The Future of PTSD Research, Diagnosis, and Treatment: Passive Sensing Technologies and Machine Learning Algorithms

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Abstract

Processing and healing from PTSD does not require conscious memory of the traumatic experience(s). However, this is a prominent aspect of the most commonly used top-down interventions for PTSD. PTSD patients may find it incredibly challenging to perform the exercises advised by their therapists due to the agony of reliving their traumatic experiences. It is also difficult for mental health professionals to monitor and assess their patients' performance, especially if the patients are restricted in their ability to track their responses outside of therapy sessions. Given individuals suffering from PTSD may not seek or have access to treatment, in addition to the vast comorbidities and complexity of the disorder, there is a high risk of PTSD going untreated and being misdiagnosed or underdiagnosed. Fortunately, there is a promising future for readily detecting and self-regulating PTSD symptomology through the employment of objective and non-invasive smart technology and passive sensing. By leveraging machine learning algorithms to predict future outcomes, PTSD treatment and diagnosis could become more efficient and effective. This paper will provide a comprehensive review of the current literature around this topic as well as a proposal for incorporating the discussed methods into new products.

Trauma Exposure and the Development of Post Traumatic Stress Disorder

The unfortunate truth about the world is that most people are quick to judge others before developing a deeper understanding of who they are and what they have experienced. Exposure to trauma is more common than one may expect and can have a detrimental impact on one's trajectory in life. Thus, it is critical to learn more before making assumptions. According to the U.S. Department of Veterans Affairs, around 60% of men and 50% of women have experienced at least one traumatic event in their lives (2018), although some studies have shown that this statistic is much higher (Lancaster et al., 2016, Benjet et al., 2016, Kessler et al., 2017). Worse yet, according to the Substance Abuse and Mental Health Services Administration, more than two thirds of children under the age of 16 have experienced at least one traumatic event (2022).

Although it is common for an individual to experience normative acute reactions following exposure to the traumatic event(s) (i.e. intrusive thoughts, issues with sleep or memory, etc.), these symptoms usually resolve on their own. However, when an individual is unable to follow the normal trajectory of recovery, this increases the susceptibility of developing a chronic psychological disorder known as Post Traumatic Stress Disorder (PTSD) (Lancaster et al., 2016), If gone untreated, PTSD can last for a lifetime. Unfortunately, many people suffering from PTSD may not seek help or treatment due to feelings of shame, fear, and guilt. These individuals may not even have the opportunity due to the striking disparities in access to treatment. Underdiagnosis and misdiagnosis are also prominent issues due to PTSD's "complex etiological milieu" as well as its "high tendency to manifest with other mental comorbidities" (Lekkas & Jacobson, 2021). Individuals who are fortunate to receive a diagnosis and treatment may not even fully benefit from treatment due to how individualized each manifestation of PTSD is.

There are several issues with the current scope of PTSD diagnosis and treatment that must be addressed, but how? Unfortunately, there is no simple answer, otherwise it would have been discovered. However, there is an abundance of research and technology already available that can potentially be combined to address several of these issues, such as passive sensing, machine learning, wearable devices, and feedback, which will be addressed in this research proposal. Given the difficulty of finding effective treatment and maintaining treatment for individuals with PTSD, and especially C-PTSD, this paper explores alternative methods for detecting and regulating PTSD symptoms.

An Overview of PTSD: Impact, Symptoms, and Prevalence

The impact of PTSD can be lifelong and debilitating. In fact, 40% of sufferers face PTSD symptoms to a substantial degree even 10 years after the initial onset (Kearns et al., 2012). PTSD accompanies a myriad of symptoms such as intrusions, somatization, avoidance of triggers, dissociation, as well as alterations in mood, cognition, sense of self and the world, and levels of arousal (e.g., hypervigilance and sleep disturbances) (U.S. Department of Veterans Affairs, 2014). Comorbidities of depression, substance use disorders, anxiety disorders as well as an increased risk of suicide are often seen in individuals with PTSD (Brady et al., 2000; LeBouthillier et al., 2015). One study investigating the cross-national epidemiology of PTSD discovered that the lifetime prevalence of PTSD was 3.9% of the surveyed sample (71,083 respondents ages 18+). Among the respondents with PTSD, half of them reported having persistent symptoms. Furthermore, only half of those who reported experiencing severe PTSD received treatment and a low percentage received specialty mental health care (Koenen et al., 2017). Thus, it is critical to push research forward for alternative interventions.

Issues with Diagnosis of PTSD in the United States

In the United States, the Diagnostic and Statistical Manual of Mental Health Disorders (DSM) is the standard classification of mental health disorders used by mental health professionals (APA, 2022). It highlights certain criteria that must be met in order to receive a diagnosis for several mental health disorders, including PTSD.

Lamentably, the current diagnostic criteria of PTSD in the DSM-5 is incredibly limiting. For example, the DSM-5's diagnostic criteria for PTSD focuses on responses associated with the traumatic event itself without realizing that more severe PTSD can lead to atypical responses even in situations not associated with the event (Ford & Courtois, 2014). There has been an ongoing debate that the current "diagnosis of PTSD is not sufficient to describe the range and intensity of symptomatology experienced in survivors of unremitting and recurrent abuse, notably abuse during early stages of development" (Jones and Cureton, 2014).

Long-term exposure to repetitive and multiple types of trauma, from which escape is difficult or impossible (i.e long-term child abuse and domestic violence), can lead to the development of complex PTSD (C-PTSD) (U.S. Department of Veterans Affairs, 2007). Studies have found distinct symptom profiles between those with C-PTSD versus PTSD, such as "greater functional impairment, greater comorbidity (including depression, anxiety and dissociation) and lower quality of life" (Cloitre et al., 2020) as well as dysregulation in emotional processing, self-organization, and relational security (Ford & Courtois, 2014). Despite this, the American Psychiatric Association (APA) has not created a distinction between C-PTSD and PTSD in the DSM-5, or a separate diagnosis to include the unique characteristics that accompany C-PTSD. Thus, it is suspected that individuals who suffer from C-PTSD are diagnosed with general PTSD or even misdiagnosed due to greater comorbidity, which could ultimately lead to discrepancies in the treatment process. In fact, those with C-PTSD may not benefit from the evidence-based psychotherapies for PTSD to the same degree and may also have higher dropout rates from therapy (U.S. Department of Veterans Affairs, 2018).

Issues with First Lines of PTSD Treatment: Directing More Attention to Bottom-Up Approaches

Cognitive Behavioral Therapy (CBT), along with the "more specialized treatments that focus on particular aspects of CBT interventions" (APA, 2017) – Cognitive Processing Therapy (CPT), Cognitive Therapy, and Prolonged Exposure (PE) – are strongly recommended by the American Psychiatric Association as the first lines of intervention for PTSD. These methods are top-down approaches, or cognitive-based approaches, which aim to help patients become conscious of, and eventually change, their thoughts, feelings, and behaviors related to the trauma. Although these interventions have shown clinically significant symptom reduction and effect size, several patients retain their diagnosis after treatment or continue to experience significant residual symptoms (Boyd et al., 2018). Placing most of the treatment focus on top-down approaches and exposure to the traumatic experience itself can lead to an intense evocation of the traumatic memories, thus unnecessarily re-traumatizing patients and resulting in high drop-out rates. Fortunately, bottom-up approaches, or body-oriented approaches, such as Somatic

Experiencing, do not require conscious memory of the traumatic experience(s) to process and heal trauma. This can potentially be more effective for individuals, especially those with trauma-related cognitive malfunction, who have not had success with top-down therapeutic interventions.

Bottom-up approaches aim to change the physiological and emotional processing of the trauma by shifting the focus to the *body's* memory of the experience(s) and how it responds to the environment. More specifically, these approaches start from the "'primitive' brain structures and their embodied reactions" and work upwards towards higher cortical systems (Kuhfuß et al., 2021). It can be incredibly difficult for individuals to access higher cortical systems when the primitive part of their brain is actively sending signals that they are in danger. Clinical psychologist, Tijana Mandić, PhD, provides a noteworthy explanation of the importance of focusing on the body in her PTSD workbook A Journey to Resilience and Beyond:

> "If you are in recovery from trauma of any kind, it is important to know about what is called your "somatic ego," which refers to the sum of your bodily sensations that you recognize as your own. According to Peter Levine, PhD, the root of trauma lies in instinctive and physiological responses in the "somatic ego." Levine notes that symptoms that occur after trauma are basically unfinished physiological responses—they are blocked, disrupted, and dissociated from normal physiological process. The goal of recovery work is to join split parts of that process into a "normal" functional whole" (Mandić, 2019).

By exploring the physical sensations that lie beneath the cognitive aspects of the trauma, individuals suffering from PTSD would develop a conscious awareness of their body's internal landscape, interoception (Khalsa & Lapidus, 2016), as well as its spatial orientation and movement, proprioception (Tuthill & Azim, 2018). This awareness would ultimately help them understand how their body responds to their environment and triggers, and therefore make it less challenging to self-regulate their symptoms and reach levels of homeostasis. Once an individual can learn to balance their nervous system, they will acquire more conscious control of their physiological responses when they attempt to process their thoughts and emotions around the traumatic experience(s).

Passive Sensing Technology

As previously mentioned, the most commonly used non-pharmacological treatment approaches for PTSD focus on cognitive-behavioral and exposure-based procedures which may not benefit all patients with PTSD (Grabbe & Miller-Karas, 2017). Additionally, mental health professionals who use these approaches often ask their patients to manually track their thoughts, feelings, and behaviors in response to triggers outside of sessions. This can be an unreasonable expectation to place on patients as they may not have the time or mental capacity to track these in moments of distress. Moreover, self-regulating symptoms outside of therapy sessions can be incredibly difficult if one does not have a thorough understanding of how their *body,* not just their mind, responds to external stimuli. Fortunately, these limitations in the treatment process for PTSD can be mediated through the utilization of passive sensing technology.

Passive sensing allows for real-time mental health surveillance due to its passive and continuous data collection (Levine et al., 2020), which would provide the opportunity to further establish research on bottom-up approaches for PTSD as passive sensing devices have the capacity to detect various physiological responses. Moreover, when incorporated with unobtrusive wearable technology or smartphones, individuals have the opportunity to continuously and passively track their own physiological data outside of therapy sessions, and thus gain awareness of their physiological responses to their environment.

There is an abundance of research using passive sensing for issues such as sleep, physical activity, cardiovascular disease, and mental health on a wide variety of devices, including pedometers, smartwatches, and smartphones (Fukazawa et al., 2019). One study installed an experimental mobile application on ten users' devices, known as eWellness, "to track a full-suite of sensor and user-log data" over the course of a month. Based solely on the continuous, passively monitored features, they were successfully able to predict anxiety and depression levels 76% of the time using machine learning algorithms (Levine et al., 2020). Another study aimed to detect rises in anxiety levels prior to being diagnosed with an anxiety disorder using smartphone's passive sensing logs and application data, showing that it is possible to detect unconscious anxiety in daily life without self assessment (Fukazawa et al., 2019). Furthermore, research has also shown that smartphone passive sensing data can "accurately detect social anxiety symptom severity and discriminate social anxiety symptom severity from depressive symptoms, negative affect, and positive affect" (Jacobson et al., 2020). Although research on passive sensing using PTSD samples in particular is limited, these are still symptoms individuals with PTSD may encounter. The following sections provide more detailed approaches targeting PTSD symptomology.

Detecting Dissociative vs. Non-dissociative PTSD through HRV Passive Sensing

Patients with PTSD experience abnormal autonomic functioning indicative of "either fight and flight behaviors or withdrawal, immobilization, and dissociation" (Williamson et al., 2014). Heart rate variability (HRV) is a useful biomarker for measuring autonomic nervous system (ANS) functioning (Singh et al., 2018), and has the potential to detect these different manifestations of PTSD (dissociative vs. non-dissociative type). A poor functioning, dysregulated ANS, as in the case of PTSD patients, is caused by an imbalance between the parasympathetic and sympathetic branches of the ANS, and can be indicated through low heart rate variability (de Souza Filho et al., 2019). One study showed that PTSD patients had decreased HRV in all situations even if traumatic stimuli was not present, indicating persistent imbalance in autonomic functioning (Keary et al., 2009). Emotion dysregulation can be caused by the inability to flexibly move between the sympathetic and parasympathetic nervous systems (SNS, PNS) in response to stimuli (Appelhans & Luecken, 2006). Thus, emotion dysregulation, which is commonly seen in C-PTSD, can be interpreted by dysregulated HRV.

Due to an under modulation of emotional responses, non-dissociative PTSD accompanies more fear-related hypoarousal symptoms and greater re-experiencing. Chronic overactivation of the SNS and decreased PNS activity can lead to this exaggerated fear response (Bian et al., 2022). In contrast, overmodulation of emotional reactions in dissociative PTSD accompanies hypoarousal and excessive activation of fear *inhibition*, leading to a blunted fear response and constricted emotional affect (Lanius et al., 2012). Dissociation can be detected through overactivation of the PNS and underactivation of the SNS, and can make it difficult for patients to attend to their physical sensations due to an impaired interoceptive ability (Krause-Utz et al. 2017).

Heart rate variability is generally measured at two frequencies. High frequency HRV (HF-HRV) is a reliable measurement of parasympathetic functioning, whereas low frequency HRV does not have a clear correlation to sympathetic functioning (Pumprla et al., 2002). Despite this, the High-frequency (HF) activity has been found to decrease under an elevated anxiety state, indicated by a decrease in PNS activity in dissociative patients, and can be isolated to discriminate between dissociative and non-dissociative PTSD patients. Moreover, trauma patients with high dissociation have been shown to exhibit lower HRV than non-dissociative trauma patients (Gosain & Kongsvik, 2017), and thus the overall HRV levels could also help discriminate between the two.

Although mental health professionals may be able to distinguish these different manifestations of PTSD during sessions, it is incredibly important for patients to be able to do so outside of sessions as well, since balancing the nervous system is a crucial component of self-regulating PTSD symptoms. Despite there being an imbalance in both dissociative and non-dissociative PTSD, it is important to be able to distinguish between the two in order to intervene accordingly. Several wearable technologies, such as the Whoop smartwatch and Apple Watch, incorporate passive sensing for heart rate variability (HRV) tracking using electrocardiograms (ECGs). It is unclear whether these monitoring devices isolate HF-HRV, but incorporating an HRV analysis with these wearable devices could provide users with distinctive information about their PNS activity in a continuous and passive manner, and thus help them detect dissociative symptoms and better learn how to self-regulate these symptoms.

GPS Passive Monitoring to Detect Functional Impairment

Avoidance of fearful situations, as well as impairments in physical health; higher levels of depression; “negative expectations of others, the world and one’s own safety; hypervigilance;

loss of interest; or feelings of alienation" are all indicators of functional impairment among individuals suffering from PTSD. Friedmann and colleagues have shown that functional impairment can be detected by analyzing temporal and spatial limitations in activity space. More specifically, they examined the association between PTSD and functional impairment in terms of movement in space (maximum radius around home per day) and time (minutes spent away from home per day) around the home through passive monitoring with a smartphone-based global positioning system (GPS). Their sample consisted of 228 women, 150 of which had PTSD, 35 were healthy trauma controls (HTC) who did not have PTSD but had a history of child abuse, and 43 were healthy controls (HC) without a history of child abuse (Friedmann et al., 2020).

After controlling for variables, Friedmann and colleagues found a statistically significant difference in the amount of time spent away from home between the PTSD and HTC groups, with HTC participants doing so for a shorter period of time than those in the PTSD group. Given the association between movement and avoidance behaviors in PTSD, this result may initially appear counterintuitive. However, they hypothesized that people with PTSD may not view *time* spent away from home as inherently dangerous, but rather that being *farther away* from home may rapidly trigger feelings of insecurity. In accordance with this hypothesis, they discovered that "the maximum radius around home per day was found to be statistically significantly smaller in both PTSD and HTC women compared with the HC group." Despite the lack of distinction between the signals of those with PTSD and a history of child abuse, their results demonstrated the viability of using GPS passive sensing as a digital biomarker of functional impairment in those who have experienced trauma and developed PTSD by observing limitations in activity space (Friedmann et al., 2020).

Prior research has shown greater functional impairment in individuals with C-PTSD compared to general PTSD (Cloitre et al., 2020). Thus, GPS passive sensing could be utilized to further establish this distinction in future research studies. When used in conjunction with other symptom detection methods, this could inform the need for a distinct symptom profile for individuals with C-PTSD in the current DSM-5 Diagnostic criteria.

Importance of Utilizing Machine Learning Algorithms for PTSD Research

The capacity of machine learning algorithms to function in high-dimensional space whilst simultaneously taking numerous variables into account is one of their special capabilities. These models may process connections and interactions among numerous predictors with minimal computational effort, in contrast to linear models which do not scale well with a high abundance of predictors. Machine learning techniques enable the useful derivation of new predictors from baseline data to differentially detect the phenomenon in question. Additionally, the design of machine learning models for training, validating, and testing guarantees that predictions are not made from the representative samples used for training (Lekkas & Jacobson, 2021). By leveraging machine learning algorithms to predict future outcomes, PTSD treatment and diagnosis could become more efficient and effective due to its vast capabilities.

Machine Learning Used in Conjunction with Passive Sensing

Detecting Emotional Dysregulation

Mood instability, also known as emotional dysregulation or instability, is a distinct symptom cluster among individuals with C-PTSD (Ford & Courtois, 2014). One study utilized machine learning techniques "to predict mood instability only using passively sensed data from both smartphone sensors and wearable sensors of individuals in situated communities" using the following sensor modalities: microphone, audio data, bluetooth, light sensor, WiFi data, and GPS. Although passive sensing was unable to capture the external factors contributing to the emotional dysregulation, they were successfully able to predict it using only three weeks of data. Provided individuals with C-PTSD may experience overall emotional dysregulation, researchers could utilize this predictive paradigm to measure the effectiveness of current treatment approaches for PTSD on individuals with C-PTSD. However, these methods may unleash concerns about data privacy that should be addressed in further research.

Predicting PTSD Diagnostic Status

Following the previously mentioned Friedmann and colleagues study, another study further explored whether these location-based digital markers from GPS passive sensing can be utilized to predict clinically validated PTSD diagnostic status due to their potential of exhibiting physical avoidance behaviors. Since machine learning techniques have proven success in evaluating the predictive validity of biomarkers obtained from passive sensing data, they believed that a machine learning construct could accurately predict "PTSD diagnostic status from traumatized controls" (women with a history of childhood abuse, HTC). They observed daily movement patterns across seven days using two GPS movement variables, "daily minutes spent away from home (DMA) and maximum daily radius traveled around home (MDR)." In contrast to the results of the Friedmann et al. (2020) study, both of these movement metrics had a clear impact on the predictions. To their success, their constructed machine learning model could accurately predict PTSD diagnosis status among the HTC group 81% of the time. Given the difficulty of differentiating diagnostic status in high risk populations, in addition to the "wide availability, low resource intensity, and clinical relevance" of GPS movement data, passive monitoring has the potential to significantly enhance the clinical diagnosis process (Lekkas & Jacobson, 2021).

Since the manifestation and magnitude of PTSD symptoms fluctuate over time, this non-invasive mechanism would help healthcare providers track their patient's fluctuations and relieve the burden of self-monitoring from patients (Lekkas & Jacobson, 2021). With further research and incorporation of other variables, this method could potentially resolve the debate on whether a separate diagnosis should be included for C-PTSD by comparing the responses in individuals who were exposed to one traumatic event to individuals who had long-term exposure to repetitive and multiple types of trauma. Although daily movement patterns have the potential to detect physical avoidance behaviors, further research is necessary for the detection of avoidance behaviors towards internal stimuli.

Given an increasing number of the population have access to smartphones, it is understandable why they were used as the primary medium for detection. However, wearable devices may be more consistent in collecting data to train the machine learning algorithms as they are directly attached to the body, unlike smartphones which users may not be holding as frequently. There has been ongoing research utilizing machine learning methods in the mental health sphere, but more research is required for the vast amount of symptoms that accompany PTSD.

Conclusion and Future Considerations

Tracking physiological data with the passive sensing methods discussed in this paper would provide sufficient evidence on the importance of utilizing bottom-up interventions for PTSD, especially for individuals who do not respond well to top-down approaches. For individuals taking prescribed medications for PTSD, these methods could help them monitor their responses to the drug. This is particularly important as pharmacological treatment is a trial-and-error process that needs consistent monitoring to ensure that it does not exacerbate symptoms. These passive sensing methods would also help expand the limited diagnostic criteria in the current DSM-5, as it would prove how atypical responses may occur even outside of stimuli associated with the traumatic event among individuals with more severe PTSD. Moreover, these methods have the potential to accelerate future research on the distinction between C-PTSD and PTSD, and ultimately provide more urgency to tailor treatment methods toward complex representations of PTSD. Tracking symptoms through passive sensing is not only beneficial for guiding mental health professionals in their practice, but could also help patients develop an awareness of their physiological responses to their environment, which is a key component in the identification of their triggers.

Incorporating machine learning techniques into passive sensing technologies has the potential to accelerate large-scale longitudinal studies on PTSD treatment and diagnosis. Since individuals with PTSD may not seek professional treatment, developing a wearable device with the following core features could provide them with an alternative method of personal treatment.

The ultimate goal of this research proposal is to utilize machine learning techniques to predict when users may experience particular PTSD symptoms based on prior passively collected physiological data from a wearable device, and provide real-time feedback on how to regulate those symptoms through a mobile application. More specifically, the wearable technology would track the user's physiological response to the feedback provided, and allow them to manually rate its effectiveness. Based on the feedback's effectiveness in regulating the symptoms, this would then train the machine learning algorithms to provide similar feedback for those symptoms in the future. The feedback would preferably focus on providing alternative, holistic interventions that focus on the mind and body connection, as the effectiveness of these approaches for PTSD, and the general population as a whole, are often overlooked in Western medicine.

If this idea were to be successful, the wearable device could further expand to connect to a home-automated system, which could help disrupt distressing symptoms through automated feedback. This would be particularly helpful for users who are having more severe physiological responses, and are thus incapable of interacting with the mobile application. Moreover, this home automated system could provide further sensory experiences, such as smell (aromatherapy) and body temperature (prominent indicator of sleep disturbance), that a mobile application is incapable of providing.

Although this may seem like an idealistic goal, given the capabilities of current passive sensing methods and the speed of technological advancement, it is certainly possible.

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