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ORIGINAL PAPER

Network Analysis of Mindfulness and Mental Health Symptoms among Firefighters: A Transdiagnostic Lens

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Abstract

Objectives Previous research has established the protective role of mindfulness against various psychological disorders and maladaptive behaviours. However, the associations between specific facets of mindfulness and diverse mental health and behavioural outcomes have not been thoroughly investigated in populations with risky occupations. The aim of this study was to examine the direct and indirect associations between the five facets of mindfulness and prevalent mental health and behavioural outcomes among firefighters, including depression, post-traumatic stress disorder (PTSD), anger, suicide risk, sleep quality, and alcohol use.

Method The assessment scores of 685 career firefighters (M_{age} = 38.40, SD = 8.64; 93.6% males; 77.7% White) including 154 (22.5%) military veterans, who completed measures of mindfulness, depression, PTSD, anger, suicide risk, sleep quality, and alcohol use, were investigated using both directional and non-directional network analysis.

Results Directional network analysis indicated the primary role of anger in triggering PTSD and impacting mindfulness, leading to alcohol use, suicidal ideation, impaired sleep quality, and depression as an outcome. Mindfulness facets of Non-reactivity, Non-judging, and Describing were negatively associated with depression, while the Acting with awareness facet was inversely linked to anger.

Conclusion This study emphasizes the clinical significance of targeting specific mindfulness facets in interventions for high-risk occupations, such as firefighters. Focusing on Non-reactivity, Non-judging, Describing, and Acting with awareness may help mitigate anger, depression, and other negative outcomes. Addressing anger management could be especially important in preventing or reducing PTSD, alcohol use, suicidal ideation, sleep disturbances, and depression, ultimately enhancing psychological well-being and quality of life.

Keywords Network analysis · Mindfulness · FFMQ · Mental health · Firefighters

Work constitutes a central pillar of human functioning and well-being. Empirical research has established the profound influence of one's occupation on health and life fulfillment, highlighting the interdependence between productivity and thriving (Basinska & Wiciak, 2013). The positive psychology movement further illuminates this relationship between vocation and eudaimonic wellness through dimensions like cognitive evaluations and emotional experiences in the workplace setting (Abramson, 2022). Within hazardous professions, however, the bidirectional impact appears

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pronounced and complex, as the inherent risks and challenges of these occupations can significantly affect both physical and psychological health.

For instance, first responders encounter daily occupational stressors with proven ties to adverse clinical outcomes (Carey et al., 2011; Grant et al., 2015). As emergencies and accidents remain intrinsically unpredictable, the firefighter role is associated with adverse psychosomatic well-being (Carey et al., 2011). Perhaps unsurprisingly, elevated rates of posttraumatic stress disorder (PTSD), depression, alcohol dependency, and sleep dysfunction distinguish firefighters relative to population baselines (Fullerton et al., 2004; Grant et al., 2015). Yet behavioral theories illuminate pathways through which repeated trauma exposure may engender psychopathological sequences among this critical workforce (Pitman et al., 2012).

The behavioral frameworks of classical and operant conditioning offers a comprehensive theoretical explanation to understand the development and perpetuation of PTSD. Classical conditioning explains how firefighters may develop stress responses to specific triggers reminiscent of traumatic events (Pitman et al., 2012; Zuj & Norrholm, 2019). Similarly, operant conditioning elucidates the role of reinforcement in the maintenance of PTSD symptoms, where avoidance behaviors are perpetuated due to the immediate relief they offer (Skinner, 1953; Zuj & Norrholm, 2019). Expanding on these principles, Keane et al. (1985) and Brewin and Holmes (2003) highlight the impact of trauma exposure and memory avoidance in the context of PTSD. They posit that the active avoidance of trauma-related memories may inadvertently sustain and intensify PTSD symptoms, as it obstructs the natural progression of psychological recovery. Similarly, dysregulated anger represents a frequently comorbid feature accompanying posttraumatic phenomenology that carries interpersonal spillover effects off duty as well (Jakupcak & Tull, 2005). As occupational hardship punctuates the firefighter experience, targeted interventions to support mental health warrant ongoing investigation so this indispensable community can thrive across personal and professional realms.

Research substantiates mindfulness-based approaches as efficacious interventions targeting mental health symptoms like depression and anxiety across varied contexts (Creswell, 2017). Mindfulness is typically defined as the awareness that manifests through paying attention to the present moment with non-judgemental and accepting attitude (Kabat-Zinn, 2013). Core practice techniques emphasize present-moment awareness, acceptance, and nonjudgmental observation of experiential phenomena. For example, Mindfulness-Based Cognitive Therapy (MBCT) was specifically developed as a relapse prevention program for major depressive disorder, teaching skills that decentralize identification with depressive rumination and disempower its escalation (Segal et al., 2018). MBCT encourages a participatory witnessing towards negative repetitive thought, rather than reflexive avoidance or suppression. This meta-cognitive ability to disidentify from difficult inner states may generalize as a protective resilience factor among high-stress groups such as firefighters as well (Cladder-Micus et al., 2021).

Certainly no panacea, mindfulness appears best conceptualized as one protective asset within a biopsychosocial model of firefighter health. Sleep deficiency and cardiovascular disease risk reflect additional occupational hazards intrinsic to an intensely demanding profession (Barger et al., 2015). However, cultivating mindfulness skills could potentially buffer against the untoward mental and physical health effects of cumulative work stress (Kemper et al., 2015). For instance, acting with awareness denotes a present-centered attentiveness associated with enhanced self-regulation and wise decision-making even amidst uncertainty. Thus, mindfulness facets may each contribute differential health benefits, though precise mechanisms await elucidation through network analytic approaches (Borsboom, 2017).

The network theory of psychopathology conceptualizes mental health disorders as interconnected webs of symptoms spanning psychological, behavioral, and physiological domains (Borsboom, 2017). Instead of categorizing variables as predictors or outcomes, network analysis examines the complex associations between all elements simultaneously, as demonstrated in the network analysis of mindfulness facets and distress variables (Barcaccia et al., 2020; Lecuona et al., 2021; Medvedev et al., 2021). Recently, Roemer et al. (2024) applied network analysis to demonstrate unique links between Big Five personality traits and five facets of dispositional mindfulness. Their research highlights the value of network science in modeling the unique interrelations underpinning these established psychological constructs.

Network relations can be nondirectional or directional. Nondirectional network is based on the assumption that node relations have no direction and are symmetrical while directional network analysis estimates probability of directionality between variables and provides more informative measures to understand complex network dynamics (Borsboom et al., 2021). Numerous empirical studies have successfully employed directed network analysis in health psychology science and practice (Christensen et al., 2020; Heeren et al., 2021; Hevey, 2018). Applying both directional and nondirectional network analysis, the present study aimed to elucidate the unique connections between mindfulness facets and mental health outcomes among firefighters. Specifically, it was hypothesized that the Non-judging, Acting with awareness, and Non-reactivity facets would demonstrate the strongest inverse relationships with symptoms like PTSD and depression. Uncovering the architecture of these multivariate associations can enrich theoretical models to inform

future interventions promoting resilience in firefighter mental health. Overall, this research constitutes an important effort in delineating pathways to inform psychosocial wellness programs for our first responders.

Method

Participants

The full sample consisted of 910 firefighters, including 209 military veterans. Out of the total sample, 685 firefighters (M_{age} = 38.40, SD = 8.64; 93.6% males; 77.7% White), who completed all measures assessing mindfulness and mental health outcomes were included in the study. Most firefighters (91.1%) have completed a college or bachelor's degree, and the remainder have completed high school. Nearly all (99.6%) of the firefighters reported being employed full-time. Among this subset, 154 individuals, accounting for approximately 22.5%, had a military veteran background. There were no significant demographic differences between the current sample (n = 685) and the full sample (n = 910), as indicated by Chi-square and t-test (all p-values > 0.05).

Procedure

Data collection occurred in the southern region of the United States from 2016 to 2018. Stringent ethical considerations were upheld to safeguard the well-being and rights of the participants. The study specifically targeted currently employed firefighters, aged 18 or above, who had formally provided informed consent to participate. Eligible firefighters were invited to participate in a comprehensive survey that consisted of a succinct yet incisive demographic questionnaire and a meticulously crafted set of assessments, specifically tailored to acquire information directly relevant to their mental well-being. This holistic approach allowed for a thorough exploration of the participants' experiences, thereby yielding valuable data crucial to the study's objectives. Participants' contributions were recognized by offering them the opportunity to participate in a raffle with various rewards, including gift cards.

Measures

Five Facet Mindfulness Questionnaire (FFMQ)

The FFMQ (Baer et al., 2006) assesses mindfulness across five distinct facets and demonstrated solid psychometric properties, which makes it an invaluable instrument in mindfulness research and clinical practice (Baer et al., 2022; Lecuona et al., 2021). The first facet, Observe, involves the capacity to attentively observe and perceive internal and external experiences without judgment. The second facet, Describing, pertains to the ability to effectively label and describe these experiences with words. Acting with awareness, the third facet, refers to the intentional engagement and present centeredness in daily activities. Non-judging of inner experience, the fourth facet, encompasses the non-evaluative acceptance of one's thoughts, feelings, and sensations. Lastly, the fifth facet, Non-reactivity to inner experience, involves allowing thoughts and emotions to arise and pass without getting caught up or reacting impulsively (Baer et al., 2022). The FFMQ is a questionnaire that includes 39 items where individuals provide their own responses using a Likert scale. The responses range from 1 = *Never*, indicating complete disagreement, to 5 = *Always,* indicating complete agreement (Baer et al., 2022). The internal reliability McDonald's ω coefficients obtained from the current data demonstrated satisfactory values for each mindfulness facet: Observe (0.87), Describing (0.77), Acting with awareness (0.92), Non-judging (0.90) and Non-reacting (0.88).

Self-Report Depression Scale for Research in the General Population (CES-D)

The 20-item CES-D was constructed by Radloff (1977) to assess depressive symptoms in non-clinical samples. The scale items reflect affective, cognitive, and somatic symptoms commonly used to diagnose depression and use a 4-point Likert scale response format ranging from 0 = *Rarely or None of the time* to 3 = *Most or all of the time,* with higher scores indicating higher levels of depression (Radloff, 1977). The CES-D assesses symptoms experienced over the past week. The scale has demonstrated strong psychometric properties in previous research, making it a valuable tool for both clinical and research purposes. The CES-D is relatively brief and easy to administer, which contribute to its widespread use in various populations to assess and monitor depression symptoms (Gomez & McLaren, 2015; St. John et al., 2013). The CES-D demonstrated good reliability with the current dataset (ω = 0.81), which was consistent with earlier reports (ω = 0.90; Cosco et al., 2017).

Suicidal Behaviours Questionnaire-Revised (SBQ-R)

The 4-item SBQ-R (Osman et al., 2001) measures self-reported suicidal behaviours. Participants rate each item on a Likert scale from 0 = *Never* to 6 = *Very likely*, with higher scores indicating a greater severity of suicidal behaviours (Osman et al., 2001). The brevity of the administration of SBQ-R, making it valuable for both research and clinical purposes, enabling the identification and monitoring of individuals at risk of suicidal behaviours. The SBQ-R appeared reliable with our data (ω = 0.81),

and similar reliability estimates were reported earlier with clinical and non-clinical samples ($\omega = 0.86$–0.94; Osman et al., 2001).

PTSD Checklist for DSM-5 (PCL-5)

The 20-item PCL-5 (Weathers et al., 2013) measures PTSD symptoms as self-reported by individuals using a 5-point Likert scale format from 0 = *Not at all* to 4 = *Extremely* (Weathers et al., 2013). The PCL-5 offers clinicians and researchers a psychometrically robust self-report tool for efficiently assessing PTSD symptom severity. This 20-item measure asks respondents how much they have been bothered over the past month by DSM-5 PTSD symptoms spanning four clusters: intrusions, avoidance, negative alterations in cognition/mood, and arousal/reactivity. Sample items range from the directly trauma-related ("Repeated, disturbing dreams of the stressful experience") to downstream impacts ("Trouble remembering important parts of the stressful experience"). The scale demonstrated sound test–retest stability as well as strong convergence with gold-standard PTSD interviews. It also provides good discrimination from other forms of psychopathology like depression or panic. The latent structure of responses maps cleanly onto DSM-5 PTSD criteria. Analyses from the current firefighter study further bolster confidence in the scale's internal consistency ($\omega = 0.94$) aligning with past reports.

Dimensions of Anger Reactions (DAR-5)

The DAR-5 (Asmundson et al., 2016) is an established tool used in psychological research to assess various dimensions of anger responses. The DAR-5 incorporates the widely utilized Likert scale format, allowing individuals to rate their agreement or disagreement with a series of statements pertaining to their anger experiences (Asmundson et al., 2016). This structured approach enables participants to provide nuanced responses by indicating the extent to which they endorse each statement. The Likert scale employed in the DAR-5 typically consists of five response options, ranging from 1 = *strongly agree* to 5 = *strongly agree* which aids in capturing the varying degrees of agreement or disagreement individuals may have regarding the statements presented. The DAR-5 assesses different dimensions of anger, including cognitive, affective, and behavioural aspects. Participants can express their perspectives on the intensity, frequency, and duration of their anger episodes (Asmundson et al., 2016; Goulart et al., 2021). Additionally, in our study, the DAR-5 demonstrated high reliability, as indicated by a $\omega = 0.90$, reflecting excellent internal consistency (Asmundson et al., 2016).

Pittsburgh Sleep Quality Index (PSQI)

The 19-item PSQI (Buysse et al., 1989*)* assesses self-reported sleep quality over the past month, including sleep latency, duration, efficiency, disturbances, use of sleep medications, and daytime dysfunction (Buysse et al., 1989). This measure employs the Likert scale format, ranging from 0 to 3 or 0 to 4. In the 0 to 3 Likert scale version, a score of 0 represents *not during the past month* or *not applicable*. Scores of 1, 2, and 3 indicate increasing levels of frequency, severity, or endorsement. In the 0 to 4 Likert scale version, a score of 0 still represents *not during the past month* or *not applicable*. Scores of 1, 2, 3, and 4 indicate varying degrees of frequency, severity, or endorsement. Generally, a score of 4 indicates the highest level of occurrence or impact (Buysse et al., 1989). The Likert scale provides a structured framework for individuals to rate their experiences, allowing researchers to quantify subjective data related to sleep quality and disturbances, and facilitating a comprehensive understanding of individuals' sleep patterns. The internal consistency of the scale was high in the current study ($\omega = 0.90$).

Alcohol Use Disorders Identification Test (AUDIT)

The AUDIT (Saunders et al., 1993) is a widely used screening tool for assessing alcohol use disorders. It consists of 10 items that capture various dimensions of alcohol consumption and related problems. The AUDIT uses the Likert scale, typically spanning from 0 to 4, with each number representing a distinct level of agreement, frequency, or severity. For instance, a response of 0 indicates *never no consumption* or *never experienced the specific problem* while a response of 4 could signify *daily or almost daily*, *high consumption* or *frequent occurrence of the problem* (Saunders et al., 1993). According to the Likert scale, the researchers evaluate alcohol consumption patterns, including the frequency and quantity of drinking. Individuals are also queried about problematic behaviours associated with alcohol use, such as difficulties in controlling consumption, blackouts, and interpersonal conflicts stemming from drinking (Saunders et al., 1993). The reliability with our dataset was $\omega = 0.90$.

Data Analyses

To investigate relations between psychological symptoms and potential protective factors—specifically the five facets of mindfulness—within firefighters, this study employed the Bayesian-Gaussian Graphical Model (BGGM; Williams & Mulder, 2020) using RStudio software (RStudio Team, 2023). Our data analyses aimed to illustrate both direct and indirect relations between facets of mindfulness and mental health outcomes, namely depression, PTSD, Anger, suicide risk, sleep quality, and alcohol use. Leveraging the Bayesian

approach of the BGGM package, we were able to estimate the posterior means, standard deviations, and credible lower and upper bounds of these associations, while also controlling for potential age effect in our sample (Williams & Mulder, 2020; Williams, 2021).

A pivotal aspect of our analyses was the application of partial correlation network analysis, which estimated unique associations between variables while accounting for all linear relations present in the data. The network models were then visualized using the graph package, with the partial correlation matrices derived from BGGM (Williams & Mulder, 2020; Williams, 2021). Each node in the network models represented a specific variable, and the relations between these nodes, termed edges, were distinguished by colour, with blue and red indicating positive and negative correlations respectively. The strength of these associations was denoted by the thickness and colour intensity of the edges (Chalmers et al., 2022). To estimate the partial correlations between nodes while accounting for all other relationships within the full set of nodes, we utilized the "explore" function in BGGM. These estimates were built upon a semi-parametric copula model using ranked likelihood. A critical aspect of our data analyses was the retention of only those relationships in the partial correlation matrix whose 95% credible intervals excluded zero. This interval indicates the range where a population parameter is likely to fall with a 95% level of certainty (Chalmers et al., 2022; Williams & Mulder, 2020; Williams, 2021). By retaining only the statistically significant correlations in the matrix, we were enabled to infer meaningful relationships between the variables in our model.

In our study, we enhanced our network analysis by integrating Directed Acyclic Graphs (DAGs), also known as directional network analyses. DAGs are a sophisticated tool for representing potential causal relationships between variables, which is invaluable in fields like epidemiology and mental health. These graphs excel in illustrating complex dependencies where one variable can influence another across various pathways, a feature that's particularly relevant for mental health clinicians, including professional counselors, clinical social workers, and psychologists, who are often concerned with the intricate interplay of different factors affecting mental health.

To ensure the robustness and reliability of our DAG-based analyses, we employed several key strategies. First, we adhered to rigorous variable selection criteria, ensuring that the variables included in the DAGs were relevant, well-defined, and measurable. This step was crucial to prevent the inclusion of extraneous variables that could obscure true directional relationships. Second, we applied advanced statistical methods to estimate the direction and strength of the relationships between variables. This involved using algorithms capable of handling large datasets and complex variable interactions with 5000 bootstrap iterations, thus increasing the reliability of our findings. Through these measures, our directional network analysis, as visualized in the DAGs, provided a robust framework for identifying and visually representing potential causal relations among variables in our network. The robustness of our DAG-based approach is supported by literature that underscores the value of these analyses in estimating unique directional links in complex datasets (Chalmers et al., 2022; Williams & Mulder, 2020; Williams, 2021).

Results

Figure 1 shows the structure of the network and the unique relations between mindfulness and risk factors. The red edges indicate a negative relationship, and the blue edges represent a positive relationship. The thickness and color of the edges indicate the strength of the relationships: darker and thicker edges signify stronger relationships (Borsboom, 2017). Non-reactivity, Nonjudge and Describe were all inversely linked to depression, while Acting with awareness was negatively related to Anger. Additionally, Describe facet was negatively linked to Alcohol and Sleep problems. However, Non-reactivity was positively associated with Age and Sleep problems. As expected, the five facets of mindfulness were positively linked together except of except for Observe and Non-judging, which were inversely related. Similarly, all risk factors such as Depression, Sleep quality, PTSD, Anger, Suicide and Alcohol were clustering together as evidenced by negatively significant links between them. Posterior correlation matrix supporting Fig. 1 is included in Supplementary Table S1 and indicates the magnitude of posterior unique correlations between nodes including significant correlations only. The posterior correlation range from small (0.10) to large (0.50) according to Cohen's interpretation.

Figure 2 shows the predictability of all nodes in the network. Nonreact, PTSD, Observe accounted for the largest proportion of variance among the other nodes, boasting an overall R^2 value exceeding 0.60. Next, Non-judgemental attitude (Nonjudge), Depression, Acting with awareness formed the second influential group of variables, each demonstrating high predictability ($R^2 > 0.50$). Describe and Anger also exhibited fairly high predictability with R^2 values ranging between 0.40 and 0.50. However, Sleep, Suicide and Alcohol were among the less predictive nodes, each presenting an R^2 value below 0.40. Age only accounted for a negligible amount of variance in the network.

Figure 3 represents a directional network of protective and risk factors associated with mental health. Directional network analysis indicated the primary role of Anger in starting the cascade PTSD and impacting mindfulness, leading to alcohol use, suicidal ideation, impaired sleep

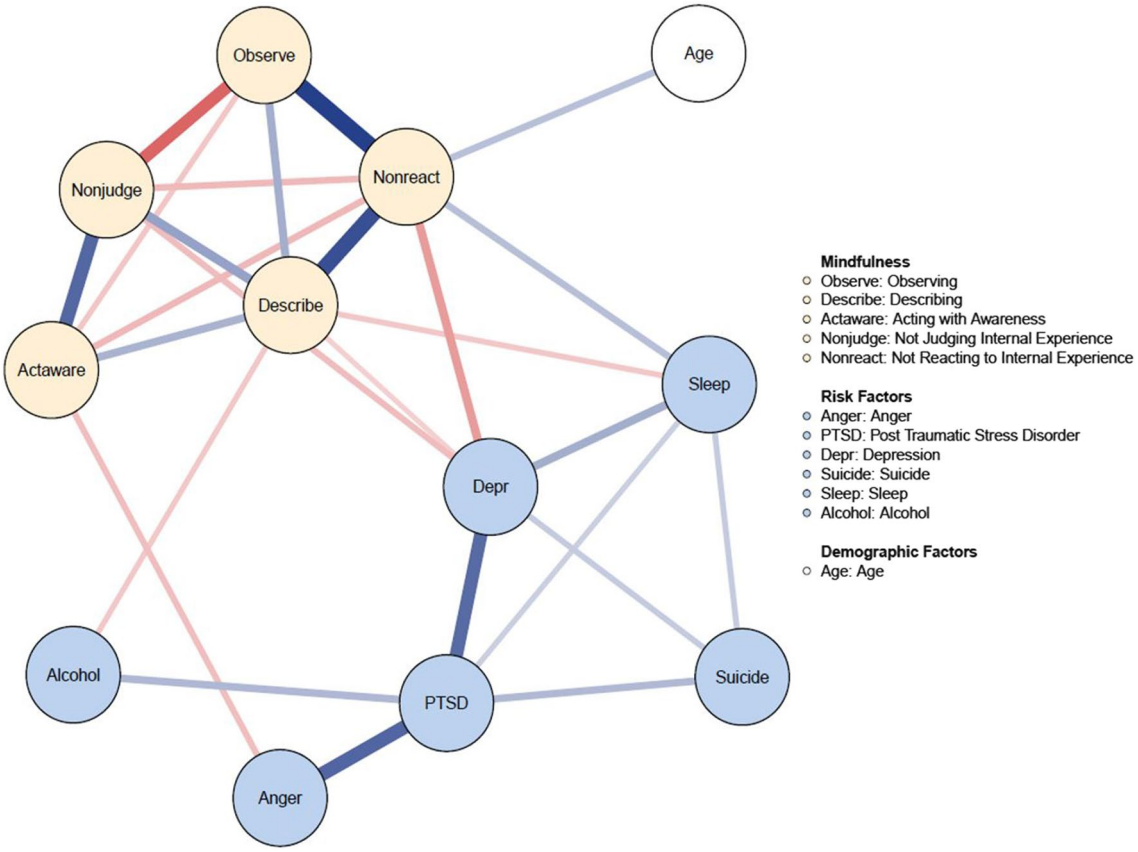

Fig. 1 The network of mindfulness facets and risk factors. The nodes represent variables and the edges unique relations between them. Edge thickness reflects the strength of the relations. Blue edges are positive associations and red edges are negative associations

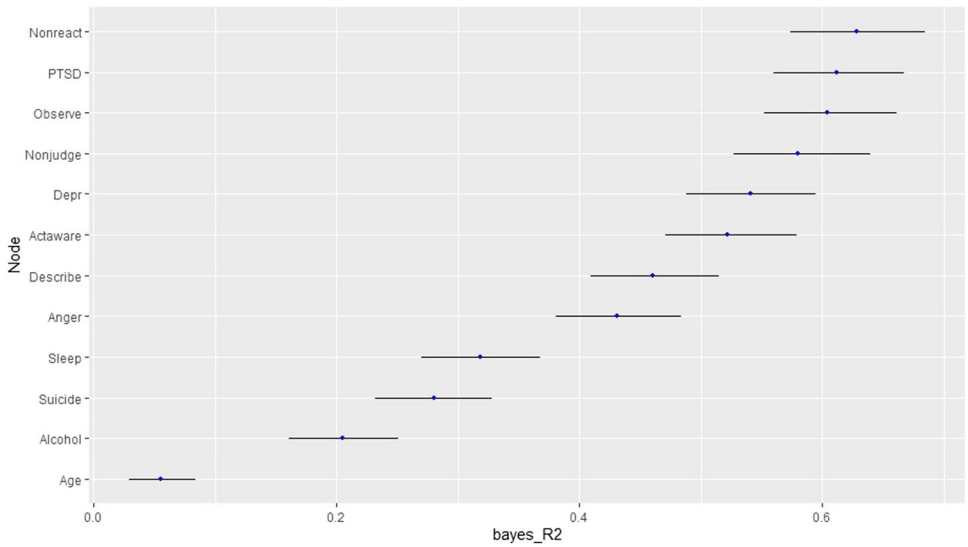

Fig. 2 Predictability of the nodes in the network

quality, and depression as an outcome. PTSD is the next strongest predictor in the network directly contributing to Depression, Sleep quality, Suicide, Alcohol consumption and negatively impacting Acting with awareness and Non-judge attitude. Depression is the endogenous variable in the network with Suicide and Sleep quality as contributing risk factors and mindfulness facets Non-reactivity, Non-judging and Describing as protective factors. Although Acting with awareness is impacted by both Anger and PTSD, it appears as the main contributing predictor of Nonjudge, Observe and

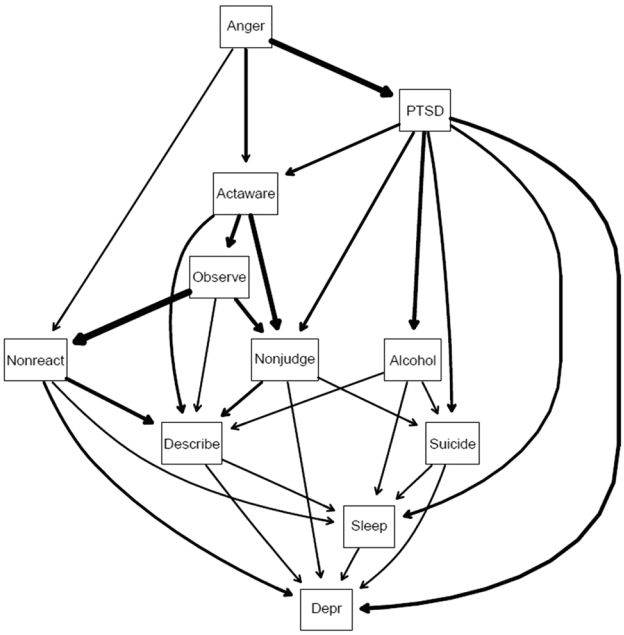

Fig. 3 Directional network of mindfulness facets and risk factors

Describe facets of mindfulness, while Observe, in turn, was strongly contributing to Non-reactivity. Describe appears as an outcome facet predicted by all other facets with Non-reactivity being the strongest predictor. Overall, this network demonstrated that Anger was the primary risk factor associated with PTSD leading to poor mental health outcomes and illustrated the buffering and protective role of mindfulness facet in this process.

Strength and direction estimates for our directional network are included in Supplementary Table S2. To ensure the reliability of our directional findings, we employed bootstrap resampling with 5000 replicates. This method enhances the robustness of our model by estimating the stability of the network structure through repeated sampling. Our Bayesian network, comprising 11 nodes and 29 arcs, displays a mix of directed and undirected arcs, underscoring the complexity and interconnectivity of the variables involved. Specifically, the presence of 22 directed arcs highlights areas of the network with more definitive directional relationships. We utilized the Hill-Climbing algorithm and BIC scoring for network learning, with a penalization coefficient tailored to balance model fit and complexity, thereby mitigating overfitting. The model statistics, including an average Markov blanket size of 7.27 and a high number of tests (934), further attest to the thorough exploration of potential relationships within the network. Our bootnet output offers strength and direction estimates for the arcs, such as a strength of 0.98 for the arc from “Observe” to “Describe”, providing a robust measure of the relationships. Strength values close to 1 indicate strong relationships, and the direction values offer quantitative evidence of the certainty of these relationships' directions. Lastly, we employed the bnlearn::averaged.network method on the bootnet output, creating a representative network that encapsulates the variability across the bootstrap samples. This averaged network serves as a consolidated view, enhancing our confidence in the robustness and reliability of our directional analysis.

Discussion

The aim of this study was to apply novel network analysis to examine links between the five facets of mindfulness, depression, PTSD, anger, suicide risk, sleep quality, and alcohol intake among firefighters and military veterans. In line with the main findings, three facets of mindfulness—specifically Non-reactivity, Non-judging, and Describing—exhibited inverse associations with depression. The facet of Acting with awareness also demonstrated an inverse link with anger. On the other hand, all adverse mental health and behavioural outcomes were interconnected, suggesting a network of distress that may be particularly prevalent in these high-risk occupations.

Our directional network analysis underscores the complexity and interconnectivity between mindfulness facets and mental health outcomes, with anger appearing to play a key role. The presence of 22 directed arcs highlights definitive directional relationships within this network. Notably, our directional analysis positions anger as a key driver of PTSD, which in turn impacts mindfulness abilities like Acting with awareness. This cascading effect subsequently influences additional outcomes like sleep disturbances, problematic drinking, suicidal ideation, and depression. These results align with prevailing theories on how uncontrolled anger can trigger downstream effects on wellbeing (Singh et al., 2021). By exploring anger's precise position and mechanisms within a broader network of distress, our study offers quantitative validation of its parental role. The strength values nearing 1 for key arcs like Anger → PTSD and PTSD → ActAware further attest to the reliability of these relationships.

Moreover, by utilizing resampling methods and tailored model scoring, we enhanced the robustness of our directional findings. The model statistics indicate a thorough exploration of the network, mitigating risks of overfitting. The averaged network created from the bootstrap samples consolidates the insights, underscoring the stability of the detected relationships. Futhermore, the connections between mindfulness facets warrant discussion, as they function collaboratively. Aligning with prior studies (Heeren et al., 2021), we observed an inverse link between Observing and Nonjudging. This suggests potential risks of judgmental reactions to one's observations without the tempering

effects from facets like Nonreactivity. Additionally, Acting with Awareness occupies a central position, aligning with conceptualizations of mindfulness emphasizing attentional engagement with the present (Kabat-Zinn, 2013). This highlights the vital role of conscious attention to one's actions.

Our findings highlight that anger management is fundamental, and techniques aimed at transforming anger constructively rather than suppressing it could prove beneficial. Ultimately, addressing anger and related impediments by boosting mindfulness facets such as Acting with Awareness may facilitate recovery from distress. However, we acknowledge these treatment speculations require empirical examination. As cross-sectional observations on a non-clinical sample, our results offer only tentative pathways to be further verified. Longitudinal interventions centered on anger and mindfulness techniques would enable more robust causal claims. By elucidating anger's mechanisms within a broader wellness network, this study lays the groundwork for targeted treatments.

Limitations and Directions for Future Research

Our research findings should be interpreted within the context of certain limitations. A significant limitation is the sample composition, which primarily consisted of white male firefighters. This homogeneity limits our understanding of the associations between mindfulness facets and mental health outcomes among more diverse groups, including firefighters who identify as female, nonbinary, or gender fluid, individuals from varied ethnic backgrounds, and those in different first responder professions. While our study acknowledges the traditional skepticism in research regarding the generalizability across diverse populations, it is crucial to also recognize the conceptual foundations that underlie the presumption of varying impacts of mindfulness based on cultural, ethnic, and gender differences. These conceptual underpinnings suggest that the experiences and effects of mindfulness practices may differ across groups due to diverse cultural norms, societal roles, and lived experiences. Therefore, the generalizability of our results to broader populations and workplaces may be limited. This highlights the imperative need for future studies to include a more diverse range of participants. Such research should not only seek to enhance the external validity of findings in this field but also delve deeper into understanding how mindfulness interacts with various cultural, ethnic, and gender identities. This approach will enable a more nuanced and comprehensive comprehension of mindfulness and its associations with mental well-being across a broader spectrum of environments.

The utilization of network analysis in our study poses several challenges that should be acknowledged. The sensitivity to different estimation methods is a challenge, as the choice of method can influence the resulting network structure. Replication and validation of the analysis are crucial to ensure the reliability and stability of the network findings. Additionally, the lack of consensus in selecting the optimal network model and the limitations associated with measurement precision and the ordinal nature of Likert-type items should be considered. Being aware of these challenges can help improve the interpretation and application of network analysis in future research.

The general limitation of our cross-sectional study is a difficulty to establish causality. While correlations indicate relations between variables, they do not provide evidence of cause and effect. Other factors, known as confounding variables, may be influencing the observed relationships. Our study focused on specific firefighting samples; however, it is important to use the study in different populations or settings to determine if the relationships hold true. Generalization is another limitation of our study. The observed relationships may be specific to the firefighters studied and may not be universally applicable. Therefore, we should be very cautious when applying the findings to other populations or situations.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12671-024-02352-3.

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Data Availability The data is not publicly available due to the ethical restrictions for collecting data from the vulnerable population.

Declarations

Ethics Statement The study was approved by the Institutional Review Board at the University of Houston (IRB ID: CR00000529).

Informed Consent All participants provided their informed consent before participating in the study.

Use of Artificial Intelligence AI tool ChatGPT-4 was used to check grammar and improve English language (OpenAI, 2023).

Conflict of Interest None.

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