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Stress response and experiential avoidance among firefighters: Preliminary insights from network analyses

Wivine Blekić[a,*], Souhaib Ben Taieb[b,c], Kendra G. Kandana Arachchige[d], Mandy Rossignol[d], Katharina Schultebraucks[a,e]

[a] Department of Psychiatry, NYU Grossman School of Medicine, New York, NY, USA
[b] Department of Computer Science, University of Mons, Mons, Belgium
[c] Big Data and Machine Learning Lab, University of Mons, Mons, Belgium
[d] Department of Cognitive Psychology and Neuropsychology, University of Mons, Belgium
[e] Department of Population Health, NYU Grossman School of Medicine, New York, NY, USA

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ABSTRACT

Firefighters are at increased risk of developing posttraumatic stress disorder (PTSD) due to exposure to potentially traumatic events during their careers. However, little is known about the prevalence of PTSD among this population, particularly when taking moderating variables into account. Using Gaussian Graphical Models and Directed Acyclic Graphs, we conducted network analyses to examine the interactions between clusters of PTSD symptoms, perceived stress, hardiness, and experiential avoidance among 187 firefighters. The data and code are published with the paper. Experiential avoidance, as part of psychological inflexibility, was found to be the only variable that interacted with PTSD symptomatology. Strong positive associations were observed between experiential avoidance and the "negative mood and cognitions" subscale of the PTSD Checklist for DSM-5 (PCL-5). Through this association, other PTSD symptoms were activated, particularly avoidance and arousal. Our findings suggest that experiential avoidance and negative mood and cognition symptoms are particularly important in the expression of PTSD symptomatology in firefighters. In addition, experiential avoidance may be used as a coping strategy to reduce perceived stress during potentially traumatic events. Therefore, experiential avoidance may be a prime target for future interventions and training focused on flexible self-regulation strategies in this population.

1. Introduction

Posttraumatic stress disorder (PTSD) is a psychiatric condition characterized by a prolonged and maladaptive response to a traumatic event that significantly impairs quality of life. Firefighters, as first responders, are a high-risk group compared to the general population due to their repeated exposure to potentially traumatic events. Studies have shown that approximately 90% of professional firefighters have encountered distressing incidents such as dealing with severely injured or dying to dead individuals, at least once in the past year (Jang et al., 2020; Skeffington et al., 2017). Therefore, firefighters are at increased risk of developing PTSD (Van Eerd et al., 2021). In addition with a PTSD prevalence of 5%–54% (Berger et al., 2012; Boffa et al., 2017; Del Ben et al., 2006; Katsavouni et al., 2016; Kim et al., 2018; Meyer et al., 2012; Obuobi-Donkor et al., 2022; Tomaka et al., 2017), repeated exposure to potentially traumatic events in this population has been linked to increased occupational burnout, alcohol abuse, and suicidal ideation and attempts (Igboanugo et al., 2021; Stanley et al., 2016). Understanding the psychological mechanisms involved in stress responses during potentially traumatic events is crucial for preventing negative mental health outcomes in firefighters.

Network theory is a novel and flexible approach to understanding psychopathology (Borsboom, 2017). This approach suggests that mental disorders arise from direct interactions between symptoms (Robinaugh et al., 2020). The methodological framework developed in response to this theoretical perspective is called network analysis, in which each symptom is represented by a node, which is connected by weighted edges (i.e., partial correlation coefficients) that represents the relationship between the nodes. Compared to correlational approaches, network analysis can provide the centrality and predictability index for each

* Corresponding author. Department of Psychiatry, NYU Grossman School of Medicine, One Park Avenue, 8 th Floor, New York, NY, 10016, USA.
E-mail address: Wivine.blekic@nyulangone.org (W. Blekić).

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node, allowing researchers to examine its importance and controllability within the whole network (Epskamp and Fried, 2018). In other words, partial correlations obtained through network analysis represent the patterns of relationships (i.e., the edges) that remain after taking into consideration all the variables and their associated correlations in the network (Contreras et al., 2019), rather than associations with dichotomous outcomes. These partial correlation networks are often estimated using regularization techniques from machine learning, which can help to remove edges that are likely to be spurious from the model, resulting in networks that are easier to interpret (Tibshirani, 1996). The goal of network analysis is to extract a general structure of a given psychopathology that can help to better understand the way symptoms interact with one another and guide therapeutic interventions.

The complexity of posttraumatic stress disorder (PTSD) makes it a particularly good target for this approach (Weems, 2020), as shown by the rapidly increasing number of studies being published using network analysis in this field. A recent meta-analysis of these PTSD networks showed that particularly strong edges were observed between symptoms from the same feature of the pathology (e.g., intrusion, avoidance, negative mood and cognition, and hyperarousal). They also showed that specific symptoms such as "*feeling detached*", "*intrusive thoughts*", and "*physiological reactivity*" were particularly important in the network (Isvoranu et al., 2021). However, the authors emphasize on the very large heterogeneity found between studies, that led them to conclude that there may not be such a thing as one overall PTSD network structure (Epskamp et al., 2021). This is coherent with the current debate regarding the heterogeneity in PTSD diagnosis (Galatzer-Levy and Bryant, 2013), along with recent studies attempting to identify subcategories of PTSD (Contractor et al., 2017, 2018). The authors suggested that future research may benefit from focusing on subpopulations (e.g., veterans) and specific types of traumatic events when aiming to construct a PTSD network structure. In addition, another review highlighted that the interpretation of network studies in PTSD-related research has been rather descriptive and proned the urge to make those analyses pertinent in a clinical point of view by linking them with potential mechanisms underlying the observed associations (Birkeland et al., 2020).

To the best of our knowledge, only two studies have used network analysis to examine PTSD among firefighters, both in Asia. The first study, using a DSM-4 based assessment, found that emotional reactivity, exaggerated startle response, and avoidance of reminders had the highest expected influences, indicating that these three symptoms were the most associated in the network (Yuan et al., 2022). However, the type of event and the prevalence of probable PTSD were not described, which limits the interpretability of the results. The second study used a DSM-5 based assessment and found that negative emotional states had the strongest centrality in the network (An et al., 2022). Additionally, using a Directed Acyclic Graph, the authors observed that the symptom of irritability/anger was on top of the graph, suggesting that it might drive some other PTSD symptoms. PTSD symptoms were assessed using a Chinese translation of the PCL-5 (Posttraumatic Stress Disorder Checklist for DSM–5) (Zhou et al., 2018) both immediately after a fire rescue event (mean PTSD score = 10.7, SD = 9.0; 3.0% above the 33-score cut-off) and three months after the event (mean PTSD score = 9.9, SD = 9.2; 1.8% above cut-off). However, a main limitation of this work was the low stability of the network (less than 0.20 for every index), which limits the generalizability of the results.

Due to the heterogeneity of these findings, further research is warranted. The main purpose of the current study is to investigate the stress response of European firefighters in the face of work-related traumatic stress. In particular, we aim to determine which hallmark feature of PTSD (e.g., intrusion, avoidance, negative mood and cognition, or hyperarousal) is most central to this response. Additionally, we aim to understand this response by considering variables that are believed to be influential in the theoretical framework of resilience, including both positive (e.g., personality trait such as hardiness) and negative (e.g., experiential avoidance, perceived stress) moderating variables (Kalisch et al., 2017; Laureys and Easton, 2020).

To do so, two network approaches are used in this study: Gaussian Graphical Models (GGMs) and Directed Acyclic Graphs (DAG). GGMs allow for feedback loops, which are important for exploring how symptoms and other variables can perpetuate each other cyclically (Epskamp et al., 2018). GGMs were used to test whether PTSD hallmark features and moderating variables are related as a network system. However, GGMs do not propose directionality. In contrast, DAGs use arrowed edges to represent predicted directionality (Briganti et al., 2022), but do not allow for feedback loops. Thus, the GGM constraints are incorporated into DAGs and vice versa (Benfer et al., 2021). DAGs were used to estimate a directional, potentially causal model of the interaction between key features of PTSD and included covariables. The tandem interpretation of GGM and DAG results allows for a more nuanced understanding of the findings (Blanchard et al., 2021). We asked participants to focus their responses on a particularly difficult work-related event in order to better understand how individuals who are frequently exposed to potentially traumatic events cope with daily stress.

2. Materials and methods

2.1. Participants

A total of 720 firefighters (mean age = 39.9 years, $SD = 10.14$, range = 18–64) were given the link to participate in the current study, conducted from March 2018 to March 2020. After giving written informed consent, participants completed a 60 min web-based survey that assessed a range of sociodemographic, psychiatric, and health variables. A total of 187 firefighters completed the entire online questionnaire. Drop-out participants did not differ from the final sample in terms of age, gender, seniority, marital status nor education level ($p > .08$ in all cases, see Table S1). See Fig. S1 for the flow chart depicting the selection process and drop-outs.

2.2. Instruments

Participants first completed a sociodemographic questionnaire including questions relative to gender, education level, marital status, type of enrollment in the fire station (professional or voluntary), and seniority in the fire station. They then completed several psychometric questionnaires and were asked to identify one event that has occurred in the context of their work and that was particularly distressing for them. Participants were asked to describe this event and complete the Criterion A section of the PCL-5 (Weathers et al., 2013) in regard to this event. The PCL-5 was then administered to determine the severity the of post-traumatic symptoms, always in reference to the work-related life-threatening event identified prior. Finally, they completed self-reported measures of perceived stress, hardiness and experiential avoidance, respectively assessed through the Perceived Stress Scale (Cohen et al., 1994; Lesage et al., 2012), Dispositional Resilience Scale (Bartone, 1995; Dufour-Pineault, 1997) and Acceptance and Action Questionnaire-II (AAQ-II) (Bond et al., 2011; Monestès et al., 2009). A full description of these measures can be found in the Supplemental Material.

2.3. Networks

It should be noted that due to our sample size, we decided to use the PCL-5 subscales as nodes (which decreases the number of nodes from 23 if using the individual symptoms to 7).

2.3.1. Gaussian graphical model

A GGM was used to estimate the undirected network. This network computed regularized generalized regressions between pairs of nodes.

Edges signify partial correlations between nodes, controlling for the effects of all other nodes (Epskamp and Fried, 2018). To identify a parsimonious set of variables for the GGM, we used both the LASSO and the Extended Bayesian Information Criterion (EBIC) for model selection (Friedman et al., 2011). The LASSO is a regularization method that adds a penalty term to the objective function that encourages the coefficients of the less important variables to be set to zero, resulting in a model with fewer variables that is more interpretable and easier to fit. The EBIC is a model selection criterion that balances the fit of the model to the data with the complexity of the model, using a penalty term (hyperparameter gamma – γ) that increases with the number of variables in the model. Our procedure estimates 100 models with varying degrees of sparsity and a final model is selected according to the lowest EBIC. The hyperparameter γ is usually set between 0 (favoring a model with more edges) and 0.5 (favoring a simpler model with fewer edges). Following recommendations based on stimulation studies (for details, see (Epskamp and Fried, 2018)), we set γ to 0.5 to be confident that our edges are genuine. We used the *estimatenetwork* function from the *bootnet* package in R (Epskamp et al., 2018) to fit the GGM using these methods. To estimate the stability of edges, we computed bootstrapped confidence regions for the edge weights with 1000 bootstrapped samples using the same R package *bootnet*.

As we were expecting the presence of negative edges in the graph, indicating inverse relationships between the variables, we chose to use the Expected Influence (EI) measure to describe the importance of each variable in the GGM instead of other indices of centrality. Many centrality measures, such as degree centrality and betweenness centrality, are based on the concept of edge connectivity and are not designed to consider negative edges (Burger et al., 2022). In contrast, the EI measure is specifically designed to be used with GGMs presenting both positive and negative edges in the graph, making it a more appropriate choice in this context. The EI of a node is the sum of the partial correlation coefficients between a node and all other nodes in the network, which measures the overall effect that a node has on the rest of the network while controlling for the effects of all other nodes. Importantly, EI considers both positive and negative relationships in its formula. To assess the stability of this centrality estimate, we performed a person-dropping bootstrap procedure (Costenbader and Valente, 2003), to calculate the centrality stability coefficient (CS-coefficient). This procedure allows us to determine whether the relative order of node centrality is retained even when the sample size is reduced. Values of at least 0.25 indicate that the centrality is stable, while values above 0.5 are preferred.

In addition, we estimated domain predictability, which quantifies how well a particular node can be predicted by all remaining nodes (Haslbeck and Fried, 2017; Haslbeck and Waldorp, 2018). In this study, R^2 was used to reflect the percentage of shared variance of a domain with surrounding domains in the network. EI and predictability are two different measures that can be used together to provide a more complete understanding of the role of a node in a GGM. EI can also be used to identify the nodes that have the most influence on the overall connectivity of the graph, while predictability measures can provide insight into the relationships between the nodes and how well the values of one node can be predicted based on the values of others.

Finally, we tested whether the nodes denoting maladaptive stress response and those denoting of perceived stress and hardiness cohere as one network or as multiple subnetworks (or “communities”). Nodes within a community are more strongly interconnected than they are with nodes outside that community. Following prior network research (Blanchard et al., 2021), we implemented the *spinglass* algorithm (Reichardt and Bornholdt, 2006), a modularity-based community detection procedure suitable for uncovering the structure of relatively small networks with negative edge values (Traag and Bruggeman, 2009). We used the *spinglass.community* function (γ = 1, start temperature = 1, stop temperature = 0.01, cooling factor = 0.99, spins = 7) of the R package *igraph* (Csardi and Nepusz, 2006). We also identified important nodes that serve as bridges between communities by computing the bridge expected influence index via the *bridge* function of the R package *networktools* (Jones, 2018). Nodes with high bridge expected influence values are especially likely to activate nearby communities. Bridge expected influence represents the sum of the edge weights connecting a given node to all nodes in the other community or communities (Jones et al., 2019).

2.3.2. Directed acyclic graph

We used Bayesian methods to estimate a DAG which gives a directed, potentially causal model of the interplay among the variables. A DAG is a directed network in which each edge has an arrow tip on one end that signifies the direction of prediction (and possibly causation), or, more conservatively, the direction of probabilistic dependency. Specifically, we used a Bayesian hill-climbing algorithm, implemented via the R package *bnlearn* (Scutari, 2010; Scutari and Nagarajan, 2013). As implemented by *bnlearn*, the bootstrap function computes the structural aspects of the network model by adding edges, removing them, and/or reversing their direction to ultimately optimize the Bayesian Information Criterion (BIC). To ensure the stability of the resultant DAG, we then bootstrapped 10,000 samples (with replacement), computed a network for each sample, and averaged across the resulting networks to produce a final network structure (McNally et al., 2017). Two DAGs were computed; the first one determined the structure of the network (i.e., whether an edge is present or not), and the second one centered on the direction of each surviving edge.

3. Results

Descriptive information regarding the seven variables (before non-paranormal transformation), including mean, standard deviation, range, skewness, and kurtosis, can be found in Table 1. The correlation matrix of the variables included in the network can be found in Table S2.

3.1. Sample characteristic

At the time of assessment, firefighters ranged in age from 23 to 64 years with a mean age of 40.83 years (SD = 10.6), and the majority were male (n = 177; 94.65%). PCL-5 scores reflecting DSM-5 PTSD symptoms ranged from 0 to 67 (M = 12.37; SD = 13.33). A total of 18 firefighters presented a score higher than the threshold of 33, resulting in a prevalence of 9.25% of suspected PTSD. The traumatic events occurred on average 7 years before the survey was completed (SD = 6.9 years, range: less than a year–29 years). The three most commonly work-related endorsed ‘worst’ traumatic events were interventions involving a dead child (n = 44, weighted 23.5%), interventions involving the death of a co-worker (n = 20, weighted 10.7%), and motor vehicle accident involving death and necessity to remove body parts from the highway/rails (n = 20, weighted 10.7%). A full description of the reported events is presented in Table 2.

Table 1
Mean, Standard Deviation (SD), Minimum (Min), Maximum (Max), Skewness, and Kurtosis of each variable.

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Perceived Stress	21.70	6.81	7	41	0.35	−0.04
Hardiness	29.33	6.72	10	44	−0.35	−0.16
Experiential avoidance	13.61	8.09	7	43	1.75	2.82
PCL_B	3.34	3.87	0	20	1.61	2.43
PCL_C	1.32	1.83	0	8	1.45	1.32
PLC_D	3.51	5.06	0	24	2.09	4.14
PCL_E	4.21	4.69	0	18	1.32	0.85

PCL = Posttraumatic Stress Disorder Checklist subscales (B = avoidance; C = intrusion; D = negative mood and cognition; E = arousal).

Table 2
Worst events endorsed by the participating firefighters.

Events	N	%
Death of a child	44	23.5
Death of a co-worker	20	10.7
Motor vehicle accident involving death and necessity to remove body parts from the highway/rails	20	10.7
High scale intervention (terrorist attacks, plane crashes, etc.)	12	6.4
Unexpected death of a victim at the end of an intervention	9	4.8
Violent individual during an intervention	9	4.8
Mistake during an intervention by a co-worker	7	3.7
Injury of a child with or without parents as witnesses	6	3.2
Intervention involving family members	6	3.2
Suicide	5	2.7
Intervention resolving in a personal injury	5	2.7
Death of an adult	5	2.7
Injury of an adult	4	2.2
Child witnessing serious injury or death of a parent	3	1.6
Harassment by a co-worker or hierarchy	3	1.6
Fire involving death	3	1.6
Murder of a family followed by the suicide of the perpetrator	2	1.1
Co-worker suicide	2	1.1
Intentional maltreatment of child	1	0.5
Investigation of a missing person's house	1	0.5
Not shared	8	4.3

3.2. Gaussian graphical model

The GGM is represented in Fig. 1. The edges represent regularized partial correlations between variables, which values are presented in Table 3. Most of the edges are positive (10) and two are negative. Some pairwise connections stand out. First, the largest edge's weight is between the negative mood and cognition subscale (PCL-D) and the arousal subscale (PCL-E) of the PCL-5 ($r = 0.45$). Second, the intrusion subscale (PCL-C) and the avoidance subscale (PCL-B) of the PCL-5 are strongly connected ($r = 0.32$). Other large connections are noted between the negative mood and cognition subscale (PCL-D) and experiential avoidance ($r = 0.25$), experiential avoidance and perceived stress ($r = 0.25$), hardiness and perceived stress ($r = -0.24$). To estimate the accuracy of the edge weights, we computed bootstrapped confidence intervals for each of the edge weights, which showed that the edges are stable, and have homogeneous confidence intervals (See Fig. S2). However, the generally large bootstrapped Cis imply that interpreting the order of most edges in the network should be done with care. A bootstrapped edge-weight difference test also showed that strongest and weakest edges are significantly different from one another (See Fig. S3).

Expected influence and predictability values are reported in Table 4. Mean node predictability ranges from 0.22 to 0.66, with an average of 0.49. This means that on average, 49% of the variance of the node in the network can be explained by its neighbors. Results for both measures are similar, showing that *negative mood and cognitions* subscale (PCL-D) had the highest EI (1.02) and predictability (0.66) values, while *hardiness* (DRS) and *perceived stress* (PSS) had the lower ones. A bootstrapped difference test showed that nodes with low EI are statistically different from EI estimates in nodes with high EI (see Fig. S4).

The spin glass algorithm detected three communities of nodes. The first community grouped all PCL subscales and experiential avoidance; the second community solely encapsulated hardiness; and a third community included perceived stress. As shown in Table 4, only hardiness, experiential avoidance, and perceived stress present non-zero bridge EI values. Experiential avoidance presents the highest bridge EI value.

Table 3
Partial correlations between nodes.

	PSS	DRS	EA	B	C	D	E
PSS	–						
DRS	−0.25	–					
EA	0.25	−0.13	–				
B	0	0	0.17	–			
C	0	0	0	0.32	–		
D	0	0	0.25	0.16	0.15	–	
E	0	0	0.17	0.11	0.19	0.45	–

Note. PSS = Perceived Stress Scale, DRS = Hardiness, EA = Experiential Avoidance, PCL = Posttraumatic Stress Disorder Checklist for DSM–5, B = Intrusion subscale of the PCL, PCL-C = avoidance subscale of the PCL, PCL-D = Negative Mood and Cognition subscale of the PCL, PCL-E = Arousal and Reactivity subscale of the PCL.

Table 4
Measures of node strength expected influence and predictability from the network.

Nodes	Expected Influence	Predictability	Bridge Expected Influence
Hardiness	−0.38	0.22	−0.38
Experiential avoidance	0.71	0.57	0.12
Perceived stress	0.01	0.38	0.01
PCL - Intrusion[a]	0.76	0.50	0
PCL - Avoidance	0.66	0.46	0
PCL - Negative Mood and Cognition[b]	1.02	0.66	0
PCL - Arousal and Reactivity	0.92	0.65	0

[a] PCL = Posttraumatic Stress Disorder Checklist for DSM–5.
[b] PCL subscale with the highest Expected Influence and Predictability scores.

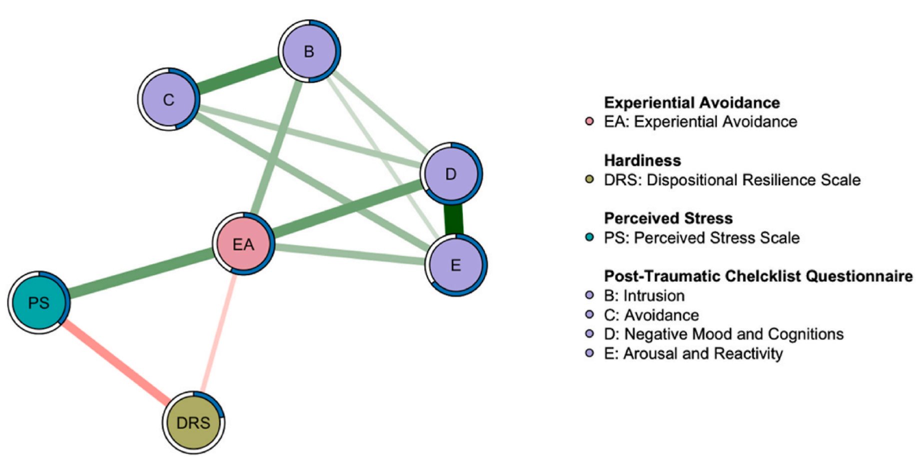

Fig. 1. Regularized partial correlation network. Each node represents the total score of a given psychometric scale. Green edges represent positive connections and red edges represent negative connections; the thicker the connection, the stronger it is. The pie chart surrounding the node represents node predictability (i.e., the percentage of shared variance with all connected nodes).

Lastly, the person-dropping bootstrap procedure confirmed that EI and bridge EI values are highly stable. The associated CS-coefficient for EI was 0.749 and BEI was 0.674, both largely above the suggested 0.5 threshold.

3.3. Directed acyclic graph

Fig. 2A and B show directed acyclic graphs (DAGs) resulting from 10,000 bootstrapped samples. For both Fig. 2A and B, edges that are present in the graph were retained because their strength was greater than the optimal cut resulting from the method of Scutari and Nagarajan (2013). Fig. 2A illustrates the importance of each edge to the overall network structure. Specifically, edge thickness reflects the change in the BIC when that edge is removed from the network. Greater thickness thus signifies that an edge is more crucial to model fit. The most important edges to the network structure connect experiential avoidance to the negative mood and cognitions symptoms of PTSD (with a change in BIC of −56.50) and negative mood and cognitions to avoidance symptoms of PTSD (with a change in BIC of −41.36). Meanwhile, the least important edge to the network structure connects hardiness to intrusion symptoms of PTSD (with a change in BIC of −2.01). The change in BIC value for each edge can be seen in Table S3.

In Fig. 2B, edges signify directional probabilities; an edge is thicker if it points from one node to another in a greater proportion of the bootstrapped networks. The thickest edges connect experiential avoidance to intrusion symptoms of PTSD (0.78; i.e., this edge was pointing in that direction in 7800 of the 10,000 bootstrapped networks and in the other direction in 2200 of the 10,000 bootstrapped networks) as well as hardiness to intrusion symptoms of PTSD (0.78). The thinnest edges connect inflexibility to negative mood and cognition symptoms (0.53) and avoidance to arousal symptoms of PTSD (0.53). The exact directional probability for each edge in Fig. 2B can be found in Table S3.

Structurally, experiential avoidance arises at the top of the DAG, directly influencing both negative mood and cognitions and perceived stress, which then influences the rest of the PTSD symptomatology.

4. Discussion

In this study, we aimed to investigate the interaction between stress response and clinically relevant variables following a potentially traumatic event in firefighters. To do so, we conducted network analyses using two distinct computational network approaches: a GGM and a DAG. One of the most striking findings was the observation that both the GGM and DAG identified experiential avoidance (EA) as a particularly influential variable. Furthermore, both models indicated that EA is primarily associated with symptoms of avoidance and arousal through negative mood and cognitions.

These results could present a new perspective on the concept of EA in relation to post-traumatic stress disorder (PTSD). Indeed, according to the Acceptance and Commitment Therapy (ACT) framework, EA is primarily linked to intrusions and avoidance symptoms. (Hayes et al., 2006). Our findings suggest that, among our sample of firefighters, EA may not only be associated with avoidance symptoms but may also be directly linked with negative mood and cognition symptoms (e.g., self-blame, rumination, etc.) and, in turn, drive avoidance and arousal (Benfer et al., 2021; Blackledge, 2004; Orcutt et al., 2020).

Two recent observations provide insight into our findings. First, Godfrey et al. (2022) found that among all PTSD clusters, only negative mood and cognition processes (i.e., worry, rumination, expressive suppression) were associated with decreased emotional regulation in firefighters (Godfrey et al., 2022). Second, the deliberate use of emotional distancing as a coping strategy, such as consciously avoiding feelings related to potentially traumatic interventions, has been acknowledged among first responders (Arble and Arnetz, 2017; Crowe et al., 2017; Laureys and Easton, 2020; Ørner et al., 2003; Young et al., 2014). Our findings gather and replicate these results. Future research should determine at a symptom level the associations between EA and specific negative mood and cognition symptoms, as these associations may have an important functional influence on the etiology of PTSD among firefighters.

The second main finding of this study Is that In both networks, perceived stress was not directly linked with symptomatology but rather buffered through EA. Results from the bridge expected influence and DAG values suggest that EA could be used as a coping strategy to decrease perceived stress during particularly distressing interventions among this population. This is in line with previous theoretical understanding of EA's function of downregulating distress (Boulanger et al., 2010). Interestingly, as described above, EA was also linked to PTSD symptomatology. Taken together these results could add evidence showing that EA may not be inherently maladaptive but appears to promote PTSD when it is inflexibly applied across situations (Orcutt et al., 2020). For example, posttraumatic growth has been linked with avoidant coping strategies among first responders, potentially because it creates the necessary space for recovery (Arble and Arnetz, 2017). However, the inflexible use of EA has also been shown to be linked with negative mental health outcome (Karekla and Panayiotou, 2011), and specifically PTSD symptomatology (Orcutt et al., 2020).

Finally, our results are in line with previous findings suggesting that trait hardiness would moderate the association between perceived stress and PTSD symptomatology. For example, firefighters with lower levels of individual hardiness were found to be more susceptible to the development of PTSD through the escalation of perceived stress (Lee

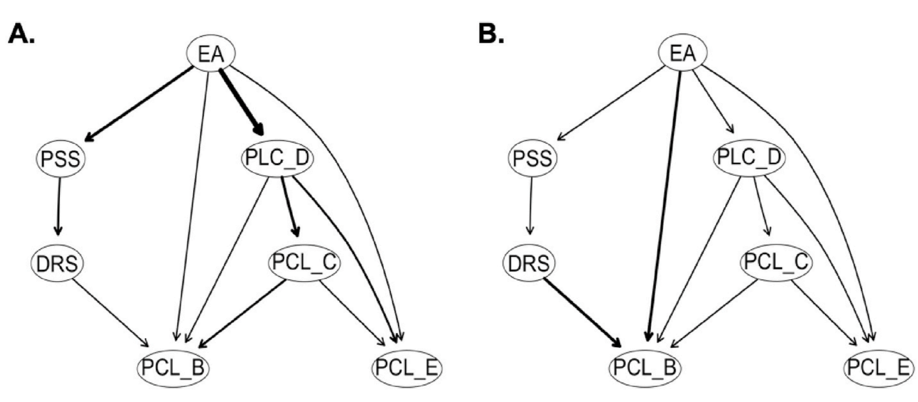

Fig. 2. Directed Acyclic Graphs (DAGs). Fig. 2A. Presence of edges: Edge thickness indicates the importance of that edge to the overall network structure, with greater thickness signifying that an edge is more crucial to model fit. Thickness reflects the change in the BIC of the model when that edge is removed. For this graph, solid lines represent that the presence of an edge improves model fit. Fig. 2B: Direction of edges: edge thickness indicates directional probability, or in what percentage of the fitted networks the edge went in that direction. Edge thickness is drawn proportionately, such that a thicker arrow indicates a higher directional probability. For this graph, a solid line indicated that an edge was present in its current direction in at least 51% of the 10,000 bootstrapped networks. For both Fig. 2A and B, exact edge weights can be found in Table S3. EA = Experiential avoidance; PSS = Perceived Stress; DRS = Hardiness; PCL_B = intrusion symptom cluster of PTSD; PCL_C = avoidance symptom cluster of PTSD; PCL_D = negative mood and cognitions symptom cluster of PTSD; PCL_E = arousal and reactivity symptom cluster of PTSD.

et al., 2014). It is important to note that while DAGs provide valuable insights into generating causal hypotheses beyond what other methods are able to do, strict causal inference requires the consideration of all covariables (Briganti et al., 2022). This study, which only included 7 nodes, is probably lacking a set of important variables playing a role in the stress response displayed by firefighters. Caution should therefore be exercised when attempting to draw strict causal inferences based on the sole variables included in this study, which must be considered as exploratory.

Taken together, these results support the idea of prevention training focused on the inflexible use of EA. It is commonly accepted that when an individual is exposed to trauma, they may engage in more EA due to the presence of posttraumatic symptoms (e.g., intrusive memories and nightmares) (Orcutt et al., 2020). However, those who naturally recover may oscillate between processing the traumatic experience and avoidance. The processing of the trauma is known to facilitate the integration of new information and decrease the emotional intensity over time, leading to recovery. However, the rigid reliance on these avoidant strategies may inhibit this process and lead to higher levels of PTSD over time. This is consistent with the broader emotion regulation and coping literature on the importance of flexibility (Bonanno and Burton, 2013). Implementing preventive as well as post-traumatic interventions focused on flexible self-regulation strategies could have a significant impact among firefighters (Bonanno et al., 2004). Psychoeducation on these processes could also be generally implemented to provide firefighters with additional tools to deal with highly emotional interventions (Bean et al., 2017; Molavi et al., 2020).

There are several limitations to consider when interpreting the findings of this study. First, our network used the subscales of the PCL-5 as nodes, and was not performed on a symptom-level due to sample size restrictions. To ensure stability within our network, we decided to decrease the number of nodes from 24 (using all PTSD symptoms) to 7 (using the subscales). The use of subscales in network analysis is not uncommon and is aligned with the existing literature specifically in PTSD. As supported by a recent meta-analysis, symptoms within the same subgroup (i.e., intrusion, avoidance, negative mood and cognition, and hyperarousal) exhibit significant connections (Epskamp et al., 2021). Including subscales of symptoms is theoretically relevant based on results from priori network analyses. By including moderating variables in our network, our results shed light on the specific subgroup of symptoms that may be particularly linked to maladaptive coping strategies. However, as mentioned earlier in this discussion, symptom-level analysis would provide further insights into the complexity of PTSD.

Second, as mentioned above we did not include several potentially relevant moderators such as depression, anxiety, or burnout, which are known to be highly comorbid with PTSD (Afzali et al., 2017; Brattberg, 2006; Garabiles et al., 2020; Gutner and Presseau, 2019; Katsavouni et al., 2016). However, we had to keep the data collection feasible for participants with time-consuming work, and therefore only asked a limited number of questions. By keeping the assessment relatively short (between 40 min and 1 h to complete), we ensured that we had enough completed responses. In addition, statistical considerations also played a role in the decision to limit the number of psychological variables assessed. The number of parameters grows quickly with each additional node (Epskamp et al., 2018). We chose to include the minimum number of nodes in the network and perform a LASSO regression to ensure that we had adequate power (more detailed information on estimating power in network analyses can be found elsewhere, such as (Epskamp et al., 2018)). We hope that future research will include these types of moderating variables. Thirds, it is worth noting that we do not know if the firefighters enrolled in this study have suffered from PTSD in the past and have returned to a low symptomatic state (which would make them *resilient*) or if they never developed PTSD (which would make them *resistant*). Even if this distinction is not clear in our sample, we do know that these firefighters are in duty, which implies that they have not encountered events that exceed their adaptive capacity. Only a small prevalence of firefighters met the threshold for probable PTSD (N = 18), which did not allow us to perform a differential network focused on these participants. Therefore, while this study highlights the mechanisms currently displayed by active firefighters to cope with potentially traumatic stress on a daily basis, it would be interesting to compare our results with a sample of firefighters who meet the criteria for probable PTSD. It is however worth mentioning that firefighters have been recognized to under-rate the emotional impact of critical incidents (Kehl et al., 2014), therefore relying on a cut-off score designed for the general population might be criticized for first responders. Finally, it is worth noting that the Acceptance and Action Questionnaire-II (AAQ-II) has been questioned as being a measure of voluntary attempts to avoid emotional distress, or rather a general assessment of psychological distress. The current study provides mixed findings regarding this question. A certain discriminant validity of the AAQ-II may be hypothesized considering the links between EA and the negative mood and cognition cluster of PTSD. However, EA was included in the same community than the PCL-5 subscales, without distinction. Without a competitive assessment of experiential avoidance, either through self-report questionnaire or behavioral measure, the discriminant validity of the AAQ-II cannot be questioned based on this study alone.

5. Conclusions

This study provides an important first step in employing network analysis to examine stress response among firefighters. To the best of our knowledge, this is the first study that included clinically relevant variables along with PTSD symptoms among a population of European firefighters. Our findings suggest that experiential avoidance plays a central role in the stress response of firefighters, potentially through negative mood and cognitions symptomatology and perceived stress. Future research should investigate the specific associations between experiential avoidance and negative mood and cognition symptoms in order to better understand the etiology of PTSD in this population. In addition, as EA might be used as a coping strategy to decrease perceived stress during potentially traumatic interventions, training and interventions focused on flexible self-regulation strategies may be beneficial in preventing and reducing PTSD symptomatology among firefighters. Considering our sample size, these results need to be considered as initial evidence of specific PTSD etiology among firefighters.

Institutional review board statement

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008, and approved by the Institutional Review Board of the University of Mons.

Data availability statement

Data supporting the findings of this study as well as *R* script are available online: https://osf.io/9jn7t/?view_only=bdb919d7bb9f4740b474583760ce8aa8.

Author contributions

Conceptualization, Wivine Blekic and Mandy Rossignol; methodology, Wivine Blekic and Mandy Rossignol; formal analysis, Wivine Blekic, Souhaib BenTaieb, Katharina Schultebraucks; data curation, Wivine Blekic and Souhaib Ben Taieb; writing—original draft preparation, Wivine Blekic; writing—review and editing, Wivine Blekic, Katharina Schultebraucks, Kendra G. Kandana Arachchige, Souhaib Ben Taieb, Mandy Rossignol; supervision, Mandy Rossignol, funding acquisition, Wivine Blekic, Katharina Schultebraucks. Wivine Blekic received

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Declaration of competing interest

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpsychires.2023.07.019.

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