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Research Paper

Feeling detached: The central role of detachment in a network study of posttraumatic stress symptoms in Public Safety Personnel

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ABSTRACT

Background: Due to the nature of their work, Public Safety Personnel (PSP; e.g., firefighters, paramedics, police officers) are frequently exposed to potentially psychological traumatic events (PPTE) and are at increased risk of developing posttraumatic stress symptoms (PTSS) compared to the general population. To date, there are a limited number of published studies that have used the statistical tools of network analysis to examine PTSS in PSP, typically relying on small, homogenous samples.
Basic procedures: The current study used a large (n = 5,319) and diverse sample of PSP to estimate a network of PTSS and exploratory graph analysis to assess alternative structures of symptom clustering, compared to traditional latent models.
Main findings: The results of the analyses estimated two symptom clusters which differed from most latent models of PTSS. *Re*-experiencing and avoidance symptoms clustered together, instead of in two clusters. Similarly, hyperarousal symptoms (hypervigilance, sleep disturbance, startle reflex, concentration difficulties) clustered in a single community instead of two or three clusters in many latent models of PTSS. The symptom of detachment played the most central role in the network and acted as a bridge symptom between numerous clusters of symptoms. The least central symptom was amnesia, which also had the most inconsistent pattern of clustering and bridging. Other bridge symptoms included negative emotions, difficulty concentrating, and reckless behaviour.
Principal conclusions: The symptom of detachment played a pervasive role in centrality and bridging in a network of PTSS in PSP. Future research is necessary to identify whether central PTSS differ across populations based on their PPTE type (e.g., combat, assault, rape) or typical environmental factors (e.g., group cohesion in PSP and military).

1. Introduction

Public Safety Personnel (PSP; i.e., correctional workers, firefighters, paramedics, police) are exposed to potentially psychological traumatic events (PPTE) at a rate that exceeds the civilian population as a function of their work (Carleton et al., 2019). PPTE include natural or human-made disasters (e.g., hurricanes, tornadoes, terrorist attacks), threatened or actual sexual violence, severe threats of harm to self or loved ones, physical violence, motor vehicle collisions, and exposure to death, all of which can be experienced directly or indirectly (e.g., via bearing witness, learning about it happening to a close significant other, being repeatedly exposed to graphic details) by the individual (Heber et al., 2023). Influenced by these high PPTE exposure rates is an increased prevalence of mental health disorders, including posttraumatic stress disorder (PTSD), in the PSP population (Carleton et al., 2018).

Adverse social and psychological outcomes in populations with high rates of PTSD include increased rates of attempted and completed suicide (Gradus, 2018), suicidal ideation (LeBouthillier et al., 2015), and substance use disorders (McCauley et al., 2012). Adverse physical health outcomes in people with PTSD include increased risk of heart disease (Edmondson et al., 2013), diabetes (Lukaschek et al., 2013), and musculoskeletal pain Sareen et al. (2007). The high psychological, social, and physical burden associated with developing PTSD conveys a

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large annually economic burden of approximately $232 billion in the United States alone (Davis et al., 2022).

There has been extensive research on factors that predict the development of mental health disorders in populations frequently exposed to PPTE and subsequent advances in science-based treatments; however, many people with mental disorders still show no marked improvement in their condition post-diagnosis and treatment (Mclay et al., 2021). A potential research-based influence that has challenged advances in PTSD treatment is the relatively narrow band of statistical tools that have historically been used in this research field, from cross-sectional (i.e., data collected at a single time point) and individual levels. In the research domain, PTSS have typically been conceptualized as manifestations of latent psychological variables (Grau et al., 2019) or neurobiological dysfunction (Newport & Nemeroff, 2000). Latent variables are proposed as higher-order variables in models of psychopathology, which comprise clusters of symptoms (e.g., Wright, 2020). The shared clustering of symptoms is proposed to manifest an unobservable latent variable, and the observable symptoms provide less information on their own than when explained by the latent variable. Latent variables are unobserved constructs inferred from observed data, representing abstract concepts like intelligence or anxiety. In contrast, factors are specific statistical entities derived from factor analysis used to explain correlations among observed variables (Borsboom et al., 2003). While latent variables are theoretical and often used in psychological models, factors are data-driven and directly tied to the statistical properties of a dataset (Brown, 2015).

The neurobiological model of mental disorders proposes that dysfunction within the nervous system manifests as symptoms of mental health conditions (Deacon, 2013). Latent variable and neurobiological models postulate that PTSS are the observable manifestation of an unobservable or difficult-to-observe variable. A challenge when interpreting PTSS through a latent variable or neurobiological model is interpreting which symptoms are most central or comprise the core of the disorder or how symptoms interact with one another to produce dysfunction and comorbidity (Borsboom, 2008). Using latent or biological models of PTSS further precludes the ability to gain granular insights of how symptoms impact each other over time to aggravate or result in a disordered state (e.g., Ebrahimi et al., 2023). The expanding repertoire of network analysis is an evolving statistical tool that allows for measuring symptom-interaction relationships is (e.g., Borsboom et al., 2021).

The theory behind network analysis (Borsboom, 2017) proposes that mental health disorders, including PTSD, may be better conceptualized if not reduced to biological or latent variables; instead, PTSD may develop and be maintained by deeply intertwined networks of feedback loops that exist within a system of variables (e.g., Borsboom & Cramer, 2013). Positive and negative feedback in these networks can become self-perpetuating and independent of the original stimulus (e.g., PPTE), leading to a self-sustained disorder. Network analysis assesses how potential variables influence one another and allows for the interpretation of which variables are prominently influential in the development and maintenance of such disordered states (Boccaletti et al., 2006). For example, common PTSS like avoidance, re-experiencing, sleep disturbance, and difficulty concentrating, amongst others, can be represented as nodes in a network.

The pattern of associations between PTSS network nodes can identify stronger or weaker patterns in symptoms interconnectivity in the disordered state, referred to as edges. Edges are the topographical link between nodes, visually representing the components in the network related to one another. The stronger an edge between nodes in a network (visually represented by thicker edges), the stronger the relationship between those symptoms. The contrast between how neurobiological models and network models explain the co-occurrence of symptoms is highlighted in how these models explain direct and indirect relationships between symptoms. Biological explanations propose that PTSS co-occur because of the underlying neurobiological dysfunction (Kelmendi et al., 2016). In a network model, these symptoms might co-occur because symptoms influence and feedback on one another (e.g., avoidance AND re-experiencing). Emerging network tools also allow for an alternative approach to assessing how and why symptoms cluster together, which may outperform existing tools, such as exploratory factor analysis under conditions when the intercorrelation between two or more clusters is high (i.e., > 0.7: Golino & Epskamp, 2017).

Community detection in network analysis identifies densely connected groups of nodes, or communities, that are more connected to each other than to nodes outside the group (Fortunato & Hric, 2016). Unlike latent variable clustering, which assumes underlying unobservable constructs that influence observed relationships, community detection directly examines structural patterns in the network without presupposing latent dimensions (Clauset et al., 2004). Community detection also differs from traditional clustering methods, such as k-means, by leveraging the topology of the network rather than relying on distance metrics or data point attributes (Lancichinetti & Fortunato, 2009). Community detection is particularly advantageous in capturing non-Euclidean relationships and complex interdependencies, making it ideal for studying interconnected systems like symptoms in psychopathology (Newman, 2006).

Bridge centrality in network analysis refers to the role of nodes that connect distinct clusters or communities within a network, serving as critical pathways for information or influence flow (Jones et al., 2021). In psychopathology, nodes with high bridge centrality often represent symptoms that link different symptom clusters, which may play a pivotal role in the persistence or exacerbation of mental disorders (Robinaugh et al., 2016).

Network analysis-based studies have been conducted on groups with PPTE exposures and subsequent PTSD diagnoses, producing mixed results regarding PTSS centrality. A study of 179 people with PTSS who reported childhood sexual abuse evidenced symptom centrality focused on becoming physiologically reactive and upset in response to trauma reminders (McNally et al., 2017). A study of 4639 American college mass shooting survivors revealed that anger or intrusions were the most central mental health symptoms (Sullivan et al., 2018). A network analysis of 158,139 treatment-seeking American Veterans (Duek et al., 2021) indicated that feeling distant or cut off from others, feeling very upset when reminded of a traumatic event, and repeated disturbing memories or thoughts of the PPTE were most central. A consistent result across PTSS network models of different populations that include DSM-5 symptoms involves amnesia symptoms as the least central node in the network (Isvoranu et al., 2021).

Disparate results across the studies do not preclude the validity of any specific study; instead, the influence of multiple factors, for example, different types of PPTE (e.g., sexual abuse; McNally et al., 2017) and different populations (e.g., students, veterans, general population), suggest heterogeneous results in different populations are the norm rather than the exception in network models. Authors have identified other study characteristics that may explain differences in network findings in samples exposed to PPTE, including the fact that community samples are typically assessed at a specific time point after a PPTE (e.g., natural disaster) while other samples (e.g., veterans) are assessed at various times since their PPTE with less information often provided about their PPTE (Birkeland et al., 2020). Multiple environmental, PPTE-type, structural (e.g., mental and physical health supports, leadership impacts, group versus individual work tasks) differences influencing cross-sectional networks and the centrality of nodes suggest network estimation of specific populations are essential instead of relying on general results from any isolated population.

A number of network analyses involving a sample of PSP before the current manuscript were identified. In a sample of 994 Chinese male firefighters using the 17-item PTSD Checklist – Civilian Version (PCL-C), exaggerated startle response and avoidance of reminders were the most central nodes in the network (Yuan et al., 2022). In a sample ($n = 342$) of treatment-seeking American firefighters and emergency medical technicians, using each of the proposed eight factors of PTSD (Gross et al., 2023), the node of *internal re-experiencing*, which encompasses intrusive memories, flashbacks, and nightmares, was the most central node (Beattie et al., 2023). Those studies that included community detection as part of their analyses in PSP samples have all relied on a combination of PTSD, generalized anxiety disorder, and major depressive disorder symptoms (e.g., Baker et al., 2023, 2024; Price et al., 2019).

As PSP play an important role in our society with a heightened risk of PPTE and increased risk of developing mental health disorders comprehensive research on their experiences and potential psychopathology is crucial. Expanding the breadth of statistical analyses, including network analysis may provide more insight into how PPTS develop in this at-risk population. The current study is designed to examine two research questions. First, when using exploratory graph analysis, how do network models of symptom clusters compare to traditional latent factor models? Second, what are the most central symptoms of PTSS in PSP compared to other populations? Both primary research questions were exploratory in nature.

2. Material and methods

2.1. Sample

Data for the current study were previously collected via a self-report survey as part of a larger study and approved by the University of Regina. Participants were recruited between September 1, 2016, and January 31, 2017, following established web survey guidelines (Ashbaugh et al., 2010). A total of n = 5364 (32.3 % women) PSP responded to all items used in the analysis and were included in the proposed study. The sociodemographic characteristics of the final sample are provided in Table 1. The current manuscript adheres to the reporting standards for cross-sectional network analysis reports (Burger et al., 2023).

Table 1
Participant demographic information.

Characteristic	*n* (%) *n = 5319*
Gender	
Men	3499 (65.8)
Women	1806 (33.5)
Transgender	3 (0.1)
Rather not say	7 (0.3)
Other	4 (0.2)
Ethnicity	
Asian	53 (1.0)
Black	26 (0.5)
Indigenous Canadian	240 (4.5)
Latinx	16 (0.3)
South Asian	22 (0.4)
Caucasian	4893 (90.2)
Rather not say	64 (1.4)
Other	90 (1.7)
PSP Profession	
Public Safety Communications Officials	271 (5.1)
Corrections Worker	745 (14.0)
Firefighter	766 (14.4)
Paramedic	750 (14.1)
Municipal or Provincial Police Officer	1261 (23.7)
RCMP	1287 (24.2)
Age (years)	
18–29	314 (5.9)
30–39	1324 (24.9)
40–49	2010 (37.8)
50–59	1404 (26.4)
60+	245 (4.6)

2.2. Measures

2.2.3. Demographics

Participants responded to a general demographics questionnaire indicating their sex, gender, age in years, marital status, ethnicity, education level, and current region of residence in Canada. Participants were also asked to confirm their PSP occupational sector (i.e., correctional workers, firefighters, municipal/provincial police, paramedics, public safety communicators, and Royal Canadian Mounted Police). The Life Events Checklist for DSM-5 (LEC-5; Weathers, Blake et al., 2013), a self-report measure of 17 potential PPTE, was used to identify participants who had experienced PPTE while employed as PSP.

2.2.4. PTSD Checklist for DSM-5 (PCL-5; Weathers et al., 2013)

The PCL-5 is a 20-item self-report measure used to assess past-month symptoms of PTSD and to screen for persons reporting clinically significant symptoms. Participants rate how bothered they were by different PTSS (e.g., "repeated, disturbing memories, thoughts, or images of the stressful experience") using a five-point Likert scale ranging from 0 (*not at all*) to 4 (*extremely*). A positive screen for PTSD is determined based on the total score (i.e., >31 is considered consistent with clinically significant symptoms) and meeting criteria on each symptom cluster (i.e., symptoms cluster B, C, D, and E; Weathers, Litz et al., 2013). In a sample of Psychometric evaluations support the PCL-5 as a reliable and valid measure of PTSS, with strong internal consistency ($\alpha = 0.94$) and test-retest reliability ($r = 0.82$) in PPTE-exposed populations (Blevins et al., 2015). The internal consistency of the PCL-5 in the current study was $\omega = 0.97$.

Between-group differences in PCL-5 scores, the percentage of participants in each group whose score was ≥ 31, total PPTE, and the most common "worst" PPTE-type across groups are provided in Table 2. For worst rated PPTE, participants were asked after completing the LEC-5 to rate which one of the 17 categories the most impactful PPTE that they experienced had belonged. For total number of PPTE, each participant was asked to estimate how many times they had experienced a PPTE aligning with the 17 LEC-5 categories. Scores could range from 0 to 11 for each category, with 0–10 being estimate true values, while 11 indicated 11 or more, creating a possible total range of 0–187 for number of estimated PPTE.

Table 2
PCL-5 total scores, number and type of PPTE across professions.

Group	Mean PCL-5 [Range] (SD)	% of group > 31 on PCL-5	Mean PPTE [Range] (SD)	"Worst" PPTE (%)
Public Safety Communications Officials	29.8 [1,91] (18.99)	37.7	77.3 [0,176] (45.81)	"Sudden violent death" (26.5)
Corrections Worker	35.8 [1,89] (19.91)	53.2	34.7 [0,178] (28.10)	"Sudden violent death" (19.8)
Firefighter	26.9 [1,92] (17.16)	31.3	64.2 [0,159] (28.57)	"Sudden accidental death" (20.6)
Paramedic	33.0 [1,87] (19.64)	46.6	70.5 [0,158] (34.28)	"Sudden violent death" (19.8)
Municipal or Provincial Police Officer	29.4 [1,90] (19.74)	47.4	65.9 [0,172] (33.29)	"Sudden violent death" (27.8)
RCMP	35.9 [1,96] (20.90)	51.8	67.7 [0,175] (35.30)	"Sudden violent death" (29.2)

Note. PCL-5 = PTSD Checklist for DSM-5; PPTE = potentially psychologically traumatic event; SD = standard deviation; RCMP = Royal Canadian Mounted Police.

2.3. Analyses

All analyses were conducted using the *R* language (R Core Team, 2021) in RStudio (v.4.2.1; RStudio Team, 2022). The first research question—identifying the dimensional structure of PTSS—was tested by conducting EGA using the *EGAnet* package (Golino et al., 2020; Golino & Epskamp, 2017). The EGA function uses the walktrap community detection algorithm, with 1000 random walks being used for the current analyses**.** A network of PTSS was estimated using the graphical least absolute shrinkage and selection operator (gLASSO). The number of dimensions to retain and their relationships were determined by a weighted network community detection algorithm (Christensen et al., 2020). A bootstrap method using 1000 iterations of the potential network was conducted, estimating the appropriate variable structure and item-loading across all iterations and measuring how many iterations are supported by the proposed network. Based on the results of bootstrapping methods, a network model of symptom clusters was produced. After the EGA model was plotted, the results were compared with traditional latent models of PTSD derived from factor analytic studies.

To address the second research question—examining the network structure of PTSS in PSP—a network was estimated, with each item of the PCL-5 as a node. Nodes were assessed for redundancy (i.e., the potential that multiple nodes assess the same construct, creating topographical overlap) using the *goldbricker* function in *networktools* (Jones, 2017), the Hittner method was used to detect dependent correlations (Hittner et al., 2003), a p-value threshold of $\leq$ 0.05 and a minimum correlation setting of 0.5 to identify redundant node pairs. A unregularized graphical Gaussian model (uGGM) was estimated using the *ggmModSelect* as a model selection algorithm in the *qgraph* package, serving as the state-of-the-art approach for large sample sizes like the present study (Epskamp et al., 2023).

The *ggmModSelect* procedure uses gLASSO to estimate the structure of 100 regularized network models ranging from sparse to dense. An unregularized network continues to be fit to each of these models with zeroes constrained accordingly. Unbiased estimates of parameters were obtained using maximum likelihood estimation. The Bayesian information criterion (BIC) for each estimated model was computed, and the model with the lowest BIC was selected. The primary measure of centrality was expected influence, which reflects the greater importance of a node in a network regardless of negative or positive correlations and is reported using standardized z-scores. Expected influence was used as a measure of centrality due to the association between symptoms with high expected influence and the severity of networks of psychopathology (e.g., Robinaugh et al., 2016). The accuracy of edge-weight estimates was assessed by nonparametric bootstrapping, using 1000 iterations and a 95 % confidence interval in the *bootnet* package (Epskamp et al., 2018).

3. Results

3.1. PTSS dimensions

The nodes (i.e. PTSS) were heuristically labelled according to the current DSM-5-TR criteria; specifically, items 1–5 of the PCL-5 were labelled as re-experiencing/intrusion nodes (Criterion B; R1–5), items 6–7 avoidance nodes (Criterion C; AV6–7), items 8–14 as negative alterations in cognitions and mood nodes (Criterion D; NACM8–14), and items 15–20 alterations in arousal/reactivity nodes (Criterion E; AA15–20). An empirical investigation was conducted to identify the number of communities to which each node belongs. The first community analysis of EGA results supported a four-community network of PTSS (supplementary Figure S1). The first community comprised all of the R and AV nodes; the second community contained two AA nodes, Irritability (AA15) and Reckless Behaviour (AA16), along with three NACM nodes, Loss of Interest (NACM12), Detachment (NACM13), and Anhedonia (NACM14); the third comprised four NACM nodes (NACM8-NACM11), Amnesia, Negative Beliefs, Blame, and Negative Emotions; and, the fourth community contained four AA nodes (A17-A20), Hypervigilance, Startle, Difficulty Concentrating, and Sleep Disturbance.

The EGA bootstrapping results indicated most nodes were replicated amongst their respective communities from the original EGA plot (supplementary Figure S2). There were four nodes replicated less frequently than others; specifically, Irritability and Reckless Behaviour (i.e., AA15, AA16) were replicated in 72 % of the bootstrapped networks and Avoid Thoughts and Avoid Reminders (i.e., AV6, AV7) replicated in 70 % of the networks. Only one node (i.e., Amnesia; NACM8) replicated in <50 % of the networks.

Table 3 presents a comparison between the clustering of PCL-5 items using EGA and the clustering of items in commonly reported latent models of PTSD. The first difference in the clustering in the EGA model is that all the R and AV nodes clustered together in a single community in 70 % of the replications, while the latent variable models consistently divide R and AV into their own factors. Consistent with the 6-factor Anhedonia (Liu et al., 2016) and 7-factor Hybrid (Armour et al., 2015) models of PTSD, the first four NACM items clustered together in EGA, which retains the NACM designation in the Anhedonia model but is referred to as Emotional Numbing in the Hybrid model (Armour et al., 2015). Previous confirmatory factor analyses of the PCL-5 using PSP samples have identified the 7-factor hybrid model as having the best fit (Ahmadi et al., 2023; Boehme et al., 2023). The current results diverged from latent PTSD models in PSP (e.g., Ahmadi et al., 2023; Boehme et al., 2023) in numerous ways. All the latent variable models include Loss of Interest, Detachment, and Anhedonia (NACM12–14) either as their own factor, as part of a factor that includes NACM items, or as part of a larger factor; in contrast, the EGA analysis clustered together Loss of Interest, Detachment, Anhedonia, Irritability, and Reckless Behaviour (NACM12-AA16). In latent models, Reckless Behaviour (AA16) does not typically cluster with Loss of Interest (NACM12), Detachment (NACM13), or Anhedonia (NACM12). The final cluster from the EGA analysis, with Hypervigilance and Exaggerated Startle (AA17–18) and Difficulty Concentrating and Sleep (AA19–20) clustering together, respectively, is also unique when compared to latent variable models, which typically propose that these four items split into different factors.

3.2. PTSS network and centrality

Fig. 1 presents the estimated PTSS network. The network is dense, indicating that the symptoms are highly connected, with many strong edges. There were two nodes with standardized $z \geq 1$; specifically, Detachment (NACM13) and Difficulty Concentrating (AA19), indicating node centrality and the largest overall weighted connectivity relative to other network nodes (Fig. 2). Statistically significant differences between expected influence centrality are detailed in supplementary Figure S3. The difference between Detachment (NACM12) and Difficulty Concentrating (AA19) was not statistically significant. The results suggested that the Detachment (NACM13) and Difficulty Concentrating (AA19) nodes were the most central in the estimated PTSS network. Although the difference in centrality between Detachment (NACM13) and Difficulty Concentrating (AA19) was not statistically significant, Detachment (NACM13) was estimated to make a larger influence in the network when considering community bridging and the total number of nodes that Detachment (NACM13) interacted with. In contrast the Difficulty Concentrating (AA19) node had less influence when bridging with other communities and was strongly connected to other Anxious Arousal community symptoms, especially Sleep Disturbance (AA20). In the PTSS network, Detachment (NACM13) had strong relationships with three other NACM items, including Loss of Interest (NACM12), Anhedonia (NACM14), and Negative Beliefs (NACM9), but also the R node of Physiological Cue Reactivity (R5) and the AA nodes of Difficulty Concentrating (AA19) and Sleep Disturbance (AA20). Edge weight

Table 3
Clustering of items from the PTSD Checklist for DSM-5 in latent variable and EGA model.

Factor Loading of Each Item								
PCL-5 Item	Description	Anhedonia	Four-factor DSM-5	Dysphoria	Dysphoric Arousal	Externalizing Behaviours	Hybrid	EGA
1	Memories	R	R	I	R	R	R	RAV
2	Dreams	R	R	I	R	R	R	RAV
3	Flashbacks	R	R	I	R	R	R	RAV
4	Cued distress	R	R	I	R	R	R	RAV
5	Cued physical reactions	R	R	I	R	R	R	RAV
6	Avoiding memories	AV	AV	AV	AV	AV	AV	RAV
7	Avoiding external reminders	AV	AV	AV	AV	AV	AV	RAV
8	Dissociative amnesia	NACM	NACM	D	N	NACM	N	NBF
9	Negative beliefs	NACM	NACM	D	N	NACM	N	NBF
10	Blame	NACM	NACM	D	N	NACM	N	NBF
11	Negative feelings	NACM	NACM	D	N	NACM	N	NBF
12	Loss of interest	ANH	NACM	D	N	NACM	AN	DRT
13	Detachment	ANH	NACM	D	N	NACM	AN	DRT
14	Numbing	ANH	NACM	D	N	NACM	AN	DRT
15	Irritability or aggression	DA	AA	D	DA	EB	EB	DRT
16	Reckless behaviour	DA	AA	D	DA	EB	EB	DRT
17	Hypervigilance	AN	AA	H	AN	AN	AN	AN
18	Exaggerated startle	AN	AA	H	AN	AN	AN	AN
19	Concentration	DA	AA	D	DA	DA	DA	AN
20	Sleep	DA	AA	D	DA	DA	DA	AN

Note. DSM-5 = Diagnostic and Statistical Manual of Mental Disorders – Fifth Edition; PCL-5 = PTSD Checklist for DSM-5; *R* = *Re*-experiencing factor; AV = Avoidance factor; NACM = Negative Alterations in Cognitions and Mood factor; *H* = Hyperarousal factor; *I* = Intrusion factor; N = Emotional numbing factor; *D* = Dysphoria factor; DA = Dysphoric Arousal factor; AN = Anxious Arousal factor; AA = Alterations in arousal; ANH = Anhedonia factor; N = Negative Affect factor, RAV = *Re*-experiencing and Avoidance, NBF = Negative Beliefs and Feelings, DRT = Dysphoria and Risk-taking.

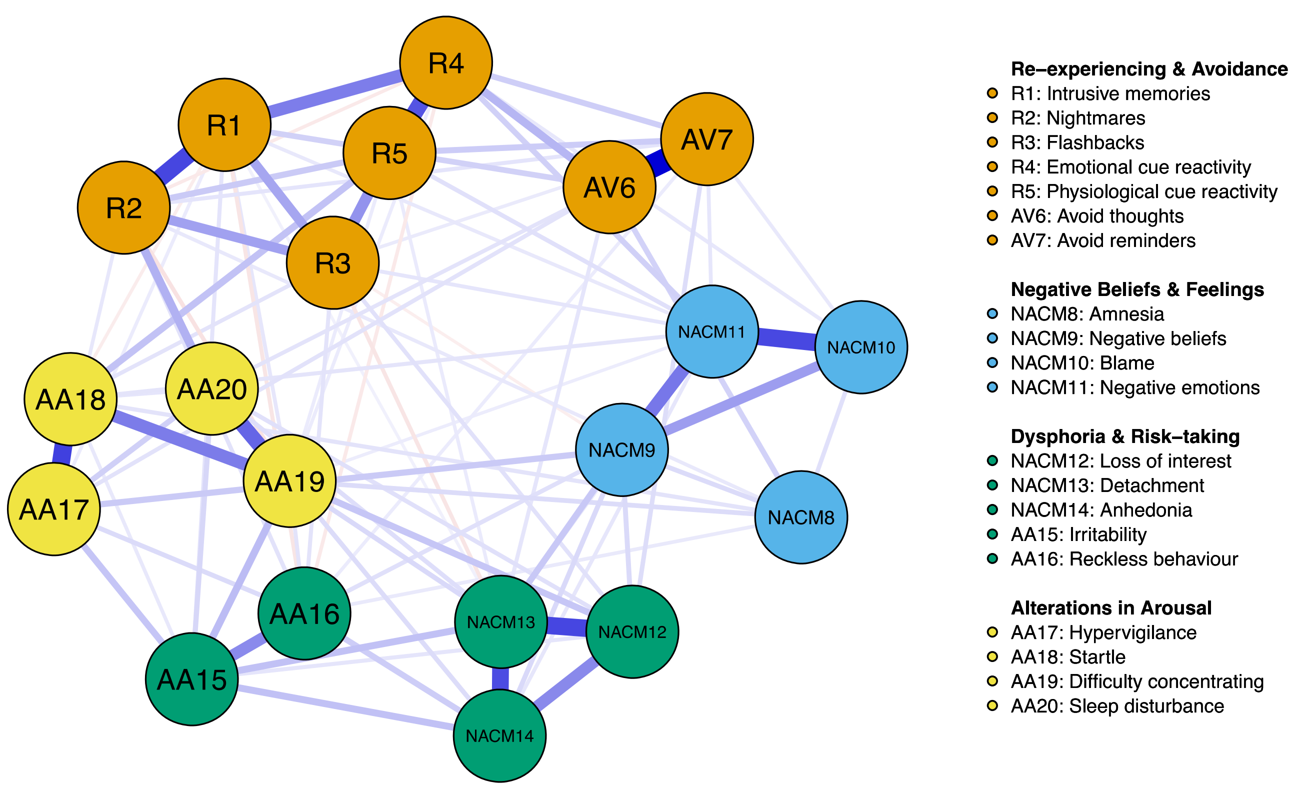

Fig. 1. Unregularized partial-correlation posttraumatic stress symptoms network with communities. *Note.* Blue edges represent positive correlations, and red edges represent negative correlations—no specific minimum/maximum. Edge weights in the network ranged from −0.05 (R4-AA16) to 0.84 (NACM11–12); AA = alterations in arousal, AV = avoidance, NACM = negative alterations to cognitions and mood, *R* = re-experiencing.

accuracy and centrality stability are provided in supplementary figures S5 and S6, respectively.

3.3. PTSS network bridges

In network theory, bridge nodes are those nodes that have a robust pattern of correlations which connect a community to another. These bridge nodes are proposed to promote the development and maintenance of networks and are a potential target of intervention, along with nodes with high centrality. Detachment (NACM13), Difficulty Concentrating (AA19), Negative Emotions (NACM11), and Reckless Behaviour (AA16) (Fig. 3) had bridge expected influence z scores of $\geq$1.

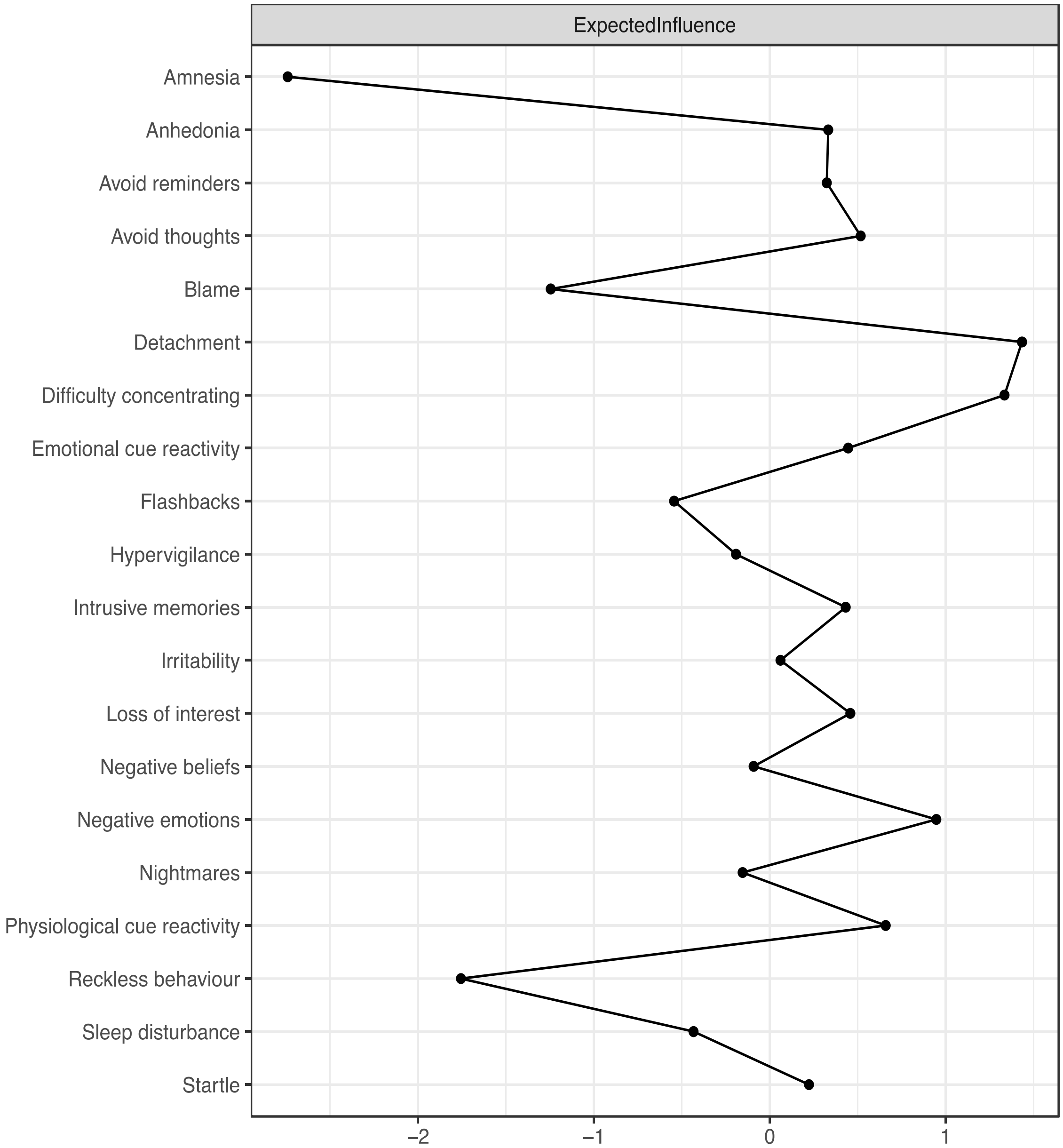

Fig. 2. Expected influence centrality metrics for a network of posttraumatic symptoms. *Note*. In total, 20 nodes were assessed for their expected influence in the network. Those nodes with a score ≥ 1 were assessed for the role of centrality in the network. Differences between expected influence should not be considered significant. For significant differences between nodes from this figure, see supplementary Figure S3.

Statistically significant differences between the four nodes identified as having strong bridge expected influence are presented in supplementary Figure S4. The bridge expected influence testing identified Difficulty Concentrating (AA19) as having a statistically significantly stronger bridge expected influence than Reckless Behaviour (AA16), and Negative Emotions (NACM11) as having a statistically significantly stronger bridge expected influence than Reckless Behaviour (AA16) and Detachment (NACM13). Difficulty Concentrating (AA19) bridged the relationship between the Anxious Arousal (AN) and Negative Beliefs and Feelings (NBF) communities through the Negative Beliefs (NACM9) node and the AN and Dysphoria and Risk-Taking (DRT) communities through the Loss of Interest (NACM12) and Detachment (NACM13) nodes. The Negative Emotions (NACM11) node bridged the relationship between the NBF and *Re*-experiencing and Avoidance (RAV) communities primarily through the Emotional Cue Reactivity (R4) node. Reckless Behaviour (AA16) had a diffuse set of relationships that bridged from the DRT community to the RAV community through multiple R nodes.

4. Discussion

The current investigation was a comprehensive assessment of a PTSS network with a sample of PSP. The investigation was primarily designed to assess the PTSS in this high-risk population through the lens of network theory. The psychometric tool of EGA was used to examine the clustering of network nodes used to represent symptoms, with the results compared against latent variable clustering models. A large network comprised of 20 nodes was estimated using appropriate methods for cross-sectional network estimation.

Unlike latent factor models of PTSD, nodes that corresponded with re-experiencing and avoidance symptoms of PTSD clustered together into a single community, instead of two separate clusters. Avoidance of trauma memories and reminders impedes recovery from PTSD, making a common element of well-validated psychological interventions for PTSD

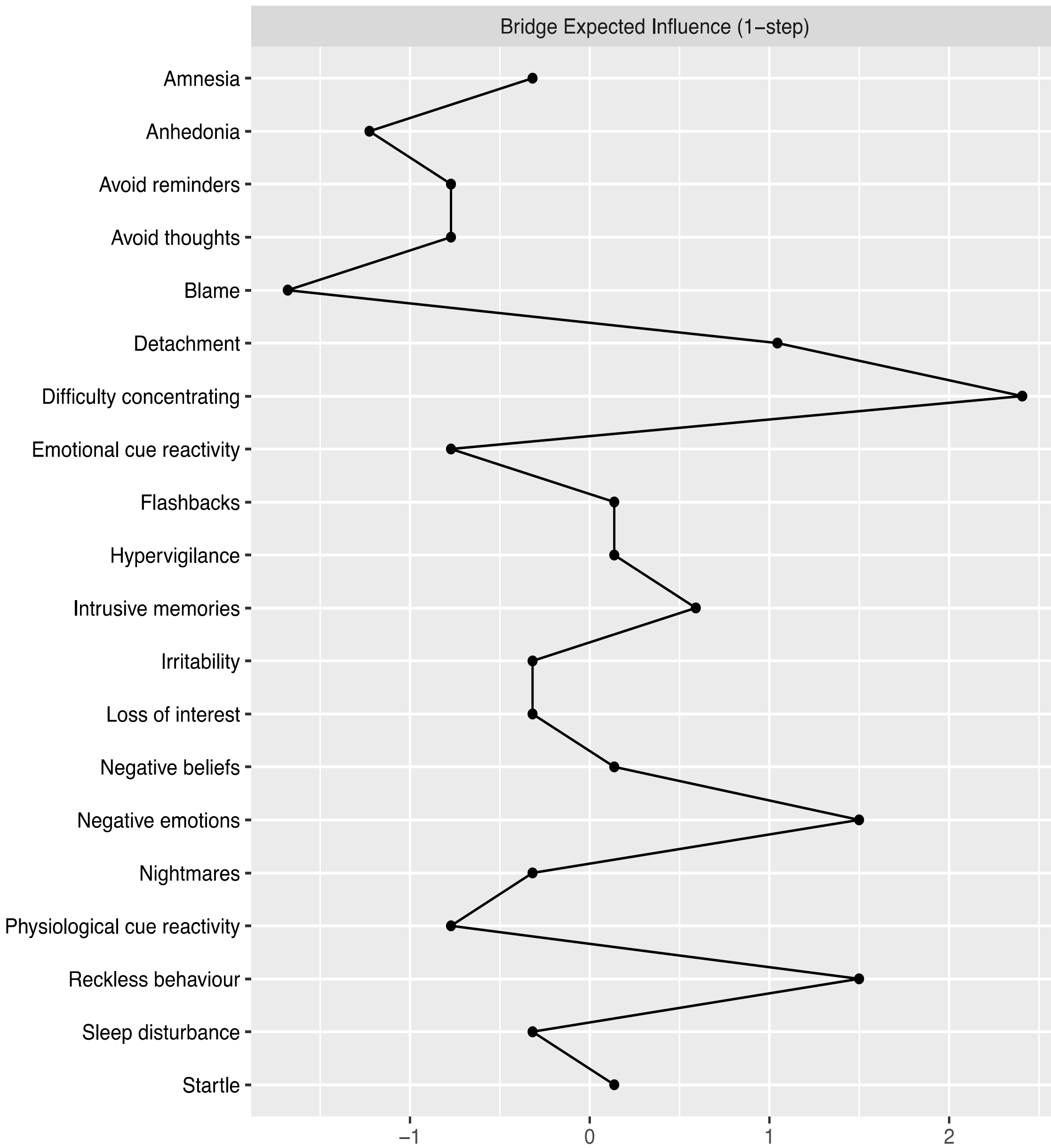

Fig. 3. Bridge expected influence from posttraumatic stress symptoms network. *Note.* In total, 20 nodes were assessed for their expected influence in the network. Those nodes with a score ≥ 1 were assessed for the role of bridging in the network. Differences between bridge expected influence should not be considered significant. For significant differences between nodes from this figure, see supplementary Figure S4.

exposure to traumatic memories while inhibiting avoidance behaviours (Foa & Rothbaum, 1998). For PSP, cues that remind them of PPTE (re-experiencing) may be unavoidable, however driving a desire to avoid due to the frequency of cues. People with PTSD are typically motivated to engage in avoidance behaviours to avoid re-experiencing intrusive memories, thoughts, and physical sensations (Hayes et al., 1999). However, PSP may experience a more intense cycle of re-experiencing and a desire to avoid because their PPTE are workplace related, instead of members of the community, who may be able to avoid external reminders.

The most central node in the estimated PTSS network represented detachment. In the context of PTSS, detachment can range on a severity spectrum from mild feelings of emotional detachment (e.g., transient anhedonia) to extreme dissociation (e.g., depersonalization, derealization). The presence of dissociative detachment symptoms may correlate with more severe psychological outcomes (Lebois et al., 2022). The PCL-5 specifically queries detachment from others. PSP are typically involved in groups—working shifts with familiar partners or co-workers regularly. Due to the reliance on other group members to perform work tasks and the comradery of the group environment, detachment from colleagues and employment may be more of a psychological challenge to PSP when compared to other individuals exposed to PPTE. The detachment from the group from having to leave employment due to psychological injuries may further increase feelings of detachment in psychological networks. Other groups organized by occupation (e.g., military), environments (e.g., group versus individual work), or types of PPTE may endorse different forms of detachment, for example detachment from self in the case of depersonalization or derealization.

At least two previously published PTSS network analyses used independent samples and reported detachment among the most central network nodes. Armour et al. (2017) assessed a large sample of U.S. military veterans, while Fried and colleagues assessed a large heterogeneous (n = 2300) sample of people receiving treatment for PTSD in the Netherlands (Armour et al., 2017; Fried et al., 2018). These findings align with the current findings indicating the central role of detachment, which has not typically been identified as one of the core symptoms in other samples. Considering the amount of time that members of the military and PSP share together and the reliance on coworkers for group functioning, safety, and comradery, detachment from those coworkers and the benefits of the group likely explain the heightened central role of detachment for these groups. Likewise, in other individuals, cultures, or populations for which regular, meaningful engagement with others is emphasized, detachment may play a more central role than those with less emphasis on groups and community.

Several bridge symptoms were detected in the network. Bridge symptoms are those with strong correlations with adjacent communities. These bridge symptoms typically make the network denser and more interconnected and influence the development of tighter interconnections between symptoms, making for networks that may be more pathological and difficult to treat. Therefore, targeting these bridge symptoms during intervention may be an important therapeutic goal. Aside from detachment and difficulty concentrating, two nodes with high expected influence, the nodes representing negative emotions and reckless behaviour played prominent bridging roles. Negative emotions bridged the relationship between symptoms of negative affect with those of re-experiencing and avoidance, while reckless behaviour had a broader pattern of connections throughout the network. Risky behaviour as a diagnostic symptom of PTSD was introduced in the DSM-5, however some researchers have questioned the validity of this symptom in the PTSD construct. The results of this study add to a growing body of literature supporting that those people who endorse risky behaviours after PPTE are at greater risk of greater PTSD severity, making it an important target of treatment (Contractor et al., 2017).

The current results have implications for current and future conceptualizations of PTSS and PTSD among PSP. First, PSP-specific measures assessing nuanced dimensions of detachment may be necessary. Among PSP, detachment from their group may play a strong role in the development and maintenance of psychological networks; however, current psychological measures of PTSS do not discriminate between forms of detachment. Detachment may be uniquely important to delineate because the term is generally ambiguous relative to other PTSS (e.g., sleep, avoidance, re-experiencing, concentration). Second, the current results may influence how PTSS are contextualized. The most central symptom in PTSS networks and other models of PTSD remains inconsistent; however, amnesia is consistently identified as least central (Isvoranu et al., 2021) and may be of little diagnostic value (McNally, 2009). The current results also bolster previous arguments to remove amnesia as a diagnostically sensitive PTSD symptom (e.g., McNally, 2009). In any case, different PPTE and different environments may impact PTSD networks, supporting the position that PTSD and trauma-related mental health challenges may be more heterogenous than current conceptualizations indicate (Galatzer-Levy & Bryant, 2013).

The current study has several strengths and limitations. The primary strength is the size and breadth of the sample, which includes thousands of PSP and large sub-groups based on gender and different PSP professions. The current study has several limitations. First, the interpretation of community clustering is comparing the current results with latent factor models. It is challenging to interpret how much of the differences in clustering of PTSD symptoms in this study are due to the sample or differences between clustering in graphs versus latent models. Future research is necessary to continue to explore under what circumstances graph or latent variable tools may be most appropriate for estimating clusters. The second is regarding the heterogenous findings of PTSS network studies (Birkeland et al., 2020). When comparing centrality and communities in this study to others, it is important to compare important differences, including the types of PPTE and the amount of time that has passed since the PPTE, which may explain between-study differences. Future network studies should report the type distribution of PPTE of their sample and the time since those PPTE, if possible, when estimating their networks to increase the ability to accurately compare differences in results. Third, PTSS were assessed at a single time point using group sums. Therefore, it is not possible to assess changes across time (temporal) relationships amongst PTSS or the central symptom for any individual.

5. Conclusions

The current study was the largest network analysis study of PTSS in a sample of PSP to date. The estimation of symptom clusters identified differences between the network structure and traditional factor analytic (i.e., latent) models of PTSD and PTSS. The most central PTSS network node represented detachment, which also played a prominent role in bridging relationships between numerous symptom clusters throughout the network. Further research is necessary to explore the specific types of detachment in PTSD and PTSS networks. The ongoing development of tools to estimate idiographic networks (i.e., assessing a single individual's symptoms across time) of psychopathology will provide further insights into whether the results of cross-sectional network studies are reliable at the individual level.

Informed consent

All participants provided informed consent before being included in this study.

Data availability

The data used for this study are available on request from the corresponding author. The data are not publicly available due to security concerns from stakeholders.

CRediT authorship contribution statement

Blake A.E. Boehme: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Omid V. Ebrahimi:** Writing – review & editing, Methodology, Conceptualization. **R. Nicholas Carleton:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Gordon J.G. Asmundson:** Writing – review & editing, Supervision.

Declaration of competing interest

All authors of this manuscript claim they have no competing or conflicts of interest

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