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RESEARCH ARTICLE

Identifying and predicting posttraumatic stress symptom states in adults with posttraumatic stress disorder

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Abstract

Between-person heterogeneity of posttraumatic stress disorder (PTSD) is well established. Within-person analyses and the *DSM-5* suggest that heterogeneity may also be evident within individuals across time as they move through social contexts and biological cycles. Modeling within-person symptom-level fluctuations may confirm such heterogeneity, elucidate mechanisms of disorder maintenance, and inform time- and person-specific interventions. The present study aimed to identify and predict discrete within-person disorder presentations, or *symptom states*, and explore group-level patterns of these states. Adults (N = 20, 60.0% male, M age = 38.25 years) with PTSD responded to symptom surveys four times per day for 30 days. We subjected each individual's dataset to Gaussian finite mixture modeling (GFMM) to uncover latent, within-person classes of symptom levels (i.e., states) and predicted those states with idiographic elastic net regularized regression using a set of time-based and behavioral predictors. Next, we conducted a GFMM of the within-person GFMM outputs and tested idiographic prediction models of these states. Multiple within-person states were revealed for 19 of 20 participants (Mdn = 4; 66 for the full sample). Prediction models were moderately successful, M AUC = .66 (d = 0.58), range: .50–1.00. The GFMM of the within-person model outputs revealed two states: one with above-average and one with below-average symptom levels. Prediction models were, again, moderately successful, M AUC = .66; range: .50–.89. The findings provide evidence for within-person heterogeneity of PTSD as well as between-person similarities and suggest that future work should incorporate additional contextual variables as symptom state predictors.

The potential for posttraumatic stress disorder (PTSD) to present differently for different people is well established: There are over 600,000 unique combinations of PTSD symptoms that meet the *Diagnostic and Statistical Manual of Mental Disorders* (fifth ed.; *DSM-5*; American Psychiatric Association [APA], 2013) diagnostic criteria (Galatzer-Levy & Bryant, 2013). Recent work has empirically demonstrated this between-person heterogeneity in terms of differences in both symptom combinations and symptom levels as well as differences in symptom covariation (Reeves & Fisher, 2020). Less is known about how PTSD changes within individuals over time. A strong body of longitudinal research has established within-person changes in symptom levels over the course of months or years as individuals move from states of disorder to recovery or from health to delayed-onset PTSD (Bonanno & Mancini, 2012). However, within-person symptom changes during periods of disorder maintenance (i.e., periods in which an individual continuously meets the PTSD diagnostic criteria) have not been thoroughly investigated. Biological, social, and behavioral theories of PTSD maintenance abound, frequently describing maintenance as a set of dynamic, within-person processes (Bryant, 2019), yet few have empirically mapped such processes within individuals across time. To uncover fundamental information about disorder heterogeneity and maintenance, the present study aimed to identify and predict within-person PTSD *symptom states*, or momentary experiences composed of categorically distinct mixtures of symptom levels, over one month of disorder maintenance.

PTSD symptoms have long been theorized to vary and covary over time. Indeed, two leading psychological theories of PTSD maintenance—emotional processing theory (Foa & Kozak, 1986) and cognitive theory (Ehlers & Clark, 2000)—hinge on the assumption that PTSD symptoms are time-varying even during periods of relative diagnostic stability (i.e., outside of disorder development and recovery). Foa and Kozak (1986) postulate that for an individual with PTSD, a tight network of physiological and behavioral fear responses exists and is easily triggered by a wide range of environmental cues (Nijdam & Wittmann, 2015). Although this framework does not specify the time elapsed between environmental cues, fear responses, and other PTSD symptoms, such as negative alterations in cognition and mood, it does imply meaningful fluctuations in symptom levels over time. According to Ehlers and Clark (2000), PTSD develops when a traumatic experience is processed in such a way that a sense of threat remains and becomes chronic. This chronic sense of threat leads individuals to make negative appraisals about the world, others, and themselves and renders them more prone to coping strategies that perpetuate the disorder, such as behavioral and cognitive avoidance. Again, although the specific timeframe of these symptoms and coping behaviors is unclear, symptom fluctuation over time is implied.

Over the past two decades, substantial attention has been paid to symptom changes that occur over the course of weeks, months, or even years (Doron-LaMarca et al., 2015; Marshall et al., 2006; Schell et al., 2004; Solomon et al., 2009); however, the growing accessibility of ecological momentary assessment (EMA) survey methods has enabled an emergent body of work focused on symptom fluctuations with increasing granularity. For example, in their study of first responders with PTSD attributed to work at the World Trade Center site following the September 11, 2001, terrorist attacks, Ruggero et al. (2021) sampled participants three times per day for 7 days. Findings showed that hyperarousal symptoms predicted increases in all other PTSD symptoms from day to day. Another common data analytic technique has been to sample PTSD symptoms in adults between one and three times per day, then calculate summary statistics of within-person day-to-day symptom variation, such as standard deviation, root mean square of successive differences (RMSSD), or autocorrelation within individuals across the sampling period (Black et al., 2016; Naragon-Gainey et al., 2012; Schuler et al., 2021). These within-person metrics have then been used to describe variation in PTSD symptoms over time, providing evidence for differences in symptom dynamics between individuals (Black et al., 2016), suggesting that within-person symptom fluctuations correlate with overall PTSD symptom severity (Schuler et al., 2021), and indicating that differences in dynamics likely exist between PTSD symptom clusters (Naragon-Gainey et al., 2012). Taken together, this work suggests that differences exist both between and within individuals over time and that these differences may not be adequately captured when collapsing across individuals or time. This aligns with what a growing body of idiographic clinical science research suggests: Although group-level models may accurately describe some individuals' experiences, this will not be the case for many individuals (Fisher et al., 2018).

To our knowledge, only one study has examined within-day, within-person changes in PTSD symptoms (Reeves & Fisher, 2020). Informed by the network theory of mental illness, which conceives of mental illnesses as a series of mutually reinforcing associations between specific symptoms rather than latent constructs (Borsboom & Cramer, 2013), Reeves and Fisher (2020) modeled within-person symptom networks using multivariate time-series data collected via EMA four times per day for 30 days. In this case, each network represented a set of contemporaneous or lagged partial correlations between symptoms within an individual. The authors observed between-person heterogeneity in symptom associations over the course of one month as well as marked differences between the within-person symptom associations they observed and the between-person associations reported in group-level network analyses of PTSD symptoms (c.f. McNally et al., 2015). These findings underscore both the heterogeneity of PTSD symptom variation and covariation over time within individuals and the necessity of individual-level modeling when investigating processes that occur over time within individuals.

Whereas Reeves and Fisher (2020) made meaningful advancements toward understanding PTSD as it presents within individuals over time, their chosen analyses presumed stationarity (i.e., that each individual data set exhibited consistency in mean, variance, and covariance throughout the sampling period). Just as random sampling enables between-subject findings to generalize to a larger population, the stationarity of data is a prerequisite for within-person findings to generalize to the future behavior of the individual under analysis. Within-person stationarity over the course of 1 month (i.e., the duration of their sampling period) is not a well-tested assumption and may lead to overly general conclusions. Further, although the authors' models showed within-day associations between symptoms, which no prior work had shown, the reported outputs represented the average contemporaneous and consecutive associations within individuals, as the selected models necessarily collapsed across time points. As such, these findings did not offer information about each individual time point within each time series; such information is necessary for detecting differential maintenance processes that may occur and vary on the scale of hours or days, as well as for deploying time point–specific interventions.

Many investigations conducted within an idiographic framework share the limitations found in the study by Reeves and Fisher (2020), wherein time-series analyses collapse across observations in a uniform, aggregate fashion. A more moment-oriented approach could take advantage of these repeated observations and provide increasingly granular temporal insights. To this end, Fisher and Bosely (2020) outlined a promising method for examining within-person fluctuations of psychopathology while addressing concerns about stationarity. In this study, Gaussian finite mixture modeling (GFMM), a data-driven statistical approach typically used to cluster individuals into groups, was used to cluster time points into states according to their various mixtures of symptom levels on a person-by-person and moment-to-moment basis. The multivariate time series data for 45 individuals with major depressive disorder (MDD) and/or generalized anxiety disorder (GAD) were subjected to GFMM person by person, clustering each individual time series into multiple person-specific classes, termed *mood states* by the authors. Each state was characterized by a specific mixture of negative affect and avoidance symptom levels, and each time point in the given individual's time series was categorized as belonging to one of the person-specific states. After identifying person-specific mood states, the authors applied a personalized machine-learning (ML) approach to predict the timing or location of each within-person state in each time series, using a set of person-specific predictors. The average area under the curve (AUC), or prediction accuracy, of the personalized models was .77, indicating that, on average, these models accurately predicted the timing of within-person states 77.0% of the time. In the context of PTSD, this data analytic approach could potentially uncover how symptoms cluster together to create a set of discrete PTSD symptom states that repeat within individuals over time.

Despite the growing popularity of ML approaches in clinical science, to our knowledge, no work to date has leveraged such data-driven approaches to characterize PTSD maintenance. In recent years, a wide range of supervised and unsupervised ML approaches have been applied to behavioral data to identify individuals at risk for developing PTSD (He et al., 2017; Karstoft et al., 2015; Kessler et al., 2014; Rosellini et al., 2018; Schalinski et al., 2016), for early prediction of PTSD after trauma exposure (He et al., 2017), and to assess the group-level associations between PTSD and common coping strategies (Christ et al., 2021) or comorbidities (Ramos-Lima et al., 2020). No known studies, however, have focused on ML approaches to identifying and predicting within-person symptom experiences. Although some extant PTSD research has used mixture-model variants that cluster trajectories in longitudinal data, such as latent growth mixture-modeling (Ma et al., 2016) and latent class growth analysis (Galovski et al., 2016), these models cluster individuals into groups as opposed to clustering time points into states. Moreover, although these methods are often referred to as person-centered, it should be emphasized that they provide inferences about groups rather than individuals. Thus, no work to date has examined latent mixtures of time points within individuals with PTSD.

In the present study, we leveraged data-driven analytic methods to uncover discrete, within-person symptom states (i.e., clusters of time points with similar mixtures of symptom levels) in adults with PTSD to gain a window into disorder maintenance. We then predicted the timing of these person-specific states using idiographic ML techniques. These techniques enabled us to model each participant's experience separately using a set of personalized predictors derived from their data alone. To explore group-level patterns of within-person symptom states, we also derived symptom states from the within-person symptom state model outputs and tested idiographic prediction models for these symptom states. We demonstrate the theoretical and clinical utility of mapping and predicting within- and between-person symptom states and discuss how these findings may be used to further understand PTSD maintenance and lay the groundwork for ambulatory interventions.

METHOD

Participants

The present study was a secondary analysis of data collected by Reeves and Fisher's (2020). Participants were 20 individuals diagnosed with current PTSD who were enrolled in a study on personalized models of traumatic stress. Study staff screened 274 individuals, 100 of whom met the initial inclusion criteria and were invited for an in-person structured clinical interview. The 174 individuals who were not invited to an in-person interview were excluded for having a score less than 38 on the PTSD Checklist for *DSM-5* (PCL-5; Weathers, Litz, et al., 2013; n = 43, 24.7%), reporting no index trauma (n = 27, 15.5%), not having daily access to a text- and web-enabled smartphone (n = 36, 20.7%), reporting personal conflicts that interfered with study participation (n = 44, 25.3%), and losing interest in the study (n = 24, 13.8%). Of the 100 participants invited for an in-person structured clinical interview, nine (9.0%) were unresponsive to phone calls from study staff and were, therefore, excluded from further study phases.

Whereas 37 participants were eligible for the EMA phase of the study, 17 did not complete the phase for the following reasons: (a) failure to complete 80% or more of the daily surveys (n = 6, 35.3%), (b) discontinued participation during the EMA study phase (n = 5, 29.4%), (c) failure to enroll in the EMA study despite eligibility (n = 4, 23.5%), and (d) technical issues (n = 2, 11.8%). As evidenced by an independent samples t test, there was no difference in PTSD symptom severity, as determined by total symptom severity scores on the Clinician-Administered PTSD Scale for *DSM*-5 (CAPS-5; Weathers, Blake, et al., 2013a), between participants who completed the EMA study phase and those who did not, $t(34) = .89$, $p = .380$. The 20 participants included in the present analyses completed an average of 108.8 (SD = 8.26, range: 93–123). Limitations related to the recruitment methods are discussed in further detail elsewhere (Reeves & Fisher, 2020).

Of the participants included in the present analyses (N = 20), 45.0% identified as White (n = 9), 35.0% as multiracial/other (n = 7), 10.0% as Black (n = 2), and 10.0% as Hispanic/Latinx (n = 2). Over half of the sample was male (n = 12, 60.0%), and the mean participant age was 38.25 years (SD = 12.51). Participant comorbidity was 65.0%, with 13 participants meeting the criteria for one or more comorbid diagnoses, including GAD (n = 6), persistent depressive disorder (n = 5), social anxiety disorder (n = 4), agoraphobia (n = 3), specific phobia (n = 3), substance use disorder (n = 2), illness anxiety disorder (n = 1), obsessive–compulsive disorder (n = 1), and panic disorder (n = 1). The modal highest level of educational attainment was a 4-year bachelor's degree, and the modal annual income was less than $10,000 (USD) per year.

Procedure

The Committee for the Protection of Human Subjects at the University of California, Berkeley (Protocol # 2015-01-7093) approved all study procedures before data collection. Participants were compensated $50 for completion of all study procedures, which included screening; baseline assessment; and 30 days of EMA surveys, administered four times per day.

Recruitment and screening

Study staff recruited participants via online and hard-copy advertisements inquiring about PTSD symptoms. Interested community members called the laboratory phone number listed on the advertisement and completed verbal consent and a phone-screen assessment of the following inclusion criteria: current PTSD diagnosis, 18–65 years of age, no current mania or psychosis, and daily access to a text- and web-enabled smartphone. In addition, index traumatic events were assessed using the Life Events Checklist for *DSM-5* (LEC-5; Weathers, Blake, et al., 2013b), and PTSD was assessed using the PCL-5 (Weathers, Litz, et al., 2013). Participants with a PCL-5 total score of 38 or higher were deemed to have probable PTSD and invited for an in-person structured clinical interview.

Baseline assessment

At the laboratory, participants provided written consent. Past-month PTSD symptoms and current diagnostic status were assessed using the CAPS-5 (Weathers, Blake, et al., 2013a). The Anxiety and Related Disorders Interview for *DSM-5* (ADIS-5; Brown & Barlow, 2014) was used to assess comorbidities. An advanced doctoral student and PhD-level clinical psychologist trained and supervised research assistants in administering both clinical interviews. Individuals who were deemed eligible for study participation after the clinical interview were invited to advance to the EMA phase.

30-day EMA phase

Participants provided their smartphone number to enroll in the EMA phase of the study. The EMA system functioned by sending participants texts with hyperlinks leading to web browser–based surveys, each of which included 34 items and took approximately 5 min to complete. Surveys were administered four times per day (i.e., morning, midday, evening, and night) for at least 30 days. In the original study by Reeves and Fisher (2020), pings per day and the number of days of EMAs were considered together for total power along with participant burden and feasibility. The authors selected four times per day for 30 days a hypothesized "best option" for easing the daily participant burden while ensuring sufficient per-person observations in the planned analyses (i.e., ~90–120 observations per person). Although many popular approaches to within-person modeling necessitate 80 or more observations per person, the optimal sampling rate for psychological phenomena and participants alike remains an open empirical question. For the present study, the EMA system was configured to collect timestamps for each survey. Participants who completed 80% or more of the daily surveys were eligible to receive the $50 compensation and were included in the present analyses.

Measures

Anxiety and related disorders

The ADIS-5 (Brown & Barlow, 2014) is a semistructured interview used to diagnose *DSM-5* anxiety, mood, and related disorders. Each diagnostic section is composed of items used to assess the dimensional aspects of the disorder's features and to provides a functional analysis of the disorder. Scoring determines whether the *DSM-5* diagnostic criteria are met as well as the severity of the symptoms. Validation data have not yet been published for the ADIS-5; however, its predecessor, the ADIS-IV, has been validated in multiple samples, demonstrating good-to-excellent interrater reliability, κs .67–.86, excluding dysthymia, $\kappa = .31$ (Brown et al., 2001).

PTSD symptoms and diagnosis

The CAPS-5 (Weathers, Blake, et al., 2013a) is a structured interview used to diagnose *DSM-5* PTSD diagnostic status and assess symptom severity. The measure is used to assess for the presence of the 20 *DSM-5* PTSD symptoms as well as symptom onset and duration, subjective distress, and symptom-related functional impairment. PTSD symptoms are assessed in relation to an index traumatic event. The CAPS-5 has demonstrated strong interrater reliability (κs = .78–1.00), test–retest reliability ($\kappa = .93$), and correspondence with a diagnosis based on the CAPS for *DSM-IV* (Weathers et al., 2018).

EMA survey items

EMA surveys included 34 items assessing *DSM-5* PTSD symptoms (26 items), positive emotions (five items), physical symptoms (one item), and sleep experiences not covered by the PTSD items (two items). The question stems for the PTSD symptom questions were based on the PCL-5, with some critical adaptations. First, to capture fluctuations related to each distinct component of various PTSD symptoms, four items on the PCL-5 were addressed via multiple EMA items, including (a) persistent and exaggerated beliefs or expectations about oneself, others, or the world (divided into three items); (b) persistent distorted cognitions about the cause or consequences of a traumatic event that leads to blame of oneself or others (divided into two items); (c) persistent negative emotional state (divided into five items); and (d) sleep disturbance (divided into two items). In addition, to capture fluctuations in PTSD symptoms conceptualized as persistent, items assessing these experiences were configured to gauge the degree to which participants experienced thoughts or emotions reflective of these persistent beliefs or states at each survey. Finally, sleep-related PTSD symptoms were each assessed only once per day, in the initial morning survey. A complete list of the survey items used to assess *DSM-5* PTSD symptoms may be found on the Open Science Framework (OSF). Participants were asked to rate the degree to which they experienced each item in the hours since the last survey, scoring responses on a visual analog slider scale ranging from 0 (*not at all*) to 100 (*as much as possible*); for the morning survey each day, participants were instructed to think about the time since waking as a reference point.

Data analysis

Our data analytic plan included three steps: (a) identify within-person PTSD symptom states using GFMM, (b) predict PTSD symptom states via idiographic ML techniques, and (c) conduct exploratory analyses to identify the presence and timing of group-level PTSD symptom states. The first two steps were included in our preregistration (see the OSF); the third step comprised an exploratory procedure to clarify the results and promote further hypotheses. Before all data analytic steps, missing data were removed via listwise deletion.

Identifying within-person PTSD symptom states using GFMM

Each participant's time series was reduced to include 12 PTSD symptoms. As GFMM analyses are sensitive to both the number of underlying constructs and the ways the constructs contrast with each other, item reduction often serves to increase the granularity of results. Here, we selected 12 items that together captured all PTSD symptom clusters. First, we included all items in the validated eight-item version of the PCL-5 (Price et al., 2016). As the 8-item PCL-5 includes Item 9 from the original 20-item PCL-5, we included the three EMA survey items that represented component parts of Item 9, resulting in a total of 10 items. We then added two additional items that we hypothesized to be central components of PTSD maintenance: shame and hypervigilance.

Data from these 12 items were then subjected to GFMM analyses. Typically, GFMM is used to identify latent classes, or groups, of individuals. Here, the method was used to group time points into states (i.e., classes), with each state defined as a distinct mixture of symptom levels. In these analyses, time points were treated as discrete and, therefore, independent, allowing the model to identify dependence. The mixture models were conducted with the *mclust* package in R (Scrucca et al., 2016) using four criteria to determine the number of classes: Bayesian information criterion (BIC; Schwarz, 1978), integrated completed likelihood (ICL; Biernacki et al., 2000), bootstrap likelihood ratio test (BLRT; Nylund et al., 2007), and the sample proportion for the smallest class. We limited model comparison to six of the possible 14 *Mclust* package parameterizations of within-class variance and covariance, excluding parameters that allowed covariance between class indicators and including those that allowed variation in distribution, volume, and the shape of variance (i.e., the EII, VII, EEI, VEI, EVI, and VVI parameters; see Scrucca et al., 2016, for more detail). Per Fisher and Bosley (2020), the best-fitting models with classes containing less than 10% of the total observations were rejected, and the *Mclust* function was rerun, constraining the number of possible classes until a best-fitting solution with all classes containing 10% or more of the total observations was identified. If no such solution was identified, the participant was excluded from the next phase of data analysis (i.e., prediction models via elastic net regression). Once a solution was identified, we applied the BLRT to the best-fitting solution, using the *mclust bootstrapLRT* function to test whether solutions with fewer or more classes provided a better fit; the BLRT supported each participant's best-fitting model. Finally, we generated forced-choice class assignments for each row (i.e., each time point) in each participant's time series using the estimated posterior probabilities for the likelihood that each row belonged in each class—an estimation that is generated during the GFMM. These assignments classified each observation in preparation for the prediction analyses.

Idiographic ML techniques: Variable selection and prediction of symptom states via elastic net regularized regression

With each time point classified as belonging to an individual class, we endeavored to identify predictors of these classes using a bottom-up, data-driven approach, person by person and class by class. First, we established the feature space (i.e., a set of all possible predictors from which our models could select a subset). Our feature space was limited based on decisions made during the study design phase before the conceptualization of the present analyses, but it did include a relatively large set of clinically relevant variables, including 34 lagged EMA items, 11 time intervals, three trends, and three cycles. In detail, these were (a) subjective reports of PTSD symptoms (26 items), positive emotions (five items), physical experiences (one item), and sleep experiences (two items) relevant to but not included in *DSM-5* conceptions of PTSD symptom presentation; (b) dummy codes for each day of the week and each ping (i.e., morning, midday, evening, night); (c) linear trend, quadratic trend, and cubic trend; (d) 12-hr cycle (twice per day), 24-hr cycle (once per day), and 7-day cycle (once per week), all generated based on methods outlined by Flury and Levri (1999).

Each time series was halved via a random number sequence in R to produce a training set and testing set. Using the *glmnet* package in R (Friedman et al., 2010), we used elastic net regularization to build prediction models for each of each person's symptom states with the training dataset. Elastic net combines two regularized regression approaches: ridge and the least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996). Ridge uses an L_2 penalization, which applies a penalty equal to the square of the magnitude of the model coefficients. LASSO employs an L_1 penalization that is equal to the absolute value of the coefficients. Due to its scalar equivalence with the model coefficients, LASSO regularization is capable of shrinking coefficients to 0, thereby entirely removing predictors and effectively selecting others. Elastic net has been shown to provide strong performance when the number of parameters is greater than the number of observations (Tibshirani, 1996).

The 47 variables in the feature space were included in the regression models as independent variables, and the dummy-coded vectors indicating the presence or absence of GFMM-identified symptom states were the dependent variables. We selected the optimal model using *k*-fold cross-validation with 10 folds and retained the model with the minimum mean cross-validated error, identified by specifying the *lambda.min* criterion in the *cv.glmnet* function in the *glmnet* package. Each elastic net regression model was run with the alpha parameter set to .50, providing an equal blend of L_1 and L_2 penalization. For cases in which all variables were excluded from the model at an alpha level of .50, models were rerun with incrementally (i.e., .05) lower alphas until predictors were identified. Prediction models were evaluated for prediction accuracy via out-of-sample testing on the testing data. Predictive accuracy was assessed via the AUC, sensitivity, specificity, and Brier scores (Brier, 1950).

Exploratory group-level analyses

To identify group-level patterns among the within-person symptom states, we created a data frame composed of the outputs from each of the within-person symptom states. The data frame consisted of one row per within-person symptom state, for a total of 66 rows across the full sample, and one column for each of the 12 PTSD symptoms, populated with each symptom's mean value in each symptom state. This data frame was then subjected to GFMM analyses using the same procedures used to identify the within-person states. Once the final model was identified, we generated forced-choice symptom state assignments for each row in each participant's time series. As with the assignments for within-persons states, we estimated posterior probabilities for the likelihood that each row belonged to each symptom state.

With each within-person observation classified as belonging to one of the group-level states in each individual time series, we then endeavored to identify predictors of these states, in the idiographic holdout data, person by person and state by state, using the same procedures as the within-person symptom state prediction models. The feature space was composed of the same 47 variables encompassing lagged EMA items, time intervals, trends, and cycles. Again, we divided each individual's time series into a training set and testing set (i.e., 50% of the data in each), generated models in the given individual's training set, and assessed the data using the testing set. Specific procedures mirrored those used in the within-person symptom state prediction models. Predictive accuracy was assessed using field-standard metrics, including the AUC, sensitivity, specificity, and Brier scores (Brier, 1950).

RESULTS

EMA time series psychometric properties

The mean number of time points per EMA time series was 127.15 (*SD* = 12.75, range: 111–168;), with an average of 18.35 observations (14.4%) with missing data (range: 2–50, *SD* = 12.88), leading to an average of 108.8 (*SD* = 8.26) complete observations per time series (range: 93–123) as could be reasonably expected given the requirement that all participants needed to complete 80% or more of the daily surveys to be included in the analyses. The average within-person mean for each of the 12 EMA items included in the present analyses was 49.77 (*SD* = 43.77) on a 100-point scale (range: 8.16–90.70). The average within-person standard deviation for each of the items was 18.57 (*SD* = 7.64, range: 6.77–33.96). The average within-person skewness for each of the items was 0.09 (*SD* = 1.58, range: -3.14–3.49), and the average within-person kurtosis for each of the items was 5.57 (*SD* = 5.28range: 1.45–21.08). For further details regarding the psychometric properties of each EMA item, see the OSF.

Within-person GFMM

For 19 of the 20 participants (95.0%), the GFMM analyses returned multiple classes with 10% or more of the total number of observations. For one participant, the analyses returned only one class with more than 10% of the total observations. Across the full sample, both the median and mode were four classes. Three participants (15.0%) exhibited two classes, six participants (30.0%) exhibited three classes, eight participants (40.0%) exhibited four classes, and two participants (10.0%) exhibited five classes, for a total of 66 classes across the 19 participants with multiple classes. Whereas some participants shared the same number of classes or exhibited classes with similar symptom level mixtures, no two participant models produced the same results. The most distinct group-level pattern identifiable by visual inspection was a subgroup of individuals ($n = 6$, 30.0%) for whom symptoms appeared to track together, resulting in one high and one low symptom class wherein all symptoms were above or below the intraindividual mean, respectively. Within the group of participants whose results fit this pattern, a portion ($n = 4$, 66.7%) also exhibited a midlevel symptom class wherein all symptoms were at or hovering around the intraindividual mean.

Variable selection and prediction of within-person symptom states

Full model syntax and output for the 66 elastic net regularized regression models, each corresponding with one of the participants' symptom classes, are posted on the OSF. The average AUC was 0.66 (range: .50–1.00), with .50 reflecting chance predictions and 1.00 indicating perfect predictions. The average Brier score was .19 (range: .04–.32). As the Brier score reflects the discrepancy between the predicted and manifest expression of symptom classes, lower scores reflect better model prediction; the present Brier score range indicates the minimum level of model imprecision was 3.7% and the maximum was 32.0%. The average specificity was .64 (range: 0.00–1.00), and the average sensitivity was .75 (range: .28–1.00).

Exploratory group-level analyses

The between-person GFMM analyses returned a two-class model consisting of one symptom class with above-average symptom levels and one with below-average symptom levels. Full-model syntax and output for the 40 elastic net regularized regression models (i.e., one per between-person symptom class per person) are posted on the OSF. The average AUC was .66 (range: .50–.89), the average Brier score was .19 (range: .08–.28), the average specificity was .69 (range: .00–1.00), and the average sensitivity was .69 (range: .00–1.00).

Exemplars

Results for three exemplar cases are visualized in Figure 1. Symptom values for each class were standardized within-person; a value of 0 represents the intraindividual mean symptom level for the given class, with elevations and reductions, therefore, on a standard deviation scale.

Participant 005

Participant 005 was a 41-year-old Latino, male-identified military veteran who reported an index trauma of witnessing a sudden violent death and had a baseline CAPS-5 score of 33. His within-person GFMM analyses returned five classes, herein termed *symptom states* (Figure 1A). State 1 was characterized by symptom levels 1 standard deviation below to 1 standard deviation above the person-specific mean, indicating a state with differential symptom activation. In contrast, in States 2–5, all symptoms tracked together, resulting in one above-average (State 2), one below-average (State 5), and two midlevel symptom states (States 3 and 4). The 116 observations for Participant 005 were classified as 16% State 1, 31% State 2, 19% State 3, 21% State 4, and 13% State 5. The personalized prediction models for his within-person states ranged in accuracy from an AUC of .63 for State 1 (specificity = .94, sensitivity = .50) to 1.00 for State 5 (specificity = 1.00, sensitivity = 1.00). In the between-person GFMM, Participant 005's 116 observations were reclassified as 50% State 1 and 50% State 2, each with a prediction accuracy of 88% (State 1: specificity = .84, sensitivity = .90; State 2: specificity = .90, sensitivity = .84). Figure 1b illustrates state assignment over time of the within- and between-person states, showing that in the between-person GFMM, within-person States 2 and 3 were reclassified as between-person State 1 and within-person States 1, 4, and 5 were reclassified as between-person State 2.

Participant 046

Participant 046 was a 45-year-old White female-identified individual who reported an index traumatic event of violent crime and had a baseline PTSD symptom severity of 49 on the CAPS-5. The GFMM of her data produced two states characterized by having most symptom levels within 1 standard deviation above the mean (States 1 and 3), one characterized by having all symptom levels below the mean (State 2), and one characterized by having a single item 2 standard deviations above the mean (State 4; Figure 1c). Her 103 observations were classified as 24% State 1, 37% State 2, 25% State 3, and 14% State 4. Prediction accuracy in the personalized models ranged from an AUC of .89 for State 2 (specificity = .85, sensitivity = .93) to an AUC of .50 for State 1 (specificity = .00, sensitivity = 1.00) and State 4 (specificity = .00, sensitivity = 1.00). In the between-person analyses, the participant's observations were reclassified as 63% between-person State 1 and 37% between-person State 2, each with an AUC of .89 (State1: specificity = .93, sensitivity = .85; State 2: specificity = .85; sensitivity = .93). Figure 1d shows that within-person States 1, 3, and 4 were reclassified as between-person State 1, and within-person State 2 was reclassified as between-person State 2.

Participant 039

Participant 039 was an 18-year-old Latina female-identified individual, with an index traumatic event of experiencing physical assault and baseline PTSD symptom severity of 30 on the CAPS-5. The GFMM analyses of her data produced three symptom states (Figure 1e). State 1 was characterized by all symptom levels within 0.50 standard deviations of the mean, State 2 was characterized by all symptom levels below the mean, and State 3 was characterized by all symptom levels above the mean. This participant's states loosely resembled Participant 005's States 2, 3, 4, and 5 (i.e., elevated symptom levels, midlevel symptom levels, and below-average symptom levels). This participant's 97 observations were classified as 45% State 1, 28% State 2, 27% State 3. The personalized prediction models for the within-person states ranged in accuracy from an AUC of .55 for State 3 (specificity = .33, sensitivity = 1.00) to an AUC of .83 for State 2 (specificity = .80, sensitivity = .14). In the between-person GFMM, this participant's observations were reclassified as 26% State 1 and 74% State 2. The personalized prediction models for the between-person State 1 had an AUC of .55 (specificity = .33, sensitivity = 1.00), and State 2 had an AUC of 0.55 (specificity = 1.00, sensitivity = .33). Figure 1f shows that within-person State 3 was reclassified as between-person State 1, and within-person States 1 and 2 were reclassified as between-person State 2.

DISCUSSION

The goal of the present study was to identify the presence and timing of discrete, within-person PTSD symptom states (i.e., clusters of time points with similar mixtures of symptom levels) via the application of data-driven data analytic methods: GFMM and within-person

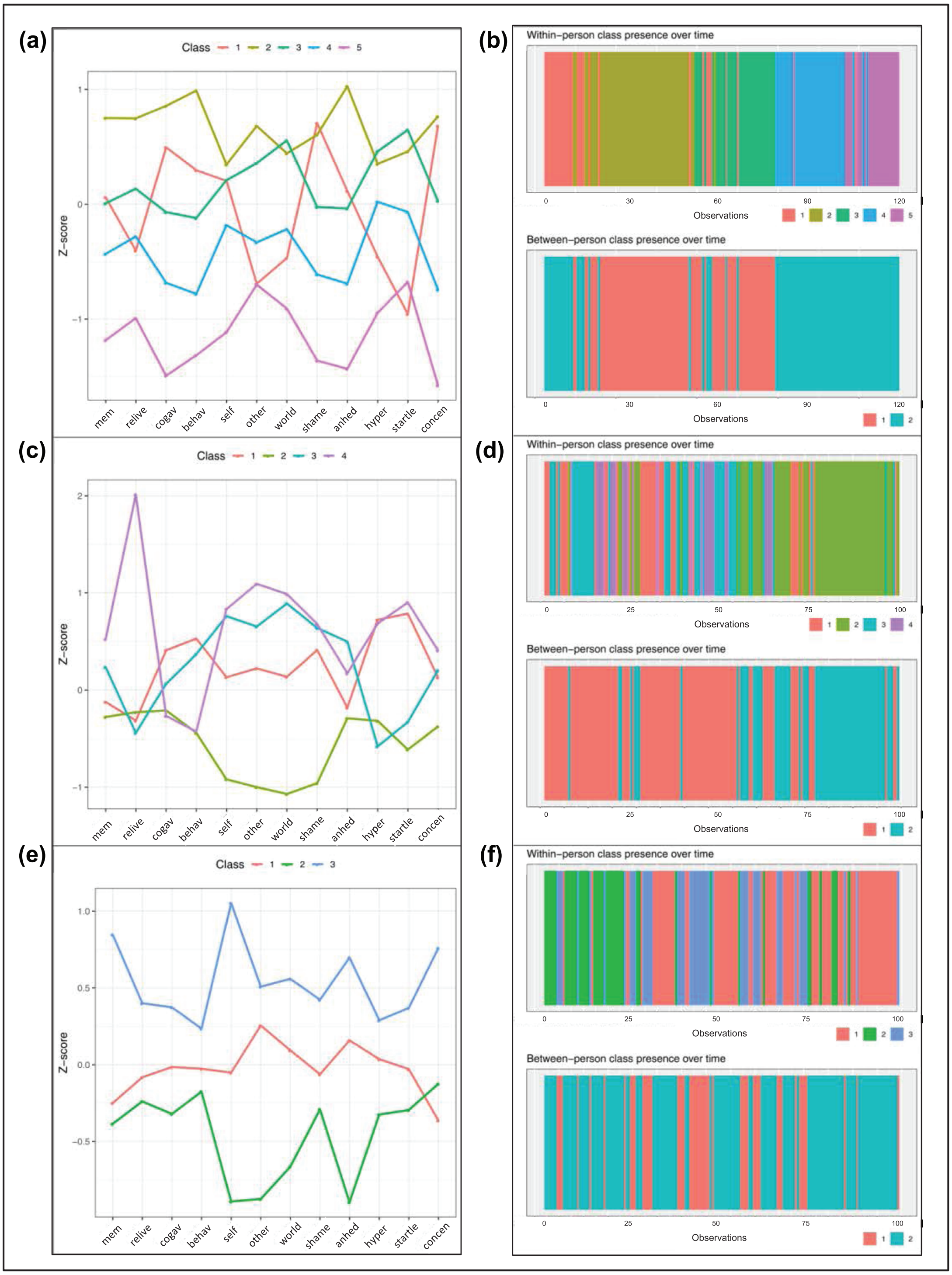

FIGURE 1 Visualization of Gaussian finite mixture model results for three exemplar case.

Note: Results for participants 005 (Panels a, b), 046 (Panels c, d), and 039 (Panels e, f) are shown. For panels a, c, and e, symptom values were standardized within-person; 0 represents the intraindividual mean symptom level for the given class. mem = intrusive memories; relive = reliving the event; cogav = cognitive avoidance; behave = behavioral avoidance; self = negative cognitions about self; other = negative cognitions about others; world = negative cognitions about world; shame = shame; anhed = anhedonia; hyper = hypervigilance; startle = exaggerated startle; concen = difficulty concentrating elastic net regularized regression, respectively. We then used the same methods to assess the presence and within-person timing of generalizable between-person clusters of within-person symptom states. We assessed a sample of adults with PTSD (N = 20) four times per day for 30 days and found that discrete symptom states were identifiable using the present methods; group-level symptom states (i.e., states derived from the outputs on the individual-level GFMM models) were also identifiable with the present methods. Pulling from a set of personalized predictors collected via daily surveys, the idiographic prediction models (one per person) were, on average, moderately successful at predicting within- and between-person symptom state presence or absence at each time point (within-person state AUC = .66, range: .50–1.00); between-person state AUC = .66, range: .50–.89). These findings provide empirical evidence for within-person, within-day heterogeneity of PTSD presentation and suggest that the diversity and heterogeneity of within-person states can be summarized at the group level by two states reflecting the activation versus deactivation (i.e., presence or absence) of PTSD symptoms. The moderate within-person predictability of both individual- and group-level states suggests that PTSD symptom changes may be better predicted by variables not included in the present analyses. However, these results also point to the notion that PTSD symptom expression exhibits idiosyncratic patterns on an individual level that, nevertheless, correspond with generalizable activation and deactivations patterns more globally.

This study affirmed and advanced prior work suggesting that individuals with PTSD may experience person-specific within- and between-day symptom fluctuations during disorder maintenance (Black et al., 2016; Naragon-Gainey et al., 2012; Reeves & Fisher, 2020; Schuler et al., 2021). Specifically, subjecting each individual's multivariate time series to GFMM one by one revealed that 19 of the 20 participants had two or more, and up to five, separate symptom states (i.e., distinct mixtures of symptom levels). This finding alone confirmed within-person symptom fluctuations over time. By locating symptom changes in time via the classification of each time point as belonging to one state, the present study lays the groundwork for time-dependent clinical interventions. Future work should test a range of sampling rates to identify the optimal rate for PTSD and its components; although the sampling rate of four times per day used in the present study afforded unprecedented granularity of analysis, whether this rate provides the fullest picture of PTSD symptom shifts remains an open question.

In the exploratory analyses, group-level patterns of the within-person symptom states were identified. By applying GFMM to the outputs from the 66 within-person GFMM models, we summarized person-level symptom variation as active or inactive. This finding makes intuitive sense: In general, individuals with PTSD are either experiencing symptoms or experiencing momentary relief. Future work should assess whether these findings generalize to larger samples and examine whether treatment outcomes differ meaningfully when momentary interventions are targeted at within- versus between-person states.

Once within-person symptom states were identified, the present findings demonstrated that the timing of these states was moderately predictable using a personalized ML approach. Specifically, when predicting within-person state timing using idiographic elastic net regularization to select from a set of personalized predictors, the average out-of-sample AUC was .66, indicating that the correct prediction was made 66% of the time. Although these findings indicate prediction accuracy better than chance (i.e., an AUC of .50 or above), they compare unfavorably to Fisher and Bosley's (2020) parallel analyses of depression and anxiety: Across 127 total within-person symptom states, the authors observed an average AUC of .77 (range: .50–1.00).

One plausible explanation for the modest prediction accuracy in the present study is that the set of predictors—comprising lagged individual PTSD symptoms, mood, and affect items, as well as time-based variables derived from each individual's time series—was insufficient. All PTSD symptoms are, by definition, intrinsically linked to a specific traumatic event, and symptoms either appear as direct, real-time reactions to event reminders or are specified as having developed or worsened following the event (APA, 2013). As posited by leading theories of PTSD maintenance, symptoms are typically triggered by internal or external event reminders (i.e., intrusive symptoms or contextual triggers, respectively), which, in turn, trigger and perpetuate avoidance and negative alterations in cognitions and mood (Nijdam & Wittmann, 2015). From this theoretical perspective, it follows that variation in external event reminders may account for variation in symptom level mixtures over time and, therefore, that the best predictors of within-person symptom states are environmental or social circumstances. If this were the case, the predictor set used in the present study would be insufficient. Another possibility is that the sampling rate may not have been optimal. Lagged predictors and outcome variables were separated by 4 hr (i.e., the average time between surveys). Although some PTSD symptoms may escalate gradually over the course of several hours, such as guilt or fear, others, particularly hyperarousal, may peak within a matter of seconds. The potential variation in fluctuation speed across symptoms indicates that testing a range of sampling frequencies and including lagged predictors from multiple different time points may be helpful.

Finally, the present findings demonstrated that person-specific prediction models of between-person symptom states were, on average, similarly accurate to those predicting the timing of the person-specific states. Specifically, the average prediction accuracy for between-person symptom states (i.e., activation or deactivation) was the same (AUC = .66), with a slightly narrower range (.50–.89). It is important to note that although the average AUC was the same for prediction models with person-specific and between-person summary classes, individual participants' average AUCs for within-person state prediction models were rarely equivalent to their average AUCs for between-person state prediction models. For example, the average AUC for Participant 039's within-person state prediction models was .68, whereas the average AUC for his between-person state prediction models was .55; that is, barely better than chance. Conversely, Participant 046's average AUC for her within-person state prediction models was substantially worse (.60) than the average AUC for her between-person state prediction models (.89). This within-person variation in prediction accuracy suggests the overall moderate prediction accuracy of the present study's models was not due to a subset of participants with difficult-to-predict fluctuations but rather indicates that the limitations of the present methods were present across the full sample.

The present study represents a unique contribution to the growing body of literature examining within-person PTSD presentation fluctuations during disorder maintenance. To the best of our knowledge, this was the first study to identify discrete, within-person PTSD symptom states during disorder maintenance; in addition, it was the first to use a personalized ML approach to predict instances of symptom state changes and to do so out-of-sample. These findings show that it is generally feasible to identify and predict, with moderate accuracy, moments of distress and that doing so on an individual basis may be clinically useful due to individual differences apparent in the present findings. The present study also lays the groundwork for future investigations into the presence and generalizability of shared states across individuals. Applying the methods outlined here to larger samples could reveal between-state dynamics that elucidate key aspects of PTSD maintenance, advancing innovation in treatment.

Several study limitations should be discussed. The sample size was relatively small, and although the findings do provide evidence for between-person heterogeneity in PTSD presentation fluctuations over time, as well as the general feasibility of predicting fluctuations using personalized ML techniques, the extent to which these findings may generalize to a larger sample remains to be tested. With each participant's time series ranging from 93 to 123 complete observations and a model selection process that required at least 10% of total observations per state, some within-person states had as few as nine observations. Although this cutoff of 10% has been used in prior work (Fisher & Bosely, 2020), additional cutoffs should be tested; the extent to which tweaking the ratio of the minimum required observations per state to the total observations would shift theoretical and clinical implications of each state, and the accuracy and utility of their corresponding prediction models is an empirical question that should be tested. Finally, as these analyses were conducted using archival data, testing person- and time-specific interventions was not possible. Whether interventions timed to coincide with specific disorder presentations improve treatment remains an open question and must be empirically assessed.

The present study builds upon past documentation of within-person PTSD symptom fluctuations to suggest that specific, clinically meaningful mixtures of symptoms may appear and reappear within individuals over time. These findings, especially if replicated on a larger scale, may be leveraged to identify subgroups of PTSD presentations. This could help clarify the mechanisms underlying the heterogeneity of the disorder, potentially leading to the classification of individuals with different symptom states at a single time point assessment into the same presentation category based on their dynamics over time. Further, assessing within-person presentation patterns in a larger sample may uncover generalizable mechanisms of PTSD maintenance. The personalized prediction models offer evidence for the general predictability of PTSD presentations. The effective equivalence in the accuracy of the models predicting within- and between-person state presence or absence, however, unfortunately offers no clarity regarding which may be the most feasible for initial momentary treatment target testing. Future work testing additional predictors and comparing within- and between-person prediction models, as well as within- and between-person symptom states, is indicated.

The present findings affirm a common clinical approach in cognitive and behavioral therapies wherein clinicians help clients to identify, describe, and plan for distressing states that occur between sessions. For clinicians open to supporting client symptom tracking, the present methods offer a data-driven understanding of client experiences that could facilitate case formulation and prompt discussion beyond what individuals can recall. Indeed, recent work comparing EMA to retrospective reporting has indicated that retrospective reporting is most strongly correlated with clients' moments of peak distress (Schuler et al., 2021). Thus, the present methods may help clinicians and clients identify nuanced variations in client experiences. For example, a clinician working with Participant 005 (Figure 1, Panels A and B), may focus on States 1–3, wherein more than 50% of symptom levels are above average, and use the timing information to help the client identify triggers for each state. Interventions may also be tailored to state nuances: For Participant 005, for example, the same intervention may be appropriate for States 2 and 3 given their relative similarity, whereas State 1 may indicate the need for a unique intervention targeted at the above-average symptoms alone. Clinicians are practiced at identifying nuanced distinctions between states of distress, yet the data analytic methods employed here may expedite this process and, in some cases, offer information outside of the immediate awareness of both clinician and client.

The present study applied an innovative methodology to identify the presence and timing of discrete, within- and between-person PTSD symptom states. The findings offer evidence for within-person, within-day heterogeneity of PTSD presentation, group-level patterns of these within-person states, and moderate predictability of both within- and between-person states. Future work should investigate the power of environmental and social factors as predictors of PTSD presentation timing and, eventually, test the utility of the symptom states presented here as momentary intervention targets.

OPEN PRACTICES STATEMENT

The preregistration, deidentified data, and data analysis scripts for this study are posted on the Open Science Framework (OSF). The materials used in these studies are widely publicly available.

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