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PTSD Symptom Interaction Among Victims of Interpersonal Violence: A Network Analysis

Robert Graziano
University of Missouri-St. Louis, rcgraz17@gmail.com

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Robert Graziano, M.A.

M.A., Clinical Psychology, University of Missouri-St. Louis, 2017
B.S., Psychology, University of North Carolina- Chapel Hill, 2015

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<u>Advisory Committee</u>

Steven Bruce, Ph.D., Chairperson

Ann Steffen, Ph.D.

Mike Griffin, Ph.D.

Carissa Philippi, Ph.D.

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“It's a dangerous business, Frodo, going out your door. You step onto the road, and if you don't keep your feet, there's no knowing where you might be swept off to.”

- J.R.R. Tolkien, The Fellowship of the Ring (1954)

Looking back, my time at the University of Missouri-St. Louis has been one of hard work, growth, discovery, and, above all, adventure. It entailed many long nights and emotional strain, and yet, seemingly with a blink of the eye, what has been the most formative, fulfilling experience of my life has concluded. When reflecting on the last five years, I am humbled in the knowledge that I been enormously fortunate in having countless people support me through both my professional and personal endeavors. Though it is simply not possible to fit the accolades all of these people deserve within a few pages of text, I would be remiss not to try.

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Abstract

Along with numerous combinations of symptoms, posttraumatic stress disorder (PTSD) is linked to high dropout and non-response rates in treatment. Poor treatment response may be due to an inaccurate conceptualization of PTSD. One newer approach to the conceptualization of psychopathology is network theory. Network theory posits that symptoms both directly and indirectly reinforce each other, with connections between symptoms varying in strength. Previous studies of network theory and PTSD have found intrusive symptoms to be highly central, but have not included samples of individuals traumatized by interpersonal violence. Because trauma type has been shown to predict symptom presentations, this represents an important gap in the literature. The current study attempts to address this by analyzing the PTSD and depression network of 83 adult female participants meeting criteria for PTSD from interpersonal violence. PTSD symptoms were measured using the Posttraumatic Diagnostic Scale. Using the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selector Operator (EBICglasso) method, and after bootstrapping the data with 95% confidence intervals based on 1000 bootstrap iterations, a partial correlation network was created to depict the network. PTSD network results showed feeling distant and intrusive symptoms to have the highest centrality. Further, anhedonia was shown to be a bridge symptom between PTSD and depressive symptoms. These results may better connect theory to impending therapeutic action by assisting in identifying specific targets for interventions when working with PTSD in victims of interpersonal violence.

PTSD Symptom Interaction Among Victims of Interpersonal Violence: A Network Analysis

Posttraumatic stress disorder (PTSD) is a debilitating condition that occurs in reaction to a traumatic experience. According to the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; *DSM-5;* American Psychiatric Association, *2013),* traumatic experiences are events in which one is exposed to death, serious injury, or sexual violence via direct exposure, witnessing the event, learning that a relative or close friend was exposed to the trauma, or indirect exposure to aversive details. The majority of the general population will be exposed to a traumatic event in their lifetime (Brunet, Monson, Liu, & Fikretoglu, 2015; Kilpatrick et al., 2013; Read, Ouimette, White, Colder, & Farrow, 2011). For adults in the United States, however, PTSD has been found to have a lifetime prevalence ranging from 6.8% (Kessler et al., 2005) to 8.3% (Kilpatrick et al., 2013). Past year prevalence has been shown to be approximately 3.5% - 3.8% (Kessler, Chiu, Demler, Merikangas, & Walters, 2005; Kilpatrick et al., 2013). Women have been found to be more likely than men to meet criteria for PTSD (Ditlevsen & Elklit, 2012; Kessler, Sonnega, Bromet, Hughes, & Nelson, 1995; Stein, Walker, & Forde 1997; Tolin & Foa, 2006). Similarly, veteran populations are more at risk to develop PTSD, as veteran rates for current PTSD have been found at 12.1% (Kang, Natelson, Mahan, Lee, & Murhpy, 2003) and 20% (Tanielian & Jaycox, 2008).

As classified by the *DSM-5* (5th ed.; *DSM-5;* American Psychiatric Association, 2013*)*, PTSD consists of four symptom clusters: intrusion, avoidance, negative alteration in thoughts or mood, and arousal. In the *DSM*-5, one intrusion symptom is required for a diagnosis, which includes a set of symptoms in which the individual remembers the trauma or feels like the trauma is reoccurring, whether awake or asleep. Additionally, one avoidance symptom is required for diagnosis, which includes avoidance of trauma related thoughts, feelings, or reminders. The negative thoughts or mood cluster involves self-blame, feeling isolated from people, having difficulty experiencing positive emotions, and a decreased interest in activities. Two such symptoms are required for diagnosis. Finally, two arousal symptoms are required, which includes hypervigilance, sleep or concentration difficulties, an increase in risky behavior, increased startle reactions, and irritability.

Using this symptom criteria, PTSD can be assessed with a number of well validated measures. The Clinician-Administered PTSD Scale (CAPS) requires administration by a trained mental health professional or paraprofessional and is often seen as the gold standard for accurate diagnosis (Cody, Jones, Woodward, Simmons, & Beck, 2017; Griffin, Uhlmansiek, Resick, Mechanic, 2004). A number of highly studied self-report measures are used as well, including the PTSD Checklist (PCL; Blevins, Weathers, Davis, Witte, & Domino, 2015), Mississippi Scale for Combat PTSD (MISS; Keane, Caddell, & Taylor, 1988), Posttraumatic Diagnostic Scale (PDS; Foa, Cashman, Jaycox, & Perry, 1997), and Impact of Event Scale (IES; Creamer, Bell, Failla, 2003). Although these self-report measures show results generally consistent with the CAPS-IV, there are concerns about a lack of specificity and over diagnosis with self-report measures (Cody et al., 2017; Griffin et al., 2004; Shalev, Freedman, Peri, Brandes, Sahar, 2018).

PTSD is associated with a number of other consequences, as it has been related to occupational impairment at work and school (Bolton et al., 2004; Breslau et al., 2004;

Kessler, 2000; Rona et al., 2004; Stein et al., 1997; Taylor, Wald, Asmundson, 2007), as well as difficulties with relationships (both with family and friends; Dekel & Monson, 2010; Laffaye Cavella, Drescher, Rosen, 2008; Kuhn, Blanchard, Hickling, 2003; North et al., 1999; Sayers, Farrow, Ross, & Oslin, 2009). Additionally, PTSD has been found to be highly comorbid with depression (Campbell et al., 2007; Kilpatrick et al., 2003) and substance abuse (Brown, Recupero, & Stout, 1995; Brown, Stout, Mueller, 1999; Kilpatrick et al., 2003). Finally, PTSD has been related to suicidal ideation (Gradus et al., 2010; Kessler, 2000; Krysinska & Lester, 2010) and death by suicide (Hyman, Ireland, Frost, Cottrell, 2012; Pompili et al., 2013) .

PTSD is common, diverse in presentation, and quite impairing, leading to a wide array of research focused on its conceptualization. This paper aims to first review some of these conceptualizations and subsequently highlight a new conceptualization (network theory) in the application to a sample of women who meet criteria for PTSD through interpersonal trauma..

Conceptualizing Psychopathology

When classifying mental disorders, conceptualizations face a challenge in addressing four key issues: etiology, categories and dimensions, thresholds, and comorbidity (Clark, Cuthbert, Lewis-Fernandez, Narrow, Reed, 2017). Etiology refers to the cause of a disorder; namely how all casual influences (genes, neurons, culture, cognitions, etc..) interact. Mental disorders are complex, as research has shown biological, psychosocial, behavioral, and cultural factors to contribute to disorder manifestation and maintenance. Thus, a classification system cannot categorize mental disorders based on a single “cause.” Instead, classification systems should involve study results from all levels of observation, whether it be behavior or anatomical, for a complete understanding of etiology. Further, the developmental trajectories of mental disorders are variable, and thus outcomes from exposure to these factors may not regularly lead to a definitive disorder.

While classification systems must account for the interplay between a host of predisposing factors, they must also provide practical clinical utility. Thus, mental health presentations are often categorized in order to achieve quick, understood language between clinicians. Because mental disorders are dimensional and their severity ranges on a spectrum, classifications may overly simplify disorders into distinct entities. Classification systems, then, must account for the complexity of mental disorders while still providing clinical utility.

Symptom thresholds have historically been used for psychopathology classification purposes. This becomes challenging because mental disorders affect individuals across a number of domains, including cognition, behavior, and emotions. For example, the PTSD symptoms of avoiding reminders of the event, intrusive thoughts about the event, and anger apply to different domains (behavior, cognition, and emotions respectively). To account for this, classifications systems provide thresholds for each dimension, to set a boundary for what classifies as a disorder. This is further complicated because symptom severity is often gauged by client self-report and clinician judgement.

Finally, current mental health classification systems often include widespread comorbidity between disorders. This is a result of the multidimensional aspect of mental disorders and significant symptom overlap. As a result, high comorbidity renders classifications less meaningful and subsequently less clinically useful.

It is important to consider the function of theoretical models within psychopathology when considering the etiology of PTSD. One of the central purposes of classifications is to inform predictions (Blashfield & Draguns, 1976). Explicitly, the utility of a classification is judged by its ability to predict responses to prevention and treatment efforts. It is therefore vital that psychopathology be based on tested theory (Berenbaum, 2013) to determine the relationships between symptoms and disorders. To this end, mechanisms of change should be a focus of study incorporated within a conceptual model. Theory should inform the process of identifying mechanisms of change, with identified, tested mechanisms then reinserted into theory development. This iterative, reciprocal relationship creates a fluidity between theory development and studies of mechanism of change that ultimately leads to gradually more informed theory. It is also important to note that classification systems can be differentially better at predicting various outcomes. For example, one classification system may be better at predicting prevention while another may be more adept at predicting treatment outcomes. Therefore, there may not be a singular most useful classification system (Berenbaum, 2013).

As mentioned, the function of psychopathology conceptualization is to predict treatment. Importantly, though studies have found significant decreases in PTSD symptoms following the completion of psychotherapy (Chard, 2005; Monson et al., 2006; Resick, Nishith, Weaver, Astin, & Feuer, 2002; Schnurr et al., 2007), treatments have been consistently associated with high dropout rates (79%: DeViva, 2014; 68%: Garcia et al., 2011; 24%, Hoge et al., 2014). Further, even if individuals do attempt treatment, nonresponse rates have been reported as high as 50% (Kar, 2011). Thus, it would seem that, while treatments have shown positive results, they may not be efficacious for a large percentage of people. A more comprehensive PTSD conceptualization, then, might improve treatments.

Conceptualizing PTSD: The *DSM* Model

The *DSM* remains the most frequently used classification system for psychopathology. The *DSM* largely functions under the disease model; mental disorders can be thought of as diseases similar to that of any medical disease (Borsboom, 2017a; McNally et al., 2014). In this view, symptoms frequently manifest with other symptoms based on the existence of an underlying mental disorder. The onset and maintenance of the underlying disorder, then, directly *causes* the symptoms (Borsboom & Cramer, 2013; Kendler, 2017). For example, according to the *DSM*, anhedonia, low self-esteem, withdrawal, and sleep problems may be caused by Major Depressive Disorder (MDD).

Although the *DSM* remains the leading authority on psychopathology, a number of limitations have been recognized within its system. First, it seems unlikely that one factor (i.e. the underlying disorder) is accountable for the myriad of phenomena seen within disorders (McNally et al., 2014). Rather than being merely independent indicators of a disease, symptoms may reinforce each other; people who ruminate are more likely to exhibit insomnia, which likely causes fatigue, thereby impairing concentration . This is entirely different from the medical model in which a singular condition causes numerous symptoms, such as a tumor causing chest pain and coughing (McNally et al., 2014). When considering causality, symptom presentations can hypothetically demonstrate multicausality (several contributing factors), equifinality (many different pathways leading to the same outcome), or multifinality (similar factors potentially leading to divergent outcomes; Ruzek & Landes, 2014).

With respect to PTSD specifically, despite the hugely diverse presentations, PTSD is characterized under one label (De Schryver et al., 2015). In fact, PTSD in the *DSM-IV* can have more than 80,000 different combinations of symptom presentations (Galatzer-Levy & Bryant, 2013). This makes it more difficult to generalize treatments. Further, not everyone reports severe symptomology from all 4 PTSD clusters, and therefore individuals may not meet diagnostic criteria. In this way, individuals may still be suffering from potentially severe symptoms of PTSD without meeting diagnostic criteria (De Schryver, Vindevogel, Rasmussen, & Cramer, 2015). Finally, approximately 80% of people suffering from PTSD suffer from co-occurring psychiatric disorders, making it difficult to discern the causality of each disorder. One disorder could cause the other, both could be caused by the same factor, one could impact the course of the other, or both could occur independently (Foa, Keane, Friedman, & Cohen, 2008).

Conceptualizing PTSD: The Fear Network

In conceptualizing PTSD, neuroscience studies have focused on neural correlates of Pavlonian fear conditioning and extinction. Pavlonian fear conditioning centers on a conditioned stimulus being paired with a conditioned response (Shin & Liberzon, 2010). For example, a driver who endures a traffic accident caused by a white van may continue to associate the feelings of a car accident (fear, panic, etc…) with white vans after the resolution of the accident. Neuroscience studies have examined fear conditioning, relating this phenomenon to neural correlates. Together, these neural correlates encompass the fear network.

Studies have identified a number of areas as being important to the fear network. First, amygdala activation has been repeatedly shown during fear conditioning (Alvarez et al., 2008; Barrett & Armony, 2009; Gottfried & Dolan, 2004; Tabbert et al., 2006). The amygdala has also been shown to be overactive in PTSD during neural attention tasks (Bryant et al., 2005) and at rest (Chung et al., 2006). Next, the ventral medial prefrontal cortex has been shown to be less activated in PTSD during trauma script imagery (Lanius et al., 2001) and extinction (Bremner et al., 2005). Further, the hippocampus has been identified as a region of interest within the fear network, having been related to decreased activation in PTSD patients during memory tasks (Astur et al., 2006 & Moores et al., 2008). Conversely, other studies have shown increased activation in the hippocampus in PTSD (Werner et al., 2009). The type of task may be what differentiates these findings (Shin & Liberzon, 2010), with the hippocampus playing an important but varied role across memory tasks. Finally, increased activation in the insular cortex has also been found to relate to PTSD across tasks involving script driven imagery (Lanius et al., 2007), fear conditioning and extinction (Bremner et al., 2005), and the retrieval of emotional stimuli (Bremner et al., 2003). Taken together, neuroscience studies have identified the amygdala, ventral medial prefrontal cortex, hippocampus, and insular cortex as being particularly involved in fear conditioning and extinction.

Although neuroscience research of the fear network presents exciting new possibilities, similar to *DSM* conceptualizations, it also has limitations. For example, the fear network model is not well connected empirically to behavioral components. Without establishing its connections to symptoms, the fear network as a conceptual model is limited in its clinical application. Further, it is unclear whether neural correlates are causal factors or simply representation of behavioral symptoms; the order of occurrence for behavioral and neural factors is not well understood (Shin & Liberzon, 2010). As such, it is difficult to prove that the fear network causes PTSD, rather than it simply being a representation of PTSD. Finally, as the fear network is focused on neural systems that are inherent to humans, it largely ignores individual differences, excluding factors such as culture and demographics.

Other Conceptualizations of PTSD: Research Domain Criteria (RDoC)

Partially as a response to the categorical nature and simplified etiology of the *DSM*, the National Institute of Health (NIH) created the Research Domain Criteria (RDoC) initiative, a conceptualization of mental health that breaks down mental disorders into dimensional constructs (Clark et al., 2017; Insel et al., 2010; Woody & Gibb, 2015). These dimensional constructs include positive valence systems, negative valence systems, cognitive systems, social process systems, and arousal regulatory systems. Positive valence systems refer to systems that govern reward-based learning, and negative valence system include systems that respond to aversive stimuli. Cognitive systems include skills like attention and memory. Finally, social process systems comprise constructs like attachment and self-understanding, while arousal regulatory systems include functions like circadian rhythm and sleep-wakefulness (Clark et al., 2017; Insel et al., 2010; Young et al., 2014). RDoC also strives to be comprehensive, incorporating research from multiple levels of analyses, including: genes, molecules, cells, circuits (neural systems and behavioral dimensions), physiology, behavior, and self-reports. Through its multi-dimensional and comprehensive level of analyses, RDoC intends to give researchers a way to analyze mental disorders beyond the categorical approach of the *DSM* (Clark et al., 2017; Woody & Gibb, 2015).

RDoC is a research approach to mental health; it is not yet intended to be utilized for clinical purposes. The goal of RDoC is not to categorize mental disorders through this system, but to understand how symptoms emerge from an alteration in a dimensional construct (Clark et al., 2017; Insel et al., 2010). RDoC was created in 2009 as a long-term approach. As a research conceptualization still in its early phase, it is presently difficult to extrapolate how RDoC conceptualizes PTSD.

The Network View of Psychopathology

One emerging view of psychopathology is network theory (Borsboom & Cramer, 2013; Borsboom, 2017a; Borsboom, 2017b; Cramer et al., 2010; Kendler, 2017; McNally et al., 2014). The main principle of network theory dictates that symptoms cause other symptoms, phenotypically creating mental disorders. Symptoms can directly reinforce each other or can indirectly cause other symptoms. For example, Symptom A (fatigue) may cause Symptom B (inattention), which may in turn causes Symptom C (self-blame). Thus, Symptom A does not directly cause Symptom C, but is an indirect prerequisite (Armour, Fried, Deserno, Tsai, & Pietrzak, 2017; Borsboom & Cramer, 2013; Borsboom, 2017a; Cramer et al., 2010; McNally et al., 2014). In this way, connections between symptoms create a network.

Symptoms also vary in their strength between each other; symptoms can be loosely connected or there may be a strong relationship (Borsboom & Cramer, 2013; Borsboom, 2017a; Borsboom, 2017b; Cramer et al., 2010; Kendler, 2017; McNally et al., 2014). This diverges from the *DSM*, which only requires individuals to endorse a set of symptoms without remarking on their connectivity (Kendler, 2017). The strength of individual symptom connections ultimately determines the strength of the network. Strong networks are characterized by a series of symptoms that are strongly connected to each other. On the other hand, weak networks, perhaps referred to as “resilient,” may be characterized by symptoms that do not demonstrate this level of connection; even one weak connection between symptoms may prevent the onset of a series of other symptoms (Kendler, 2017). Further, symptoms are not restricted to psychological symptoms (Borsboom, 2017a); networks can theoretically encompass other kinds of processes such as biological factors (genetics, neuro indices, etc…) or societal norms (political affiliation in an area, strength of gender norms in an area, etc…). For example, a network could hypothetically include the connection between anxiety about talking to others and societal expectations for socializing.

Network theory also offers an explanation for comorbidities. In addition to connections within networks, connections can exist between networks. Specifically, a specific symptom may be present within two different symptom networks, and serve as a “bridge symptom” connecting the two different networks. For example, anhedonia is a symptom common to both PTSD and depression. If an individual endorses anhedonia within the context of a PTSD network, the individual may subsequently develop a network of depression symptoms (Borsboom, 2017a; Borsboom, 2017b). In network theory, a high level of comorbidity is to be expected, as it arises from persistent patterns of connectivity that are central to psychopathology (Borsboom, 2017b).

From a diathesis-stress perspective, mental health difficulties may have a host of predisposing factors yet be commonly initiated or triggered by a stressful life event, such as the loss of a job or death of a loved one. Network theory encompasses this, as external events can activate a symptom, triggering the cascade of a network of symptoms (Borsboom, 2017a; Borsboom, 2017b; Cramer et al., 2010; Kendler, 2017). Importantly, without the stressful life event, the network of symptoms may not emerge. For example, upon the death of a loved one, a network of grief symptoms may occur that otherwise would have remained dormant. Once the symptom network is activated, symptoms may be strongly connected with each other. In this way, external events can come to a resolution, while the symptom network continues and remains self-sustaining. Thus, the presence of an event may trigger the activation of a network, but the conclusion of the event may not de-activate it. This concept is called hysteresis, with a number of factors determining whether this occurs. First, the severity of the symptoms must exceed an individual's threshold for tolerating symptoms. Next, symptoms must be well connected; symptoms must intensify rather than inhibit each other. Finally, the number and severity of external life stressor(s) that stimulated the network may factor into whether a network remains activated (Borsboom, 2017b).

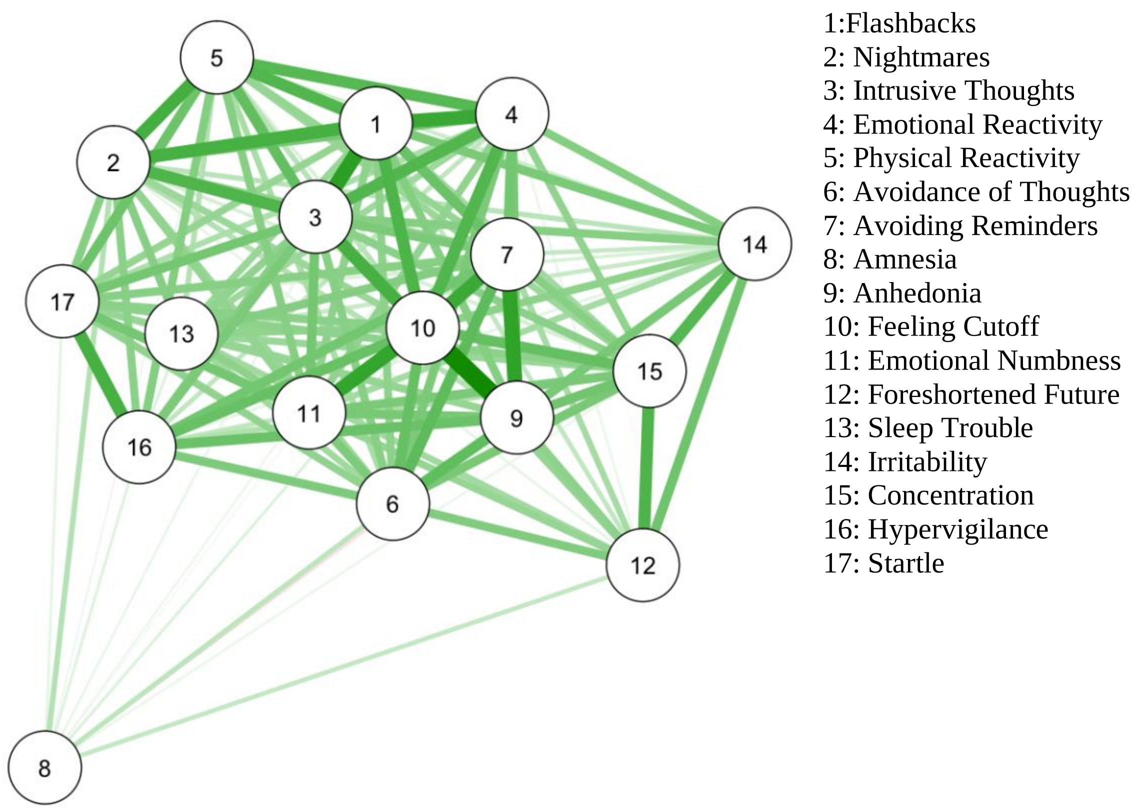
Types of Networks

Statistically, network theory is an offshoot of graph theory, a statistical analysis that depicts networks with nodes connected by edges. Within the context of network theory, nodes represent the variables of study while edges represent the connection between the variables. Although precise statistical analyses are conducted, using nodes and edges allows networks to be illustrated in a manner that can be visually interpreted quickly (Borsboom, 2017a; Borsboom, 2017b; Borsboom & Cramer, 2013; McNally et al., 2014). The network view of psychopathology always follows the same guiding principles, yet there are a number of different types of networks. Each type of network involves a different type of statistical analysis, and gives different kinds of information (McNally et al., 2014).

Association networks are the simplest networks, offering easily digestible, useful information. See Figure 1 for an example from the current study with interpretation directions. In these networks, correlations are conducted to calculate the connection between symptoms. Visually, within the network, the thickness of the edges denotes correlation magnitude; thicker edges indicate larger correlations (Borsboom & Cramer, 2013; McNally et al., 2014). This type of network offers magnitude, but does not give insight into directionality of effects. Nodes with the strongest correlations are positioned near the center of the network, while weaker connections are presented on the outer edges (Armour, Fried, Deserno, Tsai, & Pietrzak, 2017). Often times, researchers will elect to only include nodes with a certain correlation coefficient. By eliminating extraneous information, networks are easier to read without losing any practical significance (McNally et al., 2014).

Figure 1

Current Study PDS Association Network



Note. The plot above shows an association network. Green edges indicate a positive correlation (while red edges would indicate a negative relationship). The thickness of the line indicates the strength of the correlation, with thicker edges depicting stronger relationships.

The ultimate goal of network theory is to take into account the three ways a correlation between two variables can occur: direct relationship, mediation by a third variable, or a shared association with a third variable (Borsboom & Cramer, 2013; McNally et al., 2014; Pearl, 2003). First, one variable may directly relate to the other, such as in the example of insomnia and fatigue (Borsboom & Cramer, 2013; McNally et al., 2014; Pearl, 2003). Not only is there a direct relationship, there is also a likely directionality to this relationship, such that insomnia causes fatigue (Borsboom & Cramer, 2013). Second, two variables may be caused by a third variable (Borsboom & Cramer, 2013; McNally et al., 2014; Pearl, 2003). For example, avoidance of a phobia and distress over having a phobia may both be caused by the symptom of intense fear in the presence of a phobia. In this way, there may be no actual, direct relationship between avoidance and distress, but rather both exist because of the presence of fear (Borsboom & Cramer, 2013). Finally, a shared association with a third variable may create a relationship between two variables (Borsboom & Cramer, 2013; McNally et al., 2014; Pearl, 2003). For example, flashbacks of a traumatic event may be related to avoidance symptoms through a shared association with fear of trauma reminders, such that fear of trauma reminders accounts for the emergence of avoidance and flashback symptoms. However, different from the previous phobia example, flashbacks may also simultaneously cause avoidance symptoms, as having flashbacks may provoke an individual to avoid the reminder of a trauma so to avoid more flashbacks. Although association networks provide quick information that may be helpful in determining clustering of nodes, association networks are unable to disentangle these kinds of relationships and how correlations emerge (Borsboom & Cramer, 2013; McNally et al., 2014). As such, two additional types of networks are often necessary. The first, known as a concentration network, uses edges to illustrate the correlation between nodes after first controlling for the effects of all other nodes in the network. This is known as a partial correlation. By computing a partial correlation matrix, mediation and association effects are accounted for and the actual correlation between two variables can be more accurately determined (Borsboom & Cramer, 2013; McNally et al., 2014). Relative importance networks, also known as directed networks, can shed further insight on causality. Similar to concentration networks, these networks calculate correlations after accounting for all other symptoms in the network. However, these networks also indicate the directionality of effects; relative importance networks depict which symptom is the causal symptom as well as the magnitude of effect. In these networks, the thickness of edges represents the relative importance of a symptom as a predictor of another symptom, while arrows mark the direction of effect (Borsboom & Cramer, 2013; McNally et al., 2014).

It should be noted that other types of statistical networks are available. Because association, concentration networks, and relative importance networks are the ones most commonly used, a discussion of other types of networks is outside the scope of this paper.

After a network has been produced, the position of the nodes is examined, referred to as node centrality. Node centrality indicates how essential a node is to the maintenance of the entire network. There are three commonly used measures of node centrality: strength, closeness, and betweenness. Using three different indices allows for more comprehensive results, as each one gives slightly different information (McNally et al., 2014). First, the strength of a node (also referred to as degree) is the amount of edges, or other nodes, connected to it. The magnitude of correlation of these connected nodes is summated to calculate the strength of the node (McNally et al., 2014). The strength, then, does not give information on the indirect effect of a node across the network, but does demonstrate how important a node is in terms of its direct effect on other nodes. Closeness is the average distance from a given node to all other nodes in the network. A high closeness score represents a short average distance between a node and all other nodes. Although closeness is an informative statistic that illustrates the importance of a node across the network, its major downside is that it cannot be computed when one or more nodes are not connected (Borsboom & Cramer, 2013; McNally et al., 2014). Finally, betweenness is the number of times a node lies on the shortest path between two other nodes (Borsboom & Cramer, 2013; McNally et al., 2014; McNally, Heeren, and Robinaugh, 2017). For example, if the shortest path between node A and node C crosses through node B, then node B has a betweenness of at least one (McNally et al., 2014). In testing node centrality, significance testing is often used to determine if any symptom is significantly more central than others (McNally et al., 2017).

Validity of Network Theory

For functionality to matter, a theory must first be proven valid. Cramer (2013) sets six components for a viable theory: comprehensiveness, precision and testability, parsimony, empirical validity, heuristic value, and applied value. Comprehensiveness refers to the ability of a theory to explain a phenomenon, rather than just describe it. By explaining phenomena, comprehensive theories are better able to make predictions and control outcomes. Next, precision and testability refer to the measurability and testability of the components of a theory. For example, behavioral symptoms are measurable by empirically tested measures, where as social norms may be more difficult to measure. Third, parsimony refers to the simplicity of the theory, in that all other things being equal, the simpler theory is more likely to be true. Fourth, empirical validity remarks on how well a theory can predict results while also offering insight into why disconfirming evidence may exist. Fifth, heuristic value includes how much unique thought is generated by the theory; theories should offer distinctive value in generating hypotheses. Finally, applied value is the extent to which a theory is able to offer solutions for problems; theories should benefit society by providing answers to real life difficulties.

Network theory passes the standards set by the six components of a theory (comprehensiveness, precision and testability, parsimony, empirical validity, heuristic value, applied value; Cramer, 2013). First, network theory is comprehensive, as it explains a network's development through hysteresis, bridge symptoms, and the examination of the direct and indirect effect one symptom has on another. Second, it is clearly testable. However, it should be noted that replicability of network theory has been recently debated within the literature (Epskamp, Borsboom, & Fried, 2018; Forbes, Wright, Aidan, Markon, & Krueger, 2017; Fried & Cramer, 2017). Third, network theory is designed to statistically explain the connection between components and can account for shared variance with other components. Thus, network theory passes the parsimony criterion insofar as it facilitates selection of components that are the most influential. Fourth, as the function of network theory is to predict how symptoms manifest in others, it offers empirical validity. Fifth, network theory offers a way of conceptualizing mental disorders different than the most frequently used classification system, thereby spurring unique thought and contributing heuristic validity. Finally, network theory has the potential to inform treatment, thus generating applied value by offering solution to a societal problem (dysfunctional mental health).

Implications of Network Theory

Network theory offers a new way of understanding psychopathology, and subsequently has a number of implications. First, understanding mechanisms of change within a conceptualization of psychopathology is a vital step in improving prevention and treatment techniques. Network theory accomplishes this by identifying how components interact with other components (Borsboom, 2017a; McNally et al., 2014). While the understanding that symptoms cause other symptoms is not an entirely new concept, network theory offers a way of organizing this sequence of causation (Borsboom, 2017b). For example, in a network using behavioral symptoms, network theory details how a symptom may serve as a mechanism for the onset and maintenance of a different symptom in easy to digest fashion. It also deviates from the *DSM*, and raises a question of the utility of classifying networks as disorders (Borsboom & Cramer, 2013).

In regards to treatment efforts, by identifying central symptoms (Borsboom & Cramer, 2017; McNally et al., 2014), network theory can suggest which symptoms to target. Similarly, with prevention efforts, network theory may give insight on which symptom influences the onset of other symptoms, informing primary, secondary, and tertiary preventive efforts. For example, network theory may assist public health policy in deciding where to allocate funding for prevention efforts or help predict what may cause someone to relapse after symptom improvement. Similarly, by defining bridge symptoms, network theory further informs both treatment and preventive efforts; interventions that target bridge symptoms may substantially improve symptomology (McNally et al., 2014). Bridge symptoms also have the added effect of making it difficult to discern what symptoms classify as a separate disorder. Researchers have long struggled to identify boundaries between disorders; network theory proposes that this is because these boundaries simply do not exist (Borsboom & Cramer, 2013; Borsboom, 2017b).

Finally, network analysis may assist in lowering dropout rates, a problem that plagues therapeutic responses to PTSD (DeViva, 2014; Garcia et al., 2011; Hoge et al., 2014). A network analysis study could, for example, compare the symptom networks at baseline of individuals who drop out of treatment against those who commit to therapy. Predictors related to dropping out, such as younger age, lower intelligence, and less education (Rizvi, Vogt, & Resick, 2012) could also be included as nodes to better understand their relationship with other variables. This may shed insight into the underlying cause between these risk factors and behavioral symptoms, increasing rates of therapy retention.

Limitations within Network Theory

Although network theory offers an exciting new avenue of research, it is not without limitations. One of the most intriguing aspects of network theory is the potential to include almost any variable into a network. However, this strength may also serve as a weakness in multiple ways. First, if an important node is not included, analysis may yield spurious results, as the relationship between two variables may be misinterpreted. For example, within a PTSD network, if intrusive thoughts mediate a relationship between the symptoms of avoiding reminders of the trauma and anger, removing intrusive thoughts from the model may result in the inaccurate interpretation that avoiding reminders and anger are causally related. Thus, including the correct nodes can be a prerequisite in properly illustrating the connection between two variables, else researchers risk prescribing casual relations when none exist. To complicate matters, although including more variables may seem to solve this problem, more nodes also results in a need for more power (Fried & Cramer, 2017). Network studies are already historically underpowered (Epskamp et al., 2018), as network analyses require large sample sizes (Spiller et al., 2017). Although there is no single threshold for what can be recognized as a sufficiently large sample, studies often employ samples approaching 1,000 individuals. Thus, the solution to one limitation of network analysis is unfortunately difficult to accomplish as it represents another limitation. Additionally, nodes must be divergent and inherently independent of each other (Bullmore & Bassett, 2011; Butts, 2008; Butts, 2009; Rubinov & Sporns, 2010). With more similar nodes, results become less meaningful and easier to misinterpret (Bullmore & Bassett, 2011). However, it may be a challenge to identify when this is the case. For example, “difficulty focusing” and “intrusive thoughts” may simply measure the same variable of “rumination.” In this case, “rumination” should be included instead of the two nodes that compose it. It is also possible, however, that they measure different, but highly correlated concepts, such as fatigue and sleep quality (Fried & Cramer, 2017). To avoid multiple pitfalls, it is incumbent on researchers to select nodes meticulously, choosing variables that are supported by research and do not represent the same constructs.

Network theory produces results by using a singular model to explain the network of symptoms of a large sample. Although this makes results more generalizable, large samples encompass a number of individual differences. PTSD presentations within any given sample can vary greatly, and thus the symptom manifestation of any given individual in the study may not properly fit within the wider network model. Thus, although results are intended to be generalizable, results from a network analysis will not hold true for all people with the studied presentation. In a similar and perhaps more pressing issue, the heterogeneity of a sample may also yield inaccurate results. For example, if half of a given sample displayed one causal network, while the other half presented with a different causal network, network analysis would likely yield ambiguous results that are inaccurate for both halves of the sample (Fried et al., 2017). This issue of sample heterogeneity has challenged the replicability of network theory in the literature (Forbes et al., 2017; Fried et al., 2017). Importantly, network analysis does attempt to mitigate this concern by using indices of fit, displaying a number of prominent pathways between symptoms (as opposed to a singular pathway), and using multiple indices of centrality. Further, complex network estimation statistics can be included in analysis to test the stability and accuracy of results (Epskamp et al., 2018). Still, as is the case with all psychology studies, individual differences are present and studies must be interpreted cautiously.

Other limitations pertain to correlational analyses and indicative reasoning. First, although network analyses attempt to explain symptom causality, models often use cross sectional data. This makes models correlational, not causational (McNally et al., 2014). Inclusion of longitudinal data can overcome this weakness, but due to the previously mentioned limitation of sample sizes, this is increasingly difficult. Additionally, although hypotheses can be made beforehand, network theory is largely based off of inductive reasoning. In other words, experimenters may make a priori hypotheses, yet a network analysis may produce a network that displays results entirely different than the hypothesized effect. Researchers must then attempt to rationalize results to explain their validity. Thus, although network analysis may uncover mechanisms of change, these mechanisms at times may be understood or explained poorly.

Conceptualizing PTSD: Network Theory

Network theory is a fairly new approach to psychopathology, and the literature of PTSD and network theory remains sparse but informative. Table 1 lists network theory studies of PTSD and their main findings. It should be noted that no study has examined network theory with an adult sample survivors of interpersonal violence.

Table 1

Network Studies of PTSD

Authors	Type of Sample	Most Central Symptoms	Other Notable Findings
Armour et al., 2017	221 US veterans	• Flashbacks, negative trauma related emotions, detachment, and physiological cue reactivity	• Psychogenic Amnesia did not have strong connections with other symptoms in the negative cognitions and mood alterations cluster. • Concentration difficulties may be more indicative of general distress than PTSD.
Birkeland & Heir, 2017	188 individuals following a bombing attack	• Emotional numbness	• Being female was related to higher physiological reactivity and lower avoidance of thoughts and feelings. • Low levels of social support was related to sleep problems.
Bryant et al., 2017	852 patients admitted to a hospital following traumatic injury	• At the acute phase: intrusive thoughts and physiological reactivity • At the 12 month time point: startle, concentration, and intrusive thoughts	• The acute phase of trauma reactions may be characterized by fear while symptoms of negative mood and alteration may be more prominent as time progresses.
McNally et al., 2014	139 individuals following earthquake	• Hypervigilance and future foreshortening	
McNally et al., 2017	179 individuals reporting childhood sexual abuse	• Physiological reactivity, dreams about the trauma, and loss of interest	• Physiological reactivity predicted number of symptoms.

Mitchell et al., 2017	1,458 US Veterans	• Avoidance behaviors, avoiding thoughts or emotions, distressing dreams, intrusive thoughts, physiological reactivity to reminders, and hypervigilance	• Distressing dreams and concentration problems were more central for men than women, while hypervigilance and anhedonia was more central for women than men.
Phillips et al., 2018	1,050 US Veterans	• Hypervigilance, avoidance of reminders, loss of interest, and detachment	• Irritability and intrusive thoughts strongly related to high combat experience.
Ross et al., 2018	331 UK veterans	• Recurrent thoughts, nightmares, negative emotions state, detachment, and exaggerated startle	• Impairments in close relationships related largely to the negative alterations in cognitions and mood cluster, while impairments in home management was most associated with re-experiencing symptoms
Spiller et al., 2017	151 Refugees	• Emotional cue reactivity	
Sullivan et al., 2016	4,639 undergraduate students following a mass shooting	• Intrusive thoughts, anger, Sleep problems	

In one of the first studies examining PTSD through the lens of network theory, McNally, Robinaughm Wang, Deserno, & Borsboom (2014) examined 139 individuals who met diagnostic criteria for PTSD following an earthquake in China. The strongest connections between pairs of symptoms included: hypervigilance and startle, avoiding thoughts and avoiding activities, loss of interest and feeling disconnected. Hypervigilance was found to be among the most central symptoms in the network, mostly due to having the highest strength of any symptoms within the network. This indicates that hypervigilance has a strong direct connection to a number of symptoms, and is therefore one of the most relevant to the maintenance of other symptoms within the network. Additionally, belief about a foreshortened future was also found to be highly central but did not have a high strength within the network. Instead, future foreshortening was highly central due to its betweenness, suggesting that future foreshortening is important in bridging clusters of symptoms. In particular, it seems that future foreshortening was especially relevant in bridging intrusive symptoms with those related to anhedonia and emotional numbness. Finally, although this study identified a number of symptoms as strongly connected with each other in a manner consistent with the *DSM-IV*, it also showed anger/irritability to be strongly related to sleep problems and concentration difficulties. The authors suggest that the connection between anger/irritability and concentration is largely influenced by the connection between anger/irritability and sleep problems. Specifically, sleep difficulties may cause limitations in both coping and executive resources, respectively translating anger into concentration difficulties. These findings demonstrate how network analysis can be used to highlight mechanisms that may not be initially obvious.

A study examining US veterans (Armour, et al., 2017) found flashbacks, negative trauma related emotions, detachment, and physiological cue reactivity to be the most central, and thus the most important to the maintenance of PTSD for the US veteran population. Symptoms with the highest associations included: hypervigilance and startle, nightmares and flashbacks, blame of self or others and negative trauma related emotions, detachment and emotional numbness. This study also showed psychogenic amnesia to have weak connections with other symptoms in the negative cognitions and mood alterations cluster, raising the possibility that it may not be a good fit for this cluster as presented in the *DSM-5*. Finally, concentration difficulties were also strongly related to anxiety and depression, which may indicate that concentration difficulties are more indicative of general distress than PTSD. Mitchell et al. (2017) also examined a PTSD network of US veterans. Results showed avoiding reminders, avoiding thoughts or emotions, distressing dreams, intrusive thoughts, physiological reactivity to reminders, and hypervigilance to be the most central symptoms. When comparing results by sex, results showed distressing dreams and concentration problems to be more central for men than women, while hypervigilance and anhedonia were more central for women than men. Additionally, a recent study of UK veterans (Ross, Murphy, Armour, 2018) determined recurrent thoughts, nightmares, negative emotions state, detachment, and exaggerated startle to be the most central symptoms of PTSD. This study also offered a unique addition by examining the relationship between PTSD symptoms and functional impairment, finding that impairments in close relationships related largely to the negative alterations in cognitions and mood cluster, while impairments in home management was most associated with re-experiencing symptoms. Finally, a study of 1,050 US veterans found a strong connection between intrusive thoughts and irritability to be a feature of the PTSD network in veterans who have experienced high levels of combat (Phillips et al., 2018).

In a study of 151 refugees who displayed posttraumatic symptoms, Spiller et al. (2017) found hypervigilance and startle response, intrusion and difficulty falling asleep, and irritability and reckless behavior to be significantly more connected than other symptom dyads. The authors note that, although it is very possible that these symptoms dyads cause each other, a third variable may also be important. For example, rumination may be a mediating or moderating factor between the relationship between sleep problems and intrusion symptoms. Further, emotional cue reactivity was the most central symptom within the network, and psychological amnesia was found to be the least central symptom. Due to the small sample size, the authors noted that findings should be interpreted with caution and may not be largely applicable.

In a fourth study, Sullivan, Smith, Lewis, and Jones (2016) identified intrusive thoughts as the symptom with most connections. The authors suggest that intrusive thoughts are instigators of hyperarousal and being emotionally upset at triggers. In this study of survivors of a mass shooting, sleep difficulty was found to have the highest betweenness and anger had the shortest path to all symptoms (strongest connection to other symptoms). Anger was postulated to lead to avoidance behaviors through feeling detached. In a related study, Birkeland and Heir (2017) examined PTSD symptoms following a bombing. Symptoms with the highest edge weights (strongest correlation) included: intrusive thoughts and nightmares, feeling easily startled and overly alert, and feeling detached and emotional numbness. Feeling emotionally numb, concentration difficulties, feeling detached from other people, physiological cue reactivity, and feeling easily started were the most central symptoms. However, only feeling emotionally numb was found to be significantly higher in node strength (more central) than other symptoms. The authors also examined covariates, determining that being female related to higher physiological reactivity and lower avoidance of thoughts and feelings. The authors postulate that sex hormones, which augment consolidation in episodic memory, may influence the effect of stress on emotional learning and memory. Further, high severity of exposure (how one experiences the trauma) was associated with feeling emotionally numb and loss of interest in previously enjoyable activities. The authors also determined that a low level of social support was related to sleep problems and loss of interest in previously enjoyable activities. The authors propose that low levels of social support following trauma may cause sleep disturbance via increasing rumination due to a lack of emotional support. Finally, although neuroticism was linked to nightmares and loss of interest in previously enjoyable activities, it was significantly less connected to the network as a whole, and thus may not be influential to the etiology of PTSD.

In a longitudinal study of PTSD using network theory, Bryant et al. (2017) studied PTSD symptoms in individuals admitted to the hospital with a traumatic injury immediately following the aftermath of the trauma occurrence. Data were also collected one year later, and the immediate network was compared against the follow up network. Results demonstrated that in the acute phase, intrusion and physiological reactivity were among the most central symptoms. The network was much stronger on the one year follow up, with foreshortened future, sleep disturbance, social detachment, amnesia, and concentration difficulties as much more central symptoms than in the acute phase. Startle response was also found to be more central than in the acute phase, with re-experiencing symptoms demonstrating stronger connections with each other. Startle response was also linked to hypervigilance. Taken together, the symptoms found to be influential in the follow up period more resemble the fear circuitry indicative of PTSD (fear conditioning, avoidance, and sensitivity to threat) than in the acute phase. Further, in general, symptoms of negative mood and alteration were much more prominent at the one year follow up. The authors hypothesize that the immediate response to trauma is fear, while other dysphoric reactions (such as anger or frustration) occur as time progresses.

Finally, McNally et al (2017) examined adults who had experienced a childhood sexual abuse. Strong connections were shown between the following: feeling distant from others and emotional numbness, exaggerated startle and hypervigilance, loss of interest in previously enjoyable activities and concentration problems, flashbacks and intrusive thoughts, and nightmares and disturbed sleep. Strong edges were also noted among anger, difficulty sleeping, and concentration problems. The authors determined physiological reactivity, dreams about the trauma, and loss of interest to have the highest centrality, but noted that this finding should be interpreted with caution as no symptom was significantly more central than another. The authors also found physiological arousal in response to triggers predicts a number of other symptoms, such as dreams about the trauma, flashbacks, avoidance behaviors, being upset by reminders, exaggerated startle response, and lack of interest in activities that were once enjoyable. The authors thus speculate that extinguishing physiological arousal to reminders of trauma may be the most effective way of diminishing symptoms in individuals who report childhood sexual abuse.

These studies have largely studied different trauma types, which may explain the differing results. Different trauma types have been shown to produce different outcomes (Haldane & Nickerson, 2016; Wanklyn et al., 2016). This makes comparisons difficult, and more studies of each type of trauma are needed to establish firmer guidelines for networks associated with each trauma type. Some similarities can be found. Perhaps most importantly, intrusive symptoms, such as emotional or physiological cue reactivity, have frequently been found to be central to PTSD networks (Armour et al., 2017; McNally et al., 2017; Spiller et al., 2017; Sullivan et al., 2016). This suggests that intrusive symptoms may be the catalyst for other symptoms, while other symptom clusters such as avoidance and negative alterations in mood may be the result of intrusive symptoms (McNally et al., 2017). Additionally, strong connections are consistently identified between feeling detached and both feeling emotional numb and loss of interest in activities that were once enjoyable (Armour et al., 2017; Birkeland & Hiers, 2017; Bryant et al., 2017; McNally et al., 2015; McNally et al., 2017). Feeling disengaged from one's emotions (emotional numbness) may relate to disengaging emotionally from others (feeling detached) and positive activities (loss of interest; Birkeland & Hiers, 2017). Further, trauma related amnesia is often found to be not central to the PTSD network (Armour et al., 2017; Birkeland & Hiers, 2017; McNally et al., 2015; McNally et al., 2017; Spiller et al., 2017), which may indicate that it is generally not a symptom of great importance to the onset and maintenance of PTSD.

Comorbidity between PTSD and Other Disorders

Network analysis studies have also examined the relationship between PTSD networks and other disorder networks. In a study examining individuals who met criteria for both PTSD and Major Depression Disorder (MDD), Afzali et al. (2017) determined that the two disorders were largely related. The overlapping symptoms, or symptoms that are part of diagnostic criteria for both disorders, of sleep problems, irritability, concentration problems, and loss of interest (anhedonia) functioned as bridge symptoms between the disorders. Interestingly, the non-overlapping symptoms of feeling sad, feelings of guilt, psychomotor retardation, foreshortened future, and experiencing flashbacks also functioned as bridge symptoms. This suggests that bridge symptoms are not limited to symptoms that traditionally fit both diagnostic criteria. Finally, a strong connection was revealed between feelings of discouragement and feelings of hopelessness.

In a study of adults with PTSD and Borderline Personality Disorder (BPD), Knefel, Tran, and Lueger-Schuster (2016) found the two disorders to be only weakly associated. Of note, the only connections between PTSD and BPD was through either 1) the PTSD symptom of distressing dreams to the BPD symptom of chronic feelings of emptiness or 2) the PTSD symptom of internal avoidance to the BPD symptom of identity disturbance. Researchers have long questioned the role of traumatic events in the development of BPD. As this study examines only symptom presentation, and not etiology, it does not definitively report the role traumatic experiences play in BPD manifestation. Instead, this study shows how the comorbid disorders might present, and suggests to clinicians what symptoms should be prioritized within treatment. Additionally, this demonstrates that symptoms can be highly prevalent but not highly central, as hypervigilance was found to be highly reported but not very central to the network. On the other hand, feelings of worthlessness were found to be very central, but was not reported by a high percentage of the sample.

Gaps in the PTSD Network Literature

Although insights can be gleaned from previous studies, there remains gaps in the network theory PTSD literature. Specifically, no study of adults has examined the symptom network resulting from interpersonal violence. PTSD has been shown to occur following interpersonal violence (sexual abuse, childhood abuse, sexual assault, domestic violence) at a high rate (14%, McGruder-Johnson, Davidson, Gleaves, Stock, Finch, 2000; 57% following intimate partner violence, Nathanson, Shorey, Tirone, Rhatigan, 2012; 31-84% following domestic violence, Jones, Hughes, & Unterstaller, 2000). Further, as previous studies of PTSD network have shown results to vary by trauma type (Haldane & Nickerson, 2016; Wanklyn et al., 2016), it remains essential that interpersonal violence is examined explicitly. Finally, current PTSD studies have largely restricted their studies to symptoms of PTSD, while ignoring other comorbid symptoms. PTSD is comorbid especially with depression (Campbell et al., 2007; Kilpatrick et al., 2003) and substance abuse (Brown, Recupero, & Stout, 1995; Brown, Stout, Mueller, 1999; Kilpatrick et al., 2003). Thus, these symptoms may as central to the maintenance of a symptom network and should be included in analyses.

The Current Study

Purpose and Rationale

Network theory offers an alternative way to examine psychopathology that may lead to important advances in prevention and treatment. Network theory is centered on mental disorders being maintained by symptom-symptom interactions. Through studying the mechanisms by which symptoms cause other symptoms, analyses may lead to more precise and efficacious treatments. Network theory also offers an explanation for comorbidity and symptom onset with its inclusion of bridge symptoms and hysteresis respectively. With respect to PTSD, studies have already yielded important results, such as the centrality of intrusive symptoms and the relative unimportance of trauma related amnesia to network maintenance. Network theory is, however, in its infancy and needs further studies to replicate results.

This study had two primary and two exploratory aims. Both primary Aims (Aim 1 and Aim 2) analyzed the PTSD network of adult victims of interpersonal trauma. Aim 1 used a self-report measure while Aim 2 employed a clinician administered measure. Specifically, the goals for Aim 1 were to examine the overall strength of the PTSD network amongst victims of interpersonal trauma, identifying what symptoms are most central to the network, which symptoms are most strongly connected, and which symptoms may not be imperative to the maintenance of the overall network. These goals were repeated with Aim 2 in order to analyze how the PTSD network results differ from self-report and clinician administered measures. As self-report measures and the CAPS-IV have shown generally consistent results (Cody et al., 2017; Griffin et al., 2004), the hypotheses do not change based on assessment measure type (Aim 1 has identical hypotheses with Aim 2; Aim 3 has identical hypotheses with Aim 4). Finally, exploratory Aims 3 and 4 focused on the effects of depression symptoms on the PTSD networks. Aim 3 examined the effects of depression symptoms on the self-report PTSD network, and Aim 4 did the same with the clinician administered PTSD network to identify how the use of measures affects results. Results from both aims examined how depression symptoms impact the PTSD network, as the findings were compared to the findings from the primary aims. Aims 3 and 4 were exploratory due to issues of sample size; when more nodes are added, a larger sample size is needed. Thus, the sample size for the current study may not have been large enough to fully investigate these aims. Further discussion of how this study addressed this issue is detailed in the Methods section.

Hypotheses:

Within Aim 1, it is hypothesized that, using self-report measures:

Hypothesis 1a: Intrusive symptoms, such as emotional or physiological cue reactivity, will be central to PTSD networks.

Hypothesis 1b: A strong connection will be found between feeling cutoff from others and both emotional numbness and anhedonia (loss of interest in activities that were once enjoyable).

Hypothesis 1c: Trauma related amnesia will not to be central to the PTSD network.

Within Aim 2, it is hypothesized that, using clinician-administered measures:

Hypothesis 2a: Intrusive symptoms, such as emotional or physiological cue reactivity, will be central to PTSD networks.

Hypothesis 2b: A strong connection will be found between feeling cutoff from others and both emotional numbness and anhedonia (loss of interest in activities that were once enjoyable).

Hypothesis 2c: Trauma related amnesia will not to be central to the PTSD network.

Within Aim 3, it is hypothesized that, using self-report measures:

Hypothesis 3a: Sleep problems, irritability, concentration problems, and anhedonia will function as bridge symptoms between PTSD and depressive symptoms.

Hypothesis 3b: A strong connection will be found between feelings of a foreshortened future and feelings of past failure.

Within Aim 4, it is hypothesized that, using clinician-administered measures:

Hypothesis 4a: Sleep problems, irritability, concentration problems, and anhedonia will function as bridge symptoms between PTSD and depressive symptoms.

Hypothesis 4b: A strong connection will be found between feelings of a foreshortened future and feelings of past failure.

Method

Participants

The number of participants varied by aim due to missing data (Aim 1: 83 participants; Aim 2: 85 participants; Aim 3: 83 participants; Aim 4: 83 participants). For all four aims, all participants were female adults meeting criteria for PTSD. The sample was previously collected as part of a larger neuroimaging study. Participants were recruited for the study via advertising throughout the community. Inclusion criteria for PTSD participants included female sex, meeting the *Diagnostic and Statistical Manual of Mental Disorders* (4th ed., text rev.; *DSM-IV-TR;* American Psychiatric Association, 2000) criteria for PTSD (see below) after exposure to an interpersonal trauma, and right-handedness.

Participants were excluded if they reported a history of: (1) a diagnosis of a neurological disorder such as dementia, stroke, brain tumors, seizure disorder, multiple sclerosis, or encephalopathy Parkinson's Disease; (2) current comorbid alcohol or substance use disorder, schizophrenia or other psychotic disorder, obsessive-compulsive disorder (OCD), or bipolar disorder; (3) active suicidal risk as judged by the investigator. Participants were not included in the study if they showed significant cognitive or sensory limitations that may interfere with testing procedures (e.g., hearing loss or mental retardation).

Procedure

Participants were enrolled in this study as part of a larger neuroimaging study. All participants will have received a formal assessment for PTSD over two sessions at the Center for Trauma Recovery at the University of Missouri (UMSL). Data were collected over a five-year span. Assessment included a structured interview as well as clinical measures. Participants were included in the PTSD group if they met *DSM-IV-TR* criteria according to the CAPS-IV.

Measures

Demographics

Demographic information on gender, race, age, and education level was obtained.

The Clinician-Administered PTSD Scale-IV

As part of the larger study in which this sample is taken from, the CAPS-IV was used for the purpose of diagnosing PTSD and determining eligibility. The CAPS-IV is a clinician administered assessment for symptoms of PTSD. Symptoms are measured on both frequency and intensity across the three *DSM-IV-TR* symptom clusters (re-experiencing, avoidance, hyper-arousal). Participants receive a separate frequency and intensity score for each possible symptom and the two scores are added together to produce a total score. The CAPS-IV has high inter-rater reliability (.92-1.00 for frequency, .93-.98 for intensity; Hovens et al., 1994), test-retest reliability (.77-.96 for symptom clusters, .90-.98 for total score), and internal consistency (.85-.87 for symptom clusters, .94 for total score; Blake et al., 1995). Based on prior research (Orr et al., 1997), participants must have had a CAPS-IV score above 45 to meet PTSD diagnostic criteria. They must also have met the original scoring criteria by Blake et al. (1995), indicating a PTSD symptom to be present if the frequency is rated as 1 or higher and the intensity is rated as 2 or higher. PTSD symptoms were measured by the CAPS-IV for the purposes of Aim 2 and Aim 4. The individual frequency and intensity were added to give one cumulative score for each item.

Posttraumatic Diagnostic Scale (PDS)

For the purposes of Aim 1 and exploratory Aim 3, PTSD symptoms were measured by the Posttraumatic Diagnostic Scale (PDS; Foa et al., 1997). The PDS examines the severity of the 17 symptoms of PTSD according to the *DSM-IV-TR*. Participants are asked to rate the severity of each of their symptoms from 0 (“not at all or only one time”) to 3 (“5 or more times a week/almost always”), and their responses are cumulated to produce a total score. The PDS has demonstrated high face validity and high internal consistency (coefficient alpha of 0.92) Further, test-retest reliability has been showed to be high over a 2 to 3 week period (kappa = 0.74;). Sensitivity of the PDS was .89 and specificity was .75 (Foa et al., 1997; McCarthy, 2008).

Depression

Depression was measured using the Beck Depression Inventory, Second Edition (BDI-II; Beck, Steer, & Brown, 1996). The BDI-II is a 21-item self-report instrument gauging the severity of symptoms of depression in the last two weeks as listed in *DSM-IV-TR*. Respondents answer using a four-point scale ranging from 0 to 3. The BDI-II has shown high reliability and validity across populations (Wang & Gorenstein, 2013). With respect to its inclusion in Aim 3 and Aim 4, only 16 of the 21 items were included in the network, as the following symptoms appear on both the PDS and BDI-II: loss of interest in activities, sleep difficulties, irritability, foreshortened future, and concentration difficulty. No other symptoms of depression were removed as the BDI-II has been shown to have low intercorrelations (Lee, Lee, Hwang, Hong, & Kim, 2017).

Data Analyses

All data were first analyzed using SPSS 24.0 (SPSS, Inc., Chicago, IL). First, data were screened and reviewed for potential outliers, as outliers have been shown to affect network analyses (Khamis, 2005). Additionally, clinical data were analyzed, including the mean total PDS severity, mean PDS re-experiencing symptom cluster severity, mean PDS avoidance symptom cluster severity, mean PDS arousal symptom cluster severity, mean total CAPS-IV severity, mean CAPS-IV re-experiencing symptom cluster severity, mean CAPS-IV avoidance symptom cluster severity, mean CAPS-IV arousal symptom cluster severity, and mean total BDI-II scores.

Following this, data were inputted into JASP (Version 0.9 [Computer software]), a free open source statistical software from University of Amsterdam (JASP Team, 2018). JASP is a point-and-click statistical software with analyses written in either R or C++. All network analyses were conducted with JASP, and JASP network analyses and network graphs are based off the bootnet (Epskamp, Borsboom, & Fried, 2018) and qgraph (Epskamp et al., 2012) packages from R respectively.

Network Estimation and Visualization

First, to test Aim 1, an association network of PTSD symptoms was created with correlations. This resulted in a network with 17 nodes, one for each PTSD symptom on the PDS. To generate a network visualization, the Fruchterman-Reingold algorithm

(Fruchterman & Reingold, 1991) was applied. This algorithm takes into account the strength and number of connections between nodes to produce a network. Positive edges are printed in green and negative edges are shown in red. Further, the stronger a connection between two nodes, the thicker the connecting line. This process was repeated with Aim 2. For Aim 3 and Aim 4, the process was repeated with the inclusion of depressive symptoms. Depression and PTSD nodes were color coded differently for ease of visual analysis. A weights matrix table was also created. Weight matrix tables list the individual strength of connections between each variable.

Next, for all aims, a partial correlation (concentration) network, often referred to as a Gaussian Graphical Model, was created using the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selector Operator (EBICglasso) method, an operation adjusted from the Least Absolute Shrinkage and Selector Operator (LASSO) regularization method (Tibshirani, 1996). The EBICglasso method is commonly used and has been employed by previous studies (Armour et al., 2017; Mitchell et al., 2017; Spiller et al., 2017). EBICglasso estimates the partial correlation between all variables, and shrinks absolute weights to zero. Shrinkage occurs when data values are shrunk towards the mean. As a result, smaller edge weights are shrunk to zero reducing the need for a test for multiple comparisons. As part of the EBICglasso procedure, a hyperparameter is set. The hyperparameter has a positive relationship with the degree of shrinkage that occurs; increasing the parameter increases the shrinkage and results in more edges being removed. This creates a parsimonious model with nodes more likely to be genuine but may eradicate potentially relevant edges. The reverse is true as well; a hyperparameter that is too low results in a less parsimonious model with spurious edges. The hyperparameter can be set between zero, in which every node remains in the network, to a value equal to the largest correlation, in which no node remains in the network (McNally et al., 2017). To select a proper hyperparameter, multiple networks were created by testing the network with different hyperparameters. Hyperparameters were initially set at .5, the most frequently used value to initially set. The accuracy and stability of each network was examined (described in detail later in the accuracy and stability estimation section). If the network appeared unstable, the hyperparameter was lowered by .05. The network with the highest hyperparameter that displayed adequate accuracy and stability was selected. It should be noted, however, that the selection of a hyperparameter is relatively arbitrary, and is based off whether the researcher prioritizes discovery or caution (Epskamp et al., 2018).

Exploratory Aims 3 and 4

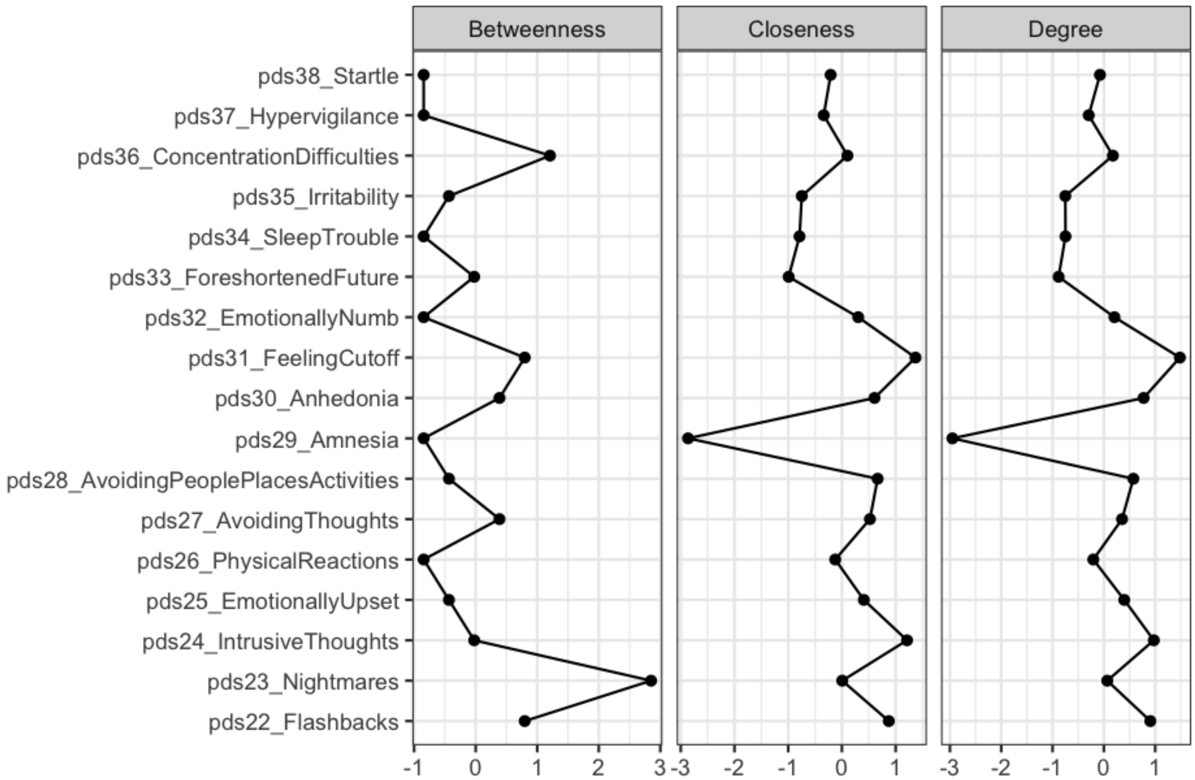
With regards to exploratory Aims 3 and 4, to examine which symptoms function as bridge symptoms, the sum of the weights of these edges was calculated (i.e., bridging strength). This process has been used in previous network studies examining PTSD and its comorbidities (Afzali et al., 2017).

Centrality Estimation

For all aims, to examine centrality for both association and concentration networks, a centrality plot was created listing the betweenness, closeness, and degree of each variable. See Figure 2 for an example from the current study with interpretation directions. Further, a centrality table was created which lists the centrality value for each node across all three centrality measures.

Figure 2.

PDS Association Network Centrality Plot



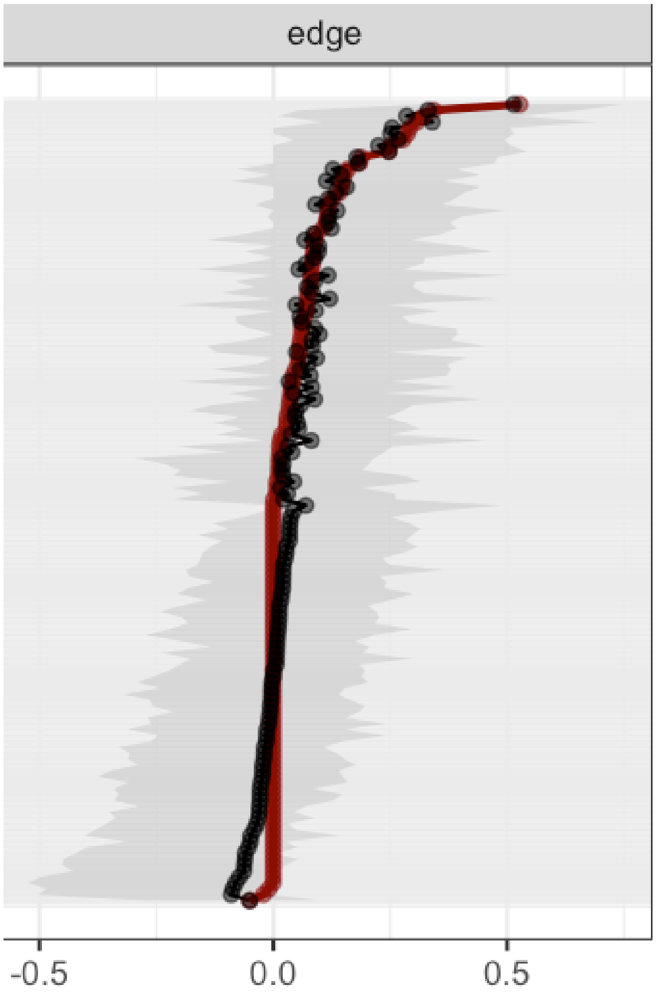
Note. The plot above shows the centrality values for betweenness, closeness and strength. Individual nodes are listed on the y-axis, with their degree of centrality on the x-axis. In this case, feeling cut off has the highest closeness and degree, while nightmares has the highest strength.

Accuracy and Stability Estimation

To ensure the accuracy and replicability of network analyses account, a series of analyses for the partial correlation networks of all aims were used (Epskamp, et al., 2017) to estimate the accuracy and stability of networks. This method is commonly used and employed by previous studies (Armour et al., 2017; Mitchell et al., 2017; Spiller et al., 2017). First, bootstrap confidence regions were used to analyze the accuracy of the edge-weights and tested for significance between edge-weights with 95% confidence intervals based on 1000 bootstrap iterations. A figure, often called an edge stability plot, was produced which depicts the 95% confidence intervals of the edge weights following bootstrapping procedure. The edge weights are depicted on top of the confidence intervals, allowing for a more accurate interpretation of the stability of the edge weights. See Figure 3 for an example and interpretation directions. Finally, a Centrality Stability Plot was produced illustrating which differences in node strength were significant following bootstrapping.

Figure 3

Current Study PDS Edge Stability Plot



Note. The plot above illustrates the stability of edge weights following bootstrapping. The red line shows the edge weights (seen on the x-axis) of the sample found from network analysis, with each horizontal line on the y-axis signifying one edge weight. Often, connected black dots are illustrated as well to show the edge weights found from bootstrapping. The 95% confidence intervals are displayed by the gray lines. When considering the stability of the edges, it is vital to compare the confidence intervals of edges to see if they truly vary from each other. When doing this, one should first examine how much confidence intervals overlap. Should they overlap greatly (as is the case in this example), this indicates that most edges likely do not vary from each other and thus results should be interpreted with care. If some confidence intervals do not overlap with each other, those are the edges that can be the most confidently interpreted (Epskamp et al., 2017). Note that this is a somewhat arbitrary process; it is incumbent on the researcher to use their best estimate of when edges seem stable. Ultimately, it is not unlikely that, regardless of adjustments and steps made toward securing edge stability, some edges can be interpreted confidently while other cannot.

Potential Adjustments

One of the major difficulties of network theory is the requirement of a large sample size. More specifically, there is a positive relationship between the sample size need and the number of nodes analyzed; in order to maintain the same level of stability and effect size, the sample size need increases as more nodes are analyzed (Epskamp et al., 2018). It should be noted that the regularization used in the EBICglasso method alleviates some of the need for a larger sample size (Epskamp et al., 2017). Previous network studies of PTSD have employed a minimum of 139 individuals in their sample. As such, this study utilized a smaller sample, which affected the accuracy and stability of the network. This is particularly true with regards to the exploratory Aim, as the inclusion of depressive symptoms increases the number of nodes. Accuracy and stability were first tested with the aforementioned accuracy and stability tests. When these tests suggested a largely unstable network, adjustments were made. Namely, as the sample size cannot be increased, there remained two solutions: lowering the hyperparameter or decreasing the number of nodes in the network (Epskamp et al., 2017). The hyperparameter was already chosen cautiously (described previously), and thus this option had been exhausted. Thus, the only option available was to remove variables; however, eliminating variables increases the chances of eliminating important variables. With regards to Aims 1 and 2, this was a difficult option to pursue as all PTSD symptoms would seem to play some role with respect to the maintenance of symptoms. Further, the EBICglasso method diminished less relevant variables. Thus, no variables were removed from Aim 1 or Aim 2. However, as Aim 3 and Aim 4 demonstrated a less than adequate level of stability, PTSD symptoms were combined based on their cluster. This has been done in a previous study (Greene, Gelkopf, Fried, Robinaugh, & Pickman, 2019). Thus, the PTSD network encompassed only three nodes, one for each cluster according to the *DSM-IV-TR*. In this case, both the original network with all possible nodes and the new network were still reported. It is worth noting that regardless of adjustments, the data need to be interpreted with caution. Replication studies remain a major need within the PTSD network literature.

Results

Demographics

No outliers were found during data screening. Table 2 illustrates the demographic and clinical data. Notably, some demographic data (age and years of education) were missing. No imputation was completed as no demographic data were used in analyses.

Table 2

Demographic and Clinical Data of Sample

	N	Mean (*SD*)
Age	72	32.17 (9.58)
Years of Education	72	14.79 (2.37)
PDS Total Score	83	29.31 (9.26)
PDS Re-experiencing Symptoms Score	83	7.86 (3.51)
PDS Avoidance Symptoms Score	83	12.05 (4.47)
PDS Arousal Symptoms Score	83	9.39 (3.01)
CAPS Total Monthly Score	85	67.57 (16.39)
CAPS Re-experiencing Symptoms Score	85	17.87 (6.35)
CAPS Avoidance Symptoms Score	85	27.20 (7.99)
CAPS Arousal Symptoms Score	85	22.51 (6.34)
BDI-II Score	83	26.06 (10.19)

Aim 1 Results

Within Aim 1, it is hypothesized that, using self-report measures:

Hypothesis 1a: **Intrusive symptoms, such as emotional or physiological cue reactivity, will be central to PTSD networks.**

Hypothesis 1b: A strong connection will be found between feeling cutoff from others and both emotional numbness and anhedonia (loss of interest in activities that were once enjoyable).

Hypothesis 1c: Trauma related amnesia will not to be central to the PTSD network.

PDS Association Results

Table 3 lists the abbreviated results for all network analyses.

Table 3

Network Results

Type of Network	Strongest Connections	Most Central Symptoms	Other Notable Findings
PDS Association	• Feeling cutoff and anhedonia • Feeling cutoff and emotional numbness	• Feeling cutoff (strength and closeness) • Nightmares (betweenness)	• Amnesia weakly related to other symptoms
PDS Partial Correlation	• Feeling cutoff and anhedonia	• Feeling cutoff (strength betweenness, and closeness)	• Amnesia and sleep problems not connected to the network
CAPS Association	• Feeling cutoff and emotional numbness	• Avoiding thoughts/feelings (strength and closeness) • Emotional Numbness (betweenness)	
CAPS Partial Correlation	• Feeling cutoff and emotional numbness	• Avoiding thoughts/feelings (betweenness) • Emotionally upset at reminders (strength)	• Many nodes not connected to the network
PDS and BDI Association	• Fatigue and loss of energy	• Feeling cutoff (strength, betweenness, and closeness)	• Bridge symptom connections included anhedonia and loss of pleasure, feeling cutoff and loss of pleasure, and fatigue and irritability • Amnesia weakly connected to other symptoms • Foreshortened future and irritability grouped with BDI symptoms; sexual disinterest grouped with PDS symptoms

PDS and BDI Partial Correlation	• Anhedonia and feeling cutoff	• Feeling cutoff (strength and closeness) • Fatigue (betweenness)	• Bridge symptoms included indecisiveness and concentration, sadness and irritability • Amnesia weakly connected to the network • Foreshortened future, irritability, sleep difficulties, and concentration difficulties appeared with the BDI symptoms; sexual disinterest was shown with the PDS symptoms.
PDS Clusters and BDI Partial Correlation	• Fatigue and loss of energy	• Fatigue (strength) • Arousal Symptom Cluster (closeness and betweenness)	• Bridge symptoms included avoidance symptoms and loss of pleasure, indecisiveness and arousal
CAPS and BDI Association	• Fatigue and loss of energy	• Loss of pleasure (strength, betweenness, and closeness)	• Bridge symptoms included loss of pleasure and emotional numbness, anhedonia and loss of pleasure • Amnesia negatively connected to many nodes • Anhedonia and concentration difficulties grouped with BDI symptoms; sexual disinterest with CAPS symptoms

CAPS and BDI Partial Correlation	• Fatigue and loss of energy	• Loss of pleasure (betweenness) • Fatigue (strength)	• Many nodes not connected to the network • Relationship between suicide and restricted affect shown to be significantly different following bootstrapping
CAPS Clusters and BDI Partial Correlation	• Fatigue and loss of energy	• Fatigue (strength) • Arousal (closeness) • Suicidal ideation (betweenness)	• Bridge symptoms included suicidal ideation and the arousal symptom cluster as well as suicidal ideation and the avoidance symptom cluster

Figure 1 displays the association network using the PDS. Visually, the network appears dense and has only positive edges. Analyses revealed particularly strong connections between feeling cut off and both anhedonia and emotional numbness. Additionally, a strong connection was found between flashbacks and intrusive thoughts, flashbacks and being emotionally upset at reminders, and anhedonia and avoiding reminders of the event. Notably, trauma-related amnesia had very weak connections to all other symptoms and visually is only remotely included in the network.

Figure 2 displays the centrality plot for the association network using the PDS. Feeling cut off demonstrated the highest strength (centrality index value of 1.481) and closeness (centrality index value of 1.369) while nightmares showed the highest betweenness (centrality index value of 2.849). Additionally, intrusive thoughts demonstrated the second highest strength (centrality index value of .974) and closeness (centrality index value of 1.212). Further, concentration displayed the second highest betweenness (centrality index value of 1.207)

PDS Partial Correlation Network

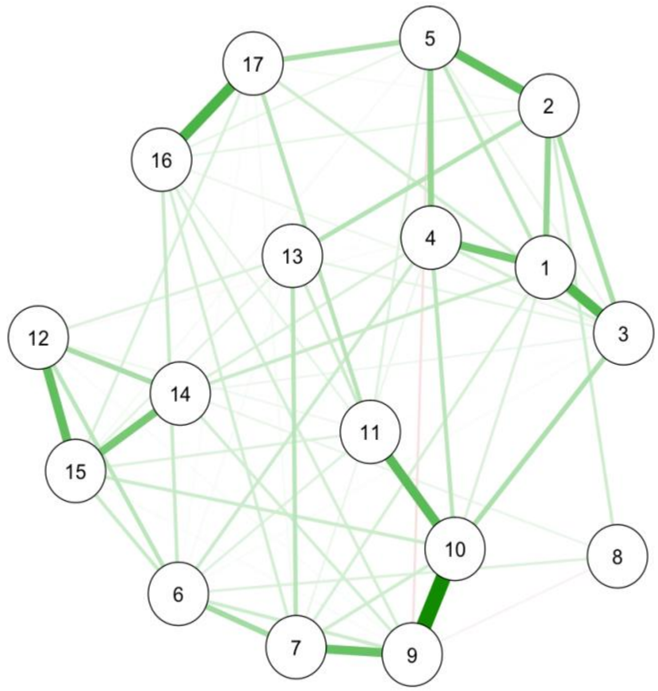
Figure 4A displays the partial correlation network using the PDS and a hyperparameter of .25. This network appears slightly dense and showed only positive connections, with feeling cutoff from others and anhedonia as the strongest connections. Trauma-related amnesia was only weakly connected to the network.

Figure 4B shows the centrality plot for the partial correlation network using the PDS. Feeling cutoff from others demonstrated the highest strength (mean bootstrapped standardized centrality index value of 2.109), betweenness (mean bootstrapped standardized centrality index value of 2.174), and closeness (mean bootstrapped standardized centrality index value of 1.486). Further, the centrality stability plot shows that, following bootstrapping, feeling cutoff from others maintained a significant difference between most other nodes, suggesting that feeling cutoff from others is significantly more central than other nodes.

Figure 4

PDS Partial Correlation Plot

A



1:Flashbacks
2: Nightmares
3: Intrusive Thoughts
4: Emotional Reactivity
5: Physical Reactivity
6: Avoidance of Thoughts
7: Avoiding Reminders
8: Amnesia
9: Anhedonia
10: Feeling Cutoff
11: Emotional Numbness
12: Foreshortened Future
13: Sleep Trouble
14: Irritability
15: Concentration
16: Hypervigilance
17: Startle

B

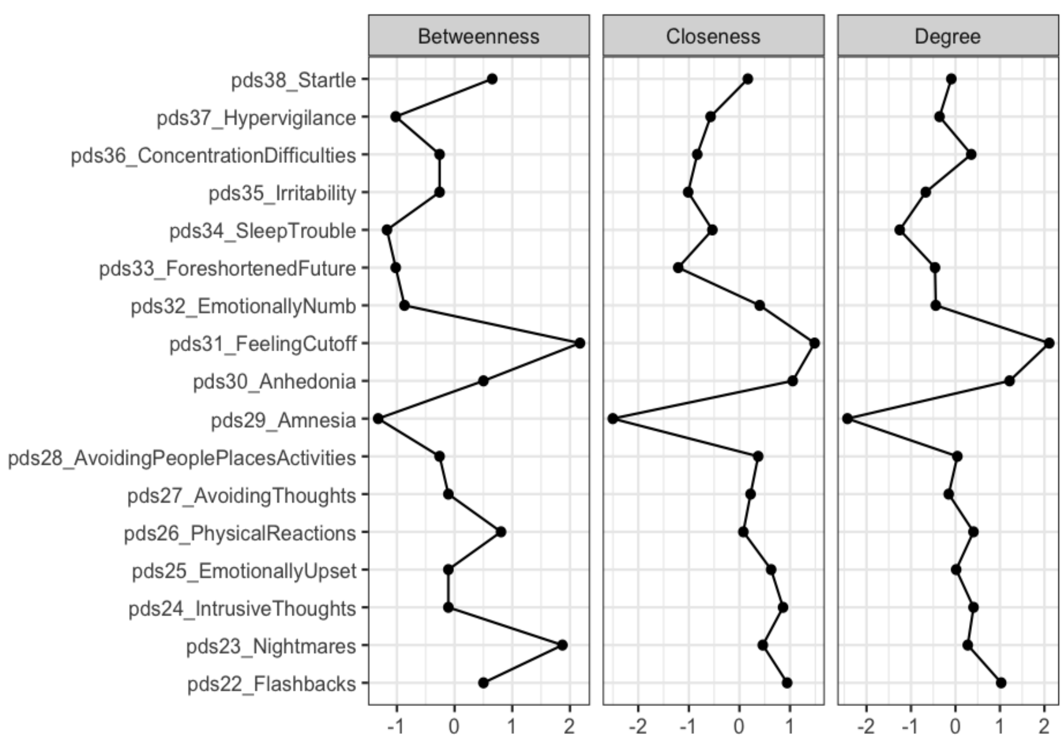


Figure 3 shows the edge stability plot. Much of the confidence intervals overlap, suggesting that the network is largely unstable. As such, the results should be interpreted with caution.

In sum, two of the three Aim 1 hypotheses were confirmed. Feeling cutoff was related to both anhedonia and emotional numbness, and trauma related amnesia was not related to the rest of the network. However, contrary to the hypotheses, intrusive symptoms were not shown to be central to either model.

Aim 2 Results

Within Aim 2, it is hypothesized that, using clinician-administered measures:

Hypothesis 2a: **Intrusive symptoms, such as emotional or physiological cue reactivity, will be central to PTSD networks.**

Hypothesis 2b**: A strong connection will be found between feeling cutoff from others and both emotional numbness and anhedonia (loss of interest in activities that were once enjoyable).**

Hypothesis 2c: **Trauma related amnesia will not to be central to the PTSD network.**

CAPS Association Network

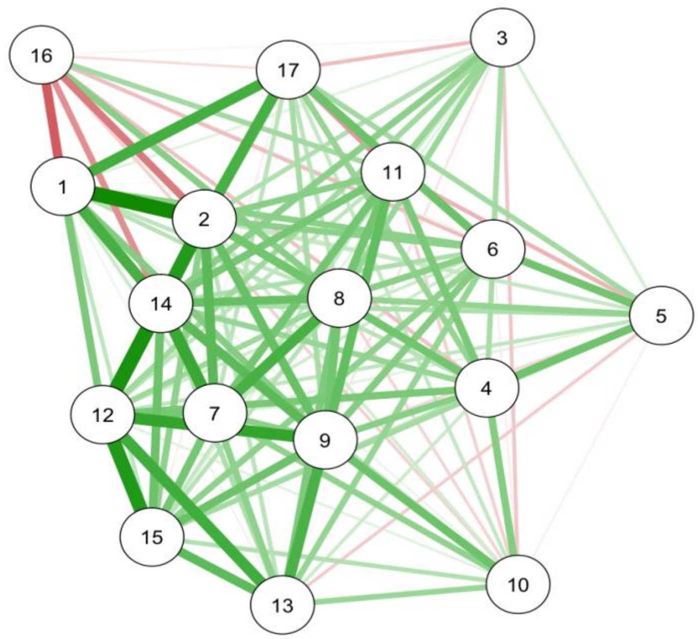
Figure 5A displays the association network using the CAPS. Visually, this network displayed a number of dense connections. The strongest associations were found between feeling cutoff from others and emotional numbness, emotional numbness and avoiding thoughts/feelings of the event, being emotionally upset at reminders and avoiding thoughts/feelings, and being emotionally upset at reminders and avoiding reminders. Notably, trauma-related amnesia had a fairly strong negative connection with both feeling cutoff from others and emotional numbness.

Figure 5B displays the association network centrality plot using the CAPS. Avoiding thoughts/feelings of the events was found to have the highest strength (centrality index value of 1.770) and closeness (centrality index value of 1.659). Additionally, emotional numbness demonstrated the highest betweenness (centrality index value of 2.232), the second highest closeness (centrality index value of 1.502), and the second highest strength (centrality index value of 1.644).

Figure 5

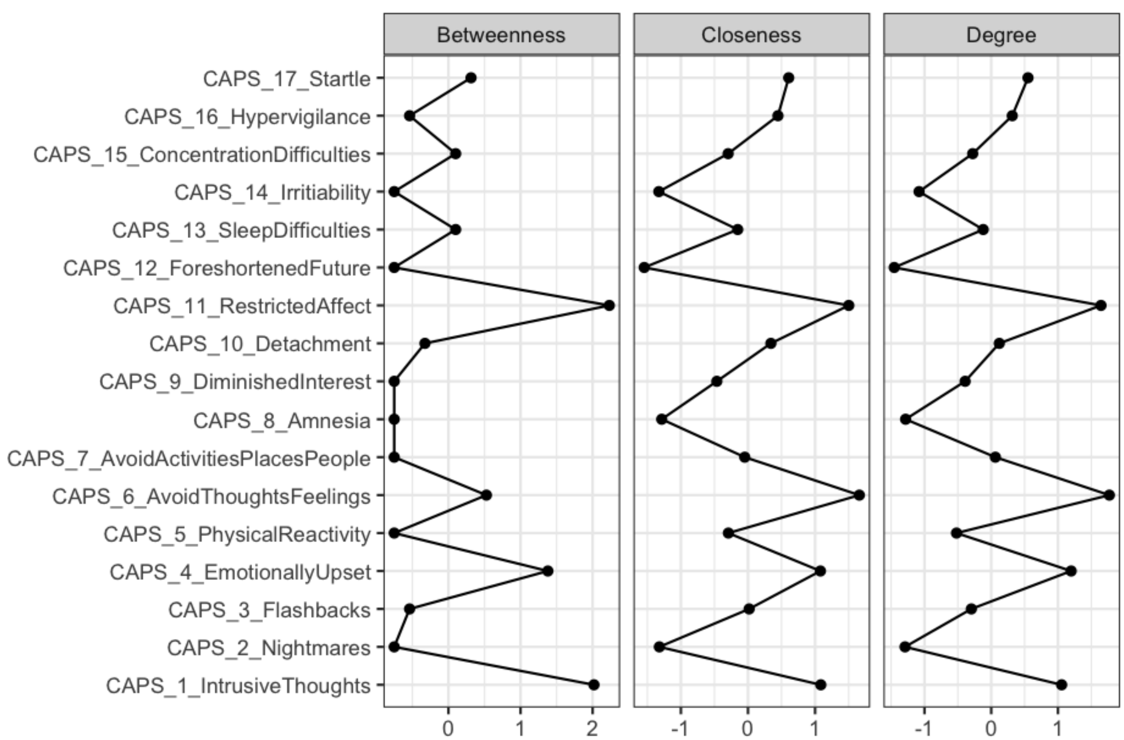
CAPS Association Plot

A.



1: Feeling cutoff
2: Emotional Numbness
3: Foreshortened Future
4: Sleep Difficulties
5: Irritability
6: Concentration Difficulties
7: Hypervigilance
8: Startle
9: Intrusive Thoughts
10: Nightmares
11: Flashbacks
12: Emotional Reactivity
13: Physical Reactivity
14: Avoidance of Thoughts
15: Avoidance of Reminders
16: Amnesia
17: Anhedonia

B.



CAPS Partial Correlation Network

Figure 6A displays the partial correlation network using the CAPS and a hyperparameter of .1. It should be note that this is a low hyperparameter value, suggesting the network to be less parsimonious model with spurious edges. Further, many of the nodes are disconnected from the network and are unrelated to each other. There were no remarkably strong connections. Of the nodes that did emerge as part of the network, the strongest connections were found between feeling cutoff from others and emotional numbness and avoiding thoughts/feelings and being emotionally upset at reminders.

Figure 6B displays the centrality plot for the partial correlation network using the CAPS. Avoiding thoughts and feelings (mean bootstrapped standardized centrality index value of 2.599) showed the highest betweenness while being emotionally upset at reminders resulted in the highest strength (mean bootstrapped standardized centrality index value of 2.183). Due to some nodes being disconnected from the network, closeness could not be calculated. However, following bootstrapping, the centrality stability plot showed no node to be significantly more central than another, indicating that these centrality results may be spurious.

Figure 6

CAPS Partial Correlation Plot

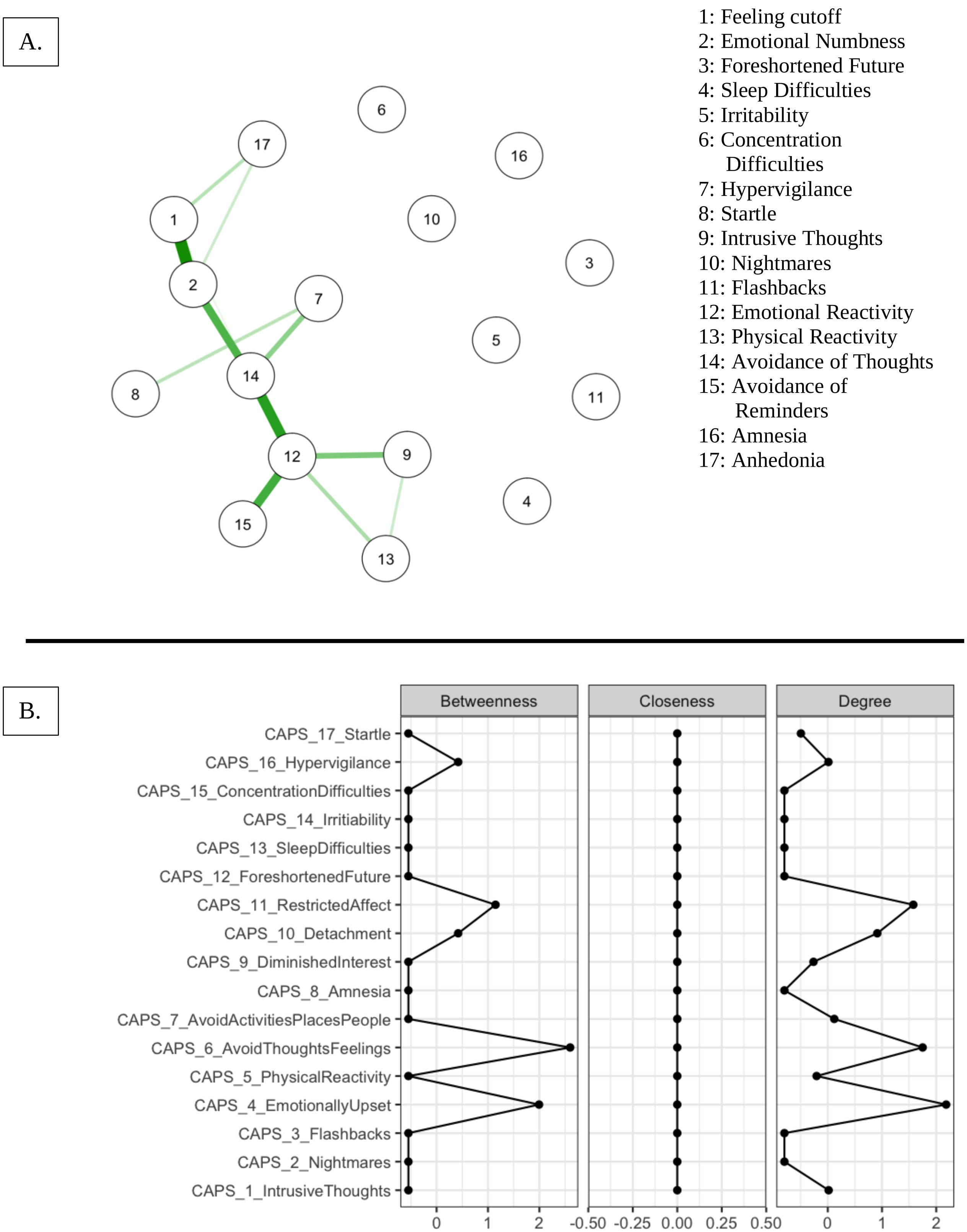
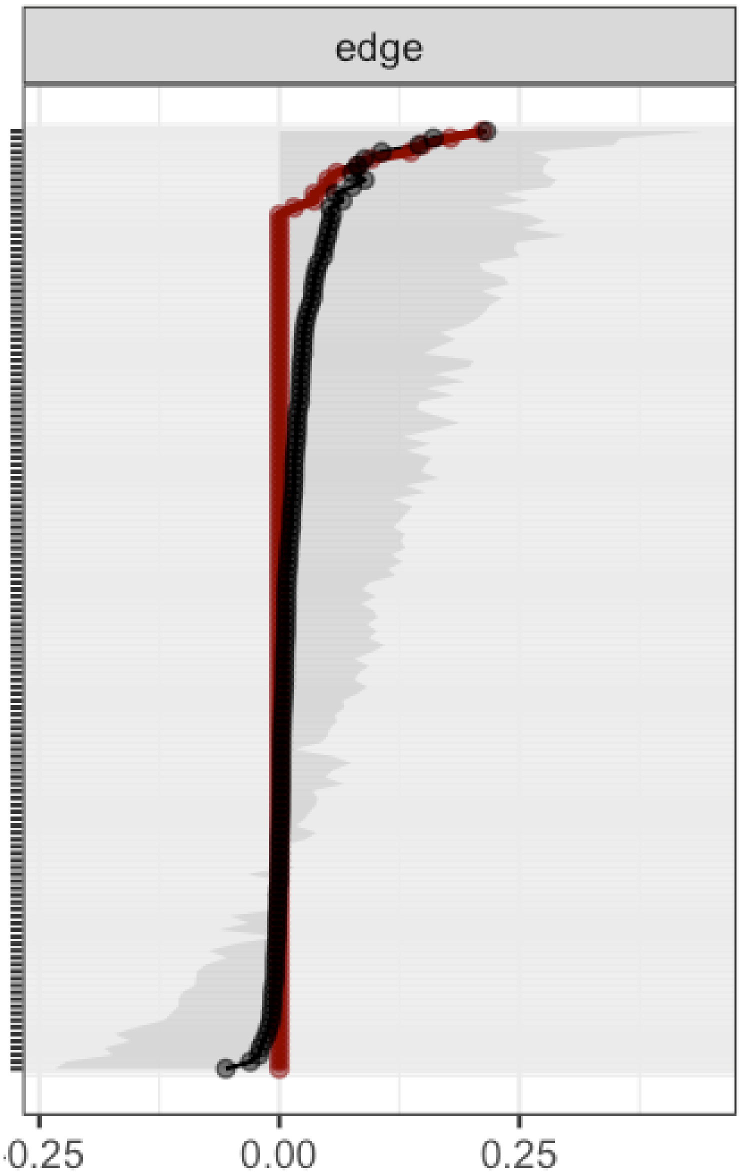


Figure 7 displays the edge stability plot. The plot shows some overlap between edge weights greater than zero, indicating that the network should be interpreted with some caution.

Figure 7

CAPS Partial Correlation Network Edge Stability Plot



In sum, hypotheses were somewhat confirmed in both models. While the association network did not show intrusive symptoms to be central, the partial correlation network identified being emotionally upset as central. Further, feeling cutoff was shown to strongly relate to emotional numbness in the association model, and while the partial correlation model lacked the density to display any strong connections, it was amongst the strongest connections in the partial correlation network. In both models, trauma related amnesia was not shown to be strongly related to the rest of the PTSD symptoms.

Aim 3 Exploratory Results

Within Aim 3, it is hypothesized that, using self-report measures:

Hypothesis 3a: Sleep problems, irritability, concentration problems, and anhedonia will function as bridge symptoms between PTSD and depressive symptoms.

Hypothesis 3b: A strong connection will be found between feelings of a foreshortened future and feelings of past failure.

PDS and BDI Association Network

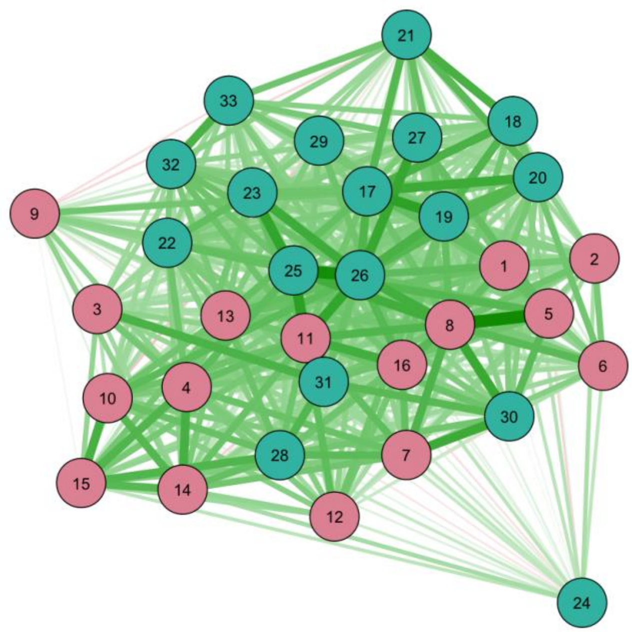
Figure 8A displays the association network using both the PDS and BDI. This network appeared very dense. Visually, symptoms from each measure were grouped together. The PDS symptoms of foreshortened future, trauma-related amnesia, and irritability appeared closer to BDI symptoms, and the BDI symptom of sexual disinterest appeared with the PDS symptoms. The network showed fatigue and loss of energy to have the strongest connection. In terms of connections across measures, anhedonia and loss of pleasure, loss of pleasure and feeling cutoff from others, and fatigue and irritability were the strongest connections in the network. Loss of pleasure showed the highest bridging strength. Further, trauma-related amnesia had weak connections to all other symptoms.

Figure 8B shows the association network centrality plot using both the PDS and BDI. Feeling cutoff from others demonstrated the strongest centrality across all three indices of strength (centrality index value of 2.224), betweenness (centrality index value of 4.130), and closeness (centrality index value of 2.298). No other node demonstrated comparable betweenness, while loss of pleasure displayed the second highest strength (centrality index value of 1.821) and closeness (centrality index value of 1.912).

Figure 8

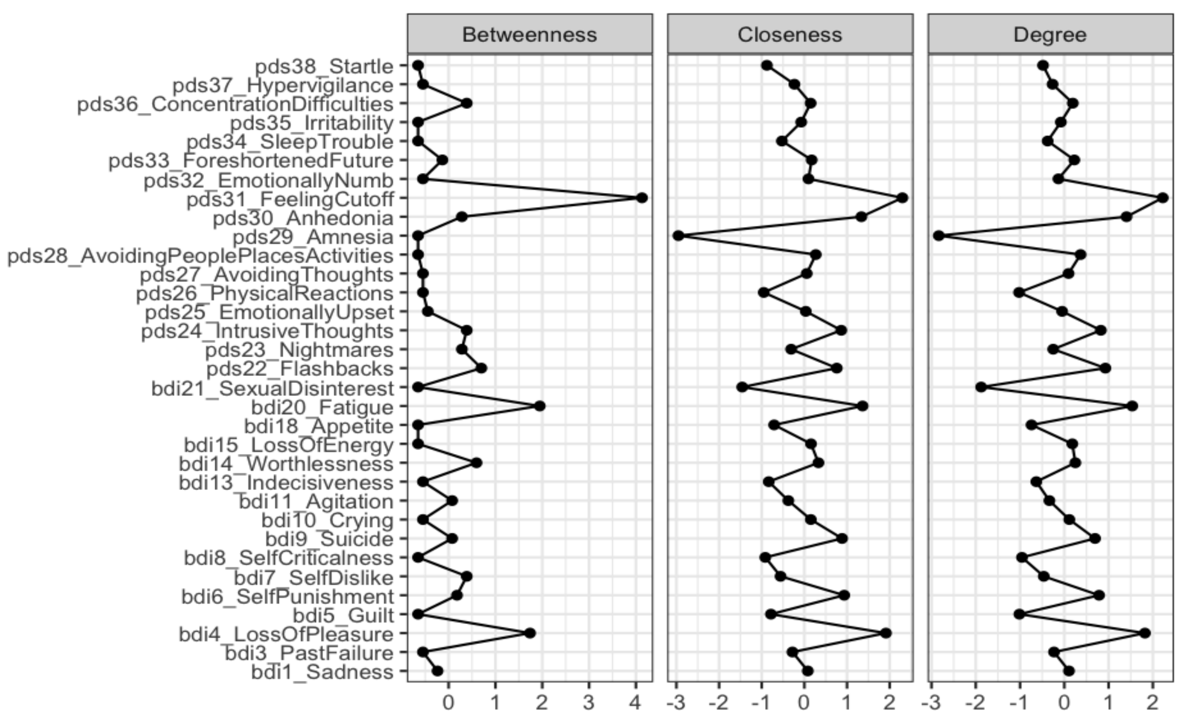
PDS and BDI Association Network

A.



Red-BDI	Green-PDS
1: Crying	17: Flashbacks
2: Agitation	18: Nightmares
3: Indecisiveness	19: Intrusive Thoughts
4: Worthlessness	20: Emotional Reactivity
5: Loss of Energy	21: Physical Reactivity
6: Appetite	22: Avoidance of Thoughts
7: Sadness	23: Avoiding Reminders
8: Fatigue	24: Amnesia
9: Sexual Disinterest	25: Anhedonia
10: Past Failure	26: Feeling Cutoff
11: Loss of Pleasure	27: Emotional Numbness
12: Guilt	28: Foreshortened Future
13: Self Punishment	29: Sleep Trouble
14: Self Dislike	30: Irritability
15: Self Criticalness	31: Concentration
16: Suicidal Thoughts	32: Hypervigilance
	33: Startle

B.



PDS and BDI Partial Correlation Network

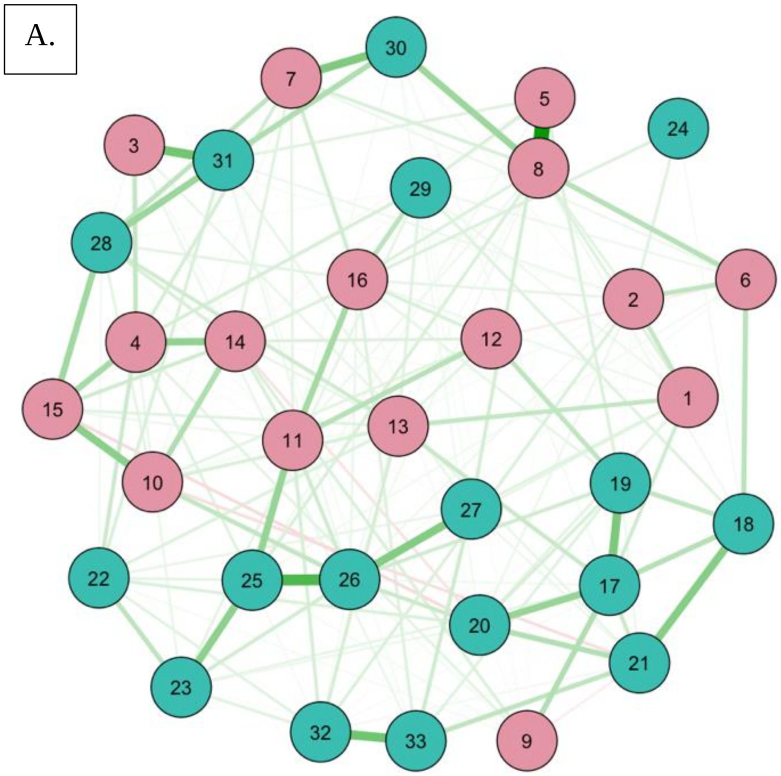
Figure 9A shows the partial correlation network using the PDS and BDI with a hyperparameter of .15. The network has a low hyperparameter value and is therefore likely to be a less parsimonious model with spurious edges. Generally, the network is not dense, although a strong connection was found between anhedonia and feeling cutoff from others. In terms of connections between measures, the strongest connections were between indecisiveness and concentration as well as sadness and irritability. Irritability demonstrated the highest bridge strength. Trauma-related amnesia was only weakly connected to the network. Many symptoms did not appear near symptoms of their respective measure. In particular, foreshortened future, irritability, sleep difficulties, concentration difficulties, and trauma-related amnesia appeared with the BDI symptoms, while sexual disinterest was shown with the PDS symptoms.

Figure 9B is the centrality plot for the partial correlation network of the PDS and BDI. Feeling cutoff from others displayed the highest strength (mean bootstrapped standardized centrality index value of 2.343) and closeness (mean bootstrapped standardized centrality index value of 1.767), while fatigue (mean bootstrapped standardized centrality index value of 2.614) had the highest betweenness. These centrality results may not be stable because the centrality stability plot showed no node to be significantly more central than another following bootstrapping.

Figure 9

PDS and BDI Partial Correlation Plot

A.



Red-BDI	Green-PDS
1: Crying	17: Flashbacks
2: Agitation	18: Nightmares
3: Indecisiveness	19: Intrusive Thoughts
4: Worthlessness	20: Emotional Reactivity
5: Loss of Energy	21: Physical Reactivity
6: Appetite	22: Avoidance of Thoughts
7: Sadness	23: Avoiding Reminders
8: Fatigue	24: Amnesia
9: Sexual Disinterest	25: Anhedonia
10: Past Failure	26: Feeling Cutoff
11: Loss of Pleasure	27: Emotional Numbness
12: Guilt	28: Foreshortened Future
13: Self Punishment	29: Sleep Trouble
14: Self Dislike	30: Irritability
15: Self Criticalness	31: Concentration
16: Suicidal Thoughts	32: Hypervigilance
	33: Startle

B.

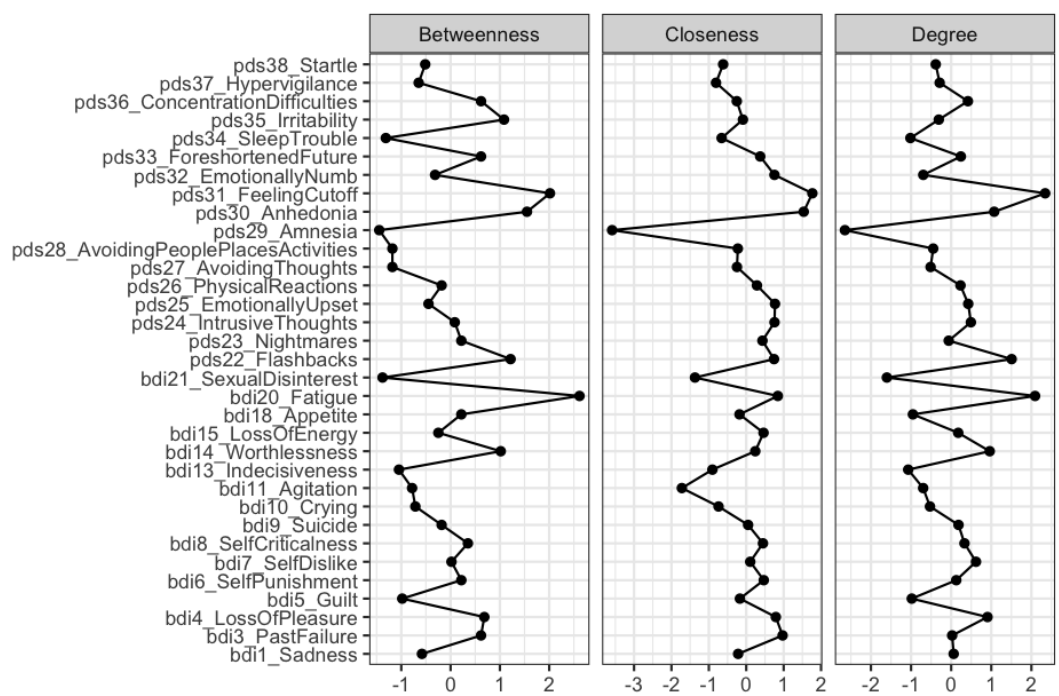
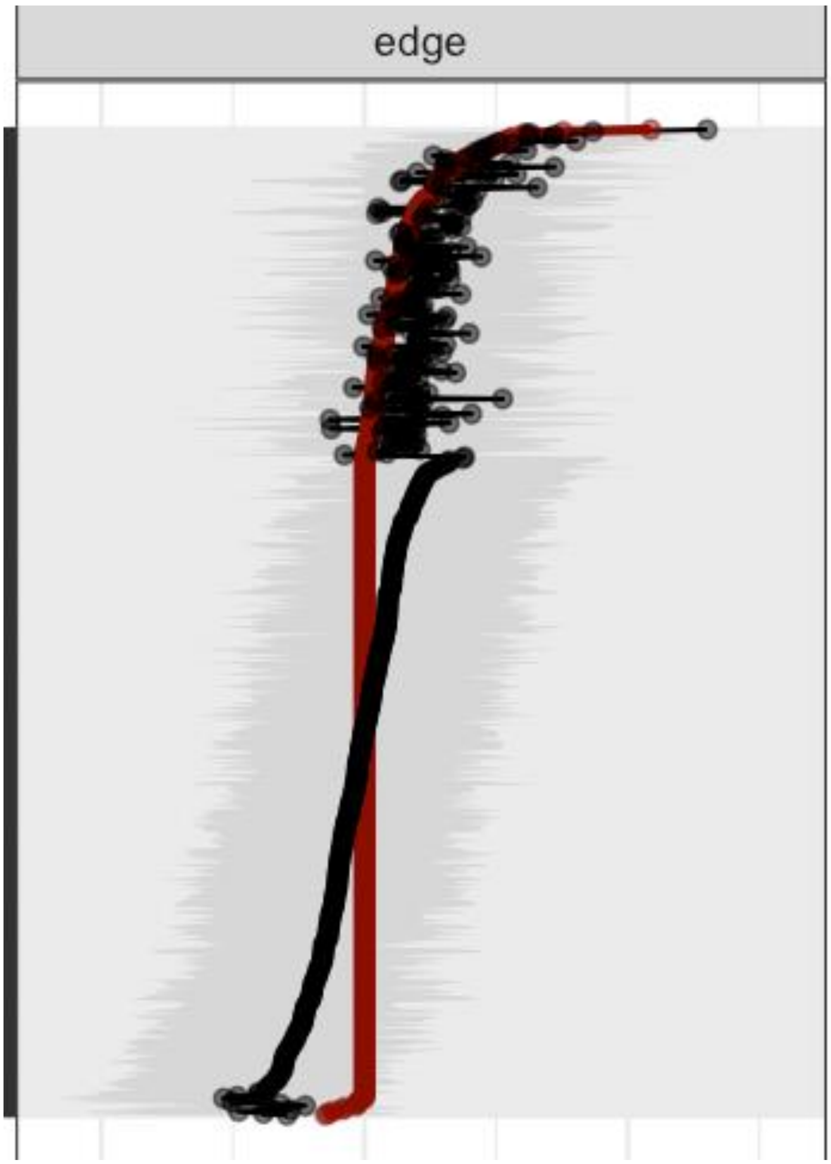


Figure 10 shows the edge stability plot. The plot shows an extremely high level of overlap showing the network to be very unstable. As such, the results should be interpreted with extreme caution.

Figure 10

PDS and BDI Partial Correlation Network Edge Stability Plot



PDS Cluster and BDI Partial Correlation Network

As described previously, the PDS symptoms were combined into three symptom clusters as a result of the instability of the network. Figure 11A shows this network with a hyperparameter of .2, somewhat higher than the chosen hyperparameter of .15 in the PDS and BDI partial correlation network. The network visually appears somewhat dense, and the strongest connection found were between fatigue and loss of energy. The strongest bridge connections were found between avoidance symptoms and loss of pleasure as well as indecisiveness and the arousal symptom cluster. The avoidance symptom cluster showed the highest bridging strength.

Figure 11B shows the centrality plot for this network. Fatigue displayed the highest strength (mean bootstrapped standardized centrality index value of 2.498), while the arousal symptom cluster had the highest closeness (mean bootstrapped standardized centrality index value of 2.150) and betweenness (mean bootstrapped standardized centrality index value of 2.598). Additionally, with bootstrapping, the centrality stability plot found no node to be significantly more central than another, indicating that centrality results may be spurious.

Figure 11

PDS Clusters and BDI Partial Correlation Plot

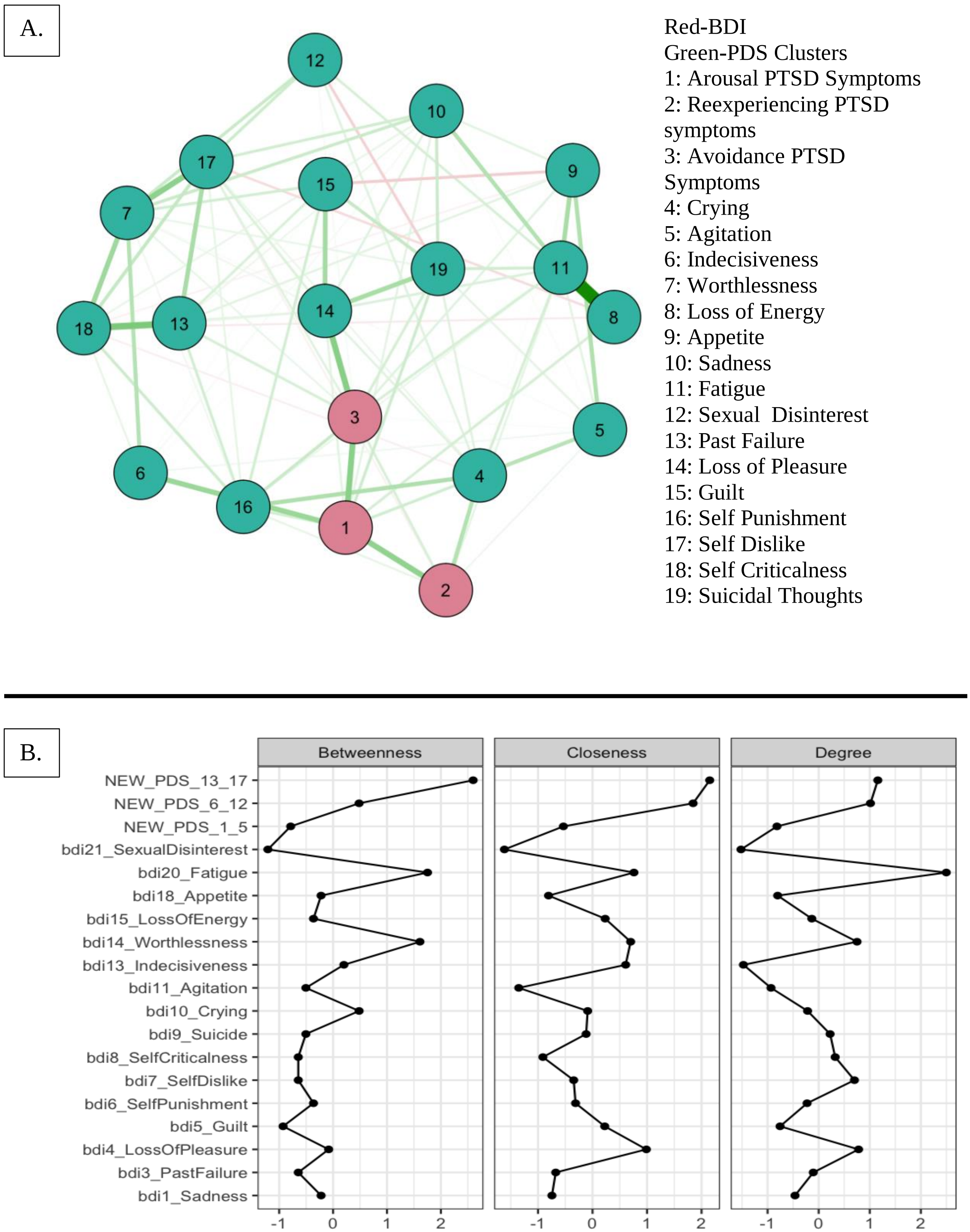
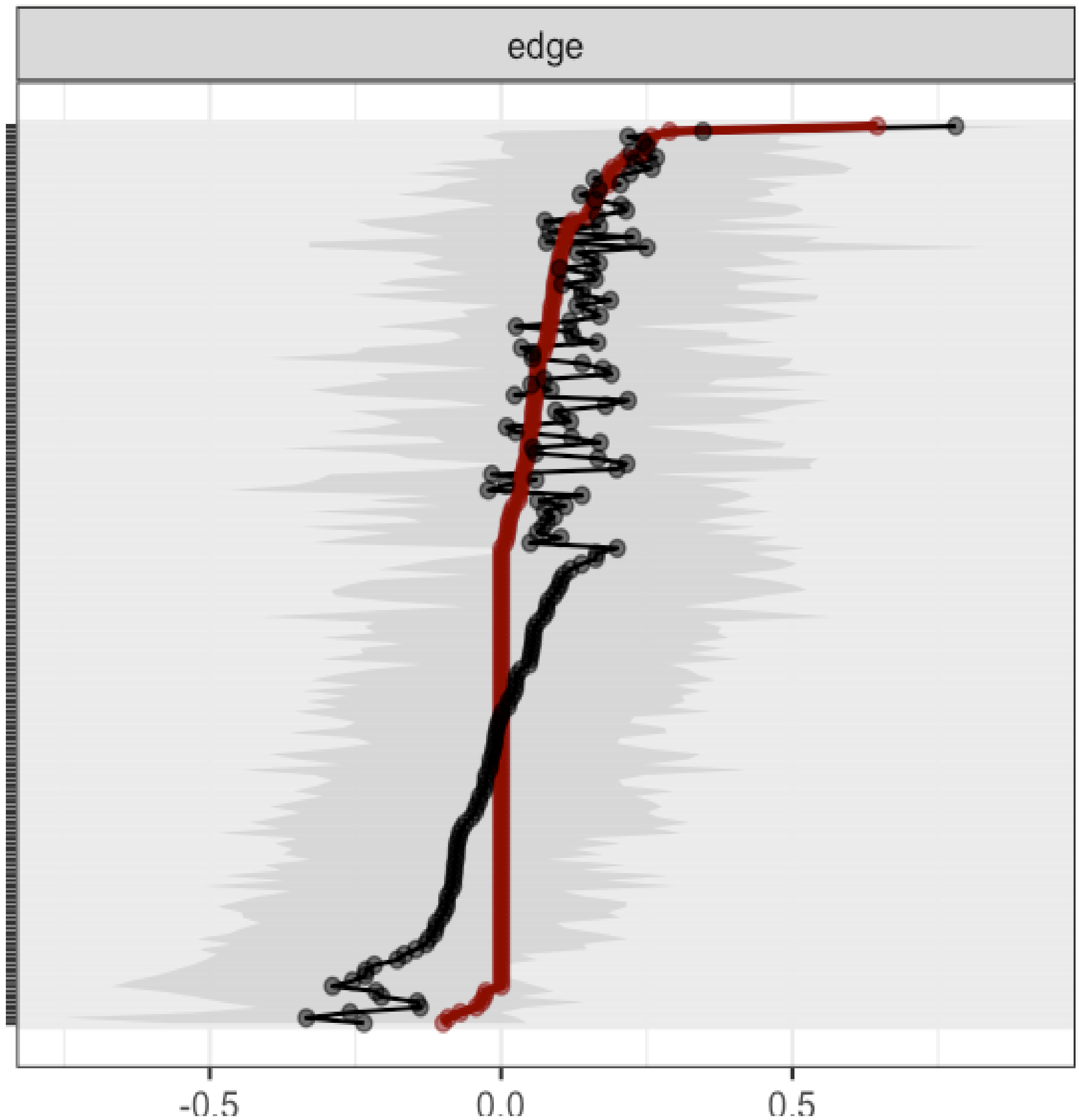


Figure 12 displays the edge stability plot. This network did not demonstrate noticeably better stability than the initial PDS and BDI partial correlation network, and thus results should be interpreted with caution.

Figure 12

PDS Clusters and BDI Partial Correlation Edge Stability Plot



In sum, as hypothesized, irritability functioned as bridge symptom in the partial correlation network. However, anhedonia, sleep problems, and concentration problems were not shows to connect the PTSD and depression networks. Finally, a strong connection was not shown between feelings of a foreshortened future and feelings of past failure.

Aim 4 Exploratory Results

Within Aim 4, it is hypothesized that, using clinician-administered measures:

Hypothesis 4a: Sleep problems, irritability, concentration problems, and anhedonia will function as bridge symptoms between PTSD and depressive symptoms.

Hypothesis 4b: A strong connection will be found between feelings of a foreshortened future and feelings of past failure.

CAPS and BDI Association Network

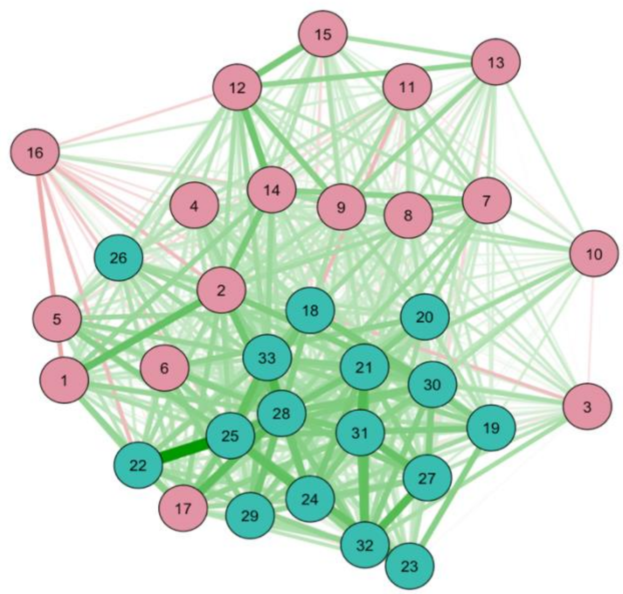
Figure 13A shows the association network using both the CAPS and BDI. The network appears very dense, with the strongest connection between fatigue and loss of energy. Of note, trauma-related amnesia was negatively connected to many nodes. In terms of connections across measures, anhedonia showed the highest bridging strength. In particular, loss of pleasure showed a strong relationship with both anhedonia and emotional numbness. In general, anhedonia and foreshortened future were grouped with the BDI symptoms, while sexual disinterest was closer to the CAPS symptoms.

Figure 13B shows the association network centrality plot using both the CAPS and BDI. Loss of pleasure demonstrated the strongest centrality across all three indices of strength (centrality index value of 2.291), betweenness (centrality index value of 3.681), and closeness (centrality index value of 2.272). Fatigue showed the second highest degree (centrality index value of 1.757), and suicidal ideation had the second highest betweenness (centrality index value of 2.399) and closeness (centrality index value of 1.635).

Figure 13

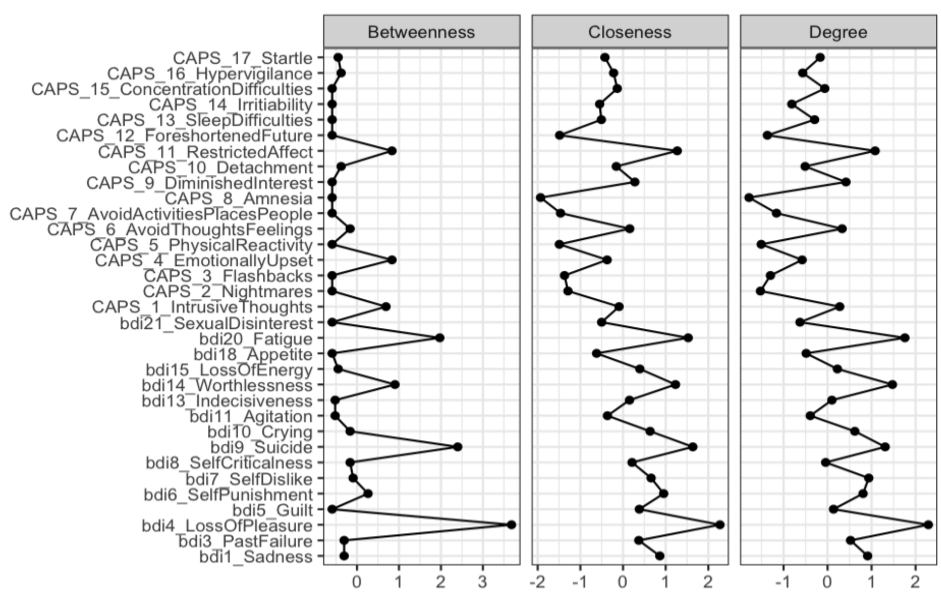
CAPS and BDI Association Network

A



Red-CAPS	Green-BDI
1: Feeling cutoff	18: Crying
2: Emotional Numbness	19: Agitation
3: Foreshortened Future	20: Indecisiveness
4: Sleep Difficulties	21: Worthlessness
5: Irritability	22: Loss of Energy
6: Concentration Difficulties	23: Appetite
7: Hypervigilance	24: Sadness
8: Startle	25: Fatigue
9: Intrusive Thoughts	26: Sexual Disinterest
10: Nightmares	27: Past Failure
11: Flashbacks	28: Loss of Pleasure
12: Emotional Reactivity	29: Guilt
13: Physical Reactivity	30: Self Punishment
14: Avoidance of Thoughts	31: Self Dislike
15: Avoidance of Reminders	32: Self Criticalness
16: Amnesia	33: Suicidal Thoughts
17: Anhedonia	

B



CAPS and BDI Partial Correlation Network

Figure 14A is the partial correlation network using the CAPS and BDI with a hyperparameter of .1. This network has a low hyperparameter value and is therefore likely to be a less parsimonious model with spurious edges. Despite this low value, many nodes are not connected to the network. In particular, many of the CAPS PTSD symptoms were not connected to other CAPS or BDI symptoms, leaving them disconnected from the network. These nodes included the CAPS symptoms of foreshortened future, sleep difficulties, startle, nightmares, flashbacks, and trauma-related amnesia, as well as the BDI symptom of sexual disinterest. It should also be noted that the network did not exist above this hyperparameter.

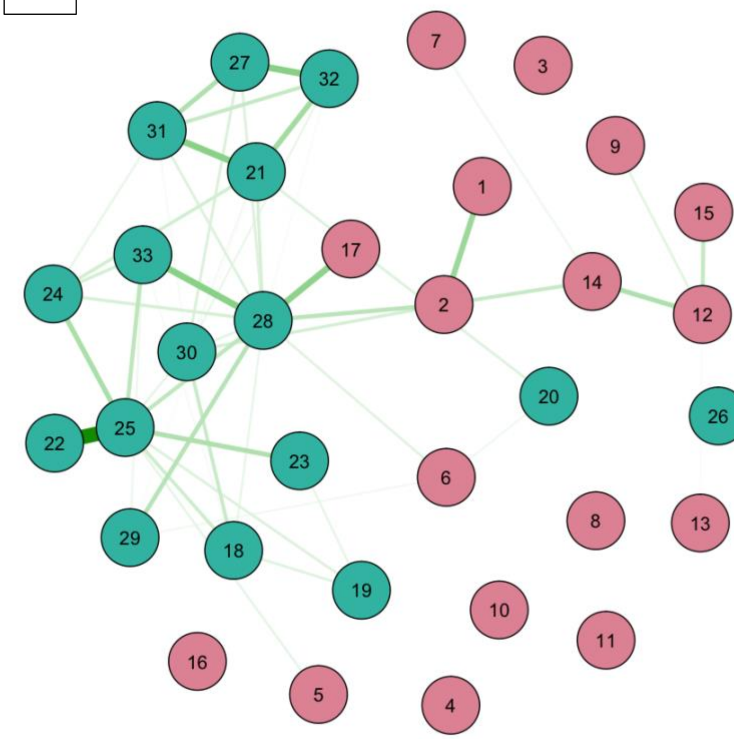
The connection between fatigue and loss of energy was the only strong connection shown. As a point of clarification, the BDI defines fatigue in terms of how tired one feels and loss of energy as a measure of one's energy level. The strongest connection across measures was between anhedonia and loss of pleasure. Loss of pleasure demonstrated the strongest bridging strength and was connected to the most nodes belonging to the other measure.

Figure 14B displays the centrality plot for the partial correlation network of the CAPS and BDI. Loss of pleasure displayed the highest betweenness (mean bootstrapped standardized centrality index value of 3.502) and fatigue showed the highest strength (mean bootstrapped standardized centrality index value of 3.238). Closeness could not be calculated due to nodes missing from the network. Following bootstrapping, a significant difference was found on the strength indices between trauma-related amnesia and both suicidal ideation and restricted affect. Finally, the edge stability plot (Figure 15) showed an extreme amount of overlap, suggesting these results are likely unstable.

Figure 14

CAPS and BDI Partial Correlation Network

A.



Red-CAPS	Green-BDI
1: Feeling cutoff	18: Crying
2: Emotional Numbness	19: Agitation
3: Foreshortened Future	20: Indecisiveness
4: Sleep Difficulties	21: Worthlessness
5: Irritability	22: Loss of Energy
6: Concentration Difficulties	23: Appetite
7: Hypervigilance	24: Sadness
8: Startle	25: Fatigue
9: Intrusive Thoughts	26: Sexual Disinterest
10: Nightmares	27: Past Failure
11: Flashbacks	28: Loss of Pleasure
12: Emotional Reactivity	29: Guilt
13: Physical Reactivity	30: Self Punishment
14: Avoidance of Thoughts	31: Self Dislike
15: Avoidance of Reminders	32: Self Criticalness
16: Amnesia	33: Suicidal Thoughts
17: Anhedonia	

B.

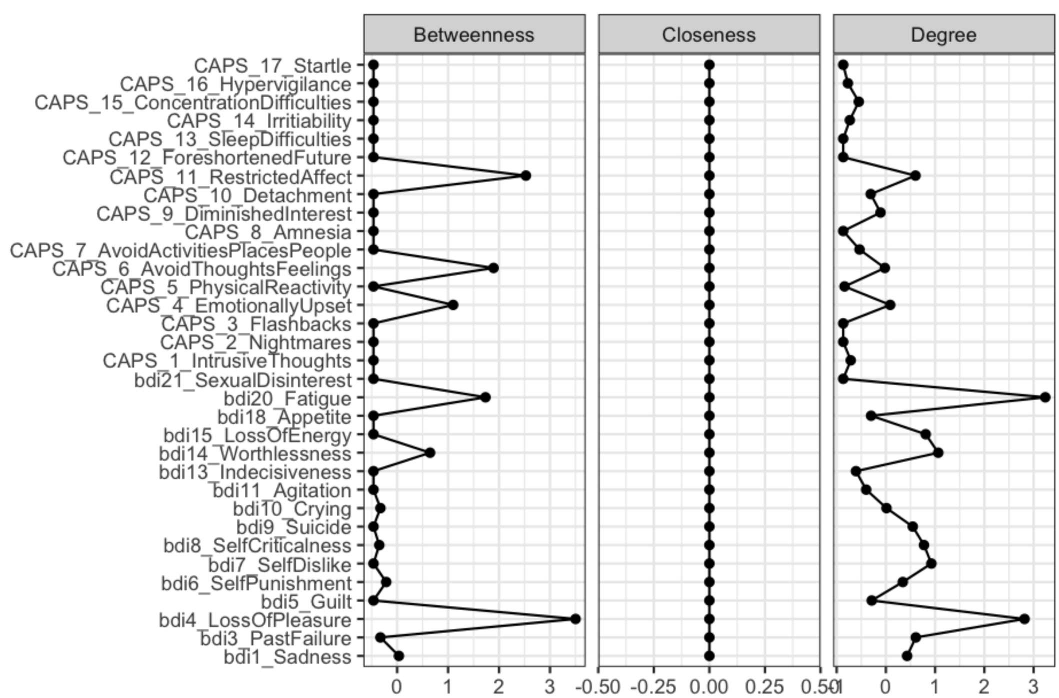
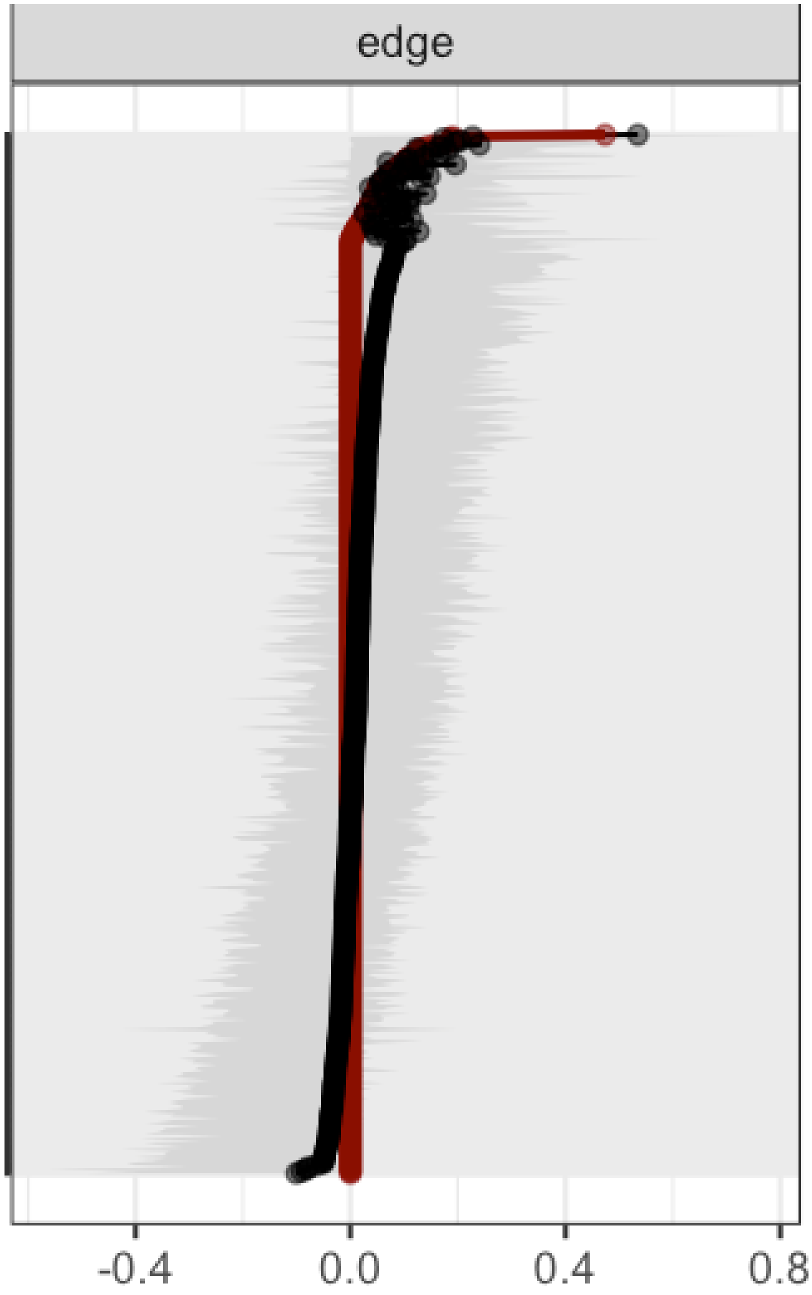


Figure 15

CAPS and BDI Partial Correlation Edge Stability Plot



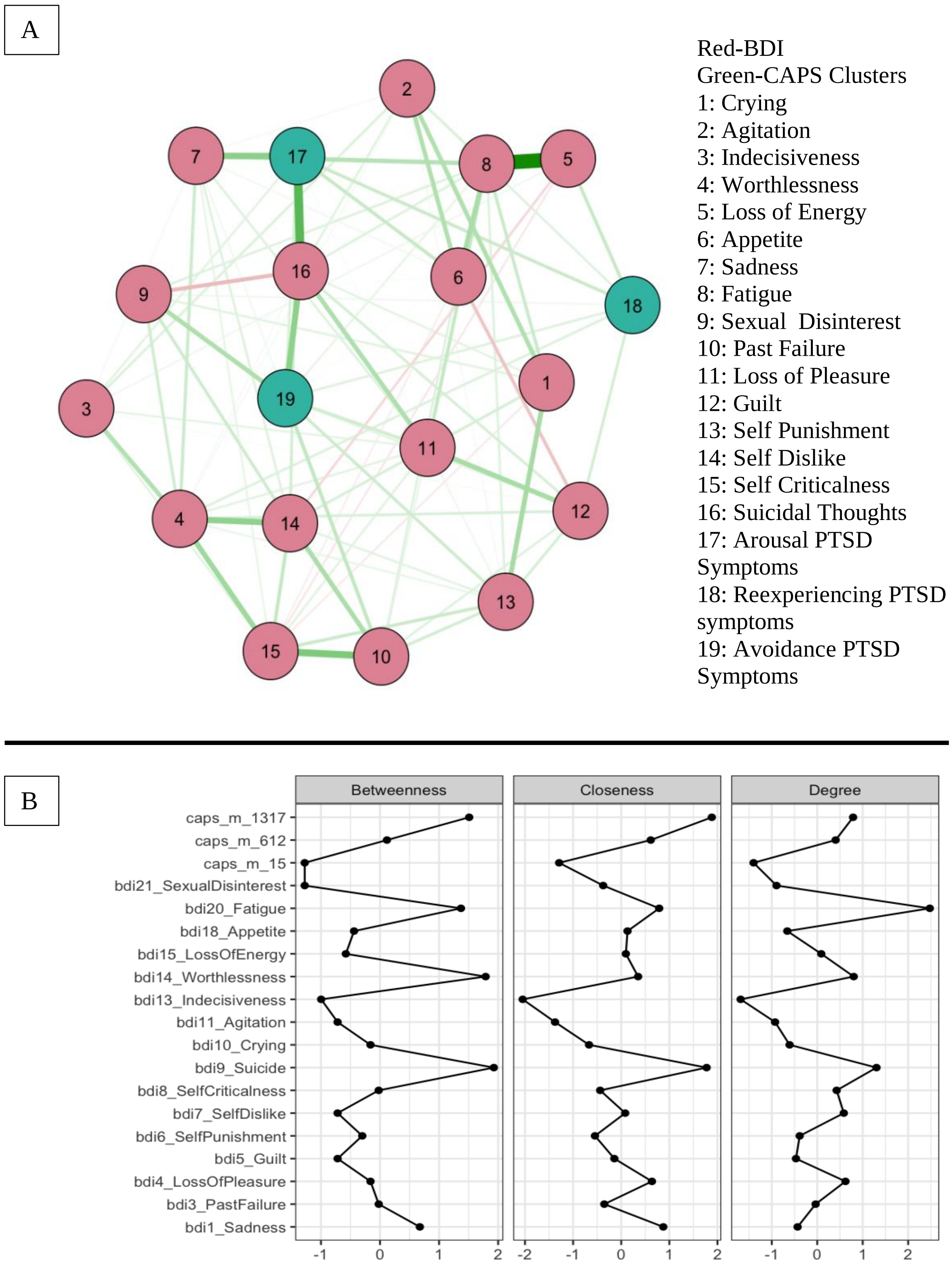
CAPS Clusters and BDI Partial Correlation Network

Figure 16A shows the partial correlation network of the CAPS clusters and BDI symptoms. The hyperparameter was set to .25. Alhough the network does not appear dense, all nodes are connected. The strongest connections were shown between fatigue and loss of energy. Additionally, the highest bridge connection was between suicidal ideation and the arousal symptom cluster as well as suicide and the avoidance symptom cluster. The arousal symptom cluster had the highest bridging strength.

The centrality plot (Figure 16B) for this network shows fatigue to have the highest strength (mean bootstrapped standardized centrality index value of 2.476), and the arousal symptom cluster shows the highest closeness (mean bootstrapped standardized centrality index value of 1.883). Additionally, suicide showed the highest betweenness (mean bootstrapped standardized centrality index value of 1.927) and second highest closeness (mean bootstrapped standardized centrality index value of 1.775). However, the centrality stability plot did not find any symptoms to be significantly different from each other after bootstrapping, suggesting that results may be spurious.

Figure 16

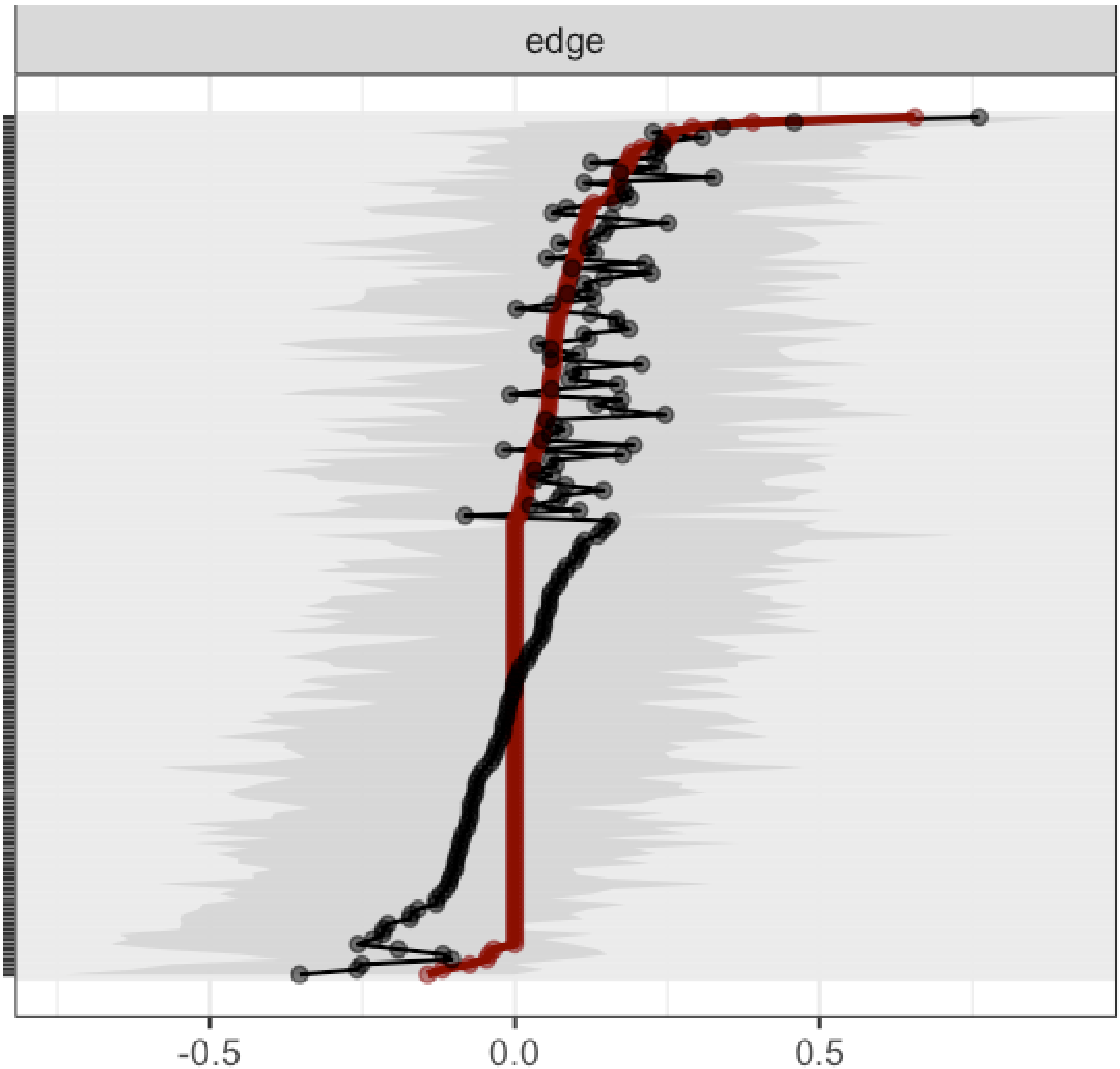
CAPS Clusters and BDI Partial Correlation Network



The edge stability plot (Figure 17) did not show the network to be more stable than the previous CAPS and BDI partial correlation network. As such, a high level of overlap is evident and thus these results may not be stable.

Figure 17

CAPS Clusters and BDI Partial Correlation Edge Stability Plot



In sum, consistent with the hypotheses, anhedonia was determined to have the highest bridge strength in the association network, while the hypotheses related to the bridging strength of sleep problems, irritability, and concentration problems were not shown. Similar to Aim 3, a connection between feelings of foreshortened future and past failures was also not found.

Discussion

This study used network theory to examine, across measurement approaches, which symptoms were most critical to maintaining PTSD in a sample of women who have experienced interpersonal violence. Additionally, an exploratory aim was to investigate how depression impacts these networks. This study filled a critical gap in the literature by being the first to study interpersonal violence with network analysis. For Aim 1 and Aim 2, some hypotheses were supported: trauma-related amnesia was shown to be weakly related to PTSD networks and a strong connection was shown between feeling cutoff from others and both emotional numbness and anhedonia. The hypothesis of intrusive symptoms being central to PTSD networks was not supported. With regard to Aim 3 and Aim 4, as hypothesized, anhedonia was found to often function as a bridge symptom between PTSD and depressive symptoms. However, other hypotheses were not substantiated. Namely, sleep problems, irritability, and concentration problems were not largely function as bridge symptoms in Aim 4 and a strong connection between feelings of a foreshortened future and past failure was not shown. Finally, across aims, the networks were often shown to be unstable, and thus, these results need to be interpreted with caution.

Aim 1 and Aim 2 Results

For Aim 1 and Aim 2, it was hypothesized that intrusive symptoms would be central to the PTSD networks based on prior studies (Armour et al., 2017; McNally et al., 2017; Spiller et al., 2017; Sullivan et al., 2016). This hypothesis was supported in Aim 2, as one centrality measure (strength) showed being emotionally upset at reminders to be central to the CAPS partial correlation network. However, Aim 1 did not show this result, as the PDS networks did not demonstrate any intrusive symptoms as central to the network. This is possibly due to this study being the first to examine victims of interpersonal violence. As discussed, PTSD symptoms resulting from various trauma types often present differently (Haldane & Nickerson, 2016; Wanklyn et al., 2016). Additionally, feeling cutoff from others and avoiding thoughts/feelings were shown to be central to the PDS and CAPS networks respectively. Although it was not hypothesized, feeling cutoff from others has received support as being a central symptom in other studies of PTSD (Armour et al., 2017; Ross et al., 2018; Phillips et al., 2018) and may simply be a central symptom in PTSD across trauma types. Conversely, avoidance of thoughts/emotions has received less support as being central, and may be more commonly central for victims of interpersonal violence than other trauma types. For example, Guina, Nahhas, Sutton, & Farnsworth (2018) used regression analysis to show sexual violence to relate to higher levels of symptoms in the *DSM-5* avoidance cluster compared to other trauma types.

Consistent with hypotheses and previous studies (Armour et al., 2017; Birkeland & Hiers, 2017; Bryant et al., 2017; McNally et al., 2015; McNally et al., 2017), a strong connection was found between feeling cutoff from others and anhedonia. This was largely true across all networks. As this is a cross-sectional study, the casual direction of this relationship cannot be determined. However, it is possible the relationship is bidirectional; individuals with PTSD may feel socially isolated and become disinterested in participating activities, resulting in less social behavior and subsequent increased feelings of social isolation. Similarly, as predicted, feeling cutoff from others was also strongly connected to emotional numbness. It is possible that individuals struggling with PTSD who feel socially isolated may engage in fewer social situations that would otherwise evoke emotions, resulting in emotional numbness. Importantly, emotional numbers and anhedonia were only weakly related to each other, suggesting that feeling cutoff from others shows the strongest role in the connections between feeling cutoff from others, emotional numbness, and anhedonia. Regardless of causation, with a high level of centrality and strong relationships with other symptoms, results show that feelings of cutoff from others may play a pivotal role in the maintenance of PTSD symptoms. This is consistent with findings that perceived social support availability is strongly related to PTSD severity (Brewin, Andrews, & Valentine, 2000; Gros et al., 2016; Simon, Roberts, Lewis, van Gelderen, & Bisson, 2019), and the subsequent recommendation that increasing social support be a part of treatment for PTSD (Brewin, Andrews, & Valentine, 2000; Gros et al., 2016; Simon, Roberts, Lewis, van Gelderen, & Bisson, 2019; Whealin, DeCarvalho, & Vega, 2008). These results further highlight the need for clinicians to assist patients in increasing social support and leveraging subsequent increased social support within gold standard treatments for PTSD such as cognitive processing therapy (CPT) and prolonged exposure (PE).

As hypothesized, trauma-related amnesia was found to weakly relate to other PTSD symptoms. This is consistent with a multitude of network studies of PTSD (Armour et al., 2017; Birkeland & Hiers, 2017; McNally et al., 2015; McNally et al., 2017; Spiller et al., 2017). This suggests that trauma-related amnesia is both an infrequent symptom of PTSD and only loosely connected to other symptoms.

Aim 3 and Aim 4 Results

In line with hypotheses from Aim 3 and Aim 4, anhedonia was shown to be a bridge symptom between PTSD and depressive symptoms in the CAPS network. This finding is consistent with a previous network study (Afzali et al., 2017) of PTSD and MDD. It may be, then, that individuals struggling with both PTSD and depressive symptoms may benefit particularly from interventions that target rejuvenating interest in activities. One such intervention is behavioral activation (BA), which has been shown to be effective in treating both comorbid PTSD and depression (Jakupcak, Wagner, Paulson, Varra, & McFall, 2010; Mulick & Naugle, 2004) and PTSD alone (Jakucpak et al., 2006). Integrating BA directly with more traditional exposure methods may be efficacious, particularly for individuals also struggling with depression. For example, Gros et al (2012) used an 8-session treatment program that incorporated imaginal exposures and behavioral activation to successfully target symptoms of PTSD in combat veterans with PTSD and depression.

Other hypotheses of Aim 3 and Aim 4 were not met, as sleep problems were not shown to function as bridge symptoms in either aim. This is contrary to a previous network study of PTSD and depression (Azfali et al., 2017). However, this discrepancy may also be due to sample sizes or a difference in types of trauma experienced in either sample.

Also contrary to hypotheses from Aim 4, concentration difficulties and irritability were not shown to function as bridge symptoms with the CAPS. However, in line with

Azfali et al. (2017) concentration difficulties and irritability received support as bridge symptoms with the self-report measures used in Aim 3. Both Aim 3 and Azfali et al. (2017) used self-report measures for PTSD, which may explain the discrepancy in the findings between Aim 3 and Aim 4. In analyses of both the CAPS and PDS networks, results also demonstrated concentration difficulties to be less connected to PTSD symptoms and grouped closer to symptoms of depression. The current study also showed similar results in the PTSD only networks, as concentration difficulties frequently were one of the least connected symptoms to the network. This evidence supports results from a previous network study of only PTSD symptoms (Armour et al., 2017) that postulated that concentration difficulties may be indicative of psychopathology more generally than PTSD specifically. Taken together, concentration difficulties may be more indicative of depression than PTSD or may potentially function as a bridge to depression from PTSD.

Finally, as indicated especially by high levels of betweenness, loss of pleasure was frequently shown to be a bridge symptom between depression and PTSD. Though loss of pleasure showed high centrality in networks using the PDS, this was particularly true when examining the networks using the CAPS. Loss of pleasure most often bridged the connection to PTSD via strong relationships with anhedonia and feeling cutoff from others.

Feelings of a foreshortened future and past failure were not shown to be strongly connected as hypothesized. Additionally, feelings of a foreshortened future, an overlapping symptom of MDD and PTSD in *DSM-IV-TR,* was more often grouped with BDI symptoms than PTSD symptoms. This adheres to the D*SM-5* (American Psychiatric

Association, 2013), in which PTSD has no symptoms similar to foreshortened future and MDD entails symptoms of recurrent thoughts of death.

Other findings not related to the stated hypotheses were found. First, fatigue was often shown to be central to the PTSD and depression networks. This high centrality was frequently driven by a high strength value, which is largely due to its frequently strong relationship with loss of energy. This is likely due to both variables measuring the same construct; future studies should consider combining these variables. Also, this finding was often found in networks that lacked a great deal of strong connections. Thus, while fatigue may be highly central for some networks, this finding should be interpreted with caution as it seems to be due primarily to its strongly relationship with loss of energy. Second, sexual disinterest was shown as being grouped closer to the PTSD symptoms than depression symptoms. This is in line with current research, as the *DSM-5* does not list sexual disinterest as a symptom of depression (the BDI-II is a *DSM-IV* measure of depression). Further, CPT, a treatment for PTSD, explicitly targets this symptom with its discussion of intimacy.

Self-Report Versus Clinician Administered Results

Different results were found with respect to whether the PTSD networks were examined using self-report or clinician administered measures of PTD (PDS or CAPS). This is most evident in results related to centrality (feeling cutoff from others being the most central symptom to the PDS networks while avoiding thoughts/feelings of the trauma being the most central symptom to the CAPS networks). However, both of these symptoms are fairly central to all of PTSD networks produced, and thus this would not seem to be a major discrepancy. This is consistent with research comparing a self-report measure to the CAPS, finding generally similar but not identical results (Griffin et al., 2004; Moshier et al., 2018).

Limitations

This study has a number of limitations. First, confidence intervals were repeatedly shown to overlap, suggesting that the networks are unstable. Additionally, centrality plots rarely showed centrality stability indices to be significantly different from each other following bootstrapping, suggesting many results may be spurious. Both of these limitations are almost certainly due to small sample sizes and reinforces the need for replication studies with larger samples. Further, this study used *DSM-IV* measures as the study began prior to the release of the DSM-5. Moreover, this study employed a female only study, and thus the external validity of these results may be limited by sex. Finally, this study used cross-sectional data. An inherent pitfall in network studies lies in prescribing relationships as cause. For example, there are a number of ways a symptom may be central to a network, and its centrality does not guarantee that it is a viable or effective target for intervention. This is particularly true with cross-sectional data. As this is the first study to examine victims of interpersonal violence, future studies are needed to ensure validity of findings.

Future Research Directions

Network analysis is a promising, burgeoning research field within the PTSD literature. However, there remains a number of critical future directions. First, as mentioned, replication studies using large, diverse, and clinical samples are needed. Few studies employ samples consisting of individuals meeting clinical diagnosis for PTSD (most use trauma exposed samples) and those that do typically feature small sample sizes.

Second, more longitudinal studies are needed. While cross-sectional studies using network analysis are valuable, network studies employing longitudinal data have the potential to illuminate causality in a meaningful ways. For example, future treatment studies of PTSD could track PTSD networks pretreatment to posttreatment, thus illustrating the mechanisms of change within treatment in a salient manner. Third, more studies are needed in each trauma type to examine differences by trauma type, especially in understudied trauma types such as interpersonal violence. A future meta-analysis of these differences may provide predictive clinical value. Finally, PTSD network studies have largely ignored the effects of diversity; future studies should compare how results differ based on cultural variables like race, SES, sexuality, gender, and religiosity.

Clinical Implications and Conclusions

This study has a number of clinical implications. First, social detachment was shown to be an important factor in the maintenance of PTSD. As discussed, PTSD interventions should consider integrating ways of improving perceived social support into traditional PTSD therapies. In particular, as social detachment was most connected to anhedonia and emotional numbness, clinicians should explore how feeling isolated may contribute to decreases in enjoying activities and feeling emotions. Making connections between these variables may increase patient motivation in improving perceived social support. Second, anhedonia was identified as a bridge symptom between PTSD and depression. Though the order of causality is unclear, interventions may benefit from incorporating pleasurable activities into trauma treatment, especially with patients who show comorbid depressive symptoms. Finally, as replicated in other studies, trauma related amnesia was shown to be only weakly connected to the rest of the network. This suggests that targeting trauma related amnesia may not hold a great deal of clinical utility in treating PTSD.

Though this study holds clinical implications, results, were shown to be potentially unstable. As discussed, further studies are needed to replicate results. Still, network theory represents an analysis still in its infancy that may hold great potential in understanding psychopathology, improving the conceptualization of psychological disorders, and subsequently improving treatments with targeted interventions at those symptoms most central to disorders such as PTSD.

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