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An Examination of Idiographic Networks of Posttraumatic Stress Disorder Symptoms

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Although the application of network theory to posttraumatic stress disorder (PTSD) has yielded promising insights, the lack of equivalence between inter- and intraindividual variation limits the generalizability of these findings to any one individual with PTSD. Instead, a better understanding of how PTSD symptoms occur and vary over time within an individual requires exploring the idiographic network structure of PTSD. To do so, the present study used an intensive repeated-measures design to estimate intraindividual networks of PTSD symptoms on a person-by-person basis. Participants were 20 individuals who met criteria for PTSD and completed daily surveys assessing PTSD symptoms; surveys were completed four times per day for approximately 30 days. Employing a recently validated method provided by Fisher, Reeves, Lawyer, Medaglia, and Rubel (2017), we used these data to estimate a contemporaneous and temporal network of PTSD symptoms for individuals on a person-by-person basis. We then calculated centrality metrics to determine the relative importance of each symptom in each idiographic network. Across all contemporaneous networks, negative trauma-related cognitions and emotions were most commonly the most central symptoms. Further, across all temporal networks, (a) negative trauma-related emotions were the most common driver of variation in other symptoms over time and (b) distressing trauma-related dreams and sleep disturbance were the most common downstream consequences of variation in other PTSD symptoms over time. We also reviewed data from two randomly selected participants to illustrate how this approach could be used to identify maintenance factors of PTSD for each individual and guide individual treatment planning.

Posttraumatic stress disorder (PTSD) is a common and highly disabling consequence of trauma exposure that confers substantial individual and societal costs worldwide (Kessler, 2000; Lowe, Blachman-Forshay, & Koenen, 2015). Despite its prevalence and associated burden, disagreements regarding the nature and scope of the PTSD diagnosis have existed since its initial inclusion in the third edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-III*; American Psychiatric Association [APA], 1980; Friedman, Resick, & Keane, 2007). Among these controversies, experts have long disputed whether the diagnosis more appropriately represents a distinct categorical entity or the extreme end of a dimension of stress response. Nevertheless, despite key differences between categorical and dimensional accounts of PTSD, each conceptualizes PTSD within the latent disease model; that is, each presumes that PTSD is an unobserved construct that serves as the common cause of its associated symptoms and their covariance (Schmittmann et al., 2013). Historically, the latent disease model has been the predominant framework for conceptualizing and operationalizing psychological disorders (Borsboom, 2008).

However, researchers have recently provided theoretical and empirical evidence that the latent disease model may be poorly fit to psychological disorders (Borsboom, 2008, 2017; Schmittmann et al., 2013). Instead, Borsboom and Cramer (2013) have proposed the network theory of psychological disorders, arguing that these phenomena are better understood as distributed networks of mutually interacting, reciprocally reinforcing cognitions, emotions, and behaviors. These reciprocal interactions are reflected in the covariance between symptoms and the visualization of these associations via a network model provides a display of the degree to which any two symptoms are related. Despite the recency of its introduction, the network approach has generated considerable enthusiasm and has been used to study a variety of psychological disorders (Borsboom, 2017; Fried & Cramer, 2017). For PTSD specifically, several recent studies have used this approach to estimate networks of PTSD symptoms in a diverse set of clinical and nonclinical samples (Afzali, Sunderland, Batterham, et al., 2017; Afzali, Sunderland, Teesson, et al., 2017; Armour, Fried, Deserno, Tsai, & Pietrzak, 2017; Birkeland & Heir, 2017; Bryant et al., 2017; Frewen, Schmittmann, Bringmann, & Borsboom, 2013; Fried et al., 2018; Greene, Gelkopf, Epskamp, & Fried, 2018; Hoffart, Langkaas, Oktedalen, & Johnson, 2019; Knefel, Tran, & Lueger-Schuster, 2016; Mitchell et al., 2017;

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Spiller et al., 2017; Sullivan, Smith, Lewis, & Jones, 2016). By estimating the network structure of PTSD, these studies have aimed to take a bottom-up, data-driven approach to identifying the symptom dynamics that hold mechanistic importance for PTSD. Experts in the field hope that these insights might provide actionable information about the factors that determine the onset and maintenance of PTSD, with the latter serving as potential candidate targets for intervention and treatment optimization (Fried et al., 2018).

Although this nascent field is promising, the PTSD network structures that populate the existing literature have largely been estimated from cross-sectional data aggregated across individuals. Although these networks describe the average association between symptoms and the relative importance of each symptom within each group, they fall short of describing how psychopathology may be organized within any one individual. This is because interindividual variability is not statistically equivalent to intraindividual variability (Hamaker, Dolan, & Molenaar, 2005; Molenaar, 2004). That is, the variance and covariance of PTSD symptoms in cross-sectional group data are not equivalent to the variance and covariance of these same symptoms for a single individual over time. Further, although some past research has estimated multilevel networks from longitudinal data as a way to address the limitations of cross-sectional PTSD networks (Greene et al., 2018; Hoffart et al., 2019), these studies still fall short of describing the person-specific nature of these intraindividual processes due to violations of the underlying homogeneity assumptions of these models (Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2005; Piccirillo & Rodebaugh, 2019). Thus, it follows that insights about the nature of PTSD gleaned from nomothetic networks are unlikely to adequately inform researchers and clinicians about processes occurring at the individual level. A better understanding of these nuanced individual-level processes instead requires directly exploring the idiographic network structure of PTSD.

It is notable that a fundamental goal of the network approach is to improve the classification and treatment of psychological disorders (Borsboom, 2017; Hofmann, Curtiss, & McNally, 2016). As noted, a commonly proposed method for achieving the latter is to directly target the most central PTSD symptoms that have been revealed in nomothetic network studies through intervention. However, as the lack of statistical equivalence between inter- and intraindividual variability limits the validity of group-to-individual inferences, current insights from cross-sectional networks are likely to translate poorly to clinical decision making, which relates to one person at a time, and may even be misleading. For example, in a recent multisite, cross-cultural network study, Fried et al. (2018) demonstrated that loss of interest in usual activities was a highly central symptom across cross-sectional networks estimated from four separate samples of individuals with PTSD. Given that this symptom is rarely the explicit focus of evidence-based treatments for PTSD, the authors suggested that future studies should examine whether targeting this symptom could improve the effectiveness of PTSD treatment. However, due to the lack of equivalence between inter- and intraindividual variability, the assumption that this symptom would similarly be the most central to the network of each individual in the sample is unlikely to hold. Instead, this symptom could easily be among the least central for a given individual, which would make direct intervention targeting this symptom unlikely to improve the effectiveness of PTSD treatment for that individual. This lack of equivalence is further compounded when considering the association this symptom may have with other symptoms over time at the individual level, which is likely to similarly vary on a person-by-person basis. Such heterogeneity in symptom structure ultimately undermines the goals of the network literature while further underscoring the need to explore idiographic network models.

Over the past decade, researchers have increasingly pushed for a renewed emphasis on idiographic methods, as these might be useful for tailoring psychological interventions to the experiences of individual patients (Fisher, 2015; Fisher & Boswell, 2016; Piccirillo & Rodebaugh, 2019). These authors have argued that idiographic methods will be critical to the creation of precision mental health systems and the personalization of assessment and intervention (Fisher et al., 2019; National Institutes of Health, 2017). Fisher et al. (2017) further argued that, through leveraging the rich individual-level information these methods provide, idiographic methods can also be used to meaningfully transform the field's approach to the classification of psychopathology. Idiographic network models are especially well suited for these tasks. This is because these methods can highlight symptom dynamics idiosyncratic to each individual while also, when averaging across separately estimated idiographic models, reveal common processes occurring across individuals. Further, the advent of smartphone-facilitated ecological moment assessment (EMA) designs facilitates the collection of the intensive longitudinal data necessary for idiographic analyses. Thus, these data can now be collected with relative ease from individuals and used to estimate idiographic symptom networks. To date, there have been three studies that have leveraged EMA paradigms to estimate within-person symptom networks (Bak, Drukker, Hasmi, & van Os, 2016; Epskamp et al., 2018; Fisher et al., 2017). Fisher et al. (2017) and Epskamp et al. (2018) used networks to examine symptom relations both contemporaneously (concurrent associations within a given window of time) and temporally (lagged associations across sequential measurement windows). To date, however, no research of which we are aware estimated idiographic symptom networks of PTSD.

The aim of the present study was to examine the potential consistency of network structures among individuals with PTSD. Consistent with other recent idiographic network research (Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017; Rubel, Fisher, Husen, & Lutz, 2018), we hypothesized that the associations among symptoms would vary in number and degree from person to person. We recruited participants who met criteria for current PTSD per the fifth edition of the *DSM*

(*DSM-5*; APA, 2013). Each participant then rated the degree to which they experienced each PTSD symptom four times per day for a minimum of 30 days. The multivariate time series for each individual was used to estimate separate contemporaneous and temporal networks of PTSD symptoms—representations of correlational relations concurrent in time and across successive moments, respectively. Finally, we calculated centrality metrics to determine the relative importance of each symptom in each idiographic network. We demonstrate how these steps provide rich individual-level data and discuss how network-based insights may be utilized to highlight possible maintaining factors and points for clinical intervention.

Method

Participants and Procedure

The present study included 20 participants with current PTSD. Participants were largely White (n = 9; 45.0%) and male (n = 12; 60.0%), with a mean age of 38.35 years (SD = 12.51). Of the non-White participants, two (10.0%) identified as Black, two (10.0%) as Hispanic/Latinx, and seven (35.0%) as multiracial/other. The modal annual household income for the present sample was less than $10,000 (USD) per year, and the highest level of education attained was a four-year bachelor's-level degree. Moreover, 13 (65.0%) participants met criteria for at least one comorbid diagnosis, which included social anxiety disorder (n = 4), illness anxiety disorder (n = 1), agoraphobia (n = 3), generalized anxiety disorder (n = 6), persistent depressive disorder (n = 5), specific phobia (n = 3), substance use disorder (n = 2), obsessive-compulsive disorder (n = 1), and panic disorder (n = 1).

Procedure

All study procedures were approved by the Committee for the Protection of Human Subjects at the University of California, Berkeley (Protocol # 2015-01-7093). The study included three phases: (a) recruitment and screening, (b) baseline assessment, and (c) a 30-day ecological momentary assessment (EMA) sampling period. Participants were compensated $50 for completion of all study procedures. Participants were not offered treatment at any point during the study as compensation for participation.

Recruitment and screening. Inclusion criteria were a primary diagnosis of PTSD, being between the ages of 18–65 years, the absence of current mania or psychosis, and having daily access to a web-enabled mobile phone that could receive text messages. Potential participants were recruited from the surrounding community via online advertisements and posted flyers inquiring about PTSD symptoms. Interested individuals were instructed to contact the study laboratory by phone and complete a brief telephone screen. Individuals who passed the phone screen were then invited to the study laboratory for a structured clinical interview. The Life Events Checklist for *DSM-5* (LEC; Weathers et al., 2013) and the PTSD Checklist for *DSM-5* (PCL-5; Blevins, Weathers, Davis, Witte, & Domino, 2015) were used to screen for index traumas and PTSD, respectively. Screened participants with PCL-5 total scores of 38 or higher were deemed to have probable PTSD and were invited for an in-person structured clinical interview.

Of the 294 individuals who were screened, 100 were eligible for an in-person structured clinical interview. Nine (9.0%) of these eligible participants were excluded after failing to respond to study personnel to schedule the in-person structured clinical interview. Of the 194 participants who were ineligible, 43 (22.2%) were excluded for having PCL-5 total scores below 38, 27 (13.9%) reported no index trauma, 36 (18.6%) lacked daily access to a web-enabled smartphone, 2 (1.0%) were not between 18 and 65 years of age, 44 (22.7%) had personal conflicts that interfered with study participation, 24 (12.4%) expressed that they were no longer interested in the study, and 20 (10.3%) failed to follow up with study personnel to complete the study screening after an initial contact.

Baseline assessment. After presenting to the study laboratory and providing written informed consent, the Clinician Administered PTSD Scale for *DSM-5* (CAPS-5; Blake et al., 2000) and the Anxiety and Related Disorders Interview for *DSM-5* (Brown & Barlow, 2014) were administered to confirm the presence of PTSD and any comorbid diagnoses, respectively. These structured interviews were administered by trained research assistants under the supervision of an advanced doctoral student in clinical psychology and a PhD-level clinical psychologist. Participants who met inclusion criteria following the structured clinical interview were deemed eligible and invited to participate in the EMA portion of the study.

30-Day EMA sampling period. To enroll in the study, each participant provided their personal mobile device number to be entered into a secure web-based survey system. This system sent text messages to each participant's phone four times per day for a minimum of 30 days; text messages contained a hyperlink to a web-based survey. Each message populated the backend of the system with a time stamp, whether the participant completed the survey or not. For each survey, participants rated the degree to which they experienced a given PTSD symptom over the preceding hours, using a visual analog slider to enter a rating between 0 (*not at all*) and 100 (*as much as possible*). Participants were required to complete at least 80% of the daily surveys to receive the $50 compensation for study participation and for inclusion in the present analyses. Of 37 eligible participants, six (16.1%) were excluded for failing to complete the minimum number of phone survey assessments for the present analyses, five (13.5%) discontinued participation during the phone survey assessment period, four (10.8%) failed to respond to follow-up with study personnel to complete study enrollment procedures, and two (5.4%) could not participate due to technical issues. An independent samples t test revealed that there was no difference in PTSD symptom severity, indexed by CAPS-5 total symptom severity scores, between participants who completed the 30-day EMA sampling period and those who did not, $t(34) = 0.89$, $p = .380$. The included participants averaged 126.15 observations during the 30-day period ($SD = 12.75$; range: 110–168).

Measures

Anxiety and related disorders. The Anxiety and Related Disorders Interview Schedule for *DSM-5* (ADIS-5; Brown & Barlow, 2014) is a semistructured clinical interview designed to diagnose current anxiety, mood, and related disorders according to *DSM-5* criteria. This updated version of the ADIS builds upon previous versions (i.e., ADIS, for *DSM-III*; AIDS-R, for *DSM-III-TR*; and ADIS-IV, for *DSM-IV*), all of which showed well-established reliability. The ADIS-IV demonstrated good-to-excellent interrater reliability for *DSM-IV* disorders (κs $= 0.67$–0.86, except dysthymia, $\kappa = 0.31$; Brown, Di Nardo, Lehman, & Campbell, 2001).

PTSD symptoms and diagnosis. The CAPS-5 (Blake et al., 2000) is a 30-item, structured clinical interview designed to diagnose lifetime, past-week, and current PTSD as well as to determine PTSD symptom severity according to *DSM-5* criteria. The CAPS-5 diagnosis has previously demonstrated strong interrater reliability (κs $= 0.78$–1.00), test–retest reliability ($\kappa = 0.93$), and correspondence with a diagnosis based on the CAPS for *DSM-IV* (*CAPS-IV*; Weathers et al., 2018).

The PCL-5 (Weathers et al., 2013) is a 20-item self-report measure that assesses, for monitoring, screening, and provisional diagnostic purposes, the 20 *DSM-5* symptoms of PTSD. A total symptom severity score can be obtained by summing the scores of each individual item. The PCL-5 has demonstrated strong internal consistency ($\alpha = .94$), test–retest reliability ($r = .82$), and both convergent (rs $= .74$–$.85$) and discriminant (rs $= .31$–$.60$) validity (Blevins et al., 2015).

Lifetime traumatic events. The LEC-5 (Weathers, Blake, et al., 2013) is a self-report measure designed to screen for exposure to sixteen potentially traumatic events that an individual has experienced, directly witnessed, or learned about in their lifetime. The LEC has demonstrated good test–retest reliability (rs $= .37$–$.80$) and adequate convergent validity (rs $= .34$–$.48$; Gray, Litz, Hsu, & Lombardo, 2004).

Ecological moment assessment survey. Following study enrollment, each participant was asked to complete surveys assessing current PTSD symptoms. Surveys were sent via text message four times per day for a minimum of 30 days. Each survey contained 37 items, including 28 items assessing PTSD symptoms outlined in the *DSM-5* (APA, 2013). The additional nine items included five that assessed positive emotional experiences (enthusiastic, positive, happy, content, and calm), two that assessed physical symptoms (fatigue and muscle tension), and two that assessed sleep experiences not captured by PTSD symptoms (total sleep time from the previous night and sleepiness). The present analyses focused exclusively on the 28 PTSD items. These items were adapted from the PCL-5 (Blevins et al., 2015).

It is important to note that certain PTSD symptoms were addressed in multiple survey items: (a) three items assessed persistent and exaggerated beliefs or expectations about oneself, others, or the world; (b) two items assessed persistent, distorted cognitions about the cause or consequences of a traumatic event that lead to blame of oneself or others; (c) five items assessed persistent negative emotional state; and (d) and two items assessed sleep disturbance were each. This approach was taken to capture fluctuations related to each distinct component of these symptoms as participants completed the daily surveys. Further, to adequately capture intradaily fluctuations in PTSD symptoms conceptualized as persistent—namely items related to (a) persistent exaggerated beliefs and expectations of oneself, others, or the world; (b) persistent distorted blame of oneself or others for the event or its consequences; and (c) persistent negative emotional state—items assessing these experiences gauged the degree to which participants experienced thoughts or emotions reflective of these persistent beliefs or states at each survey. Finally, sleep-related PTSD symptoms, including traumatic nightmares, difficulty falling or staying asleep, and experiencing unsatisfying sleep, 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 are included in the Supplementary Materials.

Data Analysis

There were four data preparation steps taken prior to estimating each participant's network. First, composite variables were calculated by averaging the ratings of the respective items for each symptom for symptoms related to (a) persistent and exaggerated beliefs or expectations about oneself, others, or the world; (b) persistent, distorted cognitions about the cause or consequences of a traumatic event that lead to blame of oneself or others; (c) persistent negative emotional state; and (d) sleep disturbance. Second, as sleep-related PTSD symptoms were only assessed once per day, the initial observation for each day was duplicated across the successive observations for each respective day, resulting in univariate time series of equal length to the other variables, which were assessed four times per day. Third, for each participant, ratings for each symptom were standardized by subtracting the mean rating for that variable from each rating and dividing by its standard deviation, resulting a matrix of standardized ratings of PTSD symptoms over the 30-day EMA sampling period for each individual. Fourth, for each individual, time stamps that accompanied each set of ratings were used to calculate the cumulative time elapsed over the 30-day EMA sampling period. Cumulative time was specifically calculated as the sum of successive differences between time stamps (placed in chronological order) across the survey sampling period for each individual. This cumulative time variable was then used to apply linear detrending to each variable. The residuals of these models were then retained as the detrended standardized time series of each variable. Cubic spline interpolation was then applied to each detrended time series to resample the unevenly sampled data—sampling intervals of 4, 4, 4, and 12 hr–to an even 6-hr sampling interval.

Consistent with a recent approach for estimating the contemporaneous and lagged relations in idiographic time-series networks (Fisher et al., 2017), single-indicator dynamic factor models were constructed for each individual on a person-by-person basis. Path models were estimated with a zero matrix for the observed errors, an identity matrix (diagonal matrix of 1s) for the factor loadings, and the variance of each variable expressed in the latent disturbances. We employed an automated search procedure, using the Lagrange multiplier test, to determine the lagged regression structure for each individual. Each individual model began by estimating all autoregressive paths and correlations between variables at time t and time $t + 1$. Starting with the regression path from time t to time $t + 1$ with the largest associated chi-square change, these paths were iteratively added to the initial model until no remaining paths associated with a chi-square change of at least 5.00 remained. Lagged regression paths backward in time (from $t + 1$ to t) were suppressed during this procedure. The fit of each individual model was evaluated using cutoffs for the Brown's chi-square goodness-of-fit test, the root mean square error of approximation (RMSEA), and the confirmatory fit index (CFI). Nonsignificant chi-square values, RMSEA values less than .060, and CFI values greater than or equal to .95 are indicative of excellent fit (see Hu & Bentler, 1999). Standardized coefficients reflecting (a) correlations at Time t and (b) lagged regression paths between t and $t + 1$ were then extracted to estimate idiographic contemporaneous and temporal networks, respectively.

For each individual, we then estimated two idiographic networks. First, we used the standardized correlation coefficients at Time t to estimate a contemporaneous network model. Specifically, a sparse partial correlation network model was generated for each participant, using the least absolute shrinkage and selection operator (LASSO) regularization method implemented in *R* (R Core Team, 2018) with the package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). As noted above, contemporaneous networks reflect symptom associations concurrent in time. Next, we used the standardized lagged regression coefficients from time t to time $t + 1$ to estimate a temporal network for each individual. These temporal networks represent the average degree to which variation in one node at time t predicts variation in itself or in another node at time $t + 1$. No regularization was applied to these associations, with *qgraph* employed as a visualization tool.

Following network estimation, we calculated the strength centrality for each node in the contemporaneous networks and both the in-strength and out-strength for the temporal networks. Strength is defined as the sum of the absolute magnitude of all edges of a given node to all other connected nodes. Based on the directional associations in the temporal networks, in-strength is defined as the sum of the absolute magnitude of all incoming paths for a given node, whereas out-strength is defined as the sum of the absolute magnitude of all outgoing paths from a given node.

Table 1
Fit Statistics for Vector-Autoregressive Structural Equation Models

ID	χ^2	*df*	*p*	RMSEA	CFI	Obs. (*N*)
002	357.28	352	.411	.04	.97	123
005	314.26	335	.786	.03	.99	122
011	382.56	350	.111	.04	.98	167
013	422.39	360	.013	.06	.97	123
014	380.14	363	.258	.05	.97	125
021	313.69	347	.900	.02	1.00	142
031	294.72	352	.988	.00	1.00	117
032	347.27	359	.662	.04	.98	110
033	392.20	359	.110	.06	.93	119
036	300.81	351	.975	.01	1.00	117
039	315.44	349	.901	.03	.99	116
043	313.30	345	.889	.02	.98	121
046	360.42	363	.528	.04	.97	115
051	397.67	349	.037	.06	.96	126
054	342.67	353	.643	.03	.98	140
061	326.89	348	.786	.03	.98	121
067	312.24	341	.866	.02	1.00	139
068	366.58	357	.352	.04	.98	128
069	347.60	322	.156	.05	.99	124
072	326.59	347	.778	.03	.99	128

Note. ID = participant identification number; χ^2 = Brown's chi-square; *df* = degrees of freedom; RMSEA = root mean square error of approximation; CFI = comparative fit index; Obs. = number of observations for a given model.

Results

Model Fit

For each individual, the fit of each idiographic dynamic factor model was evaluated using Brown's chi-square goodness-of-fit test, RMSEA, and CFI (Hu & Bentler, 1999). Table 1 provides fit statistics, degrees of freedom, and number of observations for each individual's model. All models exhibited excellent fit. However, it should be acknowledged that this is somewhat tautological given that fit criteria (i.e., chi-square change) were employed as stoppage rules for model estimation.

Idiographic Networks

Idiographic contemporaneous and temporal network visualizations for each individual are available on the Open Science Framework at https://osf.io/6vxhf/. The following section

Table 2
Average Normalized Values of Strength, In-Strength, and Out-Srength Values, Across Participants

Item	Strength	In-Strength	Out-Strength
Recurrent, intrusive memories or thoughts	0.67	0.18	0.22
Distressing dreams about the trauma	0.41	0.48	0.36
Reliving the trauma	0.57	0.39	0.36
Upset when reminded of the trauma	0.67	0.34	0.30
Physical reactions to trauma-reminders	0.65	0.33	0.24
Avoidance of thoughts or feelings	0.52	0.23	0.30
Avoidance of people, places, or situations	0.58	0.32	0.32
Difficulty remembering the trauma	0.53	0.33	0.31
Strong negative expectations or beliefs	0.83	0.26	0.36
Distorted trauma-related blame	0.59	0.28	0.31
Negative trauma-related emotions	0.75	0.29	0.40
Loss of interest or pleasure in usual activities	0.60	0.36	0.29
Feeling distant or cut off	0.60	0.22	0.32
Difficulty feeling positive	0.54	0.26	0.29
Feeling irritable or acting aggressively	0.57	0.20	0.23
Risky or self-destructive behavior	0.48	0.28	0.28
Feeling watchful or on guard	0.63	0.30	0.27
Exaggerated startle	0.58	0.39	0.33
Difficulty concentrating	0.59	0.31	0.38
Sleep disturbance	0.43	0.44	0.34
Descriptive Statistics			
Minimum	0.41	0.18	0.22
Maximum	0.83	0.48	0.40
SD	0.10	0.08	0.05

summarizes the average centrality for both contemporaneous and temporal networks across all participants. Values for strength, in-strength, and out-strength were normalized within each participant (centrality for each symptom divided by the maximum centrality value) to allow for comparison across individuals. Table 2 displays the normalized values for strength, in-strength, and out-strength across the sample.

Contemporaneous networks. Across individuals, negative thoughts about oneself, others, or the world exhibited the greatest strength, followed closely by negative trauma-related emotions. In contrast, distressing trauma-related dreams and sleep disturbance exhibited the least strength. Thus, negative trauma-related cognitions and emotions were the most densely connected PTSD symptoms across individuals, indicating that these tended to be the most commonly co-occurring symptoms at any given moment. Conversely, sleep-related PTSD symptoms were the least connected, indicating that these rarely co-occurred with other symptoms. However, given the method used for estimating sleep effects, this may be due to limited variability in the sleep-related items.

Temporal networks. Distressing trauma-related dreams and sleep disturbance exhibited the greatest in-strength across individuals, indicating that these experiences were the most commonly and strongly predicted by other PTSD symptoms over time. Recurrent, intrusive thoughts or memories of the trauma exhibited the lowest in-strength, indicating that these experiences were the least commonly predicted by other symptoms over time across individuals. Thus, to the degree that the temporal spacing in the current study maps onto the timing of intrusive thoughts and memories, these results indicate that recurrent trauma-related intrusions are generated by processes outside of other PTSD symptoms.

Negative trauma-related emotions exhibited the greatest out-strength across individuals, followed closely by difficulty concentrating, feelings of reliving trauma, distressing trauma-related dreams, and strong negative thoughts about oneself, others, or the world. Such a diverse list of predictors may reflect the limits of aggregation for understanding idiographic models. That is, because different nodes were the most densely connected and predictive of other nodes, no single node stood out as a driver of symptom variation from observation to observation. However, it is possible that the diversity of "top" predictors in the current study is spurious and driven by the relatively small between-subject sample size. It is plausible that, with larger sample sizes, a more consistent picture may emerge, with fewer principal drivers of variability.

Table 3
Normalized Values of Strength, In-Strength, and Out-Strength for Participants 013 and 039

Item	Strength		In-Strength		Out-Strength	
	P013	P039	P013	P039	P013	P039
Recurrent, intrusive memories or thoughts	0.69	0.51	0.00	0.00	0.00	0.00
Distressing dreams about the trauma	0.86	0.29	0.10	1.00	0.54	0.53
Reliving the trauma	0.70	0.37	0.00	0.00	0.45	0.65
Upset when reminded of the trauma	0.88	0.66	0.00	0.00	0.17	0.26
Physical reactions to trauma-reminders	0.83	0.42	1.00	0.20	0.00	0.29
Avoidance of thoughts or feelings	0.59	0.19	0.00	0.00	1.00	0.00
Avoidance of people, places, or situations	1.00	0.79	0.56	0.17	0.36	1.00
Difficulty remembering the trauma	0.67	0.45	0.00	0.56	0.50	0.00
Strong negative expectations or beliefs	0.78	1.00	0.37	0.00	0.00	0.00
Distorted trauma-related blame	0.72	0.54	0.15	0.14	0.96	0.52
Negative trauma-related emotions	0.62	0.60	0.00	0.26	0.12	0.32
Loss of interest or pleasure in usual activities	0.71	0.59	0.70	0.38	0.00	0.40
Feeling distant or cut off	0.70	0.54	0.00	0.18	0.00	0.57
Difficulty feeling positive	0.79	0.44	0.00	0.00	0.39	0.13
Feeling irritable or acting aggressively	0.81	0.43	0.00	0.19	0.59	0.70
Risky or self-destructive behavior	0.64	0.44	0.41	0.35	0.00	0.45
Feeling watchful or on guard	0.89	0.47	0.14	0.76	0.00	0.00
Exaggerated startle	0.83	0.31	0.20	0.18	0.19	0.42
Difficulty concentrating	0.76	0.32	0.50	0.18	0.15	0.74
Sleep disturbance	0.43	0.35	0.34	0.42	0.00	0.76

Two Individual Case Examples

The following section includes a detailed description of the results from two randomly selected participants. This step was taken to highlight the rich individual-level data provided by idiographic symptom networks and the potential these networks may hold for guiding individual treatment planning. The two individuals selected include Participant 013 and Participant 039, whom we will refer to as "Bob" and "Sara." Table 3 displays the normalized values of strength, in-strength, and out-strength for each participant.

Example 1: Bob. Bob was a 36-year-old White man with a primary diagnosis of PTSD and no comorbid diagnoses. He reported physical assault as his index trauma. Figure 1 presents Bob's contemporaneous and temporal networks. Positive associations between symptoms are depicted in green, whereas negative relationships are depicted in red. Avoidance of trauma-related people, places, or situations exhibited the greatest strength, most strongly co-occurring with being watchful or on guard, loss of interest or pleasure in usual activities, and negative thoughts about oneself, others, or the world. Thus, it appears that Bob's behavioral avoidance of reminders of his trauma were often tied to an enhanced sensitivity to possible threats, an inability to experience pleasure, and negative thoughts about himself, others, or the world.

Physical reactions to trauma reminders exhibited the greatest in-strength, being most strongly predicted by preceding avoidance of trauma-related people, places or situations, feelings of reliving the trauma, and avoidance of trauma-related thoughts and emotions. The lattermost symptom also exhibited the greatest out-strength, most strongly preceding physical reactions to trauma reminders, difficulty concentrating, exaggerated startle, and sleep disturbance. Although Bob's cognitive avoidance of trauma reminders led to reductions in other PTSD symptoms, his behavioral avoidance led to heightened physiologic reactivity. Thus, although Bob's behavioral avoidance amplified physiological symptoms, his cognitive avoidance was likely negatively reinforcing due to the resultant distress reduction.

Example 2: Sara. Sara was an 18-year-old Hispanic/Latina woman with a primary diagnosis of PTSD and comorbid major depressive disorder, generalized anxiety disorder, and panic disorder. She reported sexual assault as her index trauma. Figure 2 presents Sara's contemporaneous and temporal networks. Positive associations between symptoms are depicted in green, whereas negative relationships are depicted in red. Negative thoughts about oneself, others, or the world exhibited the greatest strength, most strongly co-occurring with distorted trauma-related blame of oneself or other, feeling distant or cut off from others, difficulty feeling positive, and feeling irritable or acting aggressively. However, this symptom had in-strength and out-strength values of zero, suggesting that these negative cognitions neither strongly predicted nor were strongly predicted by other symptoms over time. Thus, it appears that Sara's

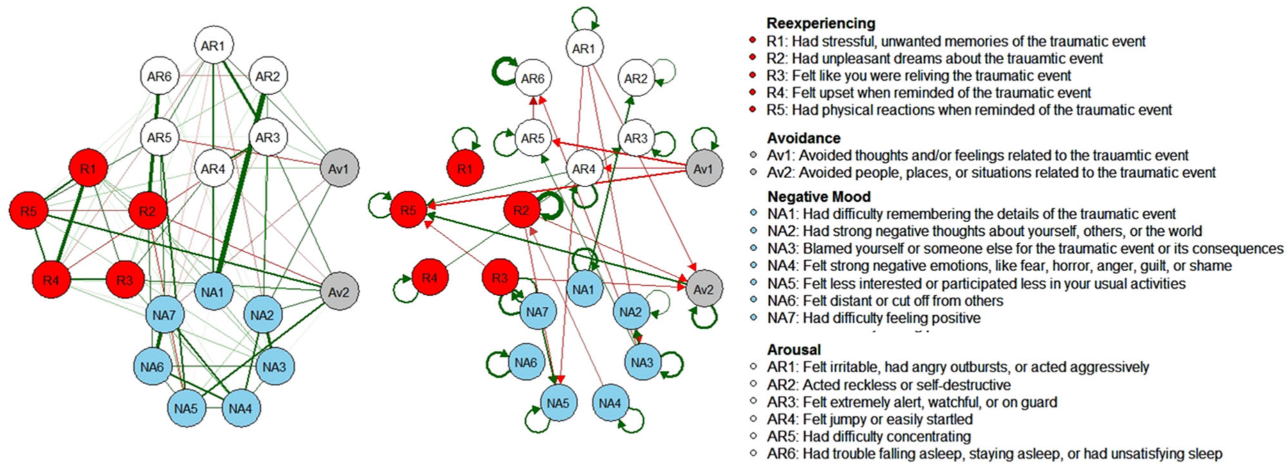

Figure 1. Contemporaneous network at time *t* (left) and temporal network of lagged associations between time *t* and time *t* +1 (right), for Bob (Participant 013).

negative trauma-related thoughts about herself, others, or the world often occurred in conjunction with negative emotional states and feelings that may promote isolation from others.

Distressing trauma-related dreams exhibited the greatest in-strength, being most strongly predicted by negative trauma-related emotions. In contrast, avoidance of trauma-related people, places, or situations exhibited the greatest out-strength, most strongly predicting feeling watchful or on guard as well as loss of interest or pleasure in usual activities. Thus, Sara's behavioral avoidance of trauma reminders led to enhanced sensitivity to threat and anhedonia. Additionally, her negative trauma-related emotions led to a reduction in the likelihood of having traumatic nightmares.

Discussion

The aim of the present study was to explore the idiographic network structure of PTSD symptoms in order to examine the consistency in network structure among individuals with PTSD. To date, PTSD symptom networks that populate the existing literature have largely been estimated from cross-sectional data aggregated across individuals (Afzali, Sunderland, Batterham, et al., 2017; Afzali, Sunderland, Teesson, et al., 2017; Armour et al., 2017; Birkeland & Heir, 2017; Bryant et al., 2017; Frewen et al., 2013; Fried et al., 2018; Knefel et al., 2016; Mitchell et al., 2017; Spiller et al., 2017). Additionally, multilevel analyses have estimated networks from longitudinal—but, nevertheless, aggregated—data (Greene et al., 2018; Hoffart et al., 2019). Such aggregations assume a degree of homogeneity in network structure that is likely untenable (Fisher et al., 2018) given the lack of statistical equivalence between inter- and intraindividual variability (Hamaker et al., 2005; Molenaar, 2004). Thus, insights from nomothetic networks are unlikely to adequately reflect processes that occur at the individual level. Instead, describing these individual-level processes requires estimating idiographic symptom networks.

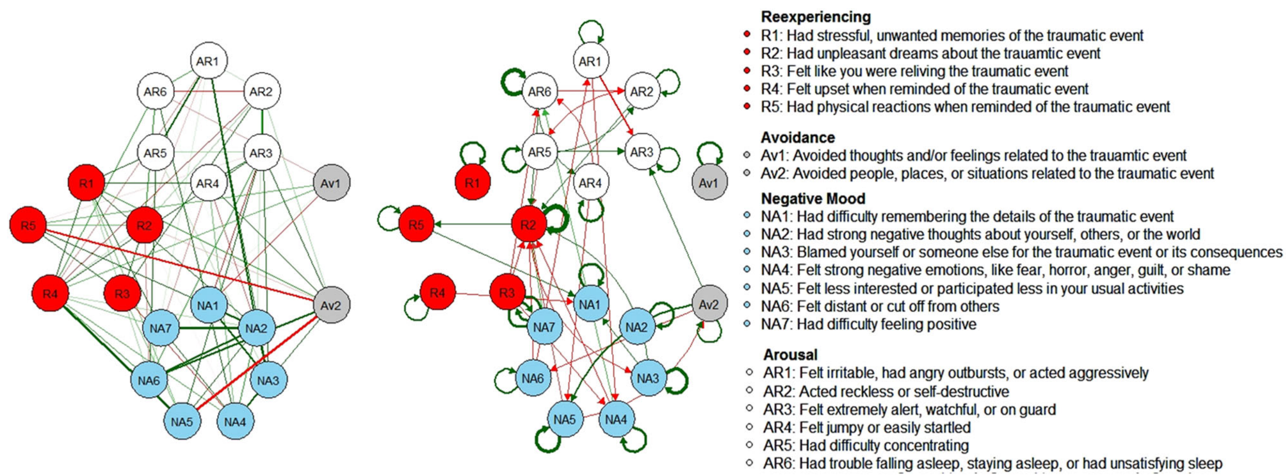

Figure 2. Contemporaneous network at time *t* (left) and temporal network of lagged associations between time *t* and time *t* +1 (right), for Sara (Participant 039).

We believe that this distinction is critical as our field moves toward adopting a more personalized model of psychological dysfunction and empirically supported care (Fisher, 2015; Fisher & Boswell, 2016; Piccirillo & Rodebaugh, 2019). The present study estimated contemporaneous and temporal networks for 20 participants with current PTSD. These models reflected the respective concurrent and time-lagged covariance between PTSD symptoms. To the best of our knowledge, this was the first study to estimate idiographic symptom networks of PTSD.

The results from the present study reinforce theoretical and empirical arguments for the importance of negative trauma-related cognitions as a prominent maintaining factor of PTSD (Ehlers & Clark, 2000; Zalta & Foa, 2012). The cognitive model of PTSD argues that these cognitions promote the misperception of ongoing threat and impede the processing of disconfirming information. This leads to reinforcement of the initial misappraisals, promoting chronicity rather than a reduction in distress over time. Consistent with this, in the present study, negative thoughts about oneself, others, or the world was most commonly the most central PTSD symptom across the contemporaneous networks. This interpretation is further bolstered by results related to negative trauma-related emotions. This symptom closely followed negative thoughts about oneself, others, or the world as a highly central symptom across the idiographic contemporaneous networks. Furthermore, negative trauma-related emotions most commonly exhibited the largest influence on other PTSD symptoms over time across the idiographic temporal networks. This is in line with the argument that trauma-related emotions linked to the overestimation of threat further exacerbate PTSD symptoms over time (Ehlers & Clark, 2000). Given this consistency, we conjecture that, despite the small between-subject sample size, the symptoms and experiences of the individuals in the present study may be representative of others with PTSD.

These results also reinforce the literature on the interplay between PTSD symptoms and sleep disturbance (Germain, 2013). In the present study, distressing trauma-related dreams and sleep disturbance were most commonly the symptoms most strongly influenced by preceding fluctuations in other PTSD symptoms across temporal networks. Although these symptoms are not exclusive to PTSD, this highlights a pathway by which symptom-related distress may disturb sleep and ultimately promote maintenance, rather than recovery, of the disorder. However, this result should be interpreted with caution. As noted, both distressing trauma-related dreams and sleep disturbance were each assessed only once per day. Given that ratings of these symptoms were duplicated across a given day to yield series of equal length to other symptoms, it may be that the autoregressions of these symptoms have been artificially inflated, which could produce a larger in-strength value. Future studies should endeavor to replicate these results and employ novel paradigms that provide intradaily measurements of sleep disturbance.

Finally, these results also highlight the importance and utility of estimating idiographic symptom networks. As noted, although cross-sectional nomothetic networks provide robust descriptions of symptom importance and symptom associations that occur at the group-level, these fall short of describing the organization or presentation of symptoms within a single individual as they occur over time (Fisher et al., 2017, 2018; Piccirillo & Rodebaugh, 2019). For example, although negative trauma-related emotions is a symptom that has exhibited high centrality in cross-sectional networks in the literature (Armour et al., 2017; Mitchell et al., 2017), the symptom was among the least central symptoms in Bob's contemporaneous network. Further, although this symptom was relatively central to Sara's contemporaneous network, it was neither among the most influential nor the most strongly influenced symptom temporally for Sara. Moreover, although Greene et al. (2018) found that exaggerated startle response exhibited the most influence over time in a nomothetic temporal network, this symptom showed relatively weak temporal influence for both Sara and Bob. Taken together, these discrepancies suggest that there may be a high degree of nuanced detail in individual-level processes that is overlooked or obscured in nomothetic networks. Given evidence for the substantial heterogeneity present in the diagnosis (Galatzer-Levy & Bryant, 2013), this may be especially pressing in PTSD. However, this heterogeneity may be lessened when the PTSD criteria outlined in *the International Classification of Diseases* (11th rev.; World Health Organization, 2018), as opposed to the *DSM*, (APA, 2013) are used. Nevertheless, future studies should endeavor to further explore the idiographic network structure of PTSD. A larger volume of work in this area would not only provide an opportunity to better understand nuances in individual-level processes, the use of large sample sizes, or samples across multiple studies, could begin to help delineate typologies of network dynamics and PTSD subpopulations defined by dynamic, mechanistic processes.

The past decade has seen several efforts to tailor psychological interventions to the needs and characteristics of each individual patient (Fisher & Boswell, 2016; Piccirillo & Rodebaugh, 2019). The present results show the potential utility of combining idiographic approaches and network theory to move the field closer to this goal. One possibility is to combine idiographic network data with data-driven algorithms to select specific interventions from larger ensembles of empirically supported techniques that are best fit to an individual. Fisher et al. (2019) provided an example of this approach in a recent open trial of personalized modular therapy for mood and anxiety disorders. The authors used idiographic pretherapy symptom data with a treatment selection algorithm to match individuals to personalized modular treatments on a person-by-person basis. For PTSD, a similar approach could be used to select a specific evidence-based PTSD treatment that best fits each individual's experience (Rubel et al., 2018). For instance, features of Bob's idiographic network revealed that his cognitive avoidance exhibited stronger temporal influence over other symptoms than his behavioral avoidance. Given that both cognitive processing (CPT) and prolonged exposure (PE) therapy are highly efficacious evidence-based treatments for PTSD (Foa, Keane, Friedman, & Cohen, 2008), a digitized system could leverage this person-specific information about Bob to preferentially select CPT over PE as a first-line treatment for Bob based on his individual experience.

Additionally, another possible application involves using idiographic models to enhance the effectiveness of exposure therapy. This could function similarly to functional analytic techniques implemented in cognitive behavioral interventions (Fisher, 2015), whereby antecedents and consequences of a presenting problem are identified and targeted to facilitate behavior change. Similar to what was described earlier, features of idiographic network models could be leveraged to augment exposure by identifying symptoms reported by an individual that are most strongly associated with avoidance and could be targeted with additional empirically supported techniques. This would provide the patient with alternative strategies to avoidance, each tailored to their individual experience. Future studies should endeavor to evaluate novel methods for leveraging information drawn from idiographic methods to understand psychopathology processes occurring within each individual and optimize treatment response on a person-by-person basis

Finally, despite its strengths, there are several limitations of the present study that are important to discuss. First, although this study represents the first, to our knowledge, to estimate idiographic symptom networks of PTSD, the four-times-per-day sampling protocol may arguably provide a relatively coarse temporal resolution of these symptoms. Whereas the present study was able to estimate effects that occurred over a 4-hr window or more, it may not have adequately captured effects that occurred more rapidly. Second, on a related note, the dynamic factor models estimated in this study used on a single time lag. This overlooks effects that unfolded over time at additional time lags, which may be important for precisely detecting feedback loops that unfold over larger windows of time. Third, to address concerns about replicability and guard against over-interpretation, several researchers have pushed for the routine testing of the stability of statistical parameters derived from network models (Epskamp & Fried, 2016; Fried & Cramer, 2017; Fried et al., 2018). However, given that these methods rely on bootstrapping routines that have not been optimized for networks estimated from time series data, we did not take this step in the present study. To address these concerns, future studies should endeavor to increase the frequency and number of observations collected from each individual to examine effects at varying time scales. Further, future researchers should endeavor to evaluate methods that can examine the stability of networks derived from time-series data, which must necessarily maintain the dependence structure of the original data to ensure valid inference. Despite these limitations, the present study represents an important exploration and extension of past research on PTSD symptom networks examining the idiographic network structure of PTSD.

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