. **Candice M. Monson:** Writing – review and editing; supervision.

CONFLICT OF INTEREST STATEMENT

Fitzpatrick, Kuo and Monson are shareholders of Nellie Health, a mental health intervention company that uses digital technologies to facilitate treatment delivery.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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