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Kevin Hoffman **April 9, 2024**

Facial and Vocal Biomarkers of Emotional Expressivity in Post-traumatic Stress Disorder

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Abstract

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By Kevin Hoffman

Posttraumatic stress disorder (PTSD) is characterized by a range of symptoms, including those that reflect exaggerated fear-related responses and deficits in feeling positive emotion. However, machine learning-based approaches have not yet examined how this difference in emotional expressivity of PTSD manifests in the face, which may differ from self-reported measures of emotion in PTSD patients. Recently, computer vision, semantic, and acoustic analysis has been limited to differentiate between PTSD and depression. We correlated biomarkers of facial expressivity, emotional expressivity, and auditory expressivity with PTSD severity using the Clinician Administered PTSD Scale DSM-5 (CAPS-5). Fifty-nine adults (mean age = 24.58; 56 women) were recruited. The Clinician-Administered PTSD Scale for DSM-5 (CAPS) was administered prior to the start of a mindfulness intervention in which the participant's face and voice were recorded. The open-source Python library OpenWillis was used to analyze overall facial expressivity. Additionally, the degree of emotional expressivity of happiness, sadness, anger, fear, disgust, surprise, and neutral were quantified as proportions of total time during the CAPS-5. Auditory variables of pause duration, silence-to-speech ratio, and rate of speech were also collected. Bivariate Pearson's correlations were conducted to compare CAPS-5 data with expressivity variables as well as analyze moderating variables of gender. Overall facial expressivity was negatively correlated with increased PTSD re-experiencing symptoms, which might indicate higher reactivity. Fear expression was positively correlated with

overall PTSD severity. The rate of speech was increased with higher re-experiencing symptoms while formant 1 variance was reduced in individuals with higher hyperarousal symptoms. These differences between specific emotions and PTSD symptom clusters validates our approach in assessing multiple emotional domains. Analysis of the expressivity of emotion types as well as how these connect to symptom change will allow us to gain a mechanistic understanding of how these emotions relate to symptomology and could potentially yield facial expression as a predictor of intervention success.

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I. Introduction

A. PTSD

a. Overview

Post-Traumatic Stress Disorder (PTSD) is a problem that may develop after exposure to traumatic events, which include assault, abuse, accidents, and other distressing experiences (Weathers, 2018). According to national estimates, PTSD affects around 12% of people in their lifetime (Kessler et al., 2005). However, these rates are higher in populations that have higher trauma exposure, and some studies show that the rates are also higher in women (Gluck et al., 2021). However, the exact symptoms experienced by someone diagnosed with PTSD are highly variable (Michopoulos et al., 2015).

b. PTSD Symptom Clusters

In the Diagnostic and Statistical Manual of Mental Disorders, version 5, several clusters of PTSD symptoms have been identified, which are used for diagnosis and treatment planning. These categories include trauma-related avoidance, re-experiencing of trauma, negative cognition and mood (which includes symptoms that reflect deficits in the ability to experience positive mood—anhedonia), and hyperarousal (American Psychological Association, 2013). Avoidance reflects behaviors and feelings related to avoiding reminders of the traumatic events (Sheynin et al., 2017). These symptoms can manifest in a tendency to withdraw from or avoid adverse situations, namely those that remind them of the events. Re-experiencing symptoms occur when individuals have recurring, unwanted memories or thoughts of the stressful experience (Michael et al., 2005). One may recall sensory fragments such as pain, sensations, or visual images of the experiences sometimes due to triggers and sometimes seemingly out of

nowhere. PTSD-diagnosed individuals report increased negative feelings and difficulty regulating those negative emotions, which comprises the negative cognition and mood symptom cluster (DiMauro et al., 2016). This can manifest in increased negative affect and increased expectation of negative mood. For example, PTSD diagnosed civilians appear to have reduced inhibition of fear (Jovanovic et al., 2010). This higher expression of fear manifests itself in intrusive worry, social fear, and intense fear reactions (Norrholm et al., 2015). Anhedonia often entails low positive affect and disinterest in typically enjoyable activities (Kashdan et al., 2006). Additionally, PTSD populations often experience emotional numbing, detachment from other people, and reduced emotional expressiveness (Weiss et al., 2020). PTSD patients with anhedonia have a reduced feeling of reward, less joy and pleasure, and weaker drives (Elman et al., 2018). The hyperarousal symptoms of PTSD include increased irritability, hypervigilance, attention disruptions, insomnia, and exaggerated startle response, and may manifest as difficulty concentrating and impulsivity. Some individuals may be diagnosed with PTSD, yet experience one or more clusters more than the others (or may have PTSD symptoms in only some clusters, putting them below the diagnostic threshold) which justifies examining each cluster individually.

c. Neurophysiology-based Biomarkers of PTSD

There are a variety of neurophysiological manifestations and biomarkers of PTSD, which include endocrine system disruption, functional differences in certain brain regions, and sympathetic nervous system variables. For example, studies have found alterations in the serotonergic system in amygdala in patients experiencing avoidance symptoms (Michopoulos et al., 2015). Patients with PTSD have been found to have higher levels of vasopressin, which suggests a neurophysiological explanation for the symptoms of increased irritability

(Michopoulos et al., 2015). Other neuroendocrine alterations include different expressions of neuropeptide Y and reduced antagonism of the noradrenergic systems (Michopoulos et al., 2015). Neuroimaging of veterans with PTSD have found stronger neural activity in the bilateral amygdala, hippocampal, prefrontal, and sensorimotor regions of the brain (Badura-Brack et al., 2017). Functional neuroimaging has found similar regions with specificity such as the medial prefrontal cortex and the sublenticular extended amygdala (Liberzon & Martis, 2006). There are also several other physiological differences in individuals with PTSD. For example, PTSD diagnosed individuals see greater skin conductance reactivity when viewing distressing images (van ’t Wout et al., 2017). Furthermore, assault survivors diagnosed with PTSD see different heart rate response compared to non-PTSD controls (Halligan et al., 2006). Additionally, it has been established that there are some deficiencies in facial mimicry in traumatized populations (Passardi et al., 2019).

d. Social Disruptions in PTSD

In addition to these neurophysiological biomarkers, there are a variety self-reported difficulties reported by individuals diagnosed with PTSD. Some work has related PTSD symptom severity with altered self-perception and perceived social desirability (Dyer et al., 2009). Indeed, PTSD-diagnosed individuals saw reduced self-reported self-compassion (Seligowski et al., 2015). Those with PTSD report greater difficult forming social attachments and maintaining social bonds (Bryant, 2016). In addition, PTSD has been associated with social isolation, which resolves as PTSD symptoms are resolved (Beidel et al., 2019). Furthermore, certain PTSD clusters such as the re-experiencing cluster are correlated with lower perceived

physical health (Zoellner et al., 2000). However, it must be noted that overreporting of symptoms occurs in self-report PTSD evaluations, so it is important to have clinicians evaluate symptomology (Frueh et al., 2000).

e. PTSD Treatment

Populations with PTSD have been responsive to several kinds of treatments. First-line treatments for PTSD include prolonged exposure therapy and cognitive processing therapy, which involve repeated, controlled, prolonged exposure to trauma-related memories (McLean et al., 2022); given that they are designed to extinguish exaggerated fear responses in the context of trauma memories (Rauch et al., 2012), they are well-suited to target fear-related symptoms of PTSD and show good efficacy in this regard. However, these treatments often fail to fully resolve all PTSD symptoms in all patients involved, and many people drop out of these first-line treatments. Other non-fear-related manifestations of PTSD (e,g, shame/guilt, anhedonia) are less responsive to these treatments (Trachik et al., 2018). Other treatments have been proposed to target these problems, including oxytocin administration to address reward-related PTSD manifestations, as well as mind-body treatments, such as mindfulness-based therapies (Lang, 2017; Stauffer et al., 2019), which may address a range of problems, from anhedonia to hyperarousal. Given the variability in treatment response and dropout in PTSD treatments, it is useful to have objective, physiologically-based PTSD biomarkers that correlate with clinical manifestations of PTSD, and which may be used to predict treatment outcomes.

B. Emotional Expressivity

a. Alexithymia and Emotional Regulation in PTSD

Many people with PTSD experience difficulties with emotional identification and regulation. PTSD has been strongly associated with alexithymia, which refers to difficulty recognizing and describing one's emotions and feelings (Zlotnick et al., 2001). This often is experienced as a deficit in emotional experience and expression (Frewen et al., 2008). Alexithymia has been associated with specific PTSD symptom clusters such as re-experiencing and hyperarousal. These symptoms sometimes are experienced as a sense of numbness or reduction in affect (Frewen et al., 2006). Thus, the emotional experience of individuals with PTSD may be altered. Increased PTSD-related alexithymia has been associated with increased prefrontal cortex activity, suggesting a mechanism (Frewen et al., 2008). PTSD symptom severity has also been associated with difficulty in regulating negative emotions (Shepherd & Wild, 2014). Indeed, PTSD-diagnosed individuals report requiring greater attention and effort in order to modulate their emotions (Tull et al., 2020). Furthermore, some individuals with PTSD find it difficult to interpret and verbally describe how they feel (Passardi et al., 2019). These symptoms ultimately lead to a disruption in emotion processing (Messman et al., 2023). Thus, there are deficits in emotional regulation that are associated with PTSD. These deficits in emotional regulation are also associated with specific symptom clusters (Ehring & Quack, 2010). Some PTSD-diagnosed individuals face greater difficulty navigating tasks while under emotional distress (Pugach et al., 2020). This also may lead to difficulty in impulse control and non-acceptance of negative emotions. With these difficulties, some work suggests that PTSD is associated with maladaptive emotional regulation strategies (Tull et al., 2020). Since PTSD has been associated with difficulty identifying and describing emotions, it is important to include other, namely physiological, measures of emotional expressivity rather than relying solely on self-perception. Namely, self-report measures and even clinician administered measures that rely

on patients accurately describing their experiences and symptoms may be difficult due to the alexithymia and emotional regulation deficits associated with PTSD.

b. Emotional Expressivity in PTSD

PTSD has been associated with abnormal emotional expressivity. For example, students with trauma exposure and PTSD diagnosis were found to report greater difficulty in emotionally expressing themselves and feel greater interpersonal sensitivity (Slanbekova et al., 2019). College aged adults with more severe PTSD symptoms reported greater difficulty with emotional expression (and emotion acceptance) (O'Bryan et al., 2015). However, the directionality of this relationship is unclear—whether PTSD symptoms preceded these difficulties in expressivity or vice versa. For example, individuals having recently experienced a traumatic event and held pessimistic outlooks on their own emotional expression were more likely to be diagnosed with PTSD 6 weeks after the event compared to those with a less negative attitude on their emotional expression (Nightingale & Williams, 2000). In another study, fear of emotional expression was the largest predictor of PTSD diagnosis (as compared to other social and demographic variables) in a sample of firefighters (Farnsworth & Sewell, 2011). In a review on emotional numbing in PTSD, researchers concluded that individuals with PTSD are still capable of the same range of emotions they had prior to the traumatic event (Litz et al., 2002). However, individuals experiencing PTSD may need stronger emotional stimuli to express the same level of emotionality. Alterations in emotional expressivity may be a part of the trauma response. For example, women with PTSD reported higher difficulty expressing positivity due to interruptions caused by difficulty describing, identifying, and modulating emotions, namely if they also reported higher childhood physical or emotional neglect (Frewen et al., 2012). Difficulties in

emotion accounted for significant variance in aggression symptoms in men exposed to interpersonal violence (Tull et al., 2007). Thus, it is important to investigate abnormalities in emotional expressivity as a potential trauma-related response that could influence the expression of PTSD symptoms. Namely, these self-perceived differences may manifest themselves in the facial expressions and in other means of emotional expression of individuals with PTSD, necessitating analysis of biomarkers.

c. Biomarkers of Emotional Expressivity for Prediction of Later PTSD or Treatment Response

Abnormalities in emotional expressivity in populations with PTSD may lead to impairment in some social interactions. Some individuals with PTSD seem to have difficulty navigating emotions during social activities (Williams et al., 2018). Adding further, this altered emotional expressivity and shift in affect can affect treatment outcomes. It seems that less emotionally-expressive individuals are less responsive to therapy treatments (Littrell, 2009). Indeed, some biomarkers can assist in elucidating whether an individual will have a significant positive outcome from treatment or not (Colvonen et al., 2017). Since some treatments require emotional engagement, the difficulty emotionally engaging with others may affect treatment outcome. Furthermore, by examining these emotional biomarkers as predictors, we may improve on assigning interventions and dedicating resources to patients who would most benefit from certain types of treatments.

Some emotion-related facial features have begun to be examined as predictors of PTSD diagnosis (Schultebraucks et al., 2022). In that study, patients who experienced a psychological trauma and went to a level-1 trauma emergency room received a clinical interview 1 month after

admission to the ED. During these interviews, the patients were evaluated for provisional PTSD diagnosis and their speech and facial expressions were recorded while they answered a set of 5 questions regarding their trauma; these recordings were analyzed using a deep learning artificial intelligence algorithm. The researchers found that greater fear and anger expressivity, reduced pitch variance, and reduced audio intensity significantly predicted PTSD diagnosis. The authors found that these findings specific to PTSD differed from those in depression, and persisted when controlled for other comorbid mental health conditions reported in their sample. Thus, there are abnormalities associated with PTSD in several emotion-related features of facial and vocal expression. Indeed, biomarkers of emotional expressivity have begun to be examined in PTSD populations.

C. Emotion Biomarkers for PTSD

a. Facial Action Coding System

One common system used to examine facial expressivity is the Facial Action Coding System (FACS), which provides a systematic method for visually determining emotions and facial movements (Pfeffer, 2023). This method involves manual rating, frame by frame, of video recordings of participant faces. Using this system, researchers have been able to predict the long-term outcomes of trauma exposure. The FACS system has been useful for detecting the present emotional state and stress levels of participants (Gavrilescu & Vizireanu, 2019). This system has also been used to find associations between individual emotions and self-reported PTSD symptoms (Bujarski et al., 2015). They examined the different emotional facial expressions of motor vehicle accident survivors, finding results that differed from self-reported emotional expression. Thus, it is important to use an objective measure of facial emotional expression,

especially due to the importance of emotional expression for social relationships. The FACS system is one tool with which facial expressions have been examined for some time, and has been employed in PTSD populations.

b. Facial Expression and PTSD

Some studies have examined the facial emotional expressions of those diagnosed with PTSD. In one study, during psychodiagnostic interviews with PTSD-diagnosed and non-PTSD individuals, participants' facial expressions were recorded and analyzed with FACS (Kirsch & Brunnhuber, 2007). The authors found less happiness and more anger expression in participants with PTSD as compared to healthy controls. Furthermore, they found that participants' facial expressivity was different during face-to-face interactions versus remote screening. One study presented PTSD and trauma-exposed non-PTSD patients with startling stimuli while recording their faces (Blechert et al., 2013). This found greater negative emotional expressions on their face, namely due to increased anger expression in those diagnosed with PTSD. In another pilot study, children who were survivors of the Great East Japan Earthquake had their emotional expressions filmed while watching images of natural scenes for two minutes before viewing 2 minutes of a comedy video (Fujiwara et al., 2015). They employed a digital form of the FACS to examine their facial expressions, and found that higher PTSD symptoms were correlated with higher neutral facial expressions. This finding suggests that individuals with greater severity of PTSD are less emotionally reactive. Similar work was performed with adult women diagnosed with PTSD or non-PTSD while showing them emotionally charged clips of contentment, amusement, sadness, fear, and anger in that order (Orsillo et al., 2004). Their facial expressions were recorded among self-report measures of emotion, which found increased negative

emotional expression via self-report but not in the face. However, other work does establish some difference in facial expression of emotion and self-report of emotion in PTSD populations (Wagner et al., 2003). When listening to audio recordings produced based on details of participant trauma experiences, those in the PTSD group reported feeling negative emotions more strongly, yet had lower negative facial emotional expression as compared to an age-matched non-PTSD control listening to the same audio. Consequently, there are distinct differences between self-report and emotional expression unique to PTSD. This makes it necessary to evaluate the physiological manifestation of emotion in the face aside from self-report. Additionally, these prior studies help establish facial expressivity of emotion as a useful biomarker of emotional expressivity in PTSD. However, the FACS system presents some difficulties due to the long time necessary for training a rater as well as the expanse of time required to manually rate every frame. Thus, most prior studies have only examined short sections of interviews for a few minutes a participant. This time burden also makes it difficult for studies to include larger sample sizes, especially since it is typically required that the same rater scores the entire sample.

c. Speech Characteristics in PTSD

There are other measures of emotional expression that have been associated with PTSD symptoms and severity, including speech patterns and other linguistic features of speech. In civilian women recounting their trauma, rate of speech was negatively related to some PTSD symptoms, namely avoidance (Fernandez-Lansac & Crespo, 2015). This finding was replicated in a study of veterans; the authors found that slower speech while discussing their PTSD-related

symptoms in the Clinician-Administered PTSD Scale (CAPS) was associated with PTSD diagnosis (Marmar et al., 2019). This suggests that individuals with PTSD speak slower during clinical interviews, although the mechanism behind this change in speech pattern has not been investigated regarding PTSD. Other speech characteristics such as pause rate and pause duration have been explored and found to be greater in individuals with greater PTSD symptoms (DeVault et al., 2013; Southee, 2020). Studies using machine learning applying large amounts of data from corpora (collections of spoken or written language in context) have found increased rate of pauses in individuals diagnosed with PTSD during clinical encounters with physicians (Banerjee, 2017). Thus, PTSD appears to be related to pausing behavior, which may be for a variety of reasons such as stopping to reflect or due to interruptions from re-experiencing symptoms. Meanwhile, another study showed that people with PTSD express words with greater neutral and negative sentiment (Sawalha et al., 2022). The PTSD group in the study used negative and neutral words more frequently than the healthy controls. One study examined specifically the frequency of words used (key word analysis) in self-narratives, which identified unique token patterns of individuals diagnosed with PTSD compared to non-PTSD individuals (He et al., 2012). Thus, there are several characteristics of speech that are associated with PTSD symptoms. Evaluation of biomarkers of speech characteristics may yield objective physiological biomarkers of PTSD similar to facial expressivity biomarkers.

d. Vocal Acoustics in PTSD

In addition, vocal acoustic variables may be useful to examine as biomarkers of PTSD symptom severity or treatment response. The fundamental frequency (F0) is the lowest frequency from speech and has been used as a biomarker for mental health conditions (Mundt et al., 2012).

F0 relates to highness or lowness of the voice, serving as a measure of pitch. Vocal prosody, including F0, is closely connected to the emotional expressivity of individuals (Busso et al., 2009). This study used a corpus produced by asking participants to read sentences with a certain emotion, finding unique F0 patterns based on emotion. It is suggested that the fundamental frequency is a means by which individuals add emotion to spoken words. Furthermore, certain features of pitch measured by F0 relates to specific emotions, with negative emotions (except anger) associated with reduced F0 frequency. Indeed, F0 has been used as a biomarker in linguistics for emotional state, including emotional stress (Probst & Braun, 2019; Protopapas & Lieberman, 1997). Furthermore, the variation of F0 can be considered a measure of monotony, with less variance in more monotonous voices, which connects itself to reduced or negative emotional expressivity (Probst & Braun, 2019). Speech analysis has found reduced F0 and less F0 variation in PTSD-diagnosed adults compared to non-PTSD adults (Marmar et al., 2019). Additionally, automated analysis of recordings found that there was a smaller standard of deviation in PTSD group compared to non-PTSD group (Xu et al., 2012). F0 and its variation has been negatively associated with not just the emotional state of trauma recall, in children, but also the amount of trauma and PTSD symptoms (Monti et al., 2021). Indeed, prosodic analysis of speech found lower F0 in the PTSD population (Ettore et al., 2023). Thus, F0 is a valuable biomarker of emotional expressivity that may have unique features in PTSD populations.

e. Formant Frequencies

Additional emotional expressivity-related vocal acoustic biomarkers are formant frequency and variation. The formants are the resonant frequencies of speech (Bozkurt et al., 2011). The first two formants, formant 1 and formant 2, mark frequencies that, when used together, produce

vowels, and are very useful for analysis (Erickson et al., 2008). The formant frequencies and their variation relate primarily to tone and connect to emotionality in speech (Rebordao et al., 2009). The first two formants have been used for assisting in the identification of several emotions such as in linguistic work aiming to identify the vocal acoustic patterns of specific emotions (Khulage, 2012). Indeed, including the formants in analysis has helped produce more accurate classification of emotions (Kim & Clements, 2015). Reduced formants have been associated with sadness and significant variation of the formants is associated with happier, more expressive speech (Erickson et al., 2008). The formant frequencies have been associated with PTSD symptoms. Reductions in the frequency of formants 1 and 2 have been found in individuals diagnosed with PTSD (Scherer et al., 2015). Lower formant 1 and formant 2 means and variance were found in PTSD populations (Ettore et al., 2023). Thus, PTSD may be associated with more monotonous, less emotionally expressive speech, measured by formant frequency and variation.

D. Artificial Intelligence (AI) Innovations in Assessing Facial Expressivity and Vocal/acoustic Biomarkers of PTSD

a. Benefits of the use of AI

New innovations in AI can help us measure emotional expressivity and thereby guide treatment direction. In the context of coding videos to analyze facial and vocal biomarkers of PTSD, AI presents a significant advantage over manual coding in terms of efficiency, reducing hundreds of hours of manual coding work (Peham et al., 2015). This permits the analysis of longer recordings, providing richer data. The FACS system requires 100 hours of training and that the same rater analyzes the entire sample in order to maintain consistency between subjects.

However, this means FACS is cumbersome, restricting the sample size and length of behavior to analyze while also allowing variability between studies since the raters are different and prone to human error. AI thus presents a method with which any researcher can more easily use while maintaining consistency between studies. Some prior research has been completed using AI to assay facial expressivity. For example, facial and auditory data have been examined by machine-learning tools to pinpoint specific markers of schizophrenia (Abbas et al., 2022). Other AI have been used to examine aspects of written or spoken language (D'Alfonso, 2020). OpenWillis is an open-source Python library utilizing a variety of machine learning tools for digital phenotyping. This allows analysis of facial expressions, speech characteristics, and vocal acoustics among other relevant video and audio variables through one library freely accessible to any researcher or clinician. Thus, this tool can be utilized in a consistent manner across a variety of studies and populations in order to objectively analyze and compare the emotion-related biomarkers of samples.

b. Current use of AI in identifying Biomarkers of Psychopathy and Treatment Response

The use of AI presents itself as an expanding opportunity to more thoroughly analyze biomarkers of emotional expressivity in mental health contexts. Open-source deep learning has found some associations between suicidality and variables of facial and auditory expression (Galatzer-Levy et al., 2021). In depression, manual rating has been seen as insufficient due to the variability between some participants, whereas applying deep-learning AI has enabled better screening than humans (Wani et al., 2023). Ultimately, AI also presents an easier to replicate method than manual rating since it is consistent between individuals, providing a more objective

method of classification or rating (Luxton, 2015). Thus, AI presents many advantages for researchers wishing to examine biomarkers including those related to emotional expressivity. PTSD specifically has seen some examination using AI, albeit limited. Some markers of arousal and mood from video and audio data have been used to differentiate between PTSD and depression, although with limited accuracy (Schultebraucks et al., 2022). Additionally, machine-learning algorithms have been used to predict PTSD diagnosis before (Othmani et al., 2023). In a review on current literature examining the use of digital biomarkers of PTSD, they identified only 6 studies examining facial or vocal biomarkers as predictors of PTSD (Wu et al., 2023). Out of these studies in the review, 5 solely examined speech characteristics while Schultebraucks et al. examined both speech and facial expressions. Namely, the studies utilized speech characteristics such as rate of speech and pauses, sentiment analysis of the valence of word choice, acoustic factors such as F0 and the formants, and other semantic variables to train either classifiers or machine-learning algorithms to predict PTSD. These trained algorithms were then used on a novel sample of patients to predict their PTSD diagnosis, finding that they can predict PTSD diagnosis from 74.99% to 97.5% depending on the algorithm and sample. This suggests that emotion biomarkers found in facial and vocal expression may be altered from PTSD. Thus, emotional expressivity may be related to PTSD symptom development, making it a useful target for assessment and intervention. However, as of now, these studies have only focused on prediction of PTSD diagnosis. No studies as of yet have employed AI to evaluate facial and vocal biomarkers across PTSD symptom severity. With deficits in describing emotions and differential emotional expressivity, it is important to examine the biomarkers of facial and vocal emotional expressivity in PTSD populations.

E. Present Study

a. Objective

The goal of this study was to use open-source deep learning tools provided in OpenWillis to examine markers of facial emotion expressivity and vocal expressivity in a diverse sample of individuals with variable PTSD symptoms enrolled in a PTSD clinical trial. Specifically, I analyzed videotaped footage of these participants as they received a gold-standard clinician-administered assessment of PTSD, the Clinician Administered PTSD Scale for DSM-5, or CAPS-5, (Weathers et al., 2018), prior to engaging in the intervention (meditative practices). I examined whether markers of facial and vocal expressivity significantly correlated with PTSD symptoms, including avoidance, re-experiencing, negative alterations in cognition and mood, and hyperarousal.

b. Hypotheses

H1a) Markers of negative emotional expressivity including reduced overall facial movement, fear expressions, anger expressions, reduced formant variance, reduced F0 frequency, and increased negative sentiment in word use will be positively correlated with overall PTSD symptom severity and H1b) particularly fear-related symptom clusters, specifically re-experiencing and hyperarousal symptoms.

H2) Markers of positive emotional expressivity including happiness expression, increased formant variance, higher F0 frequency, and increased positive sentiment in word use will be negatively correlated with overall PTSD symptom severity.

Secondarily, I conducted exploratory analyses to examine associations between facial and vocal biomarkers.

II. Materials and Methods

A. Participants

a. Recruitment

Adults between 18-65 years old (mean = 24.6, SD = 7.2) were primarily recruited through the Grady Trauma Project (GTP), an ongoing, long-standing collective of trauma and PTSD studies in inner-city Atlanta, Georgia. Participants were approached at random in the waiting rooms of Grady Memorial Hospital medical clinics; recruitment also occurred via flyers distributed in the community, and self-referrals through the GTP website. Interested individuals underwent informed consent procedures with study staff and were evaluated for eligibility criteria for a meditation clinical trial in a preliminary screening interview conducted remotely.

b. Inclusion and Exclusion Criteria

Those who endorsed a significant traumatic event on the Life Events Checklist (Weathers et al., 2013) and scored 7 or higher on the depersonalization subscale of the Multiscale Dissociation Inventory (MDI) (Briere, 2005) and who were MRI eligible were recruited. Additional inclusion criteria were: Ability to provide informed consent and willingness to participate in study. Exclusion criteria were: moderate to severe cognitive impairment, primary psychotic or bipolar disorder with psychosis, acute suicidal ideation, experienced an episode of loss of consciousness

for more than 5 minutes, experienced a head injury that resulted in symptoms lasting more than 2 weeks, severe marijuana or alcohol use disorder based on the Mini-International Neuropsychiatric Interview (MINI), physical or psychological issues that would prevent them from completing the scan/training days, or the North American Adult Reading Test (NAART) score less than 7.

Ninety participants were screened and deemed eligible for the trial. Among these 90 participants, 31 declined to be recorded or their recordings were either lost or unusable due to recording quality. Of these 59 participants, 9 had their videos, but not audio files, excluded due to poor quality of recording such as their face being only partially visible, leaving 50 individuals with videos of sufficient quality to analyze.

B. Clinical Assessment

Diagnostic Assessment (DA) interviews were performed before and after study intervention visits (the initial DA was analyzed for the present study). The DAs were performed by study staff under the supervision of licensed psychologists. The DAs consist of a series of questionnaires including the Clinician Administered PTSD Scale for DSM-5 (CAPS), which was used to assess the presence and severity of PTSD and its symptom clusters. The CAPS is considered a gold standard assessment for PTSD and is a widely used format of trauma related symptoms of PTSD. The DA interviews also included the MINI 7.0. These DAs were recorded using Zoom by the interviewer during which video and audio data were obtained at the permission of the participant.

C. Video Data Processing

Video and audio data from the DA recordings were used to obtain facial expressivity, emotional expressivity, and vocal expressivity variables. The mp4 files of video data were analyzed. We constricted the analysis to the CAPS portion of the interview. This results in videos ranging from 20 minutes to 1.5 hours depending on the length of discussion and symptoms endorsed. Periods of time in which breaks were taken were manually cut out to ensure only times when the participant's face was visible were processed. The audio was extracted from these files to produce .wav files for audio data. Additionally, 9 of the 59 participants either declined to have their faces recorded or their face was only partially visible, so only their audio was analyzed.

D. Measurement of Facial Expressivity

Data were processed on the Emory Center for Systems Imaging (CSIC) computer cluster. To process video and audio data, we employed OpenWillis, an open-source python library for digital health measurements from Brooklyn Health. A series of machine-learning functions from the library were employed for facial expressivity and vocal expressivity markers. The Facial Expressivity function utilized a facemesh model within mediapipe, a machine-learning tool, to determine 468 facial landmarks, the Euclidean distance between landmarks, and examine the landmarks' 3-dimensional displacement framewise (Thaman et al., 2022). All measurements were normalized to a baseline produced from the first 10 seconds of the CAPS questionnaire

during which the participant is listening to an introductory phrase. This normalization corrects for inter- and intraindividual variability and is standard for computer-based analysis of facial expressivity (Abbas et al., 2022). The algorithm is trained to detect the landmarks of the face to establish coordinate points across the entire face as well as determine the distance between the points in relative cm. The displacement of these points frame by frame is computed to generate framewise values of displacement. These measurements are then averaged together in order to compute a mean displacement over the entire course of the source video. The Emotional Expressivity function employed Deepface, a facial attribute analysis AI that quantifies the intensity and attribute of emotions as expressed in the face including happiness, sadness, anger, fear, disgust, surprise, and neutral (Taigman et al., 2014). These emotional expression intensity values are computed by evaluating the facial landmark patterns to produce a % prediction of landmark patterns that match each given emotion. The prediction is based on training across millions of facial expressions from over 4000 individuals. To limit Type I error, we limited the emotions under investigation in this study, selecting those identified in prior PTSD studies: happiness, anger, fear, and neutral expressions. The same baseline was used for emotional expressivity. The framewise values were compiled, producing the mean intensity scores across the entire video for each emotion.

E. Measurement of vocal expressivity

Since the interviews consisted of both the participant and the interviewer, it was crucial to separate between the two when examining the audio data. The OpenWillis speech transcription function was utilized to transform speech into text using a pre-trained model. This resulted in a

json file utilized by the speaker separation function of OpenWillis using Pyannote to identify rater prompts. It used the rater prompts to assist in identifying and separating the two speakers. The output was two audio .wav files of the rater and participant separated. These files were manually checked by running the speech transcription function on the two audio files to confirm which was the participant. Finally, the participant audio file was examined using the speech transcription function to produce all words uttered by the participant. The speech characteristics function was then employed to quantify different characteristics of speech including pause duration, pause count, silence-to-speech ratio, and rate of speech. The Natural Language Toolkit (NLTK) library was used by the function to assign labels to the words to identify the rate of verb, noun, adjective, and pronoun use. The function also employed the vaderSentiment library to examine the emotional valence of the speech and the LexicalRichness library to evaluate lexical diversity. The vaderSentiment library has manually scored the words and phrases of English to assign a positive or negative numerical value to reflect the sentiment of the word or phrase. This is normalized so that -1 is the highest negative sentiment and 1 is the highest positive sentiment. This produced positive, negative, and neutral sentiment values by word which, when averaged across the entire file, reflected the average emotional valence of the words used by the participant over the course of the video. Vocal acoustics characteristics were also analyzed in the speech of participants using the vocal acoustics function. This employed Parselmouth, which is a Python library for Praat software, to analyze the framewise acoustic properties of speech. The framewise properties were compiled to form a mean over the duration of the entire video to produce acoustic variables, namely those of the frequencies in Hertz (Hz) produced in spoken language. We focused on F0 and the first two formants due to their value in prior literature and to avoid any spurious conclusions. All output files from OpenWillis were converted into .csv

files remotely saved in CSIC, which were then downloaded from CSIC and compiled using Excel PowerQuery.

F. Data Analyses

Using SPSS v 29.0, distributions of variables were examined for violations of normality; deviations from normality were identified with the Shapiro-Wilk test. Where deviations were observed ($p<.05$), data were natural log transformed. Next, bivariate correlations were performed to examine significant associations between facial expressivity variables, including mean overall facial expressivity (regardless of emotional valence), happiness, anger, fear, and neutral with PTSD symptoms (CAPS total score and CAPS re-experiencing, avoidance, negative mood and cognition, hyperarousal symptom clusters). Bivariate correlations were also conducted with vocal expressivity variables, including rate of speech, pause rate, pause duration, vocal sentiment, F0, and formants 1 and 2 and the same PTSD symptoms and symptom clusters. For each family of tests, statistical significance was set at $p<.05$ adjusted with Bonferroni correction ($p<05/4=.0125$) to adjust for Type I error due to multiple comparisons.

H1) Bivariate correlations of negative valence biomarkers with CAPS-5 total and subscale score at pre-intervention (Pearson's r) using SPSS; statistical significance was set at $p<.05$ adjusted with Bonferroni correction ($p<.05/4$ tests).

H2) Bivariate correlations of positive valence biomarkers with CAPS-5 score at pre-intervention (Pearson's r) using SPSS; statistical significance will be set at $p<.05$ adjusted with Bonferroni correction ($p<.05/4$ tests).

Exploratory H3) Bivariate correlations of biomarkers (Pearson's r) at pre-intervention using SPSS; statistical significance will be set at $p<.05$ adjusted with Bonferroni correction.]

III. Results

A. Demographic and Clinical Characteristics

Table 1 describes clinical and demographic characteristics of this sample.

Table 1.		
Age (Mean, SD, Range)	24.6 (7.2)	18-47
	n	%
Gender		
Female	46	78
Male	13	22
Race		
White	22	37
Black	28	47
Asian	2	3
Mixed/Other	4	7
Marital status		
Single	42	71
Married/partnered	9	15
Divorced/widowed	4	7
Other	4	7
Number of Children [a]	2	3
Highest educational level		
High school	8	14

Some College	31	53
University degree	10	17
Graduate degree	7	12
Monthly Household Income		
$0-$250	6	10
$250-$499	5	8
$500-$999	6	10
$1000-$1999	14	24
$2000 or more	25	42
Employment		
Employed full-time	13	22
Employed part-time	15	25
Student	21	36
Unemployed	4	7
Retired or Disability	1	2
Previous psychological treatment [a]	19	32
Using psychotropic medication[a]	13	22
	Mean	SD
PTSD Total (CAPS Total)	25.98	12.05
PTSD re-experiencing (CAPS B)	5.36	3.88
PTSD avoidance (CAPS C)	2.81	1.99
PTSD negative cognition and mood (CAPS D)	10.7	5.8
PTSD hyperarousal (CAPS E)	7.09	3.57
LEC Experienced	3.46	2.01
LEC Witnessed	2.15	2.00

Table 1: Sociodemographic and clinical characteristics of participants. N = 59. [a] Reflects the number and percentage of participants answering “yes” to this question.

B. Descriptive Statistics

a. Facial expressivity

The mean overall change in facial expressivity for this sample = 0.0008, which represents the average displacement from baseline in the Euclidean coordinate face mesh (SD = +/- 0.001, range = -0.002–0.004). The measures of emotion expressivity were found to be significant per the Shapiro-Wilk test, justifying a log transformation of the data to establish normality. In the overall sample (non-log transformed), the most frequent emotion expressed was fear with a sample mean = .0380 higher from baseline of the proportion of facial landmarks predicting fear (SD = +/- 0.86, range = -2.20–2.10). The mean anger expressivity for this sample = 0.025 higher from baseline of the proportion of facial landmarks predicting anger (SD = +/- 0.072, range = -0.150–0.200). The mean happiness expressivity = 0.008 higher from baseline of the proportion of facial landmarks predicting happiness (SD = +/- 0.092, range = -0.260–0.380). The mean neutral expressivity = 0.009 higher from baseline of the proportion of facial landmarks predicting (SD = +/- 0.138, range = -0.230–0.190). One major outlier was found consistently near -1.000 proportion change from baseline for all emotion categories; data for this participant was excluded from further analyses (3 standard deviations from the mean).

b. Vocal expressivity

We found that neutral sentiment was predominant in the overall sample lexicon with a sample mean = 0.706 normalized, weighted sentiment score designated as neutral (SD = +/- 0.056, range = 0.555–0.848). Positive sentiment had a mean = 0.206 normalized, weighted sentiment score designated as neutral (SD +/- 0.055, range = 0.115–0.362). Negative sentiment, however, was infrequent with mean = 0.0879 normalized, weighted sentiment score designated as negative (SD = +/- 0.022, range = 0.025–0.157). The mean rate of speech = 171.4 words per minute (SD = +/- 29.7, range = 84.1–229.9). The average duration of pauses = 0.076 seconds

(SD = +/- 0.035, range = 0.023–0.187). The mean percentage of silence during participant speech = 0.320 proportion of time while silent (SD = +/- 0.250, range = 0.095–1.399). The mean F0 frequency = 100.53 Hz (SD = +/- 24.22, range = 41.72–140.66). The mean F0 variation = 9762 Hz. The average Formant 1 frequency = 648.04 Hz (SD = +/- 51.66, range = 515.17–759.3) and Formant 2 frequency = 1809.29 Hz (SD = +/- 85.89, range = 1577.36-1945-.44). The Formant 1 variance = 129983 and Formant 2 variance = 260679.

C. Associations between facial expressivity and PTSD symptoms.

Pearson correlations were conducted between individual CAPS clusters and variables of facial and emotional expressivity; correlations provided in supplementary table 1.

Bivariate correlation analysis revealed a significant negative association between overall facial expressivity and PTSD re-experiencing symptoms ($r = -0.335$, $p = 0.028$) (Figure 1); no other significant associations were observed with facial expressivity and PTSD symptom clusters ($p>.05$).

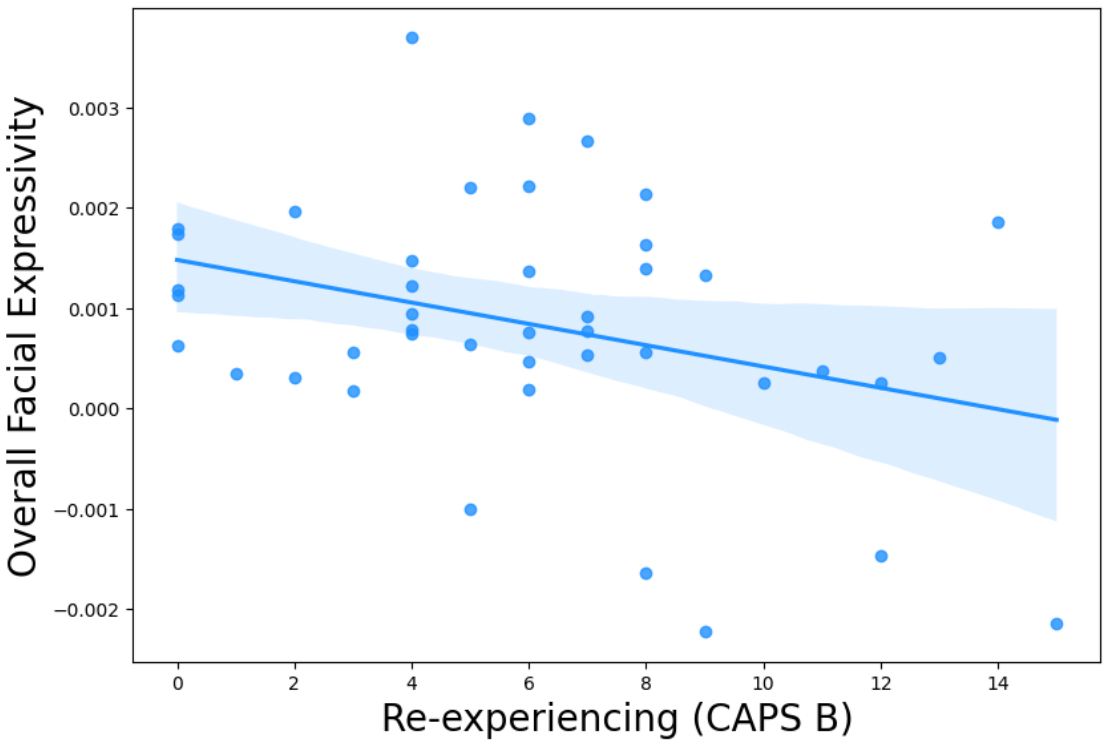

Figure 1: Associations between overall facial expressivity and re-experiencing symptoms. CAPS re-experiencing symptoms were negatively correlated with overall facial expressivity. Confidence intervals (95%) in light blue. N = 48, r = -0.34, p = 0.028.

Bivariate correlation analysis revealed positive associations between fear expression and overall PTSD symptom severity, although these associations did not meet our Bonferroni-corrected threshold (r = 0.32, p = 0.038); other similar correlations were observed for fear expression and PTSD avoidance (r = 0.35, p = 0.023), and negative alterations in cognition and mood (r = 0.33, p = 0.035), and (Figures 2, 3, & 4).

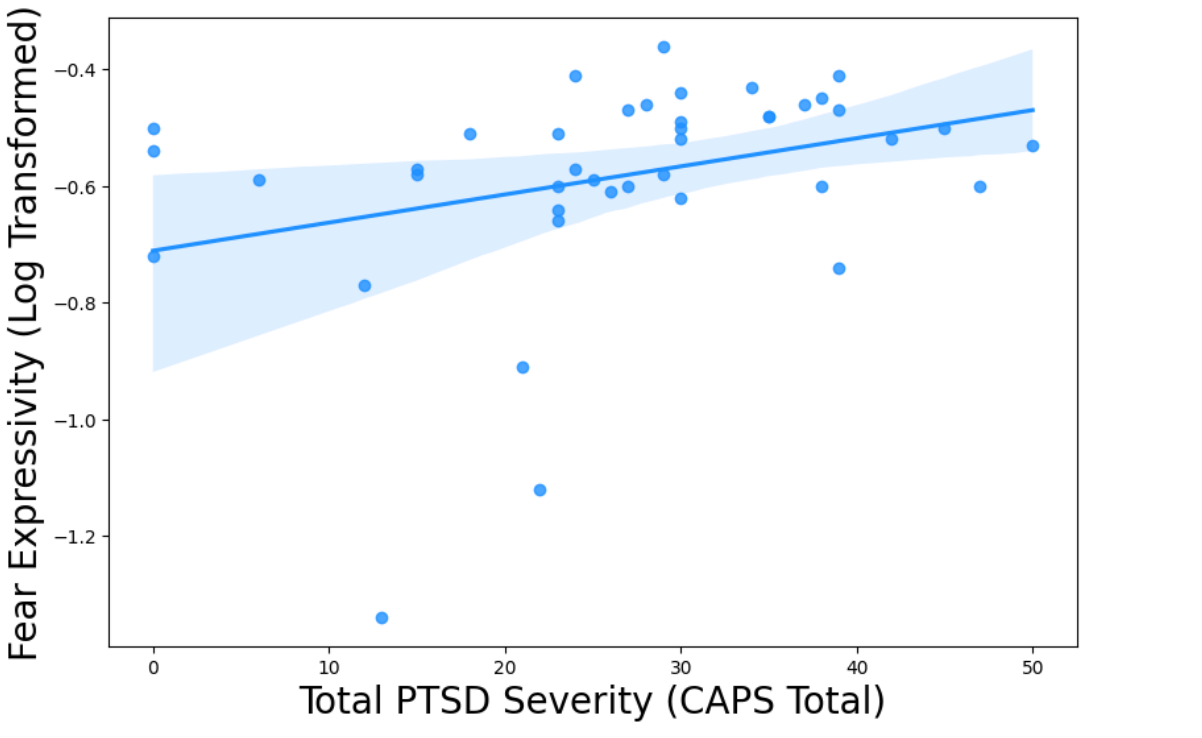

Figure 2: Associations between fear expression and PTSD symptom severity. Overall PTSD symptom severity (CAPS total score) showed a (non-statistically significant) positive association with fear expression (natural log transformed). Confidence intervals (95%) in light blue. N = 48, r = 0.32, p = 0.038.

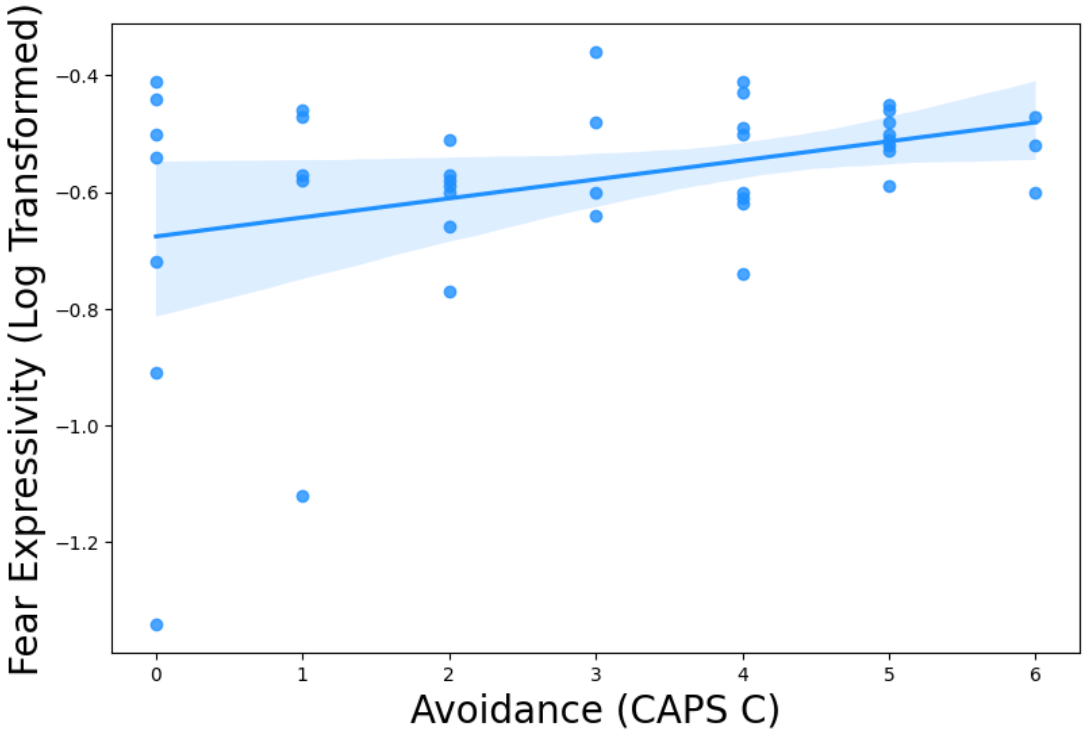

Figure 3: Associations between fear expression and PTSD avoidance symptoms. PTSD avoidance symptoms (CAPS C) showed a (non-statistically significant positive association with fear expression (natural log transformed). Confidence intervals (95%) in light blue. N = 48, r = 0.35, p = 0.023.

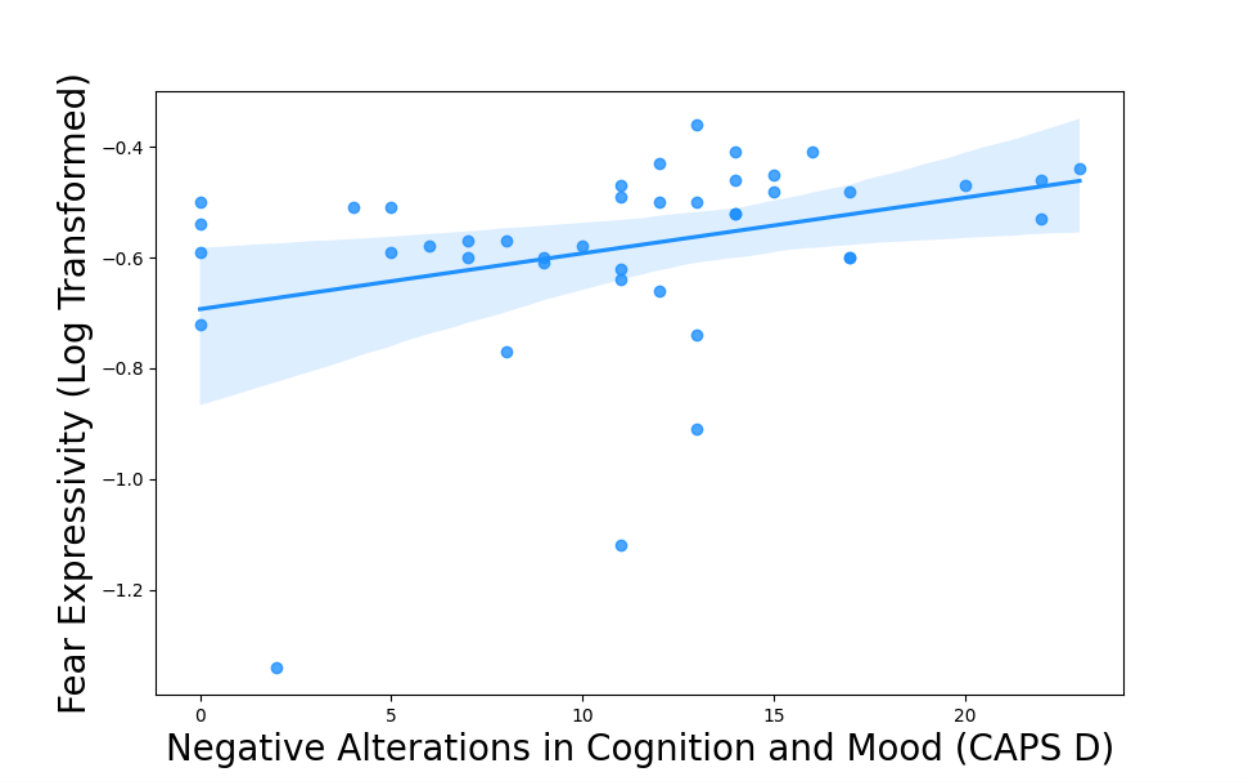

Figure 4: Associations between fear expression and PTSD negative cognition and mood severity. PTSD negative cognition and mood symptoms (CAPS D) showed a (non-statistically significant) positive association with fear expression (natural log transformed). Confidence intervals (95%) in light blue. N = 48, r = 0.33, p = 0.035.

Bivariate correlation analysis revealed statistically non-significant negative associations between neutral expression and overall PTSD symptom severity (r = -0.29, p = 0.062), negative alteration in cognition and mood (r = -0.29, p = .065), alteration in arousal and reactivity (r = -.40, p = 0.066), and distress or impairment (r = -0.27, p = .082) (Figure 5).

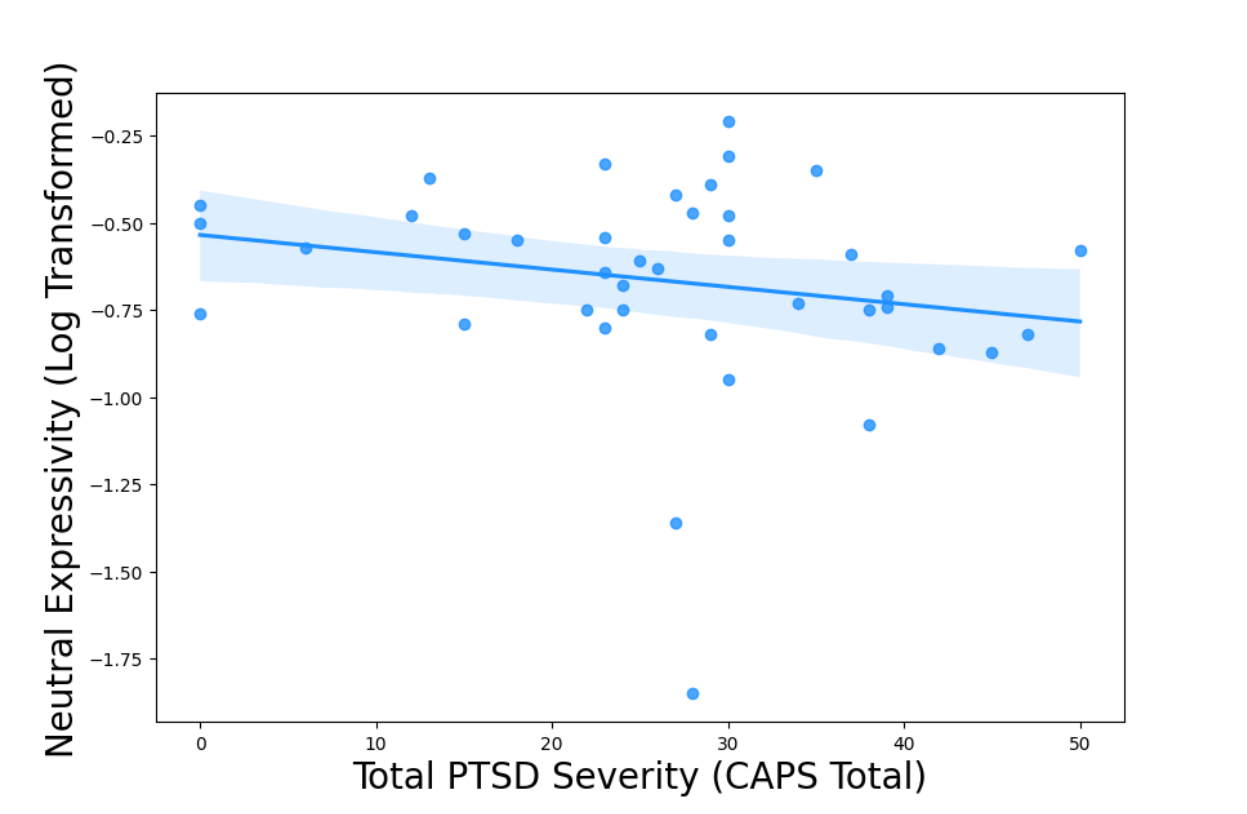

Figure 5: Associations between neutral expression and overall PTSD symptom severity. Overall PTSD symptom severity (CAPS total score) showed (non-statistically significant) negative association with neutral expression (natural log transformed). Confidence intervals (95%) in light blue. N = 48, r = -0.29, p = 0.062.

D. Vocal Expressivity

Pearson correlations were conducted between PTSD symptom clusters and variables of vocal expressivity. All correlations conducted can be found in the correlation table (supplementary table 1).

Bivariate correlation analysis revealed positive associations between positive sentiment and both overall PTSD symptom severity (r = 0.27, p = 0.049) and re-experiencing (r = 0.31, p =

0.027); although these associations did not meet our Bonferroni corrected threshold (Figures 6 and 7).

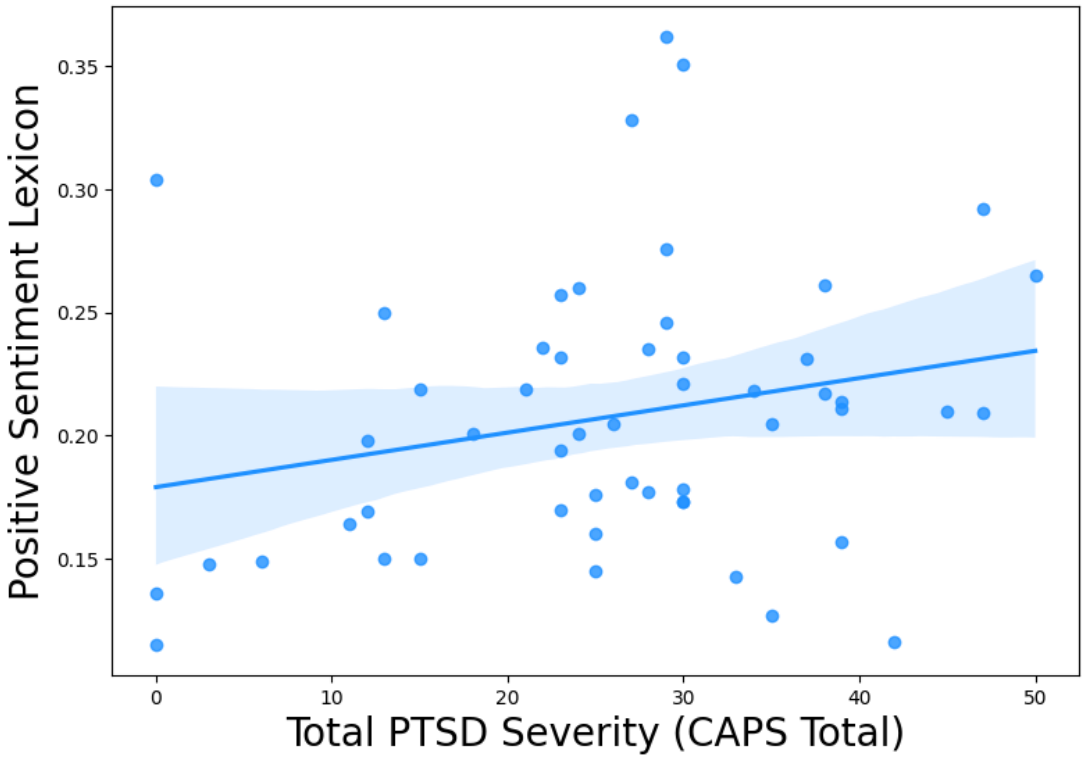

Figure 6: Associations between positive sentiment in lexicon and overall PTSD symptom severity. Overall PTSD symptom severity (CAPS total score) showed a (non-statistically significant) positive association with positive sentiment in lexicon. Confidence intervals (95%) in light blue. N = 53, r = 0.27, p = 0.049.

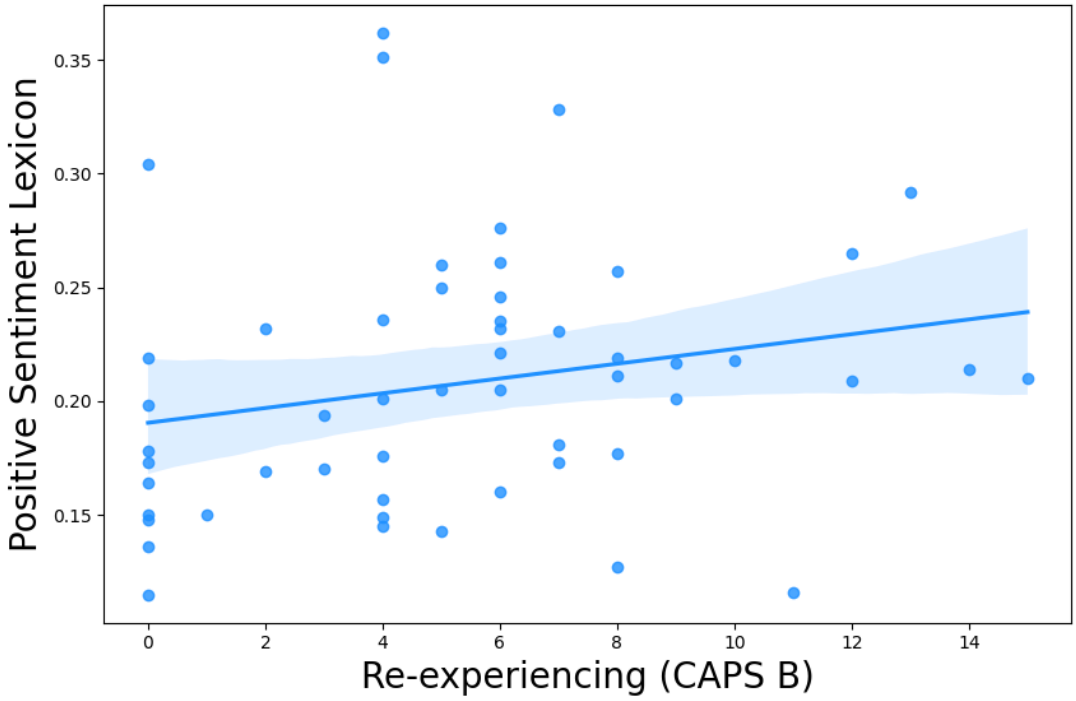

Figure 7: Associations between positive sentiment in lexicon and re-experiencing. PTSD re-experiencing symptoms (CAPS B) showed a (non-statistically significant) positive association with positive sentiment. Confidence intervals (95%) in light blue. N = 53, r = 0.31, p = 0.027.

Bivariate correlation analysis revealed a statistically non-significant positive association between both the rate of speech (r = 0.27, p = 0.049) and pause rate (r = 0.25, p = 0.073) with re-experiencing symptoms (Figures 8 and 9).

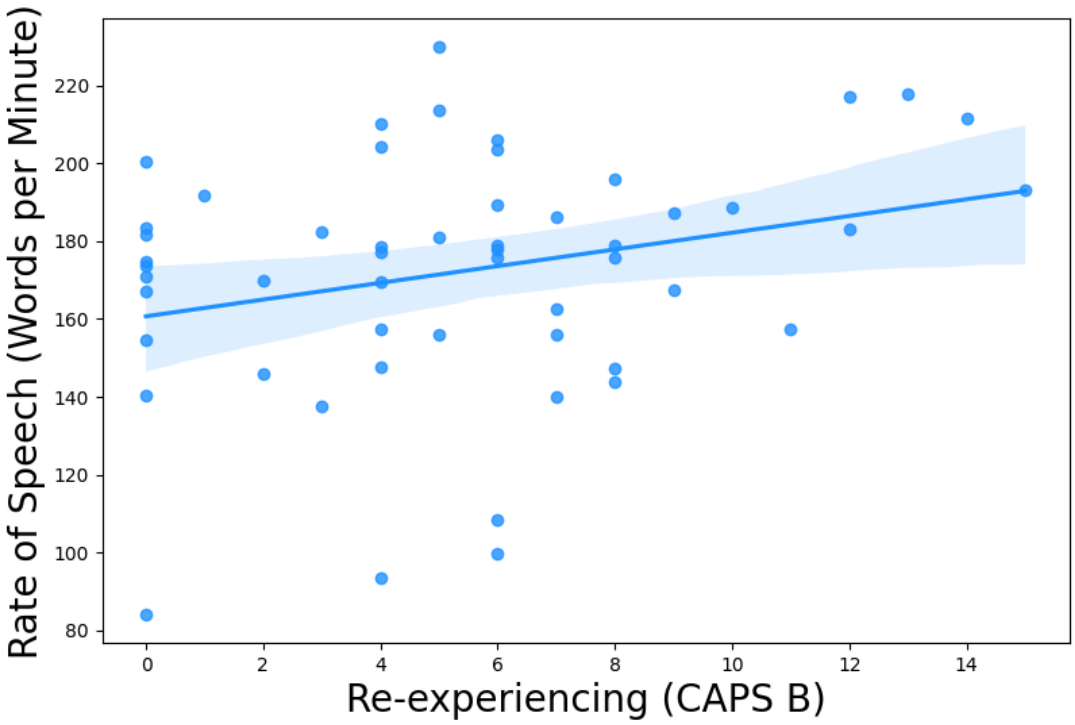

Figure 8: Associations between rate of speech and re-experiencing. PTSD re-experiencing symptoms (CAPS B) showed a (non-statistically significant) positive non-significant association with the rate of speech. Confidence intervals (95%) in light blue. N = 53, r = 0.27, p = 0.049.

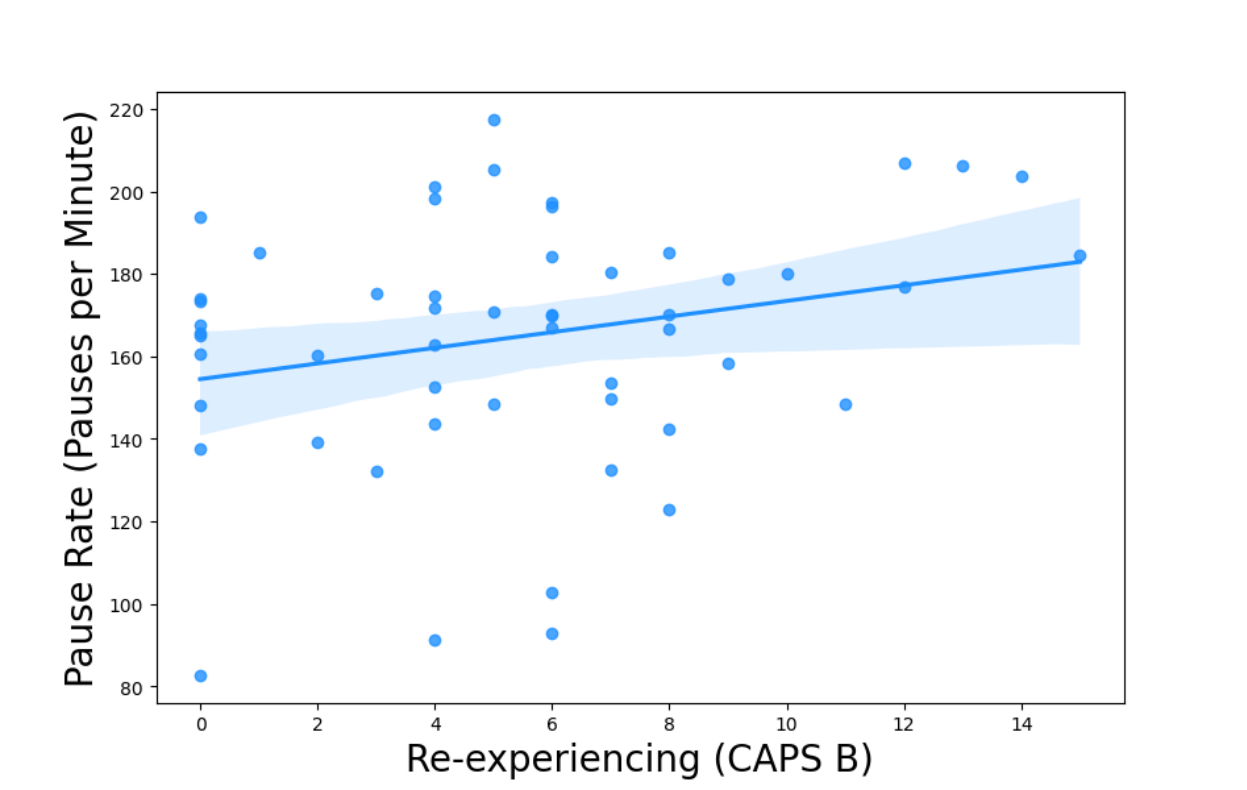

Figure 9: Associations between the pause rate and re-experiencing. PTSD re-experiencing symptoms (CAPS B) showed a (non-statistically significant) positive association with the pause rate. Confidence intervals (95%) in light blue. N = 53, r = 0.25, p = 0.073.

Bivariate correlation analysis revealed a significant negative association between Formant 1 variance and hyperarousal (r = -.31, p = 0.024) (Figure 10). No other significant or trending results were found for any vocal acoustic variables (supplementary table 3).

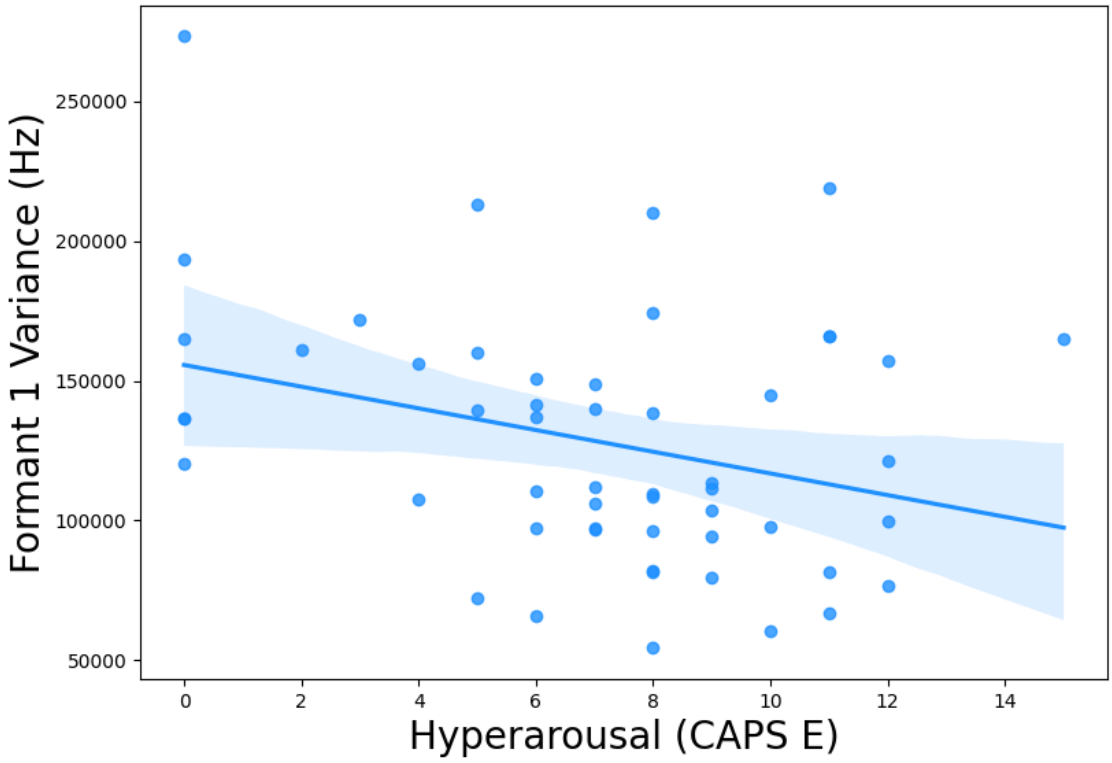

Figure 10: Associations between Formant 1 variance and hyperarousal. PTSD hyperarousal symptoms (CAPS E) showed a significant negative association with Formant 1 variance. Confidence intervals (95%) in light blue. N = 53, r = -.31, p = 0.024.

E. Associations between Facial and Vocal Expressivity

Bivariate correlation analysis revealed a significant positive association between overall facial expressivity and mean F0 (r = 0.32, p = 0.024) (Figure 11).

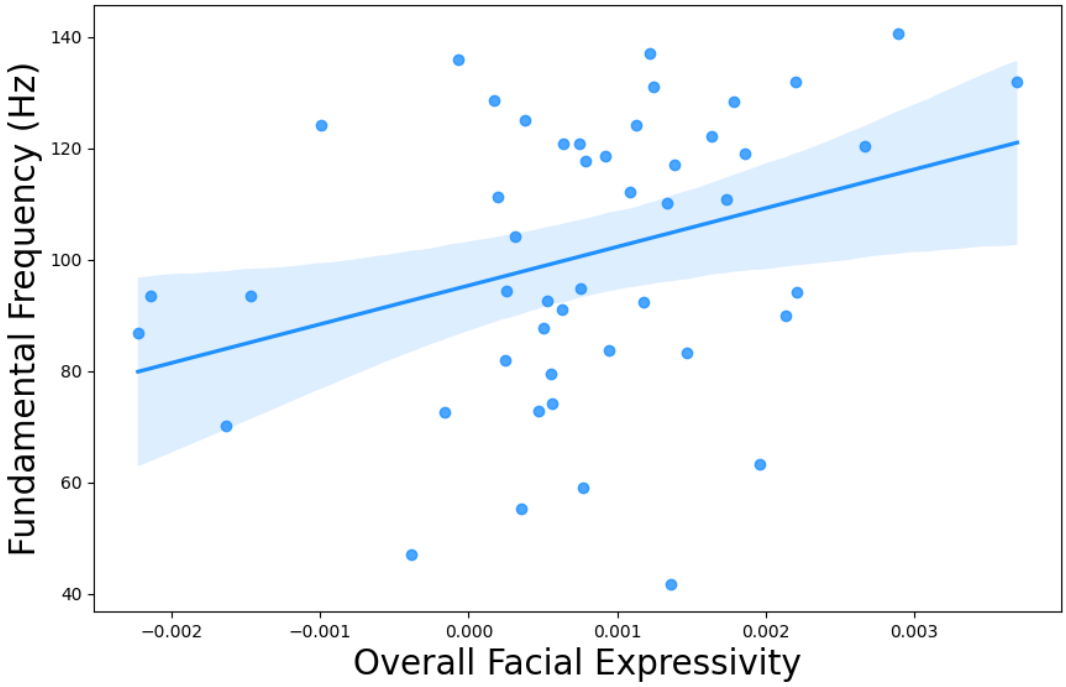

Figure 11: Associations between facial expressivity and mean F0. Overall facial expressivity showed a significant positive association with mean F0. Confidence intervals (95%) in light blue. N = 48, r = 0.32, p = 0.024.

IV. Discussion

A. Review of Study

The goal of this study was to examine potential associations between facial and vocal biomarkers of emotional expressivity and PTSD symptom severity. More specifically, we examined whether facial (anger, fear, happiness, and neutral) and vocal (F0, formants 1 and 2, rate of speech, etc.) biomarkers were associated with PTSD symptoms. I hypothesized that biomarkers of negative emotional expressivity including reduced overall facial movement, fear

expressions, anger expressions, reduced formant variance, reduced F0 frequency, and increased negative sentiment in word use would be positively correlated with overall PTSD symptom severity. Additionally, I hypothesized that markers of positive emotional expressivity including happiness expression, increased formant variance, higher F0 frequency, and increased positive sentiment in word use would be negatively correlated with overall PTSD symptom severity. The results reveal meaningful candidate facial and vocal biomarkers of emotion that may be used in research and clinical settings.

B. Facial Emotional Expressivity

In line with hypothesis 1a, we found that general facial expressivity was negatively correlated with one cluster of negative/fear related symptoms in PTSD: re-experiencing symptoms. Since re-experiencing involve re-living of trauma during day-to-day life, it is possible that this reliving interrupts individuals' ability to identify and express emotions appropriately (Michael et al., 2005). Since their regular interactions and emotional responses may be interrupted by these memories, it may be harder for individuals with high re-experiencing symptoms to express their feelings. The only individual facial emotional expression that significantly correlated with PTSD symptoms was fear; greater fear expression correlated with higher overall symptom severity as well as avoidance and negative alterations in cognition and mood symptoms. In prior studies, this greater fear expression has been used to accurately predict PTSD diagnosis (Schultebraucks, 2022). It is suggested that there may be a unique alteration on fear expression caused by PTSD, though it was unclear whether this relationship was not actually because individuals with a different fear response were more susceptible to developing PTSD. Our results indicate that fear expression may be associated with PTSD symptom severity,

suggesting it is a symptom biomarker of PTSD. Thus, there may be alterations to the fear response as a result of PTSD in order to cause this abnormal expressivity of fear. Studies have shown associations of altered processing of threat and fear symptoms in PTSD (Zoellner, 2020). For example, in a prior study that included all Black participants, biased attention to threatening facial expressions depicted in White (but not Black) faces corresponded with PTSD symptoms, particularly hyperarousal, and this biased attention to threat corresponded with greater threat responses during a fear-potentiated startle paradigm (Fani et al., 2012). Other studies have found that this altered startle response is fairly unique to individuals with PTSD (Jovanovic, 2010). Thus, this altered fear response appears to manifest itself in the face, allowing fear expression to serve as a potential biomarker of PTSD. This finding supports mechanistic work which examines neurophysiological differences in fear for those who have PTSD (Shvil, 2013) since if it manifests in the face and startle response, there is likely a mechanism relating to the development of PTSD. Interventions targeting improvement of fear and anxiety in individuals with PTSD could potentially use facial fear expression as an external measure of intervention success. Thus, we found that some biomarkers of negative emotional expressivity were indeed associated with PTSD symptoms. We also demonstrate how certain symptoms of PTSD relate to specific biomarkers of negative emotions. However, we did not see any relationships of positive facial emotional expressivity with PTSD symptoms. This differs from prior work in which PTSD individuals report feeling fewer positive emotions (Elman et al., 2018). Indeed, some studies found an increase in negative emotion and decrease in happiness expression when manually examining facial behaviors during in-person clinical interviews (Kirsch & Brunnhuber, 2007). However, the remote nature of our interviews may be different contextually in which participants while in-person more actively express positive emotions due to its importance during social

interactions (Williams et al., 2018). In other words, since positive emotions are important during interactions with others, individuals with PTSD may be better at expressing positivity when they do not feel it due to experience with anhedonic symptoms. Lastly, neutral expressions were non-significantly reduced in individuals with higher overall PTSD symptom severity as well as in negative cognition and mood and hyperarousal. Further work with larger samples is necessary to determine if these findings are replicable. It may be that with increased expression of fear and possibly anger, there is a reduction in neutral expressions (Norrholm et al., 2015). Furthermore, this does align with work that did not find any sign of neutralization of emotional expression (Orsillo et al., 2004). It would seem that, in our sample, negative facial emotions may be more strongly impacted than positive emotions. These differential results between different emotions validates our approach in assessing multiple emotional domains rather than emotionality in general. Additionally, we found that although overall facial expressivity was reduced in those with higher re-experiencing symptoms, it was not due to a reduction in any specific emotion. This may mean that although there are fewer facial movements, it may be due to alterations across multiple emotion domains rather than one in particular. Furthermore, the specificity of fear may suggest a mechanistic impact of PTSD on fear expression (Shvil et al., 2013). This is especially relevant in the context of the CAPS, since it involves recalling recent thoughts or feelings related to the symptoms of PTSD, which may lead to heightened feelings of fear during the interview.

C. Vocal Emotional Expressivity

We additionally examined whether biomarkers of speech and vocal acoustics correlated with PTSD symptoms. Overall PTSD symptom severity and re-experiencing symptoms specifically showed a non-significant positive association with positively valanced sentiment, which did not support our hypothesis. It is possible that verbal expression of positive emotion may reflect a coping strategy in response to a high level of distress; these individuals may have learned to express positive emotion through their words even when they do not feel positive emotions. A study examining veterans with and without PTSD found that emotional suppression was more common in the PTSD population (Khan, 2021). Individuals thus may more consciously behave to prevent their negative emotions by selecting words with positive sentiment in order to consciously express positivity when they do not feel it. Our findings are in contrast with another study directly examining the produced speech of individuals with PTSD, which found decreased positive sentiment in the PTSD group compared to healthy controls (Sawalha, 2022). However, this study was performed with task-focused language rather than during clinical interviews, so the context may hold some different influence in the participants' word choice. In line with Hypothesis 1b, the pause rate was increased in those with higher re-experiencing symptoms. Some other studies have found that an increased pause rate during a simulated casual conversation with a virtual human was associated with PTSD symptom severity, which was suggested to relate to psychological distress (DeVault et al., 2013). The context in which participants discuss their symptoms resulting from PTSD may help contribute to this association between pause rate and PTSD severity. The rate of speech was also increased in those with higher re-experiencing symptoms. Prior studies have found slower rates of speech for those with more severe PTSD symptoms, including during the CAPS-5 interview (Fernandez-Lansac, 2015, Marmar, 2019). However, these studies did not examine symptom

clusters, but rather, correlation with a PTSD diagnosis made prior to intervention. Thus, this finding may be specific to the context and the symptom cluster of re-experiencing.

Lastly, Format 1 variance, which reflects the monotony of the voice, showed an inverse relationship with symptoms of hyperarousal. This suggests that individuals with more of these fear-related PTSD symptoms show more monotony in their voice (Scherer et al., 2015). This suggests a reduction in emotional expressivity since emotional expressivity has been connected to the variation in formant frequency (Khulage, 2012). In other words, participants with worse hyperarousal symptoms may be less tonally expressive. This may connect with our facial expressivity finding in which fear expression was increased. Other studies have suggested that individuals who experience PTSD may face a unique pattern of fear (Zoellner, 2020). Consequently, this pattern of fear expression is likely to manifest itself in facial and vocal behavior. Thus, these biomarkers of fear may serve as a useful biomarker of fear. Additionally, this further supports studies examining the neurologic abnormalities in fear-related brain regions since there is also a physical manifestation of fear for those with PTSD. Since a similar change to the first two formants has been connected to emotional stress, perhaps this marker of tone can be used as a measure for reactivity of participants to inform clinicians, perhaps to advise if a break or a different approach is needed. Regardless, vocal biomarkers showed some association with PTSD symptoms.

D. Correlations between Facial and Vocal Biomarkers

In analysis of how the biomarkers relate to one another, we found that individuals with greater anger expressions had increased overall facial expressivity. This matches prior work seeing increased negative emotions due to anger specifically in PTSD populations (Blechert et

al., 2013). In addition, the fundamental frequency, which reflects the emotional state (Busso, 2009), was higher with greater facial expressivity. This aligns with the positive relationship established between emotional expression and F0 in which a higher F0 was associated with greater (namely positive) emotional expressivity (Busso et al., 2009). These relationships may suggest that a measure compiling multiple domains of expressivity may be useful to thoroughly analyze emotional expressivity in PTSD.

F. Limitations

Several important limitations of this study should be considered. Firstly, although AI provides a more objective lens as compared to human raters, AI algorithms have variable performance in clinical and non-clinical data samples, and thus study did not have a sufficient sample size to test performance (Thieme et al., 2020). It may be useful to include manual coding of randomly subjects to assess reliability of the algorithm. Additionally, clinician-assessed CAPS, as with every measure, holds some limitations. However, our results were consistent with the PCL-5, another measure of PTSD symptom subtypes and severity (supplementary table 2). Another limitation of this study is the limited sample size, which may affect power to detect statistically significant effects; further research with larger sample sizes is needed to replicate and extend this work. Furthermore, facial and vocal expressivity during live assessment of the CAPS involves discussion of trauma and its consequences. This is useful as it matches the context in which researchers and physicians may collect the data while performing their assessments. However, this context is very different from everyday interactions, which does seem to affect the emotionality and speech in PTSD populations in unique ways (van den Broek et al., 2010). To fully understand the impact of PTSD in facial and vocal expressivity, it is

important to evaluate across a variety of contexts and situations. Despite these limitations, we do demonstrate that PTSD symptom subtype and severity is associated with specific facial and vocal digital biomarkers.

G. Conclusions and Future Directions

We demonstrate that particular video-derived biomarkers of facial and vocal emotional expressivity corresponded with PTSD symptoms, particularly fear-related symptoms. Specifically, we found that biomarkers of fearful facial emotional expression, rate of speech, and pause rate were positively correlated with increased PTSD symptoms. We also found that overall facial expressivity and formant 1 variance were negatively correlated with PTSD symptoms. Given that greater expression of fear, as well as increased rate of speech and pause rate were linked to PTSD symptom severity, these features may be useful target biomarkers for future studies of acutely trauma-exposed populations (e.g., prospective studies that track these individuals over time) that may examine these factors as potential predictors of post-traumatic outcomes, including PTSD symptoms. These studies may examine which biomarkers are most useful predictors to responsiveness to certain treatments, potentially allowing individualized assignment to the treatment in which a patient would be most responsive to. Other clinical studies, particularly those using exposure-based methods (which target fear-based symptoms of PTSD) may wish to either examine change in these biomarkers over time and corresponding changes in clinical symptoms or as prognostic markers of treatment outcomes. Namely, studies may wish to examine the mechanistic reasons behind the observed altered fear expression. In studies examining fear attention, greater fear expressivity PTSD populations has been associated with biased fear attention towards perceived threats (Fani, 2012). Mechanistically, several cortex

regions such as the bilateral amygdalae, parahippocampal region, and the hippocampal region (Badura-Brack, 2017). However, future studies should examine these functional differences as they associate in real-time with facial expressions in order to elicit the mechanism of altered fear expression in PTSD. Furthermore, given the findings of reduced overall facial expressivity and greater monotony (reduced formant 1 variance), other studies may wish to examine these biomarkers with clinical assays of emotional numbing to assess their impact on social interactions of individuals with PTSD. Future studies may wish to examine whether improvement in these biomarkers may correlate with improvements in forming social bonds since one would expect that as emotional expressivity abnormalities are resolved, it may be easier for those with PTSD to socialize. Furthermore, these can potentially serve as biomarkers of responsiveness towards certain interventions requiring emotional openness. These biomarkers in general could allow another objective lens of examining PTSD severity and help target specific symptom clusters in interventions. Additionally, studies may wish to examine these potential biomarkers of emotional numbing with neuroimaging in order to deepen our understanding of the functional mechanisms behind these altered vocal expressions in PTSD populations.

Given the small sample size of our study, further investigation with a larger sample size is necessary to confidently assess PTSD symptoms through these biomarkers. This study used the open-source Python-based software OpenWillis, which helps pave the way to methods accessible to any researcher for biomarker analysis. Furthermore, interventions that do not just resolve self-reported symptoms, but also externally relevant variables, can be useful, namely because of how important emotionality is for social interactions (Beidel et al., 2019). Interventions that do not just improve self-perceived emotions, but also impact expressed emotions may help social

integration and social relationship forming of individuals suffering from PTSD. Future interventions may be able to examine how external emotionality influences the social networks and consequent life quality of those diagnosed with PTSD. Additionally, since we found several biomarkers of fear expression influenced by PTSD symptom severity in our findings, out findings support interventions that target re-experiencing symptoms. These interventions may be able to evaluate any changes in the fear-related expressivity in the face, which may be beneficial to measure the success of interventions as well as examining whether the fear emotional expression is altered alongside improvements in other clinical variables. This may also benefit participants in reducing the interruptions to their focus on engaging with certain interventions, thereby improving the efficacy of interventions as participants continue further with the studies. Further investigation may help determine the clinical value of these biomarkers for interpreting improvements in the emotional experience of those with PTSD. Furthermore, developing these methods may allow a combination of these different measures of emotionality in order to assess overall emotionality across face and voice and how it relates to PTSD. Since these methods assisted in exploring emotional variables in relation to PTSD, future work should explore other mental health variables, such as dissociation, as they relate to these biomarkers.

V. Supplemental Tables

Supplemental Table 1: Correlations table of Facial and Vocal Biomarkers with CAPS

	CAPS B (Re-experiencing)	CAPS C (Avoidance)	CAPS D (Negative cognition and mood)	CAPS E (Hyperarousal)	CAPS Total
Mean Facial Expressivity (N = 43)	**-.335***	-.195	.076	-.121	-.137
Log Anger (N = 43)	-.027	.002	.162	.063	.090

Log Fear (N = 43)	.170	**.348***	**.327***	.172	**.321***
Log Happiness (N = 43)	.073	.124	.129	.022	.114
Log Neutral (N = 43)	-.174	-.071	-.*288*	-.*286*	-.*291*
Negative Sentiment (N = 53)	-.179	.028	-.145	-.113	-.157
Neutral Sentiment (N = 53)	-.158	-.110	-.105	-.203	-.180
Positive Sentiment (N = 53)	**.310***	.079	.159	.195	***.247***
Rate of Speech (N = 53)	**.272***	.115	.104	.104	.188
Pause Rate (N = 53)	***.248***	.098	.089	.087	.165
Pause Mean Duration (N = 53)	-.125	.027	.033	.116	.015
Silence Ratio (N = 53)	-.078	.071	.044	.148	.052
F0 Mean (N = 53)	-.040	-.025	.078	.067	.041
F0 Variance (N = 53)	.016	-.021	-.017	.084	.018
Formant 1 Mean (N = 53)	-.072	.050	-.195	-.031	-.118
Formant 1 Variance (N = 53)	-.052	-.010	-.220	**-.311***	-.216
Formant 2 Mean (N = 53)	-.002	-.143	-.073	-.087	-.085
Formant 2 Variance (N = 53)	.034	.149	.107	.030	.096

Supplemental Table 2: Correlations of Facial and Vocal Biomarkers with PCL-5

	PCL-5 Total	PCL-5 Cluster b (re-experiencing)	PCL-5 Cluster c (avoidance)	PCL-5 Cluster d (negative cognition and mood)	PCL-5 Cluster e (Hyperarousal)	PCL-5 Anhedonia
Mean Facial Expressivity (N = 48)	-.179	**-.327***	-.264	-.074	-.030	-.069
Log Mean Anger (N = 48)	-.080	-.146	**-.306***	-.032	.099	.089
Log Mean Fear	.178	.102	.016	**.301***	.046	.*247*

Log Mean Happiness (N = 48)	-.030	.090	-.181	-.074	.045	.001
Log Mean Neutral (N = 48)	-.220	-.272	.045	-.270	-.073	-.231
Negative Vocal Sentiment (N = 59)	-.189	-.081	-.066	-.153	-.233	-.154
Neutral Vocal Sentiment (N = 59)	-.113	-.139	-.033	-.149	-.026	-.192
Positive Vocal Sentiment (N = 57)	.240	**.262***	.060	.232	.163	**.278***
Rate of speech (N = 59)	0.178	0.127	0.151	0.179	0.111	**.319***
Pause rate	0.12	0.162	0.037	0.129	0.028	0.22
Mean duration pauses (N = 59)	-0.14	-0.194	-0.082	-0.087	-0.095	-0.19
Silence ratio	0.074	-0.006	0.131	0.024	0.134	-0.007
F0 mean (N = 59)	-0.029	0.042	0.046	-0.153	0.08	*-0.219*
F0 variation (N = 59)	0.099	**.271***	-0.058	-0.035	0.125	-0.115
Form1 mean (N = 59)	0.013	0.02	0.167	-0.121	0.12	-0.154
Form1 variation (N = 59)	-0.145	-0.14	-0.104	-0.149	-0.086	-0.101
Form 2 mean (N = 59)	0.033	0.122	-0.48	-0.116	0.162	-0.082
Form 2 variation (N = 59)	0.178	0.15	0.166	0.118	0.152	0.051

Supplemental Table 3: Correlations Table between Facial and Vocal Biomarkers

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Facial Expressivity																	
2. Log Anger	*.276*																
3. Log Fear	.180	-.010															
4. Log Happiness	.255	-.009	.047														

5. Log Neutral	-.217	-.150	-.234	-.210													
6. Negative Sentiment	-.105	.009	.007	-.060	.031												
7. Neutral Sentiment	-.035	.001	-.067	-.178	.136	-.215											
8. Positive Sentiment	-.081	-.127	-.005	.217	-.*291*	-.201	**-.899**										
9. Rate of Speech	-.178	-.027	.121	.080	-.079	.118	-.057	.083									
10. Pause Rate	-.177	-.031	.098	.069	-.073	.163	-.081	.088	**.996**								
11. Pause Mean Duration	.125	.122	-.152	-.097	.120	-.177	-.159	.139	**-.863**	**-.866***							
12. Silence Ratio	.095	.104	-.141	-.110	.101	-.204	-.186	.190	**-.801**	**-.805**	**.981***						
13. F0 Mean	**.324***	.164	-.187	**.312***	-.219	-.044	-.010	-.089	-.085	-.091	.053	.014					
14. F0 Variance	.012	.065	.033	.231	-.312	.062	-.094	-.026	-.015	-.024	.017	.016	**.667***				
15. Formant 1 Mean	-.135	-.100	.226	-.090	-.049	.008	.073	.003	-.084	-.088	.070	.127	**-.430**	-.017			
16. Formant 1 Variance	-.128	-.110	.022	.051	-.002	.055	.115	-.071	-.021	-.010	-.186	-.190	**-.263**	**-.307**	.*245*		
17. Formant 2 Mean	-.083	-.028	-.061	.042	-.225	.088	.114	.003	.200	.212	**-.321**	**-.319**	.015	.180	**.272***	**.471***	
18. Formant 2 Variance	-.195	-.147	-.069	-.007	.135	.072	.192	-.205	-.094	-.077	-.021	-.031	-.033	-.020	-.007	**.283***	.100

VI. Bibliography

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