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Connecting the dots: A network approach to post-traumatic stress symptoms in Chinese healthcare workers during the peak of the Coronavirus Disease 2019 outbreak

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Abstract

Healthcare workers are at elevated risk to develop symptoms of post-traumatic stress disorder (PTSD) in response to an outbreak of a highly infectious disease. The current study set-out to model the complex interrelations between PTSD symptoms during the peak of the Coronavirus Disease 2019 outbreak in 291 Chinese healthcare workers and 291 matched control cases that were selected from the general population. For this purpose, we estimated regularized partial correlation networks. Within the network of healthcare workers, we observed a central role for avoidance of reminders of the traumatic event, physiological cue reactivity, anger/irritability, re-experiencing, and startle. We identified three clusters of closely interconnected PTSD symptoms in healthcare workers, consisting of (a) symptoms of re-experiencing and anxious arousal, (b) symptoms of avoidance and amnesia and (c) symptoms of emotional numbing and dysphoric arousal. Respectively, startle, avoidance of reminders and feeling detached emerged as bridging nodes in these communities. Although yielding highly similar network models, the PTSD symptom structure of healthcare workers showed several unique features compared to the matched control sample. This is informative for interventions aimed at targeting PTSD symptoms in healthcare workers in the context of a public health emergency.

KEYWORDS

COVID-19, healthcare workers, network analysis, PTSD, stress, symptom structure

1 | INTRODUCTION

In December 2019, the world was confronted with a new type of coronavirus, SARS-CoV-2, which is known to cause Coronavirus Disease 2019 (also referred to as 'COVID-19'). Following a rapid spread of the virus within and outside the borders of the People's Republic of China, many nations resided to far-reaching containment measures, which among other things included restricting the time spent outside and (medical) self-isolation/quarantine. On the 11th of March 2020, the World Health Organization (WHO) categorized the COVID-19 outbreak as a pandemic (WHO, 2020). The pandemic revealed how vulnerable our economic and health care systems are, depending on the availability of hospital beds, scarce medical equipment, and—not the least—the dedication and (mental) health of healthcare workers.

In line with previous coronavirus outbreaks (e.g., Severe Acute Respiratory Syndrome, or 'SARS'; Middle East Respiratory Syndrome, or 'MERS'), the recent COVID-19 outbreak has been linked to an increase in mental health complaints. In this context, it has been suggested that the COVID-19 pandemic could be considered as a

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traumatic event, resulting in increased prevalence of post-traumatic stress disorder (PTSD) symptoms (e.g., Forte, Favieri, Tambelli, & Casagrande, 2020). Healthcare workers may be at particular risk (e.g., Boyraz & Legros, 2020; Chew et al., 2020; DePierro, Lowe, & Katz, 2020), working at the frontline of what was referred to as 'the war against COVID-19'. That is, relative to other professions, healthcare workers are exposed to a high risk of infection, working under highly challenging conditions (e.g., increased workload, exposure to patients' negative emotions and mortality, inadequate protection from contamination and sleep deprivation), while being isolated from family and friends. Indeed, previous studies suggest that coronavirus outbreaks are likely to have a detrimental impact on mental well-being among healthcare workers. For instance, among a sample of healthcare workers who were active during the Hong Kong 2003 SARS outbreak, 68% reported significant job-related stress, with a total of 57% reporting elevated psychological distress (Tam, Pang, Lam, & Chio, 2004). Moreover, Maunder et al. (2004) reported elevated levels of PTSD symptoms in healthcare workers whom had been exposed to SARS patients, where findings pointed towards the importance of experienced job stress, social isolation, and health related anxiety. Similarly, following up on the psychological impact of an outbreak of MERS on healthcare workers, Lee, Kang, Cho, Kim, and Park (2018) suggested a direct relation between exposure to patients infected with MERS and level of PTSD symptoms. This is in line with findings from the most recent coronavirus outbreak, where around the globe elevated levels of PTSD symptoms have been reported in healthcare workers (e.g., Chew et al., 2020; Di Tella, Romeo, Benfante, & Castelli, 2020; Song et al., 2020; Wu & Wei, 2020).

As a result, it has been argued that coronavirus outbreaks require prompt and continuous mental health intervention (Lee et al., 2018). Such efforts seem of particular importance given that COVID-19 also negatively impacted accessibility of mental healthcare services (Castro & Perlis, 2020). Indeed, throughout the course of the COVID-19 pandemic several initiatives have been suggested to treat or prevent the occurrence of PTSD symptoms, where specific recommendations have been made for healthcare workers (e.g., Wu & Wei, 2020). At the same time, however, relatively little is known regarding how PTSD symptoms manifest within healthcare workers in the context of COVID-19, and in particular, how individual PTSD symptoms relate to one another. Such knowledge may be informative for interventions aimed at preventing or treating PTSD symptoms in healthcare workers. In this context, the network approach to psychopathology may be of particular interest (Hofmann, Curtiss, & McNally, 2016).

Relying on Markov Random Fields (Kindermann & Snell, 1980), the network approach to psychopathology conceptualizes disorders as complex networks of interacting symptoms (also referred to as 'nodes'; Borsboom & Cramer, 2013), where activation of one node may result in activation of more distal nodes in the network via intermediate nodes. For instance, in the context of PTSD anxious arousal could result into poor sleeping quality, which could further feed into having difficulties concentrating throughout the course of the day. Having difficulties concentrating has shown to increase anhedonia, which itself further predicts future concentration difficulties (e.g., Greene, Gelkopf, Epskamp, & Fried, 2018). As such, the development of PTSD could be considered as the activation of a complex network of interacting nodes, each of which may directly or indirectly activate one another (McNally et al., 2015).

Interestingly, recent findings suggest that PTSD symptom networks show high similarity across samples. For instance, Fried et al. (2018) demonstrated that network models that were obtained from different samples were highly related in terms of network structure and indicators of centrality (as indicated by correlations ranging between 0.62 and 0.75). This finding suggests that the network approach to PTSD symptoms shows high replicability (Fried et al., 2018). At the same time, however, it has been argued that PTSD symptom structures may differ, depending on type of trauma and type of population under investigation. For instance, in a recent systematic review, Birkeland , Green, and Spiller (2020) identified 20 studies investigating the interrelation between PTSD symptoms in a broad range of samples, including different trauma types (e.g., combat-related, Phillips, Wilson, Sun, Mid-Atlantic MIR-ECC Workgroup, & Morey, 2018; following a motor cycle accident, sexual assault or sudden death, Benfer et al., 2018; mass violence, Birkeland & Heir, 2017; or natural disaster, McNally et al., 2015). Birkeland et al. (2020) reported substantial heterogeneity in terms of which nodes took a more central position in the obtained network models across different samples. In this context, it has been suggested that different trauma types may result in distinct PTSD symptom patterns (Kelley, Weathers, McDevitt-Murphy, Eakin, & Flood, 2009; Stein, Wilmot, & Solomon, 2016). Importantly, as to date no study has investigated the interrelation between PTSD symptoms in the context of exposure to a highly infectious disease, warranting study of the structure of PTSD symptoms in the context of COVID-19 as this may advance our understanding of the recently observed elevated levels of PTSD symptoms in healthcare workers.

1.1 | Current study

In order to gain a better understanding of the complex interplay between stress-related complaints in healthcare professionals, we assessed the presence of PTSD symptoms in Chinese healthcare workers during the (local) peak of the first COVID-19 outbreak. Our first aim was to explore the structure and centrality of PTSD symptoms in healthcare workers amidst the COVID-19 outbreak. A second aim of the study was to identify clusters of PTSD symptoms that were more closely connected to one another in this specific at-risk population, as previous findings suggest that exposure to different types of trauma may result in a different (latent) structure of PTSD symptoms (Shevlin & Elklit, 2012). Our third exploratory aim was to model the extent to which the interplay of PTSD symptoms in healthcare workers differed from the interplay of PTSD symptoms in a matched control sample (i.e., due to differences in the level of exposure to COVID-related stressors and the different nature of COVID-related stressors healthcare workers are exposed to).

In particular, we aimed to model unique associations between PTSD symptoms in staff working under highly stressful conditions in a healthcare context, relative to a matched control condition, as well as differences between both groups in the extent to which PTSD symptoms took a central position in the network model (i.e., node centrality). Such knowledge is likely to increase our understanding of the aetiology of stress-related symptoms in healthcare workers, and may aid the development of preventative measures aimed at maintaining mental health of healthcare workers upon confrontation with an outbreak of a highly infectious disease.

2 | MATERIAL AND METHODS

2.1 | Participants

This study is part of a larger project which was launched to monitor the psychological responses of people living within the People's Republic of China to the first outbreak of the COVID-19 pandemic. The aim of this project was to investigate people's psychological response and emotional reactions in the presence of major health crises (Chen et al., 2020). The current study is limited to exploration of the network structure of PTSD complaints within Chinese healthcare workers amidst the peak of the COVID-19 pandemic. Participants were recruited via the Wenjuanxing online platform (www.wjx.cn). This platform offers functions equivalent to Amazon Mechanical Turk. Interested participants with Chinese nationality were recruited from all 34 provinces and areas of China, including Hongkong, Macau, and Taiwan. In order to be eligible for participation to the study, participants needed to hold the Chinese nationality, be 18–70 years old, should be able to read and write Chinese and have access to a computer or smartphone with Internet. 13,667 participants started the data-collection procedure for the larger project, of which 2957 did not complete the assessments and were excluded from analyses. Given the specific focus of the current study, investigating the complex associations between PTSD symptoms in healthcare workers during the peak of the COVID-19 outbreak, following groups were excluded from data-analysis: 34 patients, 2300 adolescents (<18 years old) and 69 healthcare workers which completed the questionnaire outside the peak of the (local) COVID outbreak (i.e., in a region where COVID cases were decreasing). This resulted in a sample of 8307 participants, among which 291 Chinese healthcare workers who completed the assessment procedure during the peak of the COVID-19 outbreak. Healthcare workers are defined as people who directly (e.g., doctors and nurses) or indirectly (e.g., aides/helpers, laboratory technicians and hospital administrative staff) provide services to the sick within a healthcare setting (e.g., Joseph & Joseph, 2016). In the context of COVID-19, this group also included staff from Centers for Disease Control and Prevention as well as military medical staff.

In addition, for exploratory purposes, we modelled the unique characteristics of the PTSD network structure and centrality of Chinese healthcare workers compared to a control condition consisting of people who are not employed in a healthcare setting, nor deliver healthcare services. For this purpose, we selected control cases from the remaining pool of 8016 non-healthcare workers. The study protocol was approved by the Human Research Ethics Committee of the Army Medical University (Chongqing, People's Republic of China) and all participants provided informed consent.

2.2 | Material

2.2.1 | Demographic and COVID-19 related information

Participants completed items assessing their age, gender, educational level, profession, marital status, area of residence and state of quarantine measures taken. Based on the number of confirmed cases within a region—obtained via the report of the National Health and Health Commission of China—cities were divided into six categories reflecting the impact of the epidemic within these regions (confirmed cases within a region <10, 10–99, 100–499, 500–999, 1000–9999 and ≥10,000).

2.2.2 | Severity of PTSD symptoms

A recent systematic review of PTSD symptom networks (Birkeland et al., 2020) indicates that the PTSD CheckList (PCL; Weathers, Litz, Herman, Huska, & Keane, 1993) has been most frequently used to model the complex interrelations between PTSD symptoms. The PTSD CheckList Civilian version (PCL-C; Blanchard, Jones-Alexander, Buckley, & Forneris, 1996; Weathers et al., 1993) also emerged as one of the most widely used measures to study PTSD symptoms among the Chinese population during the COVID-19 outbreak (e.g., Liang et al., 2020b, 2020a; Wu & Wei, 2020). In line with these studies, the current study relied on the Chinese version of the PCL-C to assess severity of PTSD symptoms during the COVID-19 outbreak.

The PCL-C contains 17 items corresponding to the symptoms for PTSD (e.g., '*Repeated disturbing dreams of a stressful experience from the past*') as defined in the DSM-IV (American Psychiatric Association, 2000). Items were rated using a five-point Likert scale ranging from one (not at all) to five (extremely), resulting in total PCL-C scores ranging from 17 to 85. Higher PCL-C scores reflect the presence of more severe PTSD symptoms during the month preceding the assessment, with scores ranging between 30 and 44 typically seen as indicative for moderate to moderately high severity, and scores ≥45 indicative of high severity of PTSD symptoms. The Chinese version of the PCL-C has demonstrated excellent internal consistency and convergent validity (Li et al., 2010; Yang, Yang, Liu, & Yang, 2007). The internal consistency of the PCL-C was excellent in the current study (healthcare workers: Cronbach's α = 0.92; matched control cases: Cronbach's α = 0.90).

2.3 | Procedure

Data collection took place between the 11th and 25th of February, 2020. Eligible participants entered the online survey via the Wenjuanxing platform. After providing informed consent, participants completed the demographic items and items related to the quarantine measures in place. Next, participants completed multiple questionnaires among which the PCL-C. Upon completion of the survey, all participants were provided an online health report and access to free psychological support (e.g., free consultations) organized by the Department of Medical Psychology of the Army Medical University. In addition to this form of compensation for participation to the study, a random 20% of the participants received monetary reimbursement (ranging between 10 and 100 yuan RMB).

2.4 | Statistical analyses

All analyses were conducted in R, version 3.6.1 (see supplemental materials for more detailed version information on all packages used; the corresponding R scripts and PTSD-symptom datasets are stored open access at Open Science Framework, osf.io/xp8hd/).

2.4.1 | Propensity score matching

We used propensity score matching—a technique where for each ‘treatment case’ one or more matched ‘control cases’ are selected based on a propensity score (Adelson, 2013)—to obtain a control group consisting of participants that were to a similar extent affected by COVID-19 and showed high similarity to the group of healthcare workers in terms of demographic variables, but were not employed in a healthcare setting. The propensity score refers to the probability of being in a given condition (i.e., healthcare worker) given a set of observed variables. Using the *MatchIt* package (Ho, Imai, King, Stuart, & Whitworth, 2018), we relied on the nearest neighbour method to match healthcare workers with control cases (ratio 1:1) based on age, gender, marital status, amount of confirmed COVID-19 cases in the area of residence, and quarantine status of the participant.

2.4.2 | Network analysis

Network estimation, centrality, and visualization

To model the unique associations between each of the PTSD symptoms included in the PCL-C, we estimated a Gaussian Graphical Model (GGM). Each of the PTSD symptoms appear in the model as nodes, with edges representing the partial correlations between each of the nodes. The GGM was estimated using the *qgraph* package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012), where we relied on the graphical Least Absolute Shrinkage and Selection Operator (Friedman, Hastie, & Tibshirani, 2014) to shrink small associations, likely reflecting spurious relations, to zero. We relied on the Extended Bayesian Information Criterion (EBIC) to select the model with the best fit. Hyperparameter γ was set at 0.5 (for a detailed discussion on estimation of GGMs, see Epskamp & Fried, 2018).

We plotted the obtained GGM with *qgraph*, where we relied on a modification of the Fruchterman-Reingold's algorithm (Fruchterman & Reingold, 1991) which aims to position nodes in the network based on their level of connectivity, with less connected nodes appearing more in the periphery of the model (but see Jones, Mair, & McNally, 2018). Edges reflect (regularized) partial correlations, with edge thickness corresponding to the strength of association. The colour of the edge represents the valence of the association, with blue edges reflecting positive associations and red edges reflecting negative associations. Given that the GGM is undirected, the edges do not allow interpretation of direction of effects. To foster comparison with previous literature, we used the same labels for nodes included in the network as Birkeland and Heir (2017) and Birkeland, Blix, Solberg, and Heir (2017), where items 1:5 were labelled R1:R5, reflecting symptoms related to re-experiencing the stressful event. Items 6 and 7 were labelled A1:A2, reflecting avoidance symptoms. Items 8:12 were labelled N1:N5, reflecting symptoms of emotional numbing, whereas items 13:15 were labeled DA1:DA3, reflecting symptoms of dysphoric arousal. Finally, items 16:17 were labelled AA1:AA2, reflecting symptoms of anxious arousal.

We estimated one-step expected influence (Robinaugh, Millner, & McNally, 2016), further referred to as ‘expected influence’, to examine which nodes take a more central role (i.e., are more influential) in the network model of PTSD symptoms. In contrast to other frequently used indicators of node centrality (e.g., Strength), expected influence takes into account the valence of the edges. This is important given that nodes with both positive and negative edges may be highly central in a network, while exercising relatively little influence in terms of activation of the symptom network. Expected influence aims to reflect the strength of the cumulative influence of a node within the network model (e.g., the extent to which activation of the node may result in further activation of the network; Robinaugh et al., 2016). For this purpose, for each node in the model expected influence is calculated as the summed weight of edges between that node and all directly connected nodes, taking into account the valence of the edges. In addition, we estimated the proportion of variance of each node that is explained by its neighboring nodes, also referred to as ‘node predictability’ (Haslbeck & Fried, 2017), using the *mgm* package (Haslbeck & Waldorp, 2017). Node predictability was plotted as a pie chart in the outer ring of each node.

Community detection and bridge expected influence

In order to identify clusters or ‘communities’ within the GGM, we used exploratory graph analysis (Golino & Epskamp, 2017). In particular, we relied on the *EGAnet* package (Golino, Christensen, & Moulder, 2020), which uses the walktrap algorithm (Pons & Latapy, 2005) to identify the optimal number of subnetworks within the GGM. These subnetworks form communities within the graph representing patterns of strong interconnectivity between symptoms

(Golino & Epskamp, 2017). To allow identification of the most influential bridging nodes, we estimated 'bridge expected influence' using the package *networktools* (Jones, 2020), referring to the extent to which an edge within a given community is directly connected to edges from other communities, acting as bridges between different communities. Indicators of node centrality (expected influence and bridge expected influence) were standardized to facilitate interpretation.

Network comparison

We used Pearson correlations to estimate how similar the adjacency matrices of the healthcare workers and matched control group were. In order to identify unique edges within the GGM obtained for healthcare workers relative to the matched control group, we used the *NetworkComparisonTest* package (van Borkulo, Epskamp, & Millner, 2016). In particular, we used permutation tests to test for significant differences between both networks at a single-edge level and at the level of node centrality. In addition, we tested whether the obtained networks significantly differed in terms of global network structure (structure invariance) or overall strength of connectivity (global strength invariance; van Borkulo et al., 2017). In order to correct for multiple comparisons, we used False Discovery Rate correction (Benjamini & Hochberg, 1995).

Evaluation of network properties

Following bootstrapping procedures described by Epskamp, Borsboom, and Fried (2018), we used *bootnet* (Epskamp & Fried, 2015) to model sampling variability in edge weights ('edge accuracy') and the stability of the centrality indices used. In particular, we used a case-dropping subset bootstrap to model the degree to which the order of (bridge) expected influence remained stable in subsets of the data. In order for centrality indices to be deemed stable, the obtained correlation stability coefficient should not be < 0.25 and preferably be ≥ 0.50 (Epskamp et al., 2018). In addition, we examined significant differences between edge weights.

3 | RESULTS

3.1 | Sample characteristics

The analyses pertaining the symptom structure of PTSD in healthcare workers are based on a sample of 291 healthcare workers employed in regions affected by COVID-19 in China. In addition, 291 matched control cases were selected from a pool of 8016 participants based on propensity scores. Demographic information and information regarding the extent to which both populations were affected by measures taken to prevent the spread of COVID-19 are reported in Table 1. Importantly, among the healthcare workers and matched control cases, 19.24% and 20.27% obtained a PCL-C score ≥ 30 respectively, suggesting the presence of at least moderately severe PTSD symptoms. Supplemental Figures 1 and 2 provide an overview of the distribution of propensity scores in the group of healthcare workers and matched control group. Following the matching procedure, the densities of propensity scores were highly similar for both samples, suggesting that the method used yielded a set of highly comparable control cases relative to the group of healthcare workers. In line with this, results from Pearson Chi-Square tests suggest that both groups did not significantly differ in terms of gender ratio ($\chi^2 = 0.62$, $p = 0.43$) or educational level ($\chi^2 = 0.04$, $p = 0.85$). In addition, using Fisher's Exact Tests, no significant group differences were observed for age group ($p = 0.35$), quarantine status ($p = 0.10$), or amount of confirmed COVID-19 cases in the region ($p = 0.07$). However, we did observe a significant group difference in marital status ($p < 0.01$, Fisher's Exact Test). Importantly, both groups did not differ in terms of severity of PTSD symptoms (t (580) = 0.20, $p = 0.84$).

3.2 | Aim 1: Network structure and centrality of PTSD symptoms in healthcare workers

Our first aim was to explore the structure and centrality of PTSD symptoms in healthcare workers amidst the peak of the COVID-19 outbreak. Figure 1 depicts the obtained GGM. The observed edges between A1 (Avoidance of thoughts)–A2 (Avoidance of reminders), and DA2 (Irritable/Angry)–DA3 (Difficulty concentrating) were among the strongest edges in the model. With corresponding edge weights of 0.51 and 0.45, these edges were significantly stronger than respectively 84% and 59% of the other observed edges in the model. With the exception of these edges and the negative edge between R1 (Intrusive thoughts) and N2 (Loss of interest; edge weight = –0.06), none of the other edge weights significantly differed from ≥50% of the observed edges in the model (see Supplemental Figure 3 for significant edge differences). Related to this, A2 (Avoidance of reminders) emerged as the most central node in the model in terms of expected influence, followed by R5 (Physiological cue reactivity), AA2 (Easily startled), R3 (Reliving trauma) and DA2 (Irritable/angry; Figure 2). N1 (Trauma-related amnesia) was the least central node in the model (Figure 2).

This was also reflected by levels of node predictability, the amount of explained variance of a node by its neighbouring nodes (Figure 1). That is, node predictability was lowest for N1 (Trauma-related amnesia; 29.40%). In contrast, most variance was explained for A2 (Avoidance of reminders; 65.40%), AA2 (Easily startled; 62.50%), DA2 (Irritable/angry; 62.40%) and R3 (Reliving trauma; 58.50%). On average, for the PTSD symptoms included in the model, 50.99% of variability was explained by neighboring nodes (for evaluation of network properties, see supplemental material).

3.3 | Aim 2: Detection of communities within the network of healthcare workers

Our second aim was to identify clusters of PTSD symptoms that were more closely connected to one another in healthcare workers in the

TABLE 1 Descriptive statistics

Variable	*Healthcare workers (N = 291)*	*Matched controls (N = 291)*
Age group (in years; ratio <20: 20–29: 30–39: 40–49: 50–59: ≥60)	1: 139: 89: 52: 8: 2	5: 140: 89: 41: 14: 2
Gender (ratio female: male)	220: 71	229: 62
Educational level (ratio college: postgraduate or higher)	218: 73	221: 70
Marital status (ratio married: unmarried: divorced: widowed)	166: 119: 6: 0	127: 157: 6: 1
Level of quarantine (ratio no quarantine: home quarantine with outgoing: home quarantine without outgoing: centralized isolation: medical isolation or hospitalization)[a]	263: 1: 27: 0: 0	249 : 5: 37 : 0: 0
Confirmed cases in city or area (ratio <10: 10–99: 100–499: 500–999: 1000–9999: ≥10,000)	1: 8: 112: 121: 32: 17	0: 3: 117: 100: 50: 21
Severity of PTSD symptoms (*M* [*SD*])	24.33 [7.94]	24.20 [7.56]

Abbreviation: PTSD, post-traumatic stress disorder.

[a]Centralized isolation refers to the use of quarantine centers.

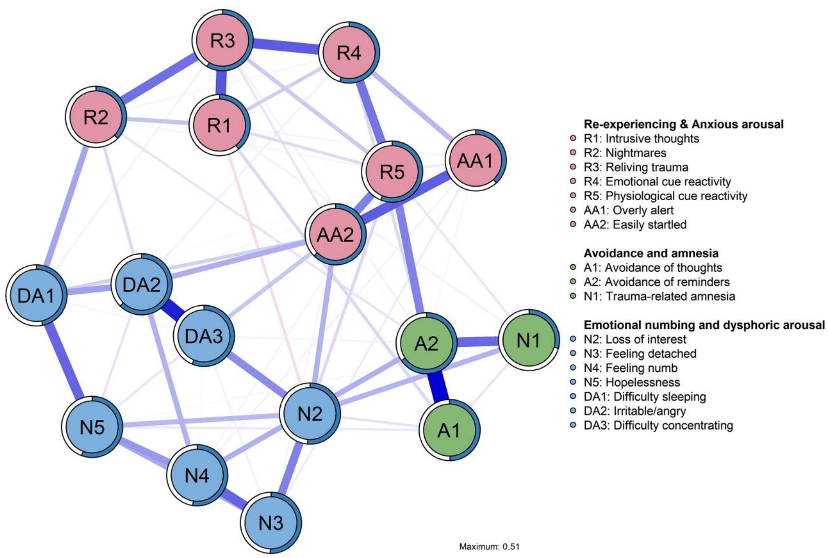

FIGURE 1 Regularized partial correlation network model for the post-traumatic stress disorder symptom structure in Chinese healthcare workers during Coronavirus Disease 2019

context of COVID-19. We detected three communities in the network model, as depicted in Figure 1, each of which reflect increased levels of interconnectivity of the nodes within the community. To clarify the role of specific PTSD symptoms in connecting each of the obtained communities with one another, we relied on bridge expected influence (Figure 3), referring to the immediate influence of the node within a given community, on nodes of distinct communities.

A first community consisted of PCL-C items 1 to 5 (R1:R5), in addition to items 16 and 17 (AA1:AA2), reflecting symptoms related to re-experiencing the stressful event as well as anxious arousal. Within this community, AA2 (Easily startled) emerged as the node with the highest bridge expected influence, exerting the strongest bridging influence on nodes from other communities. Vice versa, given the undirected nature of the network, AA2 is also most likely of being impacted by nodes from other communities. Of all nodes, R1 (Intrusive thoughts) showed lowest bridge expected influence.

A second community consisted of symptoms of dysphoric arousal (DA1:DA3) and emotional numbing (N2:N5). Within this community, N3 (Feeling detached) and N2 (Loss of interest) scored highest on bridge expected influence. In addition, these nodes emerged as one of the strongest bridging nodes in the entire model.

The third and smallest community consisted of avoidance symptoms (A1:A2) and trauma-related amnesia (N1). In this community, A2 (Avoidance of reminders) emerged as the strongest bridging node, linking symptoms of avoidance and amnesia with symptoms of emotional numbing and dysphoric arousal, as well as symptoms of re-experiencing and anxious arousal.

3.4 | Aim 3: Exploration of unique PTSD symptom associations and node centrality in healthcare workers compared to non-healthcare workers in the context of COVID-19

Our third aim was to model how the obtained PTSD symptom structure and indicators of node centrality in healthcare workers relate to the structure and centrality of PTSD symptoms in non-

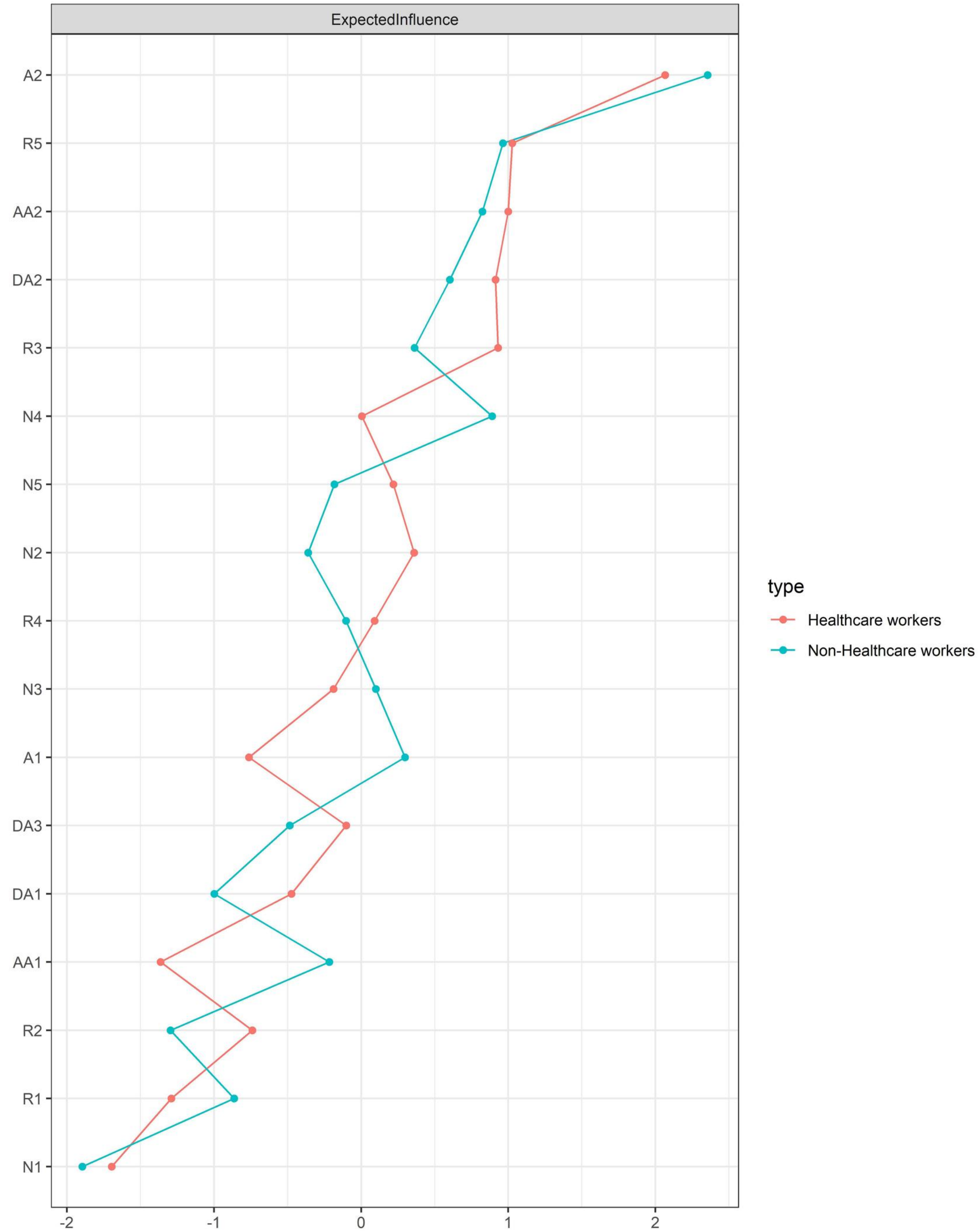

FIGURE 2 Expected influence for post-traumatic stress disorder symptoms in Chinese healthcare workers and matched controls during Coronavirus Disease 2019

healthcare workers amidst the COVID-19 crisis, as this allows to identify patterns of associations between PTSD symptoms in healthcare workers that are potentially unique for this specific population. The obtained weight matrix for the matched control group showed high similarity to the weight matrix obtained from the group of healthcare workers ($r = 0.62$; see supplemental Figure 6 for both network structures). In line with this, both groups did not significantly differ in terms of global network structure (structure invariance: $M = 0.19$, $p = 0.87$) or strength of connectivity (strength invariance; healthcare workers = 7.69, matched control group = 7.45; $S = 0.24$, $p = 0.30$). Interestingly, on a single-edge level, we did find evidence for differences between both groups. That is, after controlling for multiple comparisons the group of healthcare workers showed a unique positive association between N2 (Loss of interest) and DA3 (Difficulty concentrating; $p < 0.001$). In addition, the control condition showed a unique association between A1 (Avoidance of

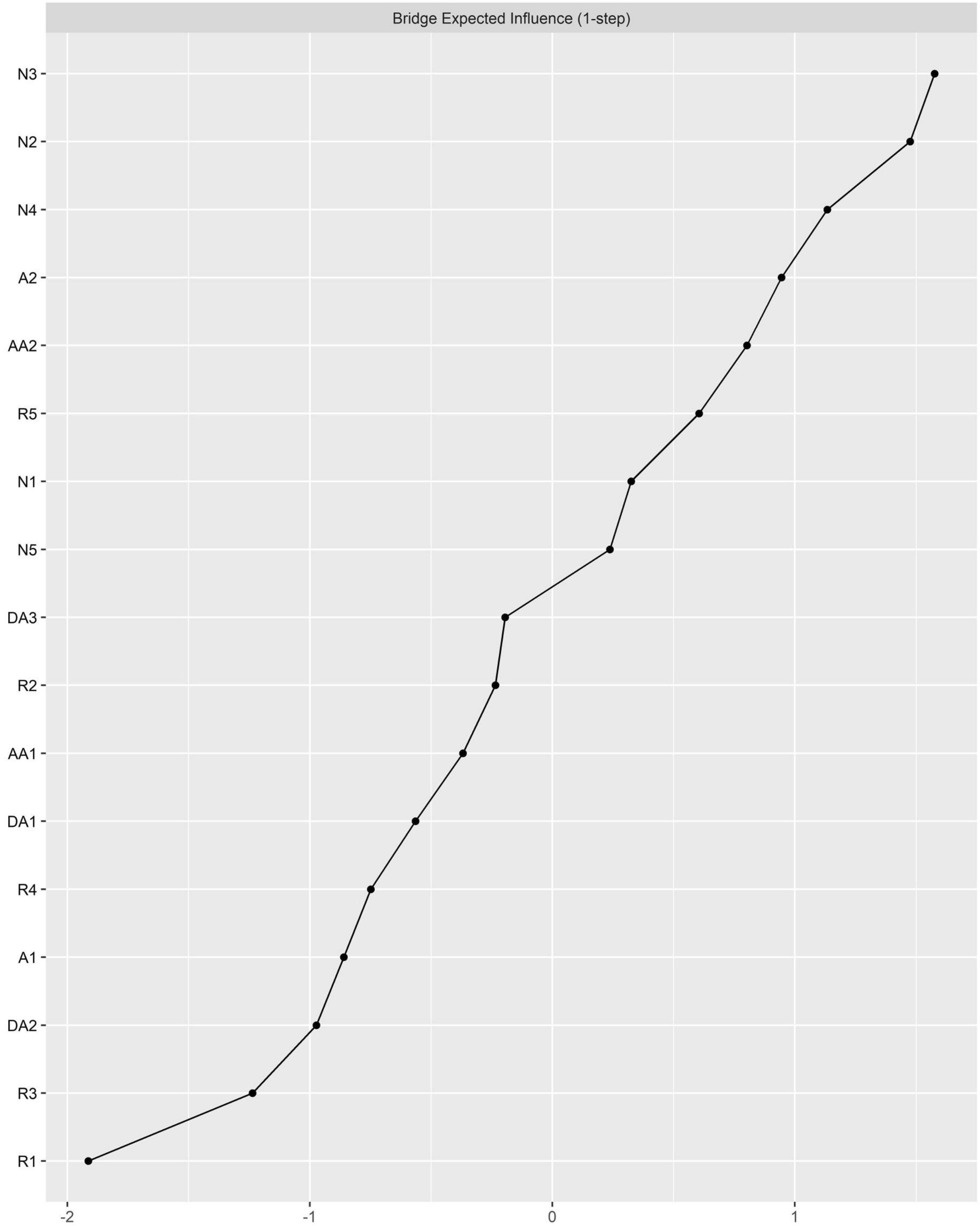

FIGURE 3 Bridge expected influence of post-traumatic stress disorder symptoms in healthcare workers during Coronavirus Disease 2019

thoughts) and AA1 (Overly alert; $p < 0.001$) which was not present in the group of healthcare workers. Related to this, both groups also differed in terms of node centrality, where node A1 (Avoidance of thoughts) scored significantly lower on Expected Influence in the group of healthcare workers compared to the matched control condition ($p < 0.001$), suggesting that this symptom obtained a less central position in the PTSD symptom structure of healthcare workers (Figure 2; for all other nodes, $p > 0.33$).

4 | DISCUSSION

The COVID-19 pandemic has shown to exert an unprecedented global impact on mental well-being (González-Sanguino et al., 2020), where it has been suggested that healthcare workers may be at particular risk for the development of PTSD symptoms (Chew et al., 2020; Di Tella et al., 2020; Song et al., 2020; Wu & Wei, 2020). However, as to date little is known regarding the constellation of

PTSD symptoms in healthcare workers who are faced with an outbreak of a highly infectious disease such as COVID-19, whereas such knowledge would be informative to interventions targeting PTSD symptoms in this specific population. Compared to PTSD symptom networks reported in previous literature, investigation of the network structure and centrality of PTSD symptoms in healthcare workers in the context of COVID-19 (Aim 1) suggests the presence of both shared as well as unique network features. In addition, our findings point towards the presence of three subnetworks (communities) of closely related PTSD symptoms (Aim 2), where analysis of bridge expected influence provides novel insights in how patterns of activity within parts of the PTSD symptom network may result in activation of more distal nodes in healthcare workers in the context of COVID-19. Third, within the context of COVID-19, small differences in network structure and node centrality emerged between the group of healthcare workers and matched control cases that were selected from the general population (Aim 3). This suggests that working in a healthcare setting in the context of COVID-19 may result in a specific pattern of interrelations between PTSD symptoms, resulting in differences in the extent to which nodes hold a central position within the network. We discuss each of these findings in more detail below.

A first aim of this study was to model the structure and centrality of PTSD symptoms of Chinese healthcare workers during the peak of the first COVID-19 infection. A review of studies in which the PTSD symptom structure was investigated in response to different trauma types using DSM-IV-based measures (e.g., Bryant et al., 2017; Fried et al., 2018; McNally, Heeren, & Robinaugh, 2017; McNally et al., 2015; Phillips et al., 2018), suggests that PTSD symptom networks typically show strong associations between symptoms of hypervigilance and startle (AA1–AA2), feeling detached, loss of interest (N3–N2) and restricted range of affect/feeling numb (N3–N4; Birkeland et al., 2020). In addition, strong associations are typically observed between avoidance of thoughts and reminders of trauma (A1–A2), intrusive thoughts and dreams (R1–R2), as well as between the presence of recurrent dreams of trauma and experienced difficulties sleeping (R2–DA1; Birkeland et al., 2020). Importantly, these associations are also typically observed in studies using PTSD measures which are aligned with the DSM-5 criteria of PTSD (American Psychiatric Association, 2013; e.g., Armour, Fried, Deserno, Tsai, & Pietrzak, 2017; Bartels et al., 2019; Gay, Wisco, Jones, & Murphy, 2020; Moshier et al., 2018; Ross, Murphy, & Armour, 2018; for a review, see; Birkeland et al., 2020). In line with these findings, within our sample of healthcare workers in the context of COVID-19, the observed edge between avoidance of thoughts and reminders of trauma (A1–A2) emerged as one of the strongest edges in the network (Figure 1, Supplemental Figure 3). In addition, each of the other edges mentioned above (AA1–AA2, N2–N3, N3–N4, R1–R2, R2–DA1) were also observed in the current study, albeit that these edges did not significantly differ from most of the other edges in the model in terms of strength of connectivity. Additionally, a strong edge was observed between symptoms of irritability and having difficulties concentrating (DA2–DA3).

These findings suggest that the structure of PTSD symptoms obtained in healthcare workers in the context of COVID-19 shows high similarity with the structure of PTSD symptoms obtained in previous studies (using different populations, including multiple trauma types, and use of different PTSD measures). At the same time, however, the structure and centrality of PTSD symptoms in the context of COVID-19 also seem to show unique features which are typically not observed in studies exploring the structure and centrality of PTSD symptoms in response to other trauma types. For instance, in a sample exploring centrality of PTSD symptoms in the context of mass violence, Birkeland and Heir (2017) found feeling numb (N4) and concentration difficulties (DA3) to be the most influential nodes in the network, albeit based on strength centrality. Moreover, a systematic review of DSM-IV PTSD symptom networks suggests that having recurrent thoughts about the traumatic event (R1) is typically one of the most central nodes in PTSD symptom networks (Birkeland et al., 2020). These nodes (N4, DA3, R1) did not appear among the most influential nodes in our sample of healthcare workers (Figure 2). In contrast, intrusive thoughts regarding the traumatic event (R1) was ranked closely to the least influential node in our model (trauma-related amnesia, N1).

Instead, avoidance of activities or situations that remind one of the stressor (A2) emerged as the most influential symptom in our network of PTSD symptoms of healthcare workers (Figure 2). As to date, avoidance of reminders of the stressor has only emerged as one of the top three central nodes in two out of 19 PTSD studies using symptom constellations as defined in the DSM-IV (Phillips et al., 2018; Russell, Neill, Carrion, & Weems, 2017; cf. Birkeland et al., 2020). Other highly influential nodes within the network model for healthcare workers mostly related to re-experiencing the traumatic event and anxious arousal. For instance, symptoms of physiological cue reactivity (R5), being easily startled (AA2), and reliving the traumatic event (R3) closely followed avoidance of reminders (A2) in terms of expected influence (Figure 2). Similarly, feeling irritable/angry (DA2), from the cluster of symptoms related to emotional numbing and dysphoric arousal, also scored high in terms of expected influence. Importantly, whereas several previous studies provide support for the central role of physiological cue reactivity (R5; five out of 19 studies) and being easily startled (AA2; four out of 19 studies), feeling irritable or angry (DA2) did not appear among the top three most influential nodes in any of the previous studies investigating PTSD symptom structures based on the DSM-IV (Birkeland et al., 2020). Instead, in nine out of 19 studies—among which networks obtained from clinical, community, and veteran samples—feeling irritable or angry (DA2) was ranked among the top three least influential nodes in the model. Similar findings were obtained for studies relying on DSM-5 criteria for PTSD (Birkeland et al., 2020), suggesting that this finding may be highly specific to the COVID-19 context. Similarly, across different DSM-versions used, more studies have reported reliving of the traumatic event (i.e., flashbacks, R3) to be among the least rather than the most central nodes in the PTSD symptom network (Birkeland et al., 2020; but see for instance Armour et al., 2017). This was also reflected by relatively high levels of predictability of these nodes in the model (Figure 1), indicating that a substantial amount of variance in these nodes was explained by neighboring nodes. Together, these findings suggest that, in contrast to most other community PTSD samples where different nodes have shown to hold a more influential position, targeting avoidance behaviour, physiological cue reactivity, anger/irritability, reliving of the traumatic event, and anxious arousal may be one of the most efficient ways to impact the entire symptom network.

The observed discrepancy between centrality of PTSD symptoms in the current study and previous studies could potentially be explained by the specific nature of the stressor under investigation and specific sampling characteristics. That is, during the first outbreak of COVID-19, healthcare workers were exposed to patients' negative emotions and mortality, in a context of scarcity of medical equipment, resulting in inability to provide adequate patient care. In addition, during the peak of the COVID-19 outbreak, healthcare workers were expected to perform their tasks under high work pressure (e.g., Tam et al., 2004) and in a condition of sleep deprivation, without adequate protection from contamination, putting oneself and direct contacts of the healthcare worker at-risk. Together, this is highly likely to prompt negative affect, among which agitation, feelings of anger and irritability. The presence and influential role of reliving traumatic events, such as flashbacks, could also potentially be explained by working conditions. For instance, a study investigating the occurrence of flashbacks among emergency nurses suggests that being involved in resuscitations in the past week in combination with other work related stressors (e.g., work conflicts) were predictive for higher occurrence of reliving the traumatic event (Kleim, Bingisser, Westphal, & Bingisser, 2015). Work conflicts are more likely to occur under situations of high work pressure. Another explanation for these findings – and high similarity in network models obtained from healthcare workers and matched control cases (cf. aim 3, further discussed below) – is that the stressor was still ongoing at the time of investigation without perspectives on progress in the near future. Instead, given the global nature of the pandemic, at the time of data collection the societal impact of COVID-19 and related concerns were likely to increase. Indeed, other studies which investigated the impact of ongoing stressors on the structure of PTSD symptoms also observed a central role for flashbacks (e.g., between-subjects network) and negative trauma-related affect, albeit not specific for irritability (Greene et al., 2018). In addition, the central role of irritability, which was closely connected to having difficulties concentrating (DA3), but also with poor sleep quality (DA1), feeling numb (N4) and indirectly with loss of interest, may also reflect the overall impact of the stressor on participants' mood states (e.g., depressive complaints). Importantly, being in a persistent negative mood state has emerged as one of the most central nodes in PTSD symptom networks based on the DSM-5 (Birkeland et al., 2020). However, this item was only introduced in the more recent version of the DSM, and as such was not included in the current network model. Finally, previous studies have typically investigated centrality of PTSD symptoms using indicators such as Strength centrality (Birkeland et al., 2020), whereas based on Robinaugh et al. (2016) the current study relied on Expected Influence. Importantly, follow-up analyses indicate that within the sample of healthcare workers, use of Strength centrality yielded highly similar findings as Expected Influence in terms of which nodes took a more central position in the network model (Supplemental Figure 7).

A second aim of this study was to explore the presence of subnetworks of PTSD symptoms within the sample of healthcare workers. Our findings suggested the presence of three distinct communities of closely interconnected PTSD symptoms in healthcare workers (Figure 1), reflecting symptoms of (a) re-experiencing and anxious arousal, (b) avoidance and amnesia and (c) emotional numbing and dysphoric arousal. These communities show strong overlap with the factor structure proposed by Simms, Watson, and Doebbeling (2002), which suggests that PTSD symptoms can be categorized in clusters of symptoms reflecting: (a) intrusion or re-experiencing of the traumatic event, (b) avoidance of trauma-related stimuli, (c) hyperarousal and (d) dysphoria. That is, the latter factor consists of symptoms of sleep disturbance (DA1), anger/irritability (DA2), problems concentrating (DA3), trauma-related amnesia (N1), loss of interest (N2), feeling detached (N3), feeling numb (N4) and hopelessness regarding the future (N5). With the exception of trauma-related amnesia (N1), which clustered together with the items of the avoidance factor (A1:A2), each of the proposed symptoms of the dysphoria factor clustered together within one community in the obtained network model. Similarly, our first community holds all items of the intrusion factor (R1:R5). However, in contrast to the four factor solution of Simms et al. (2002), both items of the hyperarousal factor (AA1:AA2) were also part of the community containing symptoms of re-experiencing (i.e., the intrusion factor of Simms et al., 2002). In contrast to the findings of the current study and the model proposed by Simms et al. (2002), it has also been suggested that indicators of emotional numbing (N1:N5) and dysphoric arousal (DA1:DA3) may form two different, yet closely connected, communities (Birkeland & Heir, 2017). These findings seem to suggest that differences between studies in sample characteristics, among which exposure to different trauma types, may result in a different manifestation and (latent) structure of PTSD symptoms (Chung & Breslau, 2008; Shevlin & Elklit, 2012). Indeed, previous network studies suggest that trauma type is an important factor in the ontology of PTSD (Benfer et al., 2018).

In this context, the obtained patterns of bridge expected influence shed light on how activation from one cluster is most likely to spread to other clusters of PTSD symptoms in healthcare workers (Figure 3). For instance, activation of the cluster consisting of symptoms of re-experiencing and anxious arousal seemed most likely to spread into activation of other clusters via feeling jumpy or startled (AA2). Similarly, within the cluster of dysphoria symptoms, as referred to by Simms et al. (2002), indicators of emotional numbing, such as loss of interest (N2) and feeling detached (N3) scored highest in terms of bridge expected influence, whereas avoidance of reminders (A2) emerged as a bridging node in the cluster of avoidance symptoms. This may be informative to clinicians who are confronted with healthcare workers showing specific profiles of activation of stress-related symptoms (e.g., reporting mostly symptoms within the community of dysphoria), where one would like to prevent further activation of the PTSD network.

A final more exploratory aim of this study was to identify unique versus shared associations between PTSD symptoms in healthcare workers compared to a matched control condition consisting of non-healthcare workers in the context of COVID-19, as well as differences in node centrality (Aim 3). The network model obtained from the group of healthcare workers did not significantly differ from the network model obtained from the group of matched control cases in terms of overall level of connectivity or network structure. However, comparison of both models on a single-edge level and in terms of node centrality suggested the presence of several unique features in the PTSD symptom network for healthcare workers compared to the group of matched control cases. That is, after controlling for multiple comparisons, we identified an additional edge within the group of healthcare workers which was situated within the cluster of emotional numbing and dysphoric arousal (N2–DA3). Although the network models are cross-sectional of nature and do not allow to draw conclusions regarding the temporal order and direction of effects, the obtained association between indicators of reduced executive control (e.g., having difficulties concentrating; DA3) and anhedonia (N2) may reflect the development of (comorbid) depressive complaints within healthcare workers (Chew et al., 2020). Second, the general population showed an additional edge between the cluster of avoidance/amnesia and the cluster of re-experiencing/anxious arousal (A1–AA1). This difference between both groups could point towards differences in the extent to which healthcare workers in a state of anxious arousal were able to engage in avoidance of thoughts regarding the stressor (i.e., they were continuously confronted with the stressors during the peak of the COVID-19 outbreak). As a result, avoidance of thoughts (A1) held a less central position in the PTSD symptom network of healthcare workers compared to the matched control sample (Figure 2). However, in both obtained network models avoidance of thoughts (A1) was ranked among the relative less influential nodes, suggesting that this statistical difference between both conditions may be of relatively little clinical importance when targeting PTSD symptoms in the context of COVID-19. That is, the PTSD symptom structure obtained from healthcare workers showed strong overlap with the network model obtained from the matched control sample that was selected from the general population, suggesting that—independent of employment in a healthcare setting—the structure of PTSD symptoms in response to COVID-19 seems to be highly similar. One explanation for this finding is that in both conditions participants were exposed to the presence of a similar stressor (COVID-19), albeit in another role. Moreover, the matched control group was selected to resemble the profile of the healthcare workers in terms of situational factors such as housing condition, quarantine status, and number of infections. Nonetheless, our findings suggest that similar interventions aimed at targeting PTSD symptoms in the context of COVID-19 could be used for healthcare workers and members of the general population.

This study is the first to investigate the structure of PTSD symptoms in the context of COVID-19. A unique feature of this study is the presence of a matched control group, allowing to identify shared versus unique features of the obtained PTSD symptom structure in healthcare workers. Another difference between the current study and previous studies, is that previous studies have typically investigated the interrelation between PTSD symptoms in the months or years following a traumatic event (e.g., Birkeland et al., 2017; Birkeland & Heir, 2017; McNally et al., 2017), whereas in line with Greene et al. (2018) in the current sample the traumatic event was still ongoing. As such, the current structure is more likely to represent how acute stress- and PTSD symptoms may develop in the context of trauma.

This study also has several limitations. A first limitation to this study is the cross-sectional nature of the design, which does not allow to make causal inferences. Related to this, the network models presented in the current study are undirected. As such, obtained edges between nodes may be indicative for the presence of a unidirectional or bidirectional relation between these nodes, where no interpretation should be made regarding the direction of effects. This data-analytical approach should mostly be interpreted as exploratory, where edges allow hypothesis generation regarding potential causal pathways which should be further investigated in confirmatory studies. It would be interesting for future studies to model the interrelation between PTSD symptoms in the context of COVID-19 using prospective designs (e.g., ecological momentary assessment). For instance, Greene et al. (2018) assessed fluctuations in PTSD symptoms over a period of one month in civilians exposed to violence in the context of the Israel-Gaza War and modelled temporal dynamics of PTSD symptoms and patterns of co-occurring network activity using multilevel vector autoregressive modelling. A similar approach could be used to model the dynamic relations between stress symptoms in the context of exposure to a highly infectious disease. Second, the current study relied on a Chinese version of the PCL-C. This well validated measure has been widely used in previous studies investigating the presence of PTSD symptoms in China in the context of COVID-19 (e.g., Liang et al., 2020b, 2020a; Wu & Wei, 2020). In addition, use of the PCL-C allows for immediate comparison of our findings with previous literature in which the 17-item version of the PCL was used (e.g., Birkeland et al., 2017; Birkeland & Heir, 2017; Fried et al., 2018; McNally et al., 2015; McNally et al., 2017). A disadvantage of this measure, however, is that the PCL-C was developed based on the DSM-IV criteria of PTSD (for an overview of differences between the PCL-C and the more recently developed DSM-5 based version of the PCL, see supplemental material). As a result, no inferences can be made regarding the role of PTSD symptoms that have been more recently added to the DSM-5 (i.e., negative beliefs, negative affect, blaming self or others and risk taking behaviours). In this context, being in a negative persistent state has shown to be a highly central node in DSM-5 PTSD network structures (Birkeland et al., 2020). At the same time, with the exception of these specific PTSD symptoms, the PCL-C and PCL-5 show strong overlap. As such, while acknowledging that the current network of PTSD symptoms is incomplete in light of the DSM-5, it still contains most of the key features of PTSD and to our knowledge is the first study to shed light on how these symptoms interrelate in a specific at-risk population (healthcare workers) in the context of an outbreak of a highly infectious disease. As a result, our findings provide immediate implications for clinical practice and allow generation of specific hypotheses regarding the structure of PTSD symptoms which require further investigation in confirmatory studies. Finally, the current study investigated the structure of PTSD symptoms in Chinese healthcare workers in the context of COVID-19. It is possible that these findings show limited generalizability outside Chinese populations given that nations strongly differed in how they were affected by COVID-19.

5 | CONCLUSIONS

The current study set-out to model the structure and centrality of PTSD symptoms among Chinese healthcare workers in response to the 2019 outbreak of the SARS-CoV-2 virus. In line with previous studies, trauma-related amnesia emerged as the least central symptom in the network. Our findings suggest a central role for symptoms reflecting avoidance of reminders of the traumatic event, physiological cue reactivity, feelings of anger or irritability, reliving the trauma, and startle, some of which—compared to previous literature—seem to be highly specific to the trauma type or population under investigation in the current study (Aim 1). In addition, we detected three communities of closely connected symptoms within the PTSD symptom network structure of healthcare workers, where analysis of bridge expected influence sheds light on how activation within one community is likely to spread to other communities within the network (Aim 2). Finally, our findings also suggest that, in the context of COVID-19, the network models obtained from healthcare workers and the general population sample show unique features, among which specific edges and differences in terms of node centrality (Aim 3). However, overall the network structure of PTSD symptoms for healthcare workers showed high resemblance to the network structure of PTSD symptoms obtained from a matched control sample selected from the general population, suggesting that similar mechanisms may be underlying the development of stress-related symptoms during the COVID-19 pandemic in healthcare workers and other members of the general population. This is informative to future interventions aimed at the prevention and treatment of PTSD symptoms in the context of exposure to a highly infectious disease.

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DATA AVAILABILITY STATEMENT

The dataset presented in this study is part of a larger project which was launched to monitor the psychological responses of people living within the People's Republic of China to the first outbreak of the COVID-19 pandemic, supported by the National Social Science Fund of China (17XSH001) and the key projects of People's Liberation Army of China (BLJ19J009). Anonymized data for the main analyses and the corresponding scripts can be accessed via Open Science Framework (osf.io/xp8hd/).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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