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Research paper

Day-to-day dynamics of facial emotion expressions in posttraumatic stress disorder

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ABSTRACT

Facial expressions are an essential component of emotions that may reveal mechanisms maintaining posttraumatic stress disorder (PTSD). However, most research on emotions in PTSD has relied on self-reports, which only capture subjective affect. The few studies on outward emotion expressions have been hampered by methodological limitations, including low ecological validity and failure to capture the dynamic nature of emotions and symptoms. Our study addresses these limitations with an approach that has not been applied to psychopathology: person-specific models of day-to-day facial emotion expression and PTSD symptom dynamics. We studied a sample of World Trade Center responders ($N = 112$) with elevated PTSD pathology who recorded a daily video diary and self-reported symptoms for 90 days (8953 videos altogether). Facial expressions were detected from video recordings with a facial emotion recognition model. In data-driven, idiographic network models, most participants (80 %) had at least one, reliable expression-symptom link. Six expression-symptom dynamics were significant for >10 % of the sample. Each of these dynamics had statistically meaningful heterogeneity, with some people's symptoms related to over-expressivity and others to under-expressivity. Our results provide the foundation for a more complete understanding of emotions in PTSD that not only includes subjective feelings but also outward emotion expressions.

Outward emotional expressions are an understudied aspect of posttraumatic stress disorder (PTSD). Clinical theories propose outward emotion expressions associated with PTSD reflect pathophysiological and psychological mechanisms. Based on the observation that some trauma-exposed individuals over-regulate and appear unemotional, whereas others under-regulate and are highly expressive has led to hypotheses about neurobiological differences between people (Lanius et al., 2006, 2010) and variation in strategies for coping with trauma (e.g., emotional avoidance/numbing vs. impulsivity/dyscontrol; Horowitz, 1986a; Litz et al., 2000). Emotion expressions are also directly tied to social functioning. Abnormalities in these non-verbal behaviors affect communication and may contribute to psychosocial difficulties that are common in PTSD (Schuman et al., 2019; Scoglio et al., 2022). Furthermore, from a basic science perspective, nearly all theories define emotion as multicomponential, with internal, subjective feelings and external expressions (Scherer, 2000). Thus, any understanding of emotions in PTSD would be incomplete without knowing the role of outward expressions.

Methodological challenges of assessing outward expressions have posed a major barrier to studying their role in PTSD. Some work has used electromyography (EMG) to measure emotional expressions (Pole, 2007), but this method is limited by low ecological validity (Wolf, 2015). Another approach has involved human raters coding facial expressions from videos of participants recorded in laboratory settings while being interviewed or watching emotionally evocative film clips. Studies of emotional expressions in PTSD using this method have been

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limited by very small samples (*Ns* < 20), which yielded small effect sizes and inconsistent findings (Foa et al., 1995; Kirsch and Brunnhuber, 2007; Orsillo et al., 2004; Sullivan et al., 2018; Wagner et al., 2003).

More recently, advances in artificial intelligence (AI) technology allow for automated detection of facial expressions and head movements from video recordings (Cohn et al., 2018). AI-based assessments enable analysis of larger samples and more rigorous investigation of links between emotion expressions and psychopathology like PTSD. Most clinical research using AI to study emotion expressions has been on depression, with findings consistently showing a relationship between symptoms, facial expressions, and head movement (Abbas et al., 2021a, 2021b; Girard et al., 2014; Pampouchidou et al., 2020; Ringeval et al., 2019; Wang et al., 2020; Yin et al., 2019). Growing literature on depression shows these methods have potential to track clinically relevant behavior at scale.

The few studies to date that have applied AI-based assessments to PTSD find some promising results, but also highlight a need for more work. On the one hand, it has been shown that facial expressions are among the top predictors of PTSD alongside measures of natural language and speech acoustics, and PTSD status can be predicted from facial expressions and head movement alone with modest accuracy (Schultebraucks et al., 2022; Tavabi et al., 2020). On the other hand, a clear picture hasn't emerged on the specific emotional expressions related to PTSD, with conflicting findings on which emotional expressions are the strongest markers (Fujiwara et al., 2015; Scherer et al., 2014; Schultebraucks et al., 2022). One reason for differences in associations between PTSD and emotional expressions may be that there is wide variation between people in how their symptoms relate to emotion expressions.

Another limitation of the small but promising literature linking PTSD to facial expressions is that this work has only used cross-sectional designs, and most often in laboratory settings. This is problematic because the links between emotions and symptoms are dynamic and contextualized. That is, emotions and trauma-related distress are elicited by daily life situations, people modulate their emotional expressions to cope with trauma-related distress (symptom → expression), and effectiveness of the coping strategy can either alleviate or worsen their symptoms over the long-term (expression → symptom) (Seligowski et al., 2015). Thus, a person's typical *temporal sequencing* of emotion expressions and symptoms over time, in real-life situations, could reveal more information about mechanisms underlying their problems, with better ecological validity, than a cross-sectional snapshot in the laboratory.

1. Current study

This study aims to advance understanding of emotions in PTSD with a new approach to studying emotion expressions. Specifically, we studied the dynamics of emotion expressions and PTSD symptoms assessed in the everyday lives of 112 World Trade Center disaster responders. Participants completed daily video diaries and self-reported PTSD symptoms for 90 days, and emotion expressions were extracted by AI from the recordings. These unique data allowed us to address questions about emotions in PTSD that have never been studied before including: do emotion expressions dynamically track with symptom fluctuations? If so, which expressions? What is the temporal ordering of symptoms and expressions? And perhaps most importantly, do the majority of people exposed to trauma share the same emotion/symptom dynamics or are there subsets of people with different dynamics?

To answer these questions, we used data-driven person-specific network models. This method preserves each person's unique temporal patterns of emotion expressions and symptoms and allowed us to identify dynamics shared by subsets of the sample. Given the novelty of these data, and lack of empirical precedent on this topic, our data-driven approach was ideal for generating insights about emotion expressions in PTSD. Importantly, our goal was not to determine subjective feelings linked to symptoms, as there is not a one-to-one correspondence of facial expressions to felt emotion (Barrett et al., 2019). Instead, we aimed to provide foundational knowledge about regularities in emotion expressions and symptoms needed to advance this area of research and fill gaps in understanding about emotions in PTSD.

2. Methods

Data, code, full model output, and Supplementary materials are on the Open Science Framework page for this study (https://osf.io/ujp5n/?view_only=c3bacbff48bc45b0adb4bdad1b93f61a).

2.1. Participants

This sample comes from a project that is aiming to develop tools for automated monitoring of PTSD symptom severity. Data collection for the project began in 2022 is still active. Participants are World Trade Center disaster responders recruited from the Stony Brook World Trade Center Health Program. Potential participants were identified based on data from their most recent clinic visit. To be eligible for participation, responders had to have elevated PTSD symptoms (i.e., PTSD checklist for the *DSM-IV* [PCL] scores ≥33). Due to the study protocol's complexity, responders with cognitive impairment were ineligible for participation (i.e., Montreal Cognitive Assessment [Nasreddine et al., 2005] score ≤18). The total number of participants included in this study was 112 after applying exclusion criteria (detailed in the Analytic Plan). Participants were mostly White (60 %; 4 % Black/African American, 6 % other/multi-racial, 29 % not recorded/refused to answer) and male (84 %), with an average age of 59.87 (range = 42–79).

2.2. Procedure

Participation involved an in-person laboratory session and a 90-day daily diary protocol. During the initial session, participants were consented and received training on the daily diary protocol. This protocol consisted of the participant recording a video on their personal smart device and completing a brief self-report survey of PTSD symptoms each day. For the video recordings, participants discussed their experiences that day. Participants were trained to discuss emotionally relevant topics, and could talk about a topic of their choosing or follow example prompts (e.g., "tell me about the worst part of your day," "describe when you felt most happy today"). Video recordings were required to be between 3 and 10 min long. Participants received $5 per post (i.e., survey and video) for a maximum compensation of $450 over the course of the study.

Adherence and data quality were closely monitored. Study staff reviewed videos daily to ensure adequate lighting and orientation to obtain facial expression data. If problems with the video recordings were identified, or the daily surveys were not being completed consistently, study staff contacted participants to troubleshoot issues.

2.3. Measures

2.3.1. Daily PTSD symptoms

PTSD symptoms were assessed using 8 items adapted from the PCL-5 (Weathers et al., 2013). This scale has been validated for use in ambulatory assessment settings (Ruggero et al., 2021). Participants were rated symptom severity on a scale from 1 ("not at all") to 5 ("extremely"). Total PTSD symptom severity was calculated by averaging all items (within-person internal consistency [ω] = 0.84).

2.3.2. Emotional expressions

Emotional expressions were obtained from the daily video diaries. Facial expressions and head movements were extracted from the recordings using FaceReader version 8.0, a commercially available automated emotion classification software (Noldus, 2019). FaceReader uses a deep neural network to recognize facial emotion expressions from

image pixels in each video frame (Bulat and Tzimiropoulos, 2017; Gudi et al., 2015). The present study assessed intensity of neutral, happy, angry, sad, surprised, disgusted, and fear expressions. Facial emotion arousal (i.e., overall activation of facial action units), and head movement (Abbas et al., 2021a, 2021b). FaceReader was trained to classify the basic emotions described by the Facial Action Coding System (FACS; Ekman et al., 1987), which is among the most psychometrically rigorous and widely used rating systems for facial expressions (Cohn and Ekman, 2005; Ekman and Rosenberg, 1997). For our analyses, we took the mean intensity level of each emotional expression from each video. Prior research indicates FaceReader is one of the most accurate facial emotion expression recognition algorithms, with good convergence with manually coded facial emotions and comparable accuracy to human raters (Dupré et al., 2020; Gupta et al., 2022).

We refer to the variables measured by FaceReader as emotional expressions, and use the emotion labels used by FaceReader, but we do not interpret these variables as reflecting a particular *subjective* emotional state. Rather, we use these labels as a shorthand to describe different facial muscle movement configurations defined by FACS.

2.4. Analytic plan

We used an idiographic network modeling approach called Group Iterative Multiple Model Estimation (GIMME). GIMME uses a unified structural equation modeling framework to uncover contemporaneous and lagged relations in a set of time-series variables for each individual in a sample (Gates and Molenaar, 2012; Luo et al., 2023). For our study, we used GIMME to search all possible contemporaneous paths (i.e., covariances) reflecting the co-occurrence of emotion expressions and PTSD symptoms from day-to-day and cross-lagged paths reflecting relations between emotion expressions and next-day PTSD symptoms (and vice versa).

GIMME only estimates individual-level models. Model fitting proceeds in two basic steps: a group-level and individual-level path search. First, the GIMME algorithm searches for group-level paths that improve fit for the majority of individual models (i.e., 51 % of the sample in our analyses). Group-level paths represent relations between emotional expressions and PTSD symptoms that are shared by most participants. Modification indices are used to determine the increment in fit associated with a path. In the second step, the group-level paths identified in step one are re-estimated in each individual's model to serve as a baseline for identifying individual-level paths. Starting the individual-level models with this group-level information improves the correct detection of paths (Gates and Molenaar, 2012). Additionally, autoregressive effects for every variable were freely estimated for each participant to increase the accuracy of path recovery (Lane et al., 2019). For the individual-level search, GIMME frees paths that are significant for an individual until the model fit criteria are satisfied (i.e., excellent fit for two of four indices defined as root mean square error of approximation [RMSEA] or standardized root mean squared residual [SRMR] $\leq$0.05 or non-normed fit index [NNFI] or comparative fit index [CFI] $\geq$0.95). Missing days of data were accommodated by full information maximum likelihood estimation, as is the default in GIMME (Beltz and Gates, 2017).

The final result of GIMME is a separate model for each participant consisting of group-level and individual-level paths. Each temporal path estimated by GIMME can be conceptualized as an individual difference variable reflecting emotion-related symptom processes (i.e., relatively stable patterning of symptoms and emotional expressions). Given that the model included nine emotional expression variables, this means that we estimated each participant's standing on a total of 27 individual differences (18 cross-lagged effects, 9 covariances).

2.5. Ensuring statistical robustness of results

GIMME prevents spurious results with several safeguards throughout the model-building process. During the group-level search, *p*-values for modification indices used to determine the number of participants for whom freeing a given path would significantly improve their model are Bonferroni corrected for the sample size, and *p*-values for paths in individual models are also Bonferroni corrected. During the individual-level search, highly stringent path selection criteria are applied such that no paths are freed after the global fit criteria are satisfied and *p*-values for modification indices used to determine if a path improves the model are Bonferroni corrected. Multiple simulation studies have shown that the number of false positives recovered by GIMME are very low (Gates and Molenaar, 2012; Beltz and Gates, 2017; Nestler and Humberg, 2021), even with sample sizes much smaller than the present study (e.g., 25 participants; Lane et al., 2019).

We took several additional measures to ensure the robustness of our results. First, we followed established standards of interpreting only those paths that were significant in >10 % of the sample (Groen et al., 2022). Second, we confirmed that heterogeneity in each of these common paths were statistically significant in our sample using accepted criteria (Bolger and Zee, 2019; Goldring and Bolger, 2021). These criteria are: 1.) the standard deviation (SD) of effects has a confidence interval that does not contain zero and 2.) the SD is >25 % the size of the average effect.[1]

2.5.1. Data exclusions

Several exclusion criteria were applied to the available sample (N = 167; n = 11,068 recordings) for our analyses. To ensure data quality, we excluded video recordings with fewer than 1800 valid frames (i.e., less than 1 min of readable video) (n = 858 recordings excluded). Participants with fewer than 45 observations were also excluded (n = 46) based on simulation studies showing that path recall in GIMME with ten variables shows adequate performance with 30–60 observations (Lane et al., 2019). Finally, we excluded participants whose individual models were non-positive definite[2] (n = 9). As a result, the analytic sample size was 112 participants, with an average of 88 observations per person (range = 45–106).

3. Results

Descriptive statistics, bivariate between- and within-person correlations among study variables, and non-focal GIMME results are in the Supplementary materials.

Visual depiction of the idiographic network models produced by GIMME are in Fig. 1. A model was estimated for each participant with paths representing the temporal dynamics between emotional expressions and symptoms. As can be seen in the examples, participants varied in the number of paths in their models. Most participants in the sample (80 %) had at least one significant emotion expression/symptom path in their model. Fig. 2 shows how much participants differed in the number of paths connecting emotion expressions to symptoms. Modal participant had one such path, but some had as many as eight. This variation reflects individual differences in the complexity of emotion-related processes underlying their symptoms.

Six emotion/symptom paths were sufficiently common across individual models to warrant examination (i.e., significant in over 10 % of the sample; Groen et al., 2022). These common paths were the contemporaneous associations of symptoms with (1) arousal, (2) head

[1] A third criteria is that the inclusion of random effects improves model fit, but this criterion is only for nomothetic models, and cannot be applied to GIMME.

[2] Exploratory analyses indicate that data sparsity is a likely source of misfit for these models. Participants excluded for non-positive definite models were those who had the fewest consecutive pairs of observations (i.e., they had more gaps in data), which impacts the ability to reliably estimate cross-lagged and autoregressive paths.

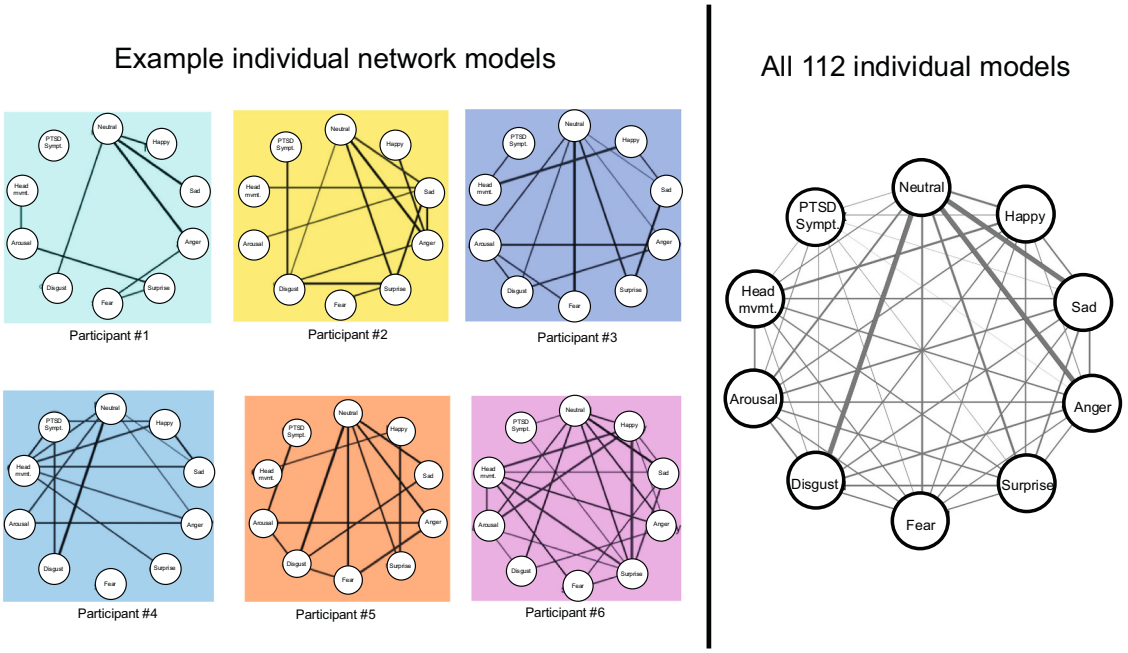

Fig. 1. Depiction of select GIMME model results.
Note. Left panel shows results of randomly selected person-specific models, right panel shows all paths from every person-specific model combined. Circles = variables, lines = covariance paths. Width of lines in the right panel correspond to number of participants with that path. Cross-lagged paths are not depicted for ease of interpretation.

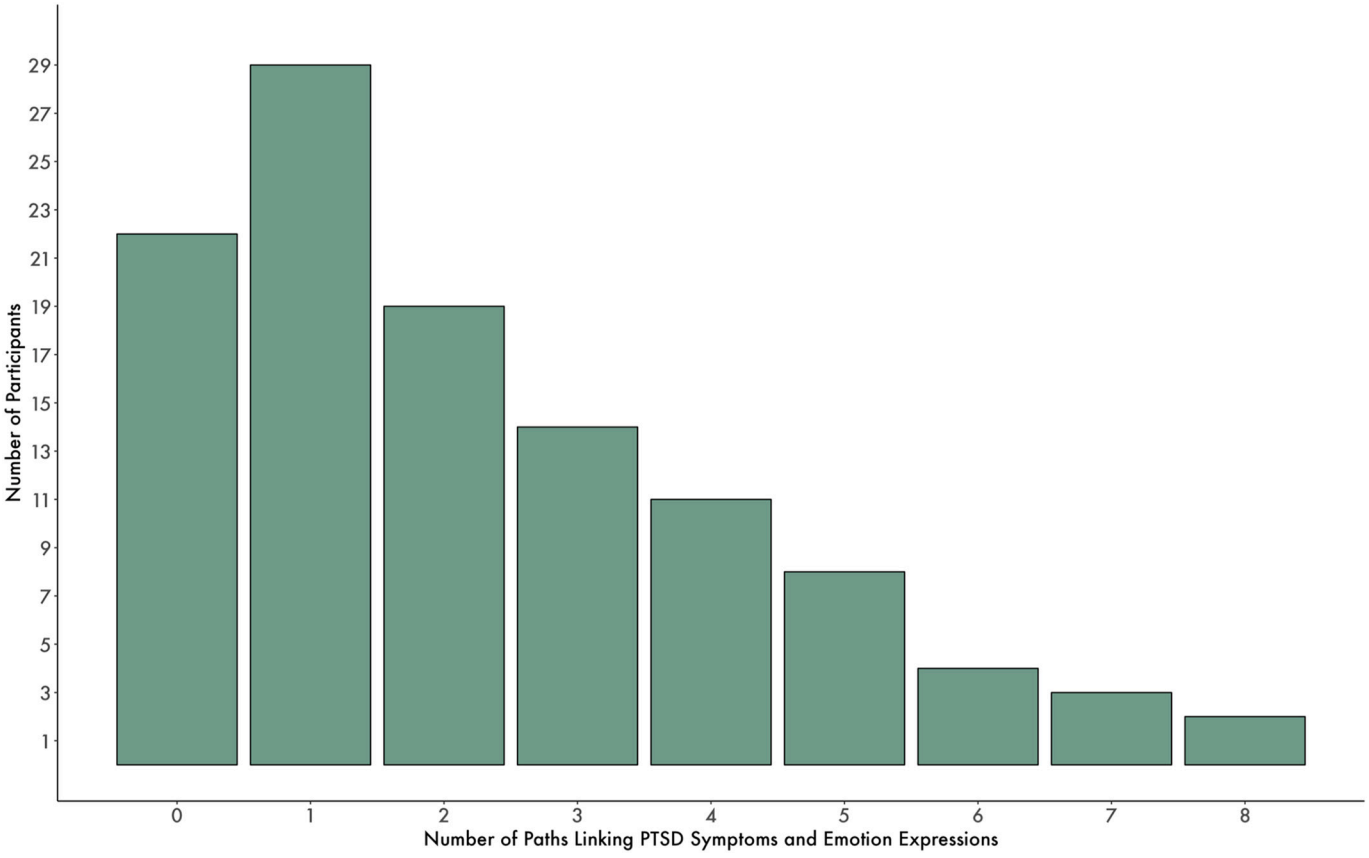

Fig. 2. Histogram for number of emotion expression/symptom paths per person.
Note. Paths were estimated in person-specific network models. The histogram shows there is considerable variability between people in the complexity of expressions and symptom dynamics, with fewer paths indicating a more consistent symptom-expression signature and more paths indicating more complex patterns.

movement, (3) scared facial expressions, and (4) neutral facial expressions as well as the cross-lagged associations of (5) angry facial expressions and (6) neutral facial expressions predicting next-day symptoms. There was statistically significant variability between people in the effect size and sign of each path. Each person's standing on these individual differences in expressivity processes are depicted in Fig. 3. For each path, the association was significantly positive for 4–7 % of the sample and significantly negative for 4–12 % of the sample. Importantly, because all paths satisfied criteria for meaningful heterogeneity, this indicates that these subsets of participants are not statistical artifacts (results of heterogeneity tests are in the Supplementary materials). Thus, a statistically reliable subset of people's symptoms relate to *increases* in emotional expressiveness while for another subset symptoms relate to *dampening* of emotional expressiveness.

By estimating each person's standing on these key individual differences, we can obtain a personalized profile of emotional expressivity that characterize their day-to-day functioning. To illustrate this idea, Fig. 4 provides profiles for six participants along with interpretations. Fig. 5 shows the complete model for participant #108 for the full context of their day-to-day emotion/symptom dynamics.

Taking each person's entire profile of dynamics into account reveals another finding: 17 % of the sample are *over-expressors* with exclusively positive links between symptoms and expressivity, 22 % are *under-expressors* with exclusively negative links, and 44 % are over and under-expressive depending on the temporal ordering and specific emotion expressed (the remaining 17 % did not have paths linking symptoms and expressivity). These results provide evidence against the simple classification of symptoms into heightened vs. dampened emotions proposed in some prior work (e.g., Lanius et al., 2006, 2010).

4. Discussion

This study determined that there are links between emotion expressions and PTSD symptoms. Reliable individual differences in the sequencing of expressions and symptoms that we found can stimulate hypotheses about distinct maintenance mechanisms. Our results provide an initial foundation for a more complete understanding of emotions in PTSD that includes outward emotion expressions.

We found that for almost every trauma-exposed person in our sample, their symptoms were consistently tied to at least one emotion expression. Given the high volume of real-world data available for each participant (i.e., 88 days per person, on average), these results add some of the clearest evidence to date that outward emotion expressions are relevant to PTSD. On top of this foundational finding, we showed people differ in the types of expressions that typically track their symptoms. This raises the question of what is driving these dynamics?

These patterns may be governed by emotion regulation processes thought to maintain a wide array of symptoms. Indeed, the most common paths we found align with *DSM* criteria for PTSD. For example, angry outbursts (Criterion E1) could map onto the bidirectional associations between angry expressions and symptoms, whereas feelings of detachment (Criterion D6) could be reflected in the covariance of neutral expressions and symptoms. However, the *DSM* lumps all symptoms into a single diagnosis, including all emotion-related symptoms, but we found that a given emotion-related process is only characteristic of up to 12 % of trauma-exposed individuals in our sample. This result

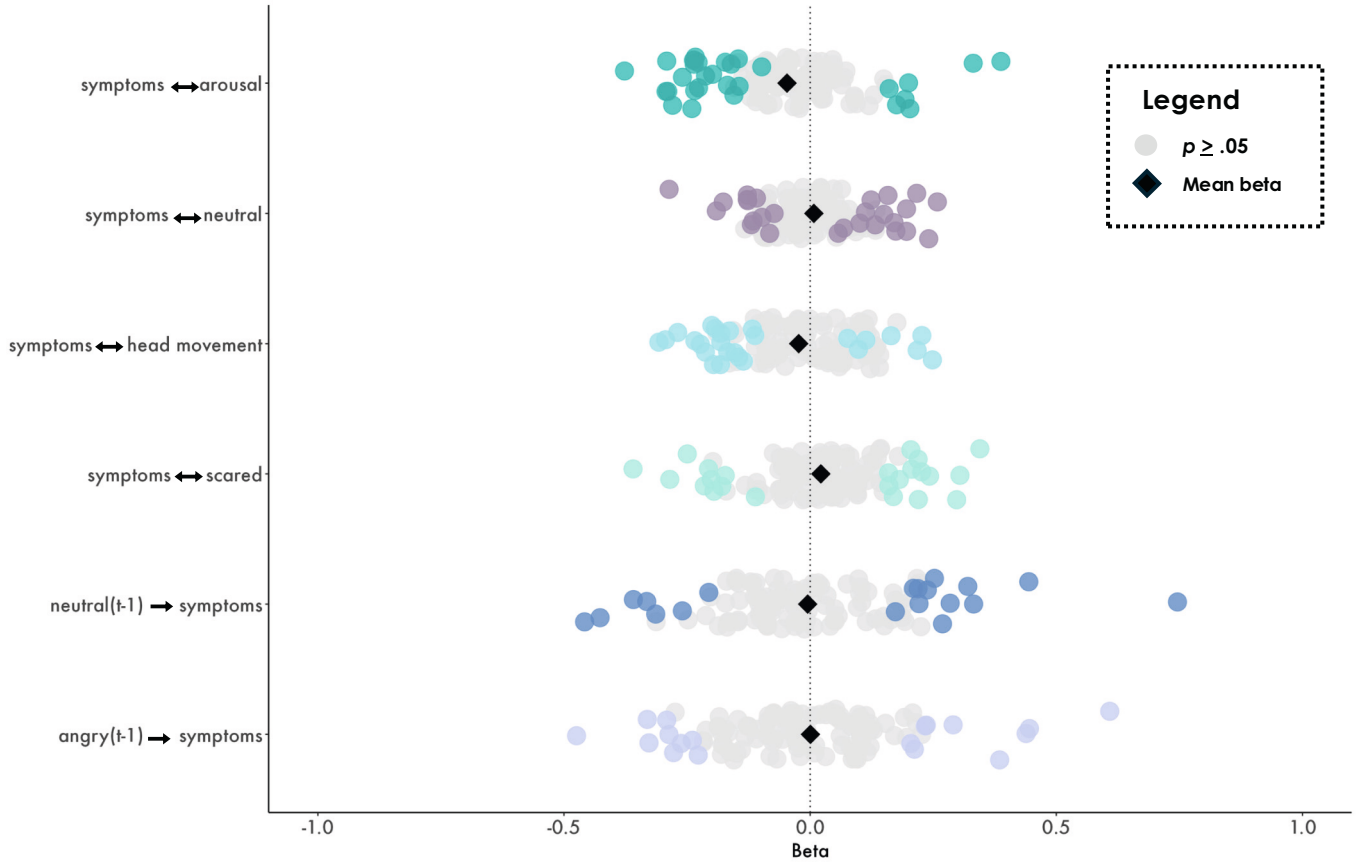

Fig. 3. Individual differences in most common emotional expression/symptom processes.
Note. This is a plot of path estimates (in standardized betas) from the person-specific network models. Each point represents a participant. The focus is on the most common dynamics, with ↔ = covariance and → = cross-lagged path. Colored points are significant ($p < .05$). Overall, this plot shows that for every path, there are subsets of participants with significantly negative paths (decreased expressivity related to symptom fluctuations) and subsets with significantly positive paths (increased expressivity related to symptom fluctuations).

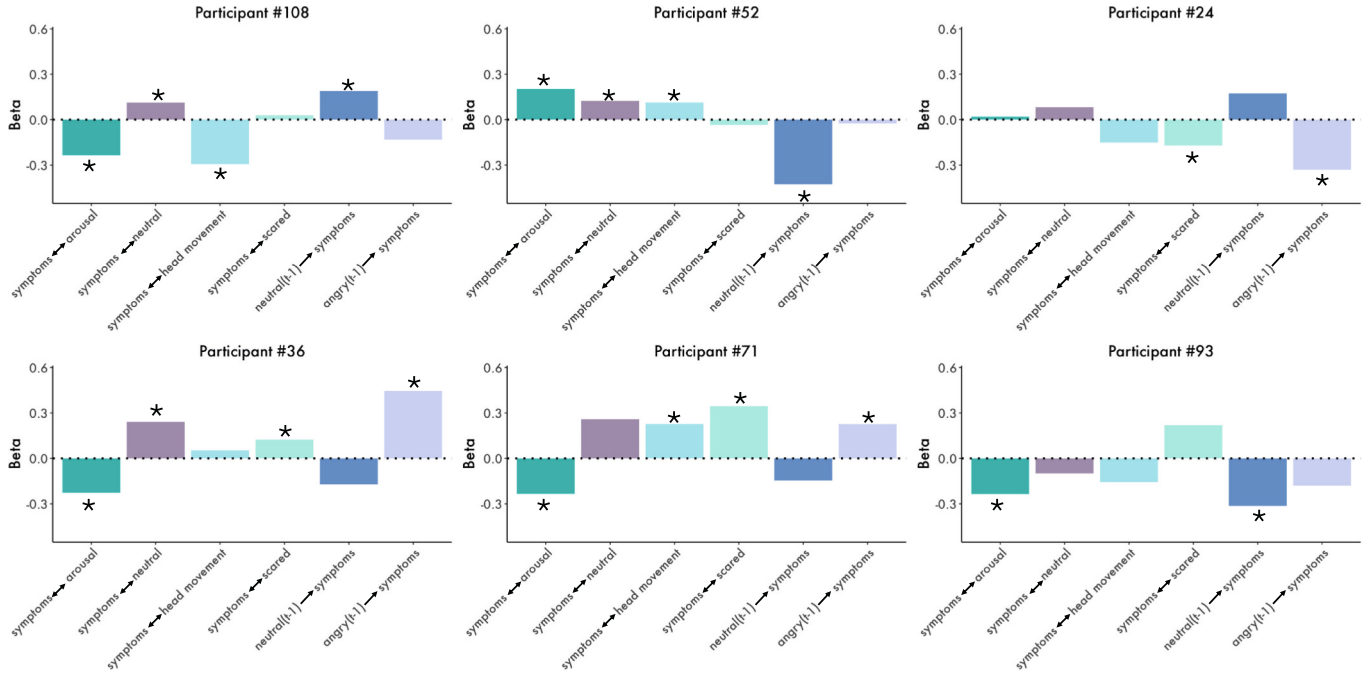

Fig. 4. Examples of emotional expressivity profiles for real participants.
Note. ↔ = covariance, → = cross-lagged path. * = statistically significant path. To provide examples of how to interpret the profiles, participant #52 tends to have more intense facial expressions, more neutral expressions, and more head movement than usual on days their symptoms worsen, suggesting an emotionally labile presentation. In contrast, participant #36 tends to have less intense facial expressions, more neutral expressions, and more scared expressions when their symptoms worsen suggesting overall emotional dampening but an uptick specifically in fearfulness. Participant #36 also tends to have worse symptoms after expressing more anger than usual. Perhaps this participant fluctuates between having a threat response to trauma cues involving heightened fear and suppression of emotion at times and at other times reacting with anger, which only temporarily staves off their distress, and then worsens the next day.

reinforces that defining PTSD as a unitary construct ignores the presence of distinct, clinically relevant profiles of emotional expressivity.

Of the most common processes, there were four emotion expressions that tend to co-occur with symptoms: overall facial expression intensity, neutral expressions, head movement, and fearful expressions. Their co-occurrence suggests that these expressions are behavioral markers of how people react when their symptoms are triggered by the day's events. Facial expression intensity, neutral expressions, and head movement reflects global physiological and emotional arousal, whereas fear expressions may more specifically reflect an experience of threat (Ekman, 1992). Furthermore, for each of these behavioral markers, there were subsets of people who become more expressive and others who become less expressive. This finding aligns with proposed mechanisms of dysregulated emotional overexpression and suppression thought to perpetuate symptoms (Horowitz, 1986b; Lanius et al., 2006, 2010; Litz et al., 2000). Conceptualizing expressivity along a common continuum aligns with evidence for shared neural circuits underpinning over and under modulation of emotions in PTSD (Chiba et al., 2021). Thus, these behavioral markers hold potential to parsimoniously organize and quantify *DSM* criteria describing marked alterations of arousal, reactivity, and negative mood (e.g., feelings of detachment) and could map more directly to the underlying mechanisms.

We also found two common predictive processes in which emotional expressions lead to increases in symptoms (i.e., cross-lagged paths). These paths suggest that a person's reaction to a day's events set off an emotional cascade that makes them more vulnerable to experiencing symptoms the next day. One of these predictive processes was of neutral expressions–a marker of general (low) emotionality–predicting next-day symptoms. For 5 % of the sample, higher expressivity (i.e., less neutral) predict increases in symptoms, suggesting that increased general emotionality on one day makes this group more susceptible to symptoms later on. In contrast, for the 5 % of the sample for whom more neutral expressions predict increases in symptoms, their symptoms may be perpetuated by a tendency to suppress or numb emotions. This dynamic may reflect the boomerang effect of emotional suppression theorized to maintain PTSD for some people (e.g., Frewen and Lanius, 2006; Horowitz, 1986a).

The second, common predictive path was between angry expressions and next-day symptoms. Anger has well-established associations PTSD pathology with meta-analyses finding large effect sizes between PTSD and both the suppression of anger ("anger in") and outwardly directed anger ("anger out") (Olatunji et al., 2010; Orth and Wieland, 2006). Our findings extend this research on subjective feelings of anger to angry facial expressions. Of course, we cannot say whether expressions track with feeling angry, but there is a clear parallel with 5 % of people having an "anger out" profile in which they tend to have worse symptoms the day after expressing more anger than usual and another 6 % of people have an "anger in" profile of having worse symptoms after expressing less anger than usual. If replicated, these paths could be indicators of people whose symptoms are exacerbated by the release or suppression of anger, or at the very least, changes in people's typical angry expressions (whether or not they actually feel angry) could be perceived by their social network in ways that exacerbate their symptoms.

4.1. Implications for research and clinical practice

Having established evidence that emotion expressions track with symptom fluctuations, and that there is meaningful heterogeneity in these dynamics, our results point toward a fresh direction in research on the etiology and treatment of trauma-related pathology. Once emotion expression phenotypes have been replicated and validated, they could provide a more precise guide for research on pathophysiology or behavioral mechanisms than existing phenotypes. Indeed, efforts to date aiming to identify neural biomarkers of PTSD have yielded highly variable results, even when using dimensional measures (Abi-Dargham et al., 2023; Lobo et al., 2015; Patel et al., 2012). Future research could,

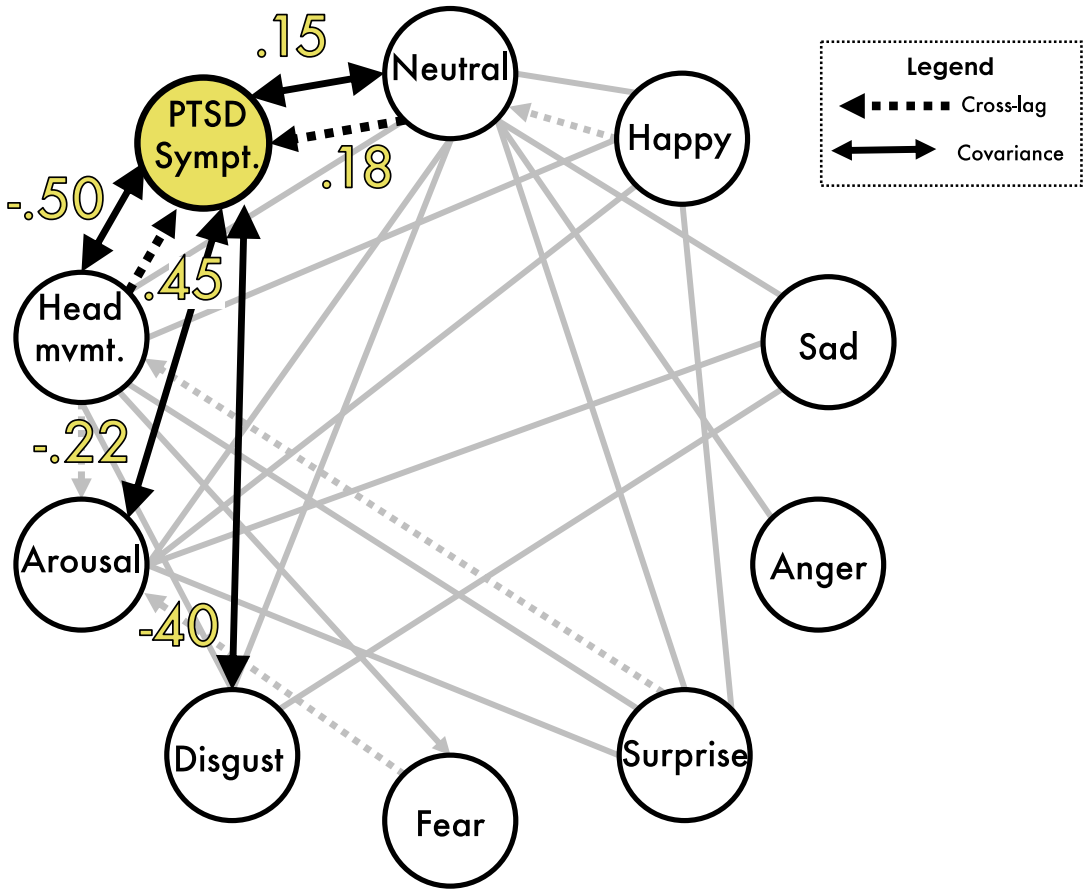

Fig. 5. Example of individual network model for participant #108.
Note. Parameter estimates are standardized betas. Only estimates for paths connected to symptoms are shown. Autoregressive paths were freely estimated but not depicted. When this participant feels more trauma-related distress they move their head less, they have more neutral expressions, less intense emotional expressions overall, and specifically less disgusted expressions, consistent with psychomotor slowing and emotional numbing. They also tend to have worse symptoms on days after having more neutral expressions, suggesting a maladaptive feedback cycle in which they suppress emotional expression when distressed which then leads to even worse symptoms the next day. This participant tends to have worse symptoms after days they moved their head more than usual as well, suggesting that although they have psychomotor slowing when they're symptomatic (i.e., negative symptoms ↔ head movement path), psychomotor agitation may be an early warning sign for them.

for example, test whether expressivity profiles correspond to specific genotypes or signatures of neural activation when exposed to emotion-eliciting images. On the behavioral level, an example application could be identifying mediators that account for why anger expressions lead to worse symptoms for a subset of patients, while neutral expressions do for another subset. Understanding the behavioral mechanisms could be informative for personalized treatment selection.

Findings from this study also have clinical implications. Currently, clinicians routinely assess emotion expressions, but the assessments are impressionistic, imprecise (e.g., labile, flat, euthymic), and there is no formal framework to integrate their observations into case conceptualization and treatment planning. One possibility is using AI during telehealth sessions to automatically detect subtleties in expression that may not be observable to humans. Clinicians could then augment their own judgments with data from this tool for a more comprehensive assessment of a patient's emotional state and proximal risk for an uptick in symptoms. Knowing a patient's emotion expressivity profile, in turn, could enable delivery of targeted and timely treatment. For example, a patient who tends to appear aloof before their symptoms worsen and unintentionally pushes away social supports could benefit from social signaling interventions (Gilbert et al., 2020). In sum, our results suggest that individual differences in emotion expressivity can—and perhaps should—have a more prominent role in the assessment and treatment of PTSD.

4.2. Limitations

There are some limitations of our study that can be addressed in future work. First, because our sample were mostly White, mostly male, and in mid to late adulthood, the common expressivity processes we found may not extend to people of other races, genders, or younger populations. However, results would be comparable and generalizable to other, important populations including veterans, first responders, and primary care patients with trauma history. Second, emotional expressions elicited in a video diary may not generalize to other settings. At the same time, by allowing participants to choose the topics they talked about in the videos, this should offset this limitation to an extent by increasing generalizability. Third, our sample size was modest. There were, however, a very large number of observations per person, which is more important for detecting true paths than the number of participants (Lane et al., 2019). That said, replicating our results in larger samples will increase confidence in our conclusions.

4.3. Conclusion

Observable emotional expressions are a core component of emotions and figure prominently into theories of PTSD, yet they have not been systematically researched or incorporated into clinical practice. By addressing methodological challenges of studying emotion expressions

that held back previous efforts, we found there are meaningful individual differences in how emotional expressivity relates to symptoms. These results take us a step closer toward a more mechanism-based approach of understanding, assessing, and diagnosing PTSD.

CRediT authorship contribution statement

Whitney R. Ringwald: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Scott Feltman:** Formal analysis, Data curation. **H. Andrew Schwartz:** Writing – review & editing, Project administration, Funding acquisition. **Dimitris Samaras:** Writing – review & editing, Funding acquisition. **Christopher Khudari:** Writing – review & editing, Investigation. **Benjamin J. Luft:** Writing – review & editing, Project administration, Funding acquisition. **Roman Kotov:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Benjamin Luft reports financial support was provided by National Institute for Occupational Safety and Health. Roman Kotov reports financial support was provided by National Institute for Occupational Health. Andrew Schwartz reports was provided by National Institute for Occupational Safety and Health. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2025.03.109.

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