Network Models of Posttraumatic Stress Symptoms across Trauma Types

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Abstract

Evidence suggests that posttraumatic stress (PTS) disorder (PTSD) symptom presentations may vary as a function of index trauma type. Network analysis was employed in the present study to examine differences in PTS symptom centrality (i.e., the relative influence of a symptom on the network), and PTS symptom associations across three trauma types: motor vehicle accident (MVA), sexual assault (SA), and sudden accidental/violent death of a loved one (SAD). The final sample comprised 554 female undergraduates who had experienced a MVA ($n = 226$), SA ($n = 222$), or SAD ($n = 106$) per Diagnostic Statistical Manual—Fifth Edition (DSM-5) criteria. Within the pooled network, anhedonia and dysphoria emerged as the most central symptoms, while trauma-related amnesia was the least central. The SA network was largely consistent with the DSM-5 conceptualization of PTSD. In contrast, the SAD network was the least consistent with the DSM-5 conceptualization of PTSD, and centrality estimates for the SAD network were inconsistent with the MVA and SA networks. Findings of the current study suggest a need to consider index trauma type as an important factor in the ontology of PTSD. Findings also add to the ongoing discussions about the suitability of SAD as a PTSD-relevant trauma type and about the importance of trauma-related amnesia as a PTSD symptom.

*Keywords:* Posttraumatic stress, Trauma, Network analysis, Criterion A
1. Introduction

Psychopathological presentations (i.e., disorders) have historically been treated as latent constructs that give rise to a set of symptoms, wherein symptoms are reflective of an underlying disorder (i.e., the ‘reflective model’; as discussed in Armour, Fried, Deserno, Tsai, & Pietrzak, 2017 and Borsboom & Cramer, 2013). A more contemporary conceptualization of psychopathology acknowledges that symptoms directly interact with (i.e., reinforce) one another in a systematic way that gives rise to a set of established symptoms (Fried & Cramer, 2017). In response to an increasing preference for this approach, network models have gained popularity. Network analysis provides a statistical and visual framework for investigating covariance amongst symptoms. Within the visual network are nodes (i.e., symptoms) that are connected through edges (i.e., associations among symptoms), wherein symptoms that are centrally located in the network are thought to have greater influence in comparison to symptoms that are peripherally located within the network (Armour et al., 2017). Thus, the network approach is well-suited for investigating the etiology of psychopathology as a set of mutually causal symptoms (Borsboom & Cramer, 2013). The network approach has been applied to a number of mental disorders (Borsboom, 2017; Fried et al., 2018), and its popularity in the psychopathology literature continues to grow (Fried & Cramer, 2017).

Posttraumatic stress (PTS) researchers have embraced network analysis as a method of attempting to understand how clusters of symptoms interact with one another to reinforce the prolonged stress response observed in individuals with PTS. Network analysis has been applied to PTS in community samples (Afzali et al., 2017), veterans (Armour et al., 2017), refugees (Spiller et al., 2017), and survivors of child abuse (Knefel, Tran, & Lueger-Schuster, 2016). However, symptoms emerging as highly central in PTS networks have differed across studies.
For example, emotional cue reactivity (Spiller et al., 2017), negative trauma-related emotions (Armour et al., 2017), and hypervigilance (McNally et al., 2015) have each separately emerged as the most central PTS symptom. It follows that some have urged for more replication of network studies in order to clarify patterns of PTS networks across samples (Borsboom et al., 2017; Forbes, Wright, Markon, & Krueger, 2017; Fried et al., 2018). It may be that different sample-level attributes account for inconsistent results across PTS networks to date. The type of index trauma (e.g., physical assault, natural disaster) that is associated with the onset of PTS symptoms (i.e., the index trauma) might be one such difference. However, to date, trauma type has not been examined in the context of PTS networks.

Some evidence suggests that differences in the index trauma associated with PTS may contribute to variation in PTS symptom severity and prevalence, such that individuals who experience interpersonal traumas (e.g., sexual assault) may be more likely to develop PTS, and exhibit higher symptomatology, compared to those who have experienced non-interpersonal traumas (e.g., natural disasters; Ditlevsen & Elklit, 2012; Kelley, Weathers, McDevitt-Murphy, Eakin, & Flood, 2009; Reisnick, Kilpatrick, Dansky, Saunders, & Best, 1993; Smith, Summers, Dillon, & Cougle, 2016). Additionally, differences in symptom patterns across trauma types have emerged. Kelley et al. (2009) directly compared PTS symptom profiles across civilian traumas through profile analysis and found significant symptom pattern differences across sexual assault (SA), motor vehicle accident (MVA), and sudden unexpected death of a loved one (SUD) groups. Specifically, those who had experienced SA or SUD showed more severe symptoms that were conceptually linked to interpersonal loss (e.g., detachment, restricted range of affect), compared to those who had experienced MVA. Similarly, Shevlin and Elklit (2012) used confirmatory factor mixed modeling and found that the latent structure of PTSD differed across
four trauma groups: bereaved, rape survivors, refugees, and MVA survivors. In a comparison of veterans with either combat, sexual, or civilian trauma, Graham et al. (2016) used a series of logistic regressions to reveal differential symptom-level endorsements based on precipitating trauma type. For example, those who experienced combat were more likely to experience detachment and loss of interest, compared to those who endorsed a sexual or civilian trauma. Although these studies provide preliminary evidence that PTS may differ across trauma types, studies to date have been limited in their methodology such that they are not able to speak to the differences in the relationships (i.e., covariance) amongst symptoms within the disorder.

Given the observed differences in PTS symptom severity, prevalence, and symptom profiles across different trauma types, it stands to reason that different trauma types may give rise to differing PTS networks. Specifically, central symptoms may differ as a function of trauma type. Differences in the structure of PTS networks based on index trauma may have important clinical implications. Specifically, identification of the most central symptoms in a network may clarify possible core antecedents or consequences within the symptom network. When a central symptom is a core antecedent, intervening on this symptom may cause a cascading effect in which more peripheral symptoms in the network are positively impacted. Highly central symptoms that are not necessarily antecedents within the network may maintain existing feedback loops. Targeting these symptoms may disrupt these feedback loops, weakening associations between the highly central symptoms and symptoms that they are associated with (Fried et al., 2018). An improved understanding of how trauma type may affect the ontology of PTS could improve treatments for PTSD.

In the present study, we compared PTS networks in three trauma groups: MVA, SA, and sudden violent or accidental death (SAD). These three groups were chosen based on the work of
Kelley et al. (2009). Specifically, Kelley et al. (2009) noted that these three trauma types are prevalent and confer risk for PTSD, but are conceptually distinct, such that they confer differential risk for PTSD and involve different levels of exposure. However, Kelley et al. (2009)’s SUD group was based on DSM-IV Criterion A, in which death of a loved one due to natural causes was included. Thus, our use of the DSM-5 definition of sudden accidental/violent death of a loved one replaces the SUD group and is an important update to the previous results of Kelley et al. (2009). Additionally, the present study makes use of multiple samples, which has been suggested as more accurate and generalizable (Fried et al., 2018). Thus, the primary aims of the present study were to (a) replicate patterns found in PTS network studies to date and (b) extend the application of network analysis to PTS by examining differences in networks as a function of index trauma type.

2. Method

2.1 Participants and procedure

Four samples were combined for the current study. Sample 1 consisted of 554 participants (Lee, Weathers, Sloan, Davis, & Domino, 2017), sample 2 consisted of 721 participants (Silverstein, Lee, Witte, & Weathers, 2017), sample 3 consisted of 2,223 participants, and sample 4 consisted of 1,998 participants, resulting in an initial total sample of \( N = 5,496 \). In sample 4, only 974 participants were instructed to complete the Posttraumatic Checklist for DSM-5 (PCL-5; Weathers, Litz et al., 2013), resulting in an initial subsample of 4,472. All participants were undergraduates from a large Southeastern university who were recruited through the university’s research pool. Participants completed a battery of questionnaires related to “a very stressful life event” and were compensated with extra credit.
Trauma exposure was assessed through participants’ responses on the Life Events Checklist for DSM-5 (LEC-5; Weathers, Blake et al., 2013) and by reviewing participants’ narrative descriptions of their index event. Index events were initially classified as meeting DSM-5 Criterion A if participants endorsed their worst event on the LEC-5 as having either happened to me directly or witnessed it and endorsed that my life was in danger, someone else’s life was in danger, or the event involved sexual violence. Index events were also coded as DSM-5 Criterion A if they endorsed having learned about it happening to a close family member or close friend and the event involved accident or violence or sexual violence. Index events that did not meet any of these requirements, including data that were missing responses needed to clarify Criterion A status, were coded as not meeting DSM-5 Criterion A and were excluded from the final sample.

Next, two graduate students independently reviewed participants’ narrative descriptions of their index event to verify DSM-5 Criterion A status. Raters independently provided a confidence rating of “low” or “high” regarding if the index event met DSM-5 Criterion A status. If the raters were confident with their decision, they gave a high confidence rating. If the raters were not confident with their decision, they gave a low confidence rating. Low confidence ratings were given in the event that narratives were extremely vague and more information would be needed in the narrative to absolutely confirm Criterion A status. Events with low confidence ratings were excluded in the analyses to increase confidence that all events met Criterion A. Disagreements between the raters were resolved through discussion among the raters and an expert in the field of traumatic stress. This resulted in the initial retention of 1,313 participants.
Because of the high proportion of females in the sexual assault group (91.5%), males were removed from the final sample \((n = 299)\). Participants who reported an index event that was either a motor vehicle accident (MVA), sexual assault (SA) or sudden accidental or violent death of a loved one (SAD) were included in the analyses. Participants with Criterion A events that did not fall into the three categories of interest, or whose trauma fell into more than one of the categories of interest (e.g., sudden accidental death from a motor vehicle accident) were removed from the sample \((n = 386)\). Finally, 74 participants had no symptoms of PTSD (as indicated by a PCL-5 score of zero), and were thus removed from the final sample.

Of the final sample \((N = 554)\), 226 reported a motor vehicle accident (MVA) group, 222 reported a sexual assault (SA), and 106 reported a sudden accidental or violent death (SAD). Groups did not differ with regard to age \((F[2] = 1.84, p = .16)\) or race \((F[2] = 0.38, p = .68)\). The average age for the pooled sample was 19.78 \((SD = 1.65)\). With regard to race, 90.1% self-identified as White, 6.1% as Black, 1.4% as Asian, 0.5% as American Indian or Alaskan Native, 0.2% as Native Hawaiian or Pacific Islander, and 1.6% as some other racial background. Additionally, 2.7% of the sample self-identified as Hispanic.

### 2.2 Measures

**Life Events Checklist for DSM-5 (LEC-5).** The LEC-5 (Weathers, Blake et al., 2013) is a 17-item checklist of potentially traumatic events. The checklist provides a list of sixteen potentially traumatic events (e.g., serious motor vehicle accident, sexual assault, physical assault), and one item in which the participant can write-in another stressful experience not captured by the checklist. For each event, participants indicate whether the event happened to them directly, they witnessed it, they learned about it happening to a close family member or friend, it was part of their job, they are not sure whether they experienced the event, or the event
did not apply to them. Consistent with Bovin et al. (2016), an extended version of the LEC-5 that provides the additional information required to ensure an event meets Criterion A (e.g., exposure to actual or threatened death, serious injury, or sexual violence; American Psychiatric Association [APA], 2013) was used in the present study. Specifically, after identifying the events that were experienced in one of the ways described above, participants selected which event they considered the worst and responded to follow-up questions that clarified their Criterion A status. Participants were instructed to reference this event when completing the PTSD Checklist-5 (Weathers, Litz et al., 2013).

**PTSD Checklist-5 (PCL-5).** The PCL-5 (Weathers, Litz et al., 2013) is a 20-item self-report measure designed to assess DSM-5 PTSD criteria B, C, D, and E (APA, 2013). Participants rated how much they have been bothered by each symptom in the past month (0 = *not at all* to 4 = *extremely*) in relation to the potentially traumatic event that they identified as most distressing on the LEC-5. Higher scores indicate greater PTS symptoms. Consistent with evidence suggesting that PTSD is not a discrete clinical syndrome, but rather a dimensional construct (e.g., Broman-Fulks et al., 2006; Forbes, Haslam, Williams, & Creamer, 2005; Ruscio, Ruscio, & Keane, 2002), PCL-5 items were summed to create an overall total score for use as a continuous variable. Internal consistency for the PCL-5 scores were excellent in the final sample (pooled sample $\alpha = .94$; MVA $\alpha = .93$; SA $\alpha = .95$; SAD $\alpha = .93$).

**2.3 Data Analytic Strategy**

A total of 0.7% of data were missing. Missing data was handled using the built-in pairwise deletion feature in *rgraph*. For network comparison tests (see below), only complete observations were used. Next, analyses were conducted in four steps: network estimation, network inference, network stability, and network comparison (Fried et al., 2018). All analyses
were conducted in R using RStudio (Version 1.1.419, 2009-2016). The R-packages *qgraph*, *bootnet*, *NetworkComparisonTest*, and *EstimateGroupNetwork* were used for analyses. First, a network with the pooled sample (i.e., all three trauma types) was analyzed. Networks were then analyzed for each of the three groups independently.

**Network estimation.** First, given that PCL-5 data are ordinal, polychoric correlation matrices were calculated for the three groups of interest. In network estimation, Pairwise Markov Random Fields (PMRF) networks are undirected (i.e., suitable for cross-sectional data) networks that estimate the edge (i.e., association) between two nodes (i.e., symptoms), after accounting for the edges between all other nodes (i.e., symptom associations) in the network. As such, PMRF networks are analogous to partial correlation networks. For this study, weighted Gaussian Graphical Modeling (GGM; see Epskamp & Fried, 2016), a form of PMRF, was used to estimate the networks. GGM is used for non-binary data, where all nodes are assumed to be normally distributed. Additionally, a graphical lasso (i.e., *glasso*; least absolute shrinkage and selection operator) procedure was used, such that small partial correlations (i.e., trivial edges) were reduced to zero and not depicted in the network. This procedure limits the concern of multiple testing (Knefel et al., 2016). The depicted network utilizes the Fruchterman-Reingold algorithm, wherein nodes with the strongest edges are more central in the network, and nodes with weaker edges are on the periphery. The network estimation returns a network graph depicting non-spurious edges (i.e., relevant associations between symptoms). Edges can be positive (depicted by a green line) or negative (depicted by a red line), and thicker edges indicate stronger associations (Fruchterman & Reingold, 1991).

**Network inference.** Node centrality is traditionally calculated using three indices: strength, closeness, and betweenness. Strength of a node is representative of the sum of weighted
edges for that node, and thus it indicates how directly connected one node is to the network as a whole. Closeness is representative of the average distance of one node to all other nodes, and therefore serves as a measure of how indirectly connected a node is to the network. Betweenness is representative of the number of times a specific node lies between the shortest edge connecting two other nodes. Thus, betweenness serves as an index of how connected one node is to other nodes in the network (Armour et al., 2017). Higher levels of strength, closeness, and betweenness indicate that the node is more central (i.e., integral) to the network.

**Network stability.** Network stability for the pooled network and each of the three networks was estimated following procedures outlined by Epskamp, Borsboom, & Fried (2017), in which the *bootnet* R-package was used to bootstrap the 95% confidence intervals (CIs) around each edge weight. Additionally, correlation-stability (CS) coefficients were calculated for each of the three centrality measures (strength, closeness, betweenness), to elucidate whether the measures of centrality were stable and thus reliable indices for each of the estimated networks. CS-coefficients above 0.25 indicate moderate, and above 0.50 indicate strong, stability (Epskamp et al., 2017).

**Network comparison.** Three pairwise comparison tests were run (MVA and SA, SA and SAD, MVA and SAD) using the *NetworkComparisonTest* (NCT) package in R. The NCT assesses whether edges statistically differ across groups by taking the edge that differs the most across the two groups, and directly comparing it. For comparisons with unequal sample sizes (i.e., SA and SAD; MVA and SAD), the larger group (i.e., SA and MVA) was subsampled five times to match the sample size of the SAD group (see Fried et al., 2018 for precedence). Holm-Bonferroni correction is built into the NCT function to overcome multiple testing.

### 3. Results
3.1 Posttraumatic stress symptoms

The average score on the PCL-5 for the pooled sample was 18.37 ($SD = 16.19$; range: 1-77). Total scores on the PCL-5 differed significantly by trauma type ($F[2] = 15.79, p < .001$). Specifically, and consistent with previous research (Kelley et al., 2009), participants in the SA group reported a higher level of symptom severity ($M = 22.99, SD = 18.25$; range: 1-77) than those in the MVA ($M = 14.54, SD = 13.39$; range: 1-60) and SAD ($M = 17.00, SD = 16.19$; range: 1-73) groups. Rates of probable PTSD, as defined by a PCL-5 total score of greater than or equal to 33 (Weathers, Litz et al., 2013), were 25.4% in the SA group, 12.0% in the MVA group, and 13.0% in the SAD group. In the pooled sample, avoidance of thoughts and feelings about the trauma had the highest mean ($M = 1.50, SD = 1.32$). Highest means across the groups were as follows: MVA: feeling upset at reminders of the trauma, $M = 1.16, SD = 1.17$; SA: avoidance of thoughts and feelings about the trauma, $M = 1.60, SD = 1.21$; SAD: feeling upset at reminders of the trauma, $M = 1.73, SD = 1.21$. Engaging in risky behavior had the lowest mean across all three groups (pooled: $M = 0.42, SD = 0.87$; MVA: $M = 0.36, SD = 0.75$; SA: $M = 0.61, SD = 1.06$; SAD: $M = 0.36, SD = 0.75$).

3.2 Network estimation

The network for the pooled sample is depicted in Figure 1. Networks for each of the three groups are depicted in Figure 2. In the pooled sample, 11 negative and 96 positive edges emerged. With the exception of trauma-related amnesia (Cluster E), all symptoms grouped well within their designated clusters. While the average betweenness for Cluster E was 45, indicating an average of 45 times that a Cluster E node was between the shortest edge connecting two nodes in the network, the betweenness for amnesia was zero. Summed edge weights indicated total strength of 9.36. Results from bootstrapping the edge-weights indicated that 70% of edges,
across all estimated networks, had a 95% confidence interval that included zero, indicating that most edges did not significantly differ from one another. The top four reliably strong edges (i.e., significantly different from other edges in the network) for each network are displayed in Table 2.

Different patterns emerged between three trauma type networks. While the SA group had few and weak negative edges (four), the MVA and SAD groups exhibited several negative edges (14 in each). In the SA network, negative edges existed across, rather than within, symptom clusters. For example, blame (item 10; Cluster D) was negatively associated with startle (item 18; Cluster E). In the MVA and SAD networks, however, one negative association, per network, appeared within clusters. Specifically, blame was negatively associated with feeling distant toward others (item 13; Cluster D) in the MVA network even though those symptoms should be positively related based on theory. In the SAD network, startle (item 18; Cluster D) and negative beliefs (item 10; Cluster D) were negatively associated. Most negative edges were across symptom clusters (e.g., from unwanted memories [item 1] to risky behavior [item 16] in the SAD network; from difficulty experiencing positive feelings [item 14] to hypervigilance [item 17] in the MVA network). The number of edges was similar across networks, with both MVA and SA networks containing 96 edges, and the SAD network containing 93 edges.

3.3 Network stability

Stability coefficients for strength (.10), closeness (.10), and betweenness (.10) in the pooled network indicated that each of the centrality indices were equally reliable. However, given that strength was the most reliable index of centrality in each of the individually estimated networks (MVA: .10; SA: .10, SAD: .07), only strength will be reported as the primary index of centrality. Indices of strength, betweenness, and closeness were highly correlated in the MVA (\textit{rs}}
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= .68 -.83) and SA (rs = .63-.73) networks, and less highly correlated in the SAD network (rs = .49-.84).

3.4 Network inference

Correlation of strength between networks varied. Pearson correlations were used, as polychoric and Pearson correlations were highly consistent (rs ranging .95-.97). The MVA and SA networks demonstrated the strongest correlations of strength (r = .64). The SAD network, however, exhibited correlations with the MVA and SA networks that were small to medium in size (r = .09 and .35, respectively). Figure 3 depicts strength estimates for the pooled and individual networks. In all but the SAD network, amnesia (item 8) emerged as the least central symptom. Blame toward self or others (item 10) also emerged as having a low centrality estimate in the SA and SAD networks, but not in the MVA network. Difficulty experiencing positive feelings (item 14) had consistently high centrality estimates, as did strong negative feelings (item 11). Overall, centrality estimates for the SAD network were inconsistent with the MVA, SA, and pooled networks.

3.5 Network comparison

Comparison of the MVA and SA networks indicated statistically different network edges (p = .046). Additional probing of the statistical difference indicated that one edge in the MVA and SA groups statistically differed. Specifically, the edge between strong negative beliefs (item 9) and anhedonia (item 12) was positive and fairly strong in the MVA network (.20, roughly twice as large as the other MVA edges) compared to the SA network, in which this edge was not retained (i.e., assigned a weight of zero) using the glasso procedure. Subsample network comparisons between the SAD and MVA groups and SAD and SA groups indicated that these networks were not statistically different (mean p = .50 and .52, respectively). Global strength
(i.e., sum of edge weights) did not appear to differ between MVA and SA networks (global strength = 9.16 and 9.35, respectively, \( p = .45 \)), SA and SAD networks (SAD global strength = 8.99, \( p = .33 \)), or MVA and SAD networks (\( p = .73 \)).

4. Discussion

To our knowledge, this is the first study to examine and compare DSM-5 PTS network differences across trauma types (e.g., SA, MVA, and SAD). In addition to comparing the networks across trauma types, we sought to examine and describe the PTS network for each trauma type, as well as the full sample. The SA network appeared to be most conceptually similar to PTSD as defined by DSM-5. Specifically, symptoms were related to one another in a theoretically consistent manner (i.e., within-cluster associations were positive; few negative associations across clusters) and were grouped based on their DSM-5 designated clusters. In contrast, the SAD network appeared to be the least consistent with DSM-5, in that several symptoms were related to each other in theoretically inconsistent directions and symptoms did not always group within their respective clusters. The SA and MVA networks differed in global strength and on the association between strong negative beliefs and anhedonia. No other statistically significant differences emerged across these two networks.

This study adds to extant literature investigating DSM-5 PTS networks, irrespective of trauma type. In the pooled network of 554 individuals, the most central PTS symptoms were experiencing strong negative emotions and trouble experiencing positive emotions—two symptoms that have been implicated as central in other studies of DSM-5 PTSD (Mitchell et al., 2017; von Stockert, Fried, Armour, & Pietrzak, 2018). These two symptoms may be considered part of a “non-pure” form of PTSD, perhaps reflecting the co-morbidity between PTSD and major depressive disorder (MDD; Mitchell et al., 2017). However, Mitchell et al. (2017) found
that experiencing strong negative emotions and trouble experiencing positive emotions remained central symptoms even after removing individuals who met diagnostic criteria for MDD. Thus, it appears that these symptoms are important in activating the PTSD symptom network.

Importantly, these symptoms were among those removed from the most recent version of the International Classification of Diseases (ICD-11) diagnosis of PTSD, as they were thought to be nonspecific (i.e., overlapping with other disorders; Stein et al., 2014). However, our results, bolstered by other studies of DSM-5 PTSD (Armour et al., 2017; Mitchell et al., 2017; von Stockert et al., 2018), suggest that these symptoms are important in the activation of the PTS network, and therefore should be considered part of the PTSD diagnosis.

Amnesia emerged as the least central symptom in the pooled network. This finding is consistent with evidence suggesting that trauma-related amnesia may not be an important or reliable symptom of PTSD (Friedman, 2013). Our results suggest that, if amnesia were removed as a symptom, the PTS network would remain largely unchanged. Our results are consistent with other network (Armour et al., 2017; Fried et al., 2018, McNally, Heeren, & Robinaugh, 2017; Spiller et al., 2017) and confirmatory factor analyses (Armour et al., 2012; Liu et al., 2014; Simms, Watson, & Doebbling, 2002), which have found that this symptom performs poorly (e.g., low factor loadings, low centrality). Some research suggests this symptom is typically only endorsed by those who report the highest levels of symptom severity (Kilpatrick et al., 2013, Miller et al., 2013). It may be that amnesia demonstrates low centrality because it is not endorsed as highly as other symptoms, leading to restricted variability in responses, and distorted centrality. However, in following methods utilized by McNally et al. (2017), it does not appear that restricted variability influenced network structure. Alternatively, current assessment tools may not clearly describe trauma-related amnesia, leading to confusion from participants and
patients, or, it may be that amnesia is not a true feature of PTSD. However, psychometric research and network analysis is unable to speak to those possibilities. More rigorous interviews, in which individuals provide feedback as to their understanding of trauma-related amnesia questions may help untangle this issue.

Our findings also shed light on the debate regarding whether sudden unexpected or accidental death of a loved one should be considered a stressor or trauma. Prior to *DSM-5*, this category included death of loved ones due to natural causes and was the most commonly reported traumatic event (Breslau & Kessler, 2001). This criterion was revised in *DSM-5* so the learning about the actual or threatened death of a close family member or close friend is only considered a trauma if the event is “violent or accidental” (e.g., homicide, suicide; Friedman, 2013). Our results suggest that the symptom presentation resulting from events from this category may be substantively different from prototypical traumatic events. Global strength was lowest in the SAD network, compared to the other networks, although this difference did not reach statistical significance. Additionally, there were more negative edges in the SAD compared to the SA network, and some of these negative associations emerged in theoretically inconsistent ways (e.g., negative edges within symptom clusters). There were also fewer edges overall, which indicates that more edges were considered trivial (i.e., shrunk to zero using the *glasso* procedure). The negative associations between symptoms might suggest that (a) symptoms in this group are truly inversely related, contrary to what theory would suggest, or (b) the group’s symptom presentation has high collinearity, leading to problems in accurately estimating edge weights. The latter explanation is consistent with the low stability observed in the SAD network, which suggests that this group’s network is least likely to be replicated in another sample of individuals who experienced SAD. High collinearity could be a function of the low level of
symptoms reported in this group (i.e., many instances of “0”s selected) endorsed in a non-
 systematic way (i.e., low endorsement of symptoms is not restricted to a select set of symptoms). Therefore, our results suggest that SAD may lead to a less cohesive symptom expression compared to other traumatic events (e.g., SA, MVA). It could be that individuals who have experienced the sudden accidental or violent loss of a loved one do not experience symptoms in a systematically similar way, or it may be that PTSD symptoms do not accurately capture the nature of the distress that these individuals face. Consistent with this rationale, some have suggested that complex grief may be a disorder in its own right, separate from PTSD or MDD (i.e., persistent complex bereavement disorder; Prigerson et al., 2009, Robinaugh, LeBlanc, Vuletich, & McNally, 2014). Additionally, the exposure level of the SAD group is inherently distinct from the SA and MVA groups. By definition, sudden death cannot be directly experienced by respondents, whereas sexual assault and motor vehicle accidents may have been directly experienced. However, the low stability and theoretically inconsistent associations between symptoms observed in this group suggests comparisons between the SAD group and SA and MVA groups, respectively, should be interpreted with caution.

In the SA and MVA networks, some differences emerged. The overall test for statistically different edges indicated that the association between strong negative beliefs and anhedonia differed between groups. Specifically, the association was positive and fairly strong in the MVA network and non-existent in the SA network. Additionally, some differences in symptom centrality emerged. For example, feeling upset at reminders was more central in the SA network, whereas irritability was more central in the MVA network. It is important to note that this does not mean those that have experienced SA are more likely to experience feeling upset in response to reminders of their index trauma. Rather, if this symptom is present in an individual who has
experienced SA, it may be more likely to activate other symptoms of PTSD, compared to an individual who has experienced MVA. The stimuli associated with SA, compared to MVA, (e.g., the survivor’s own physical body) may be particularly more salient and pervasive than, say, a car. Thus, it might be expected that an intrusive symptom is more central, given that the potential reminders are always present.

Study findings should be interpreted in light of several limitations. First, the stability of each of our three networks, and the pooled network, was not within the recommended threshold (CS-coefficients >.25). However, it may be that the threshold is overly conservative. Previously published networks of PTSD have reported levels of stability that either did not surpass or just met Epskamp et al. (2017)’s recommendation (Birkland & Heir, 2017; McNally et al., 2017; Santos, Fried, Asafu-Adjei, & Ruiz, 2017). Regardless, low stability may be due to relatively low levels of symptomatology. Consistent with the above explanation, the group with the highest level of symptomatology, the SA group, was the network that was most theoretically consistent with DSM-5 PTSD. Relatedly, although research supports examining PTSD as a dimensional, rather than categorical, construct (Broman-Fulks et al., 2006; Forbes et al., 2005; Ruscio et al., 2002), it is important to replicate these findings in a clinical sample. Additionally, the present study may not have been sufficiently powered to detect additional differences in network structures. Although power analyses have yet to be developed for network analysis, our pooled sample size is consistent with or larger than previously published PTS network analyses (Afzali et al., 2017; Knefel et al., 2016; McNally et al., 2015).

This research also speaks to some of the potential problems with the current state of network analysis. Network analysis in psychopathology, and attempts to statistically compare networks, is a relatively new methodology. One potential issue with cross-sectional network
analysis is the use of pairwise Markov Random Fields (PMRFs), as was used in the current study. PMRFs require large samples because they require a large number of parameters. To avoid the problem of multiple testing, regularization procedures are used (e.g., glasso), which reduces the probability of estimating false positives (Fried & Cramer, 2017). However, this may be an overly conservative approach and we may be sacrificing accuracy for specificity. Second, as described by Fried and Cramer (2017), the field recognizes that it is likely that “multiple network structures are present in one population” (p. 1010). This may explain some of the observed heterogeneity across PTSD networks. The authors describe that similar issues arose for structural equation modeling (SEM), and latent class analysis and cluster analysis were subsequently developed to address those problems. Similar mixture models for network analysis do not yet exist. However, if these methods are developed, they may help us understand how factors such as time, trauma type, and gender influence the structure of PTSD networks.

Despite these limitations, results of the present study have potential clinical implications. Specifically, identification of the most central symptoms in a network may clarify possible core antecedents or consequences within the symptom network. For example, intervening upon central symptoms may cause a cascading effect in which more peripheral symptoms in the network are positively impacted (if symptom is an antecedent), or it could potentially disrupt a feedback loop (if symptom is both an antecedent and consequence). Although cross-sectional studies are unable to elucidate whether the central symptom is the cause or consequence of another symptom, intervening on “the most central node might be a viable heuristic” (Fried et al., 2018, p. 345). In the pooled network, experiencing strong negative emotions and trouble experiencing positive emotions were highly central. Thus, interventions that aim to increase positive emotions, such as engaging in pleasurable activities (i.e., behavioral activation;
Jacobson et al., 1996), may indirectly target other symptoms of PTSD. To take a more tailored approach, clinicians may wish to target specific symptoms based on the index trauma. For example, our results suggest that targeting re-experiencing symptoms in SA survivors, and difficulty experiencing positive emotions in MVA survivors, may prove to be especially fruitful in reducing other PTSD symptoms. This could have implications in selecting treatments for trauma survivors. For those whose intrusions are more central, prolonged exposure may be more successful in addressing other symptoms in the network, whereas behavioral activation may be more beneficial for those whose most central symptoms is anhedonia.

The current study compared PTSD network differences as a function of trauma type. We examined and compared the networks of 554 undergraduate students who had endorsed SA, MVA, or SAD as their index trauma. Additionally, we examined the pooled network for this sample. Findings indicated that, similar to other published studies, experiencing strong negative emotions and trouble experiencing positive emotions were highly central symptoms in the pooled network, whereas amnesia was least central. The SA network appeared to be the most consistent with current DSM-5 conceptualization of PTSD, whereas the SAD network appeared least consistent. We also observed differences in symptom associations and centrality, as a function of trauma type. These differences have clinical implications, such that targeting central symptoms may be more effective at disrupting peripheral symptoms of PTSD. Furthermore, differences in network structure by trauma type has implications for our conceptualization of the ontology of PTSD.
References


Footnote

The two-tailed Pearson correlation coefficient between all PCL-5 symptom centrality indices and standard deviations revealed a non-significant relationship, $r(18) = -.11, p = .65$. Thus, the network structure (i.e., centrality) does not appear to be influenced by node variance.
Table 1. List of abbreviated symptom names, corresponding symptom indicator (number), and $DSM$-5 symptom cluster.

<table>
<thead>
<tr>
<th>#</th>
<th>Symptom Abbreviation</th>
<th>$DSM$-5 Symptom Cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Unwanted Memories</td>
<td>B</td>
</tr>
<tr>
<td>2</td>
<td>Dreams</td>
<td>B</td>
</tr>
<tr>
<td>3</td>
<td>Flashbacks</td>
<td>B</td>
</tr>
<tr>
<td>4</td>
<td>Upset Reminders</td>
<td>B</td>
</tr>
<tr>
<td>5</td>
<td>Physical Reminders</td>
<td>B</td>
</tr>
<tr>
<td>6</td>
<td>Avoid Thoughts</td>
<td>C</td>
</tr>
<tr>
<td>7</td>
<td>Avoid Reminders</td>
<td>C</td>
</tr>
<tr>
<td>8</td>
<td>Forgetting</td>
<td>D</td>
</tr>
<tr>
<td>9</td>
<td>Negative Beliefs</td>
<td>D</td>
</tr>
<tr>
<td>10</td>
<td>Blame</td>
<td>D</td>
</tr>
<tr>
<td>11</td>
<td>Strong Negative Feelings</td>
<td>D</td>
</tr>
<tr>
<td>12</td>
<td>Anhedonia</td>
<td>D</td>
</tr>
<tr>
<td>13</td>
<td>Feel Distant</td>
<td>D</td>
</tr>
<tr>
<td>14</td>
<td>No Positive Feelings</td>
<td>D</td>
</tr>
<tr>
<td>15</td>
<td>Irritable</td>
<td>E</td>
</tr>
<tr>
<td>16</td>
<td>Risky Behavior</td>
<td>E</td>
</tr>
<tr>
<td>17</td>
<td>Hypervigilance</td>
<td>E</td>
</tr>
<tr>
<td>18</td>
<td>Startle</td>
<td>E</td>
</tr>
<tr>
<td>19</td>
<td>Concentration</td>
<td>E</td>
</tr>
<tr>
<td>20</td>
<td>Sleep</td>
<td>E</td>
</tr>
</tbody>
</table>
Table 2. Top four most reliably strong edge weights per network.

<table>
<thead>
<tr>
<th>Network</th>
<th>Node 1</th>
<th>Node 2</th>
<th>Mean edge weight</th>
<th>Lower 95% CI</th>
<th>Upper 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled</td>
<td>Hypervigilance</td>
<td>Startle</td>
<td>.50</td>
<td>.39</td>
<td>.50</td>
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<tr>
<td>Pooled</td>
<td>Anhedonia</td>
<td>Feel distant</td>
<td>.45</td>
<td>.31</td>
<td>.58</td>
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<tr>
<td>Pooled</td>
<td>Avoid thoughts</td>
<td>Avoid reminders</td>
<td>.49</td>
<td>.40</td>
<td>.60</td>
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<tr>
<td>Pooled</td>
<td>Concentration</td>
<td>Sleep</td>
<td>.46</td>
<td>.36</td>
<td>.56</td>
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<tr>
<td>MVA</td>
<td>Feel distant</td>
<td>No positive feelings</td>
<td>.63</td>
<td>.47</td>
<td>.79</td>
</tr>
<tr>
<td>MVA</td>
<td>Concentration</td>
<td>Sleep</td>
<td>.57</td>
<td>.36</td>
<td>.69</td>
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<tr>
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<td>Irritability</td>
<td>Risky behavior</td>
<td>.47</td>
<td>.10</td>
<td>.64</td>
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<tr>
<td>MVA</td>
<td>Flashbacks</td>
<td>Physical reminders</td>
<td>.38</td>
<td>.20</td>
<td>.55</td>
</tr>
<tr>
<td>SA</td>
<td>Feel distant</td>
<td>No positive feelings</td>
<td>.63</td>
<td>.47</td>
<td>.79</td>
</tr>
<tr>
<td>SA</td>
<td>Concentration</td>
<td>Sleep</td>
<td>.57</td>
<td>.36</td>
<td>.69</td>
</tr>
<tr>
<td>SA</td>
<td>Irritability</td>
<td>Risky behavior</td>
<td>.47</td>
<td>.10</td>
<td>.64</td>
</tr>
<tr>
<td>SA</td>
<td>Flashback</td>
<td>Physical reminders</td>
<td>.37</td>
<td>.20</td>
<td>.55</td>
</tr>
<tr>
<td>SAD</td>
<td>Avoid thoughts</td>
<td>Avoid reminders</td>
<td>.52</td>
<td>.24</td>
<td>.70</td>
</tr>
<tr>
<td>SAD</td>
<td>Hypervigilance</td>
<td>Startle</td>
<td>.49</td>
<td>.23</td>
<td>.73</td>
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<tr>
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<td>Anhedonia</td>
<td>No positive feelings</td>
<td>.42</td>
<td>.07</td>
<td>.63</td>
</tr>
<tr>
<td>SAD</td>
<td>Startle</td>
<td>Concentration</td>
<td>.37</td>
<td>.10</td>
<td>.63</td>
</tr>
</tbody>
</table>

*Note. Pooled = pooled network, N = 554; MVA = motor vehicle accident network, N = 226; SA = sexual assault, N = 222; SAD = sudden accidental or violent death, N = 106. CI = confidence interval.*
Figure 1. Regularized partial correlation network for the pooled ($N = 554$) sample. Thicker lines are indicative of stronger associations. Green lines represent positive associations and red lines represent negative associations. See Table 1 for a list of symptom names.
Figure 2. Regularized partial correlation network for motor vehicle accident (MVA; $N = 226$), sexual assault (SA; $N = 222$), and sudden accidental or violent death (SAD; $N = 106$) groups. See Table 1 for a list of symptom names.
Figure 3. Standardized node strength (centrality) for the pooled ($N = 554$), motor vehicle accident (MVA; $N = 226$), sexual assault (SA; $N = 222$), and sudden accidental or violent death (SAD; $N = 106$) networks. Table 1 for a list of symptom names.