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Beyond the Mind's Eye: How AI is Unraveling the Mysteries of Mental Health

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Abstract : *Due to the reliance on subjective techniques like patient self-reports and therapist assessments, diagnosing mental health problems including PTSD, anxiety, and depression can be challenging. These approaches may result in uneven diagnosis, belated interventions, and restricted access to care, particularly in underprivileged or isolated locations. In order to identify indicators of mental health problems more accurately and effectively, this research suggests an AI-powered diagnostic tool that analyses text, speech, and video. The application uses sophisticated AI models, including as transformers and LSTMs, to identify patterns linked to certain illnesses, giving clinicians a more trustworthy and impartial evaluation. Fairness, openness, and data privacy are highly valued in the tool's design, guaranteeing its moral applicability in practical settings. In order to increase access to mental health treatments, increase the accuracy of diagnoses, and ultimately improve patient care and results, an AI technology supplements the knowledge of mental health professionals. Individuals with high trait anxiety also displayed high baseline state anxiety but a muted physiological response to acute stressors. Overall, these results demonstrate the potential for using machine learning tools to identify objective biomarkers useful for diagnosing and monitoring mental health conditions like anxiety and depression.*

IndexTerms **-** Artifical Intelligence Mental Health, Psycholog, Diagnosis

1. Introduction

The first is to identify individuals at high risk for developing PTSD, but who have not yet manifested its symptoms (risk assessment). Individuals who are identified as high risk for the future devel opment of PTSD would be eligible for prevention efforts. Risk factors for the development of PTSD following a traumatic event include ,peritrauma and post-trauma factors Recently, researchers have developed screening measures, known collectively as statistical prediction instruments (SPIs), that quantify these risk and resilience factors for the purpose of identifying indi viduals who may be vulnerable to PTSD following trauma exposure before symptoms actually develop. In a recent exam ple of such an approach, O'Donnell et developed and validated a screening instrument that prospectively identifies, during hospitalization, civilian adults at high risk for developing PTSD and/or major depression. Results showed that the screening instrument had a sensitivity of 0.82 and a specificity of 0.84 when predicting PTSD and a sensitivity of 0.72 and a specificity of 0.75 in predicting Major Depression. Marx et tested a similar screening instrument for combat-related PTSD among Vietnam veterans using previously collected cross sectional data. Drawing on the findings of King et al, 2 Marx et al ,5 focused on those risk-resilience factors that were found to have the strongest relations with combat-related PTSD status. The resulting instrument, the PTSD SPI, displayed excellent sensitivity (0.90) and good specificity (0.80). These results suggest that it is feasible to develop instruments that could identify veterans and service members who might be prone to develop PTSD following trauma exposure. However, before this instrument or others like it are used for this pur pose, it is necessary to conduct additional research using a longitudinal research design with a heterogeneous sample of active duty military personnel and/or veterans. Once such instruments have been validated with new data collected in subsequent studies, they will be of tremendous value to local and national level screening programs conducted by the Departments of Defense (DoD) and Veterans Affairs (VA) in the identification of at-risk individuals for outreach, thorough evaluation, and early intervention efforts. In addition to risk assessment, screening provides an oppor tunity for early detection or identification of acute PTSD cases and individuals who are experiencing some PTSD symptoms but do not meet full criteria. Screening also affords the possi bility of discovering previously unidentified cases of more chronic and severe PTSD. Such individuals would be candi dates for currently available evidence-based interventions. Historically, the field has relied upon a variety of PTSD screening tools. Many of the early screening instruments, such as the PTSD-Keane scale of the Minnesota Multiphasic Personality Inventory the Impact of Events and the Mississippi Scale for Combat-related PTSD8 contained items that did not necessarily correspond to PTSD diagnostic criteria. Today, the most widely used screening tools have items that directly correspond to PTSD diagnostic criteria in the fourth edition of the Diagnostic and Statistical Manual of Mental Disorders .One such scale is the Post-traumatic Diagnostic Scale .

2. Literature Survey

Pharmaceutical businesses have been able to expedite their drug research process with the use of AI technology in healthcare. However, it automates the process of identifying targets. Furthermore, AI in medicine facilitates the repurposing of drugs through the analysis of off-target molecules. Consequently, AI discovery of drugs expedites and decreases repetitious effort in the artificial intelligence and healthcare sectors.

There are several treatments that top biopharmaceutical companies have found. Pfizer is using IBM Watson, a system that is based on machine learning, to assist in the discovery of immuno-oncology medicines. While Roche affiliate Genentech is depending on a system using artificial intelligence from GNS Healthcare in the Massachusetts city of Cambridge to help with its hunt for cancer medicines, Sanofi has decided to use Exscientia's artificial intelligence technology to look for pharmaceuticals for metabolic diseases. Similar partnerships or internal initiatives exist at almost all of the big biopharmaceutical companies. If those who support these approaches are right, artificial intelligence (AI) and the use of machine learning will usher in an exciting new period of more efficient, affordable, and rapid drug development. While some experts are dubious, the majority think that such instruments will become increasingly important in the future. This shift presents opportunities as well as challenges for scientists, especially when the methods are combined with automation In a clinical study, individuals get newly made medications to evaluate their efficacy. It has cost a lot of money and time to complete this. But the success rate is really low. Clinical trial digitization has therefore shown to be advantageous for AI as well as the healthcare industry. Moreover, healthcare and artificial intelligence help to eliminate laborious data monitoring processes.

AI algorithms may be used in conjunction with a productive digital infrastructure to clean, aggregate, code, preserve, and retain clinical trial data. Additionally, enhanced EDC or electronic data capture could facilitate seamless system integration and lessen the effects of mistakes made by people in data collecting.

Artificial intelligence has an impact on patient outcomes in the medical field. Medical AI companies develop a system that supports the patient on all fronts. Clinical intelligence also provides insights to patients to assist them improve their quality of life by analyzing their medical data. A few noteworthy clinical intelligence technologies that enhance patient care are as follows: One possible method to detect high-risk mothers and lower maternal mortality as well as postpartum complications is the following: Using artificial intelligence and electronic health data to predict whether expectant moms are much more likely to experience complications during delivery (AI). Making more patients eligible for regular and highacuity (i.e., more complex and frequent) care during their pregnancy by utilizing digital technologies. High-risk maternal women who give birth at low-acuity clinics run a greater risk of experiencing severe maternal morbidity as compared to giving birth in higher-acuity facilities with stronger resources and professional experience. Certain medical robots help patients in conjunction with medical professionals.. An additional instance of technology in use is a smart prosthesis. With the option to wrap them with bionic skin while connecting them to the individual's muscles, such bionic limbs connect sensors that make them more accurate and reactive compared to natural body parts. Robots can assist in surgery and recuperation. For example, Cyberdyne's HAL, or Hybrid Assistive Limb exoskeleton uses sensors applied to the skin to effectively detect electrical impulses in the patient's body and respond with movement at the joint. This technology aids in patients' rehabilitation from conditions that cause lower limb disorders, such as strokes and spinal cord injuries.

3. Methodlogy

3.1 Participants

Forty (40) participants were recruited between the ages of 18 and 35 (mean = 25.15 / SD = 5.04; 43.5% Female / 56.4% Male) with no diagnosed psychiatric disorders or psychotropic medication use (based on self-report). Participants were recruited from the local community through the Wharton Behavioral Lab. Basic non-PHI demographic information (e.g., age, sex, level of education) was collected and a unique subject ID number was assigned to each participant (Supplementary Table 1). Participants were instructed to not engage in exercise or consume caffeinated beverages for a minimum of two hours prior to their scheduled visit time. Study personnel explained the purpose, potential risks of the experiment and completed the informed consent process with each participant following protocols approved by the University of Pennsylvania's Institutional Review Board (IRB) in compliance with the Helsinki Declaration. All participants gave written informed consent filed with the University of Pennsylvania's IRB. At baseline, participants were outfitted with a wireless EEG headset (microEEG, Bio-Signal Group Corp., Acton, MA) and multiple HR/GSR sensors (Shimmer GSR+, Shimmer Inc., Boston, MA; E4 Wristband, Empatica Inc., Boston, MA). iMotions (Copenhagen, Denmark) was used to synchronize all the devices.

3.2 Procedure

Trait anxiety survey was administered online prior to the visit via Qualtrics. On the session day, set-up, and calibration was carried out upon arrival. Following initial briefing and set-up, participants were asked to relax for 10 minutes. The first 5 minutes were considered baseline control (BC) and the physiological readings during the session were measured relative to this epoch. The next 5 minutes were considered baseline period (B). Participants' self-reports – both subjective units of distress (SUDS) and state anxiety

(SA) -- were obtained during the baseline period. Then, participants played a simple video game for 10 minutes after 2 minutes of practice. In the game, they picked berries from a virtual berry patch[13]. Then the cold pressor test (CPT) was administered to induce temporary acute physical stress. During this task participants were provided with an arm wrap made of cold gel packs (35-40 ºF). The cold gel packs were placed around their dominant forearm for three minutes. The wrap is designed to be stressful and uncomfortable but not painful or dangerous. Following this task, participants were instructed to quietly rest for 6 minutes. Second set of self-reports – both SUDS and SA -- were obtained at the beginning of the rest period. After the quiet rest, participants were asked to talk about something or engaged in casual conversation for three minutes. Following this, the Trier Social Stress Test (TSST) was administered. In this epoch the participants were asked to prepare and deliver a short speech to a socially evaluative audience. Participants were provided with pen and paper to take notes and informed that they had three minutes to prepare a five-minute speech about interviewing for their ideal job .

3.3 Data Analysis

All data processing and statistical analyses were carried out on MATLAB and Python. It is made available under a CC-BY-NC-ND 4.0 International license. (which was not peer-reviewed) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. The copyright holder for this preprint State-Trait Anxiety Inventory (STAI): All participants completed the STAI (11), which was used for assessing both trait and state anxiety. There are 20 items for assessing trait anxiety and 20 for state anxiety. All items are rated on a 4-point scale, with higher scores indicating greater anxiety. Subjective Units of Distress Scale (SUDS): Participants completed the SUDS both at baseline and following each stress induction task. The SUDS is a widely used tool for assessing the subjective intensity of distress and other internal experiences, such as anxiety, anger, and agitation. The scale ranges from 1 to 100, with 100 signifying the most intense feelings. HR/Heart Rate Variability (HR/HRV): Heart rate data was obtained throughout the duration of each session through the use of an E4 Wristband. The E4 is equipped with a PPG sensor which measures blood volume pulse (BVP). From this measurement both HR and HRV were derived. HRV is the beat-to-beat alteration in heart rate that can be used as a noninvasive biomarker for autonomic nervous system activity. Standard time and frequency domain derivatives of HRV were calculated. Electrodermal Activity (EDA) / Galvanic Skin Response (GSR): Electrodermal activity (EDA) was continuously recorded throughout the duration of each session through the use of a Shimmer GSR+. The GSR sensor monitors skin conductivity which reflects the variations in the electrical characteristics of the skin. Skin conductance is modulated by sympathetic activity and it is directly correlated with emotional arousal. EEG Activity: microEEG was used to obtain EEG signals throughout the duration of the session. Signals were collected at a 250 Hz sampling rate from electrode channels along the scalp. EEG signals were first re-referenced to the average of the two earlobes and then filtered between 1 and 50 Hz. Next, epochs were extracted and probabilistically improbable data points (3 SD from mean) were detected as artifacts and removed. Additional artifact detection to remove eye blink and movement artifact components was subsequently performed using independent component analysis. All the preprocessing was done using EEGLAB. For each epoch, Welch's power spectral density estimate was used to transform data from the time domain to the frequency domain in order to decompose the signal and calculate absolute and relative band powers, asymmetries, and coherence in addition to the phase of the EEG channel signals. Band powers calculated included delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), low beta (13-25 Hz), high beta (25-30 Hz), and gamma (30-50 Hz) from the prefrontal, frontal, temporal, parietal, and occipital brain regions.

3.4 Classifier design

Following preprocessing, different features were extracted from the HR and EEG data (Supplement table 3). Average data (1 to 3 min) from different epochs (stress vs control) were then used to train the classifier. Different machine learning algorithms (Supplementary table 2) were trained on the data streams. Data was upsampled to ensure class balance. Dataset was split up into partitions (2-10), where data from all-but-one partitions were used as the training set and left-out data was used as the testing set. This was repeated for all partitions, so that each epoch was part of the test set at least once. Cross-validation also helped to detect and limit overfitting. Feature selection was carried out to reduce the feature set size. Grid search was implemented to optimize the parameters used. Grid search and feature selection were carried out It is made available under a CC-BY-NC-ND 4.0 International license. The primary metrics used to indicate each model's performance were accuracy, sensitivity, and specificity. For the classifier implemented to identify individuals with trait anxiety, leave-one-out crossvalidation approach was followed. In this case one participant's data was left out of the training dataset. The remaining 38 participants' data was used to train the different algorithms. Other training and testing set ratios were also tested.

3.5 Generalized linear model with mixed effects

To take advantage of the continuous nature of the trait anxiety scores, we developed generalized linear model with mixed effects– including/excluding fixed effect terms, including other interactions terms for fixed effects, including random slopes for the participants, etc, were also tested. Since the trait anxiety score distribution is right skewed and all-positive, it was modelled using a "Gamma" distribution with an "identity" link function. All analyses were carried out in Matlab using the "fitglme" function.

4.Results

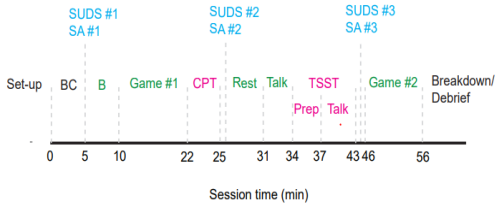

Figure 1

In this study, 39 participants experienced two types of stressors, cold pressor test (CPT) and Trier social stress test (TSST), in the following order (Fig 1). They also played a simple decision making game both before CPT and after TSST. They were engaged in casual conversation (Talk epoch) and also received a rest period during the session (Fig 1). Overall, a session lasted approximately 60 minutes (refer to Methods for more details).

Self-reported responses to induced stress

To determine each participants' stress response, we first examined their self-report scores for subjective units of distress (SUDs) and state anxiety (SA). An example participant whose data is plotted in reported a strong response to the applied stressors. This participant showed a low baseline score a slightly elevated score post-CPT and a much more elevated score post-TSST. Some participants, like the one whose data is plotted did not report an increase in stress. For this participant, scores remained close to baseline for SA and decreased from baseline for SUDS We chose an arbitrary threshold for stress response to identify self-reportedstrong responders from weak/non-responders for illustrative purposes. Twenty-three of 39 participants qualified as strong responders based the arbitrary threshold For the population, the average change in state anxiety was and the change in SUDS scores was 320±61%. Overall, the self-reports reflected an increase in anxiety (SA) and distress (SUDS) with the application of the stressors.

Physiological response to stressors Electrodermal activity (EDA) refers to variation in the electrical properties of the skin in response to sweat secretion.

In summary, individual participant's EDA, HR, HRV and FAS responded to the two stressors. Although changes in these measures reflected changes in self-reported state anxiety, this relationship did not reach statistical significance. This could partly be due to mismatch between physiology and self-report. To address this possibility, in the next section we describe how these measures can be combined using machine learning algorithms to decode stressful epochs, which can be defined objectively.

4. CONCLUSIONS AND FUTURE DIRECTIONS

Examined the stress responses of healthy participants using self-reports and multiple physiological measures. Participants were exposed to 2 kinds of acute stressors and engaged in five non-stressful activities. During this experience, we observed robust changes in EEG, HRV, HR, GSR that were weakly correlated with increases in self-reported stress. By combining select features from these different measures using a machine learning-based algorithm, stressful states could be identified from non-stressful states with ~96% accuracy. Further, individuals with high trait anxiety were identified with ~84% accuracy using a decision tree to optimally combine physiological measures with self-reported state anxiety. While individuals with high trait anxiety displayed high baseline state anxiety, their response to acute stressors was muted. Identifying stressful states and non-stressful states In this study, we used several physiological measures to understand individual responses to a stressor. GSR has been extensively used to measure stress response [22] and, even in this study, GSR increased with stress induction. However, GSR as a measure was not as sensitive as heart rate or EEG-based measurements in identifying stress states. HRV reliably declines with increases in stress and in our study HRV also decreased with self-reported increases in stress-induced state anxiety. Nevertheless, HRV-based measures lacked the specificity of EEG. That is, many non-stressful epochs were wrongly identified as stressful epochs, limiting the utility of HRV in this context. Several recent studies have attempted to combine different physiological measures to improve the ability of an algorithm to identify stress states. By combining select features from these physiological modalities using a support vector machine, we achieved high sensitivity and specificity indeed more than that achieve using any independent measure alone.

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6. References

1. Managing Stress and Anxiety | Anxiety and Depression Association of America, ADAA.
2. Kessler RC. Posttraumatic stress disorder: The burden to the individual and to society. J Clin Psychiatry. 2000.
3. Kessler RC, Berglund P, Demler O, Jin R, Merikangas KR, Walters EE. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the national comorbidity survey replication. Arch Gen Psychiatry. 2005.
4. Bandelow B, Michaelis S. Epidemiology of anxiety disorders in the 21st century. Dialogues Clin Neurosci. 2015.
5. Evans TM, Bira L, Gastelum JB, Weiss LT, Vanderford NL. Evidence for a mental health crisis in graduate education. Nat Biotechnol. 2018.
6. John-Baptiste AA, Li L, Isaranuwatchai W, Osuch E, Anderson KK. Healthcare utilization costs of emerging adults with mood and anxiety disorders in an early intervention treatment program compared to a matched cohort. Early Intervention in Psychiatry. 2019.
7. Grupe DW. Decision-making in anxiety and its disorders. Decis Neurosci An Integr Perspect. 2016;327–38.
8. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders (5th Edition). American Journal of Psychiatry. 2013.
9. Raymond JG, Steele JD, Seriès P. Modeling trait anxiety: From computational processes to personality. Frontiers in Psychiatry. 2017.
10. Shackman AJ, Tromp DPM, Stockbridge MD, Kaplan CM, Tillman RM, Fox AS. Dispositional negativity: An integrative psychological and neurobiological perspective. Psychol Bull. 2016.
11. Spielberger CD. State-trait anxiety inventory: A comprehensive bibliography. Consult Psychol Press. 1989.
12. McEwen BS. Physiology and neurobiology of stress and adaptation: central role of the brain. Physiol Rev. 2007.
13. Robins LN. Epidemiology: Reflections on Testing the Validity of Psychiatric Interviews. Arch Gen Psychiatry. 1985.
14. Knowles ES, Coker MC, Scott RA, Cook DA, Neville JW. Measurement-Induced Improvement in Anxiety: Mean Shifts with Repeated Assessment. J Pers Soc Psychol. 1996.
15. Sharpe JP, Gilbert DG. Effects of repeated administration of the beck depression inventory and other measures of negative mood states. Pers Individ Dif. 1998.
16. Windle C. Test-Retest Effect on Personality Questionnaires. Educ Psychol Meas. 2007.
17. Shrout PE, Stadler G, Lane SP, McClure MJ, Jackson GL, Clavél FD, et al. Initial elevation bias in subjective reports. Proc Natl Acad Sci. 2018.
18. Allen AP, Kennedy PJ, Cryan JF, Dinan TG, Clarke G. Biological and psychological markers of stress in humans: Focus on the Trier Social Stress Test. Neuroscience and Biobehavioral Reviews. 2014.
19. Campbell J, Ehlert U. Acute psychosocial stress: Does the emotional stress response correspond with physiological responses? Psychoneuroendocrinology. 2012.
20. Nater UM, Ditzen B, Strahler J, Ehlert U. Effects of orthostasis on endocrine responses to psychosocial stress. Int J Psychophysiol. 2013.
21. Urwyler SA, Schuetz P, Sailer C, Christ-Crain M. Copeptin as a stress marker prior and after a written examination—the CoEXAM study. Stress. 2015.
22. Healey JA, Picard RW. Detecting stress during real-world driving tasks using physiological sensors. IEEE Trans Intell Transp Syst. 2005.
23. Zhai J, Barreto A. Stress detection in computer users through noninvasive monitoring of physiological signals. Biomedical Sciences Instrumentation. 2006.
24. De Santos Sierra A, Sánchez Ávila C, Guerra Casanova J, Bailador Del Pozo G. A stress-detection system based on physiological signals and fuzzy logic. IEEE Trans Ind Electron. 2011.
25. Katsis CD, Katertsidis NS, Fotiadis DI. An integrated system based on physiological signals for the assessment of affective states in patients with anxiety disorders. Biomedical Signal Processing and Control. 2011.
26. Willmann M, Langlet C, Hainaut JP, Bolmont B. The time course of autonomic parameters and muscle tension during recovery following a moderate cognitive stressor: Dependency on trait anxiety level. Int J Psychophysiol. 2012.
27. Karthikeyan P, Murugappan M, Yaacob S. Multiple physiological signal-based human stress identification using non-linear classifiers. Elektron ir Elektrotechnika. 2013.
28. Seoane F, Mohino-Herranz I, Ferreira J, Alvarez L, Buendia R, Ayllón D, et al. Wearable biomedical measurement systems for assessment of mental stress of combatants in real time. Sensors (Switzerland). 2014.
29. Kukolja D, Popović S, Horvat M, Kovač B, Ćosić K. Comparative analysis of emotion estimation methods based on physiological measurements for real-time applications. Int J Hum Comput Stud. 2014.
30. Wijsman J, Grundlehner B, Liu H, Penders J, Hermens H. Wearable physiological sensors reflect mental stress state in office-like situations. Proceedings of the 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction (ACII 2013). 2013.