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ORIGINAL RESEARCH

The Relationship Between Cognitive Emotion Regulation Strategy and Mental Health Among University Students During Public Health Emergency: A Network Analysis

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Background: Public health emergencies pose threats to mental health, and cognitive emotional regulation can be a crucial coping strategy. This study explored the relationship between cognitive emotion regulation strategies and mental health among university students during the COVID-19 pandemic using network analysis.

Methods: 1100 university students completed questionnaires assessing depression, anxiety, somatization, and cognitive emotion regulation strategies. Network analysis was conducted to identify network structures and bridge symptoms.

Results: (1) In the depression network, the strongest edge is D1 (Little interest)-D2 (Feeling down), while D2 emerged as the node with the highest centrality. C1 (Self-blame), C8 (Catastrophizing), D6 (Feeling bad), and D9 (Suicide) are bridge symptoms. (2) In the anxiety network, A2 (Uncontrollable worrying)-A3 (Worrying too much) were identified as the strongest edge, and A2 exhibiting the highest centrality. C1 (Self-blame), C8 (Catastrophizing), and A6 (Easy annoyance) are bridge symptoms. (3) In the somatization network, the strongest edge is S14 (Fatigue)-S15 (Sleep disturbances) and S9 (Palpitations) exhibited the highest centrality. C1 (Self-blame), C3 (Rumination), C8 (Catastrophizing), S9 (Palpitations), and S14 (Fatigue) are bridge symptoms.

Conclusion: Self-blame and catastrophizing are important bridge symptoms for cognitive emotion regulation strategies and mental health networks, so cognitive behavioral therapy, focusing on self-blame and catastrophizing as intervention targets, could most effectively improve mental health during public health emergencies.

Keywords: cognitive emotion regulation, mental health, network analysis, public health emergency, COVID-19

Introduction

Public Health Emergencies (PHEs) refer to unexpected events that pose significant threats to community health and require immediate intervention and coordinated response efforts.[1] Examples of such emergencies include outbreaks of infectious diseases, like Ebola Virus Outbreaks, H1N1 Influenza Pandemic and COVID-19 pandemic. Public health emergencies not only pose a direct threat to people's physical health, but also have a profound impact on individual mental health.[2] In these emergency situations, people may face the grief of losing loved ones, friends, or colleagues,[3] as well as the disruption of daily life and increased economic pressure, and various other difficulties.[4] These stressors can result in anxiety,[5] depression,[6] somatization.[7] Especially for those located in the epicenter of the outbreak or heavily affected areas, they are more likely to experience significant mental health impacts.[8] Therefore, when responding to

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public health emergencies, we should not only focus on people's physical health, but also attach greater importance to the assistance for mental health.

When dealing with the psychological stress, people have different coping strategies for example, positive thinking, problem solving, escapism, etc. According to Lazarus and Folkman's (1984) stress and coping theory, coping strategies have two forms of outcome: problem-focused and emotion-focused coping.[9] Studies have found that emotion-focused coping, such as cognitive emotional regulation, is closely related to mental health.[10,11] Cognitive emotional regulation refers to the process by which individuals utilize cognitive strategies to regulate their emotional responses during emotional experiences.[12] It includes some positive cognitive regulation strategies, such as acceptance, reappraisal, positive coping, and so on. Through these positive strategies, individuals can better understand and deal with their own emotions, reduce the impact of negative emotions, and improve their mental health level.[13] There are also some negative cognitive emotion regulation strategies, such as self-blame, catastrophizing, rumination, and so on, which can undermine mental health and cause anxiety and depression.[14] Therefore, both enhancing positive cognitions and reducing negative cognitions have significant improvement on mental health. Exploring the most critical cognitive targets for improving mental health during Public Health Emergencies holds important practical application value.

While there have been many studies examined the impact of cognitive emotion regulation strategies on mental health, the majority of them have relied on conventional statistical techniques based on latent variables.[15] Latent variable model, however, has a number of shortcomings.[16] For example, it take the latent variable as the underlying cause of the symptoms, which may ignore the correlations between symptoms and oversimplify intricate mechanisms of psychological variables.[17] Moreover, latent variables models largely concentrate on the co-occurrence of symptoms while ignoring their interconnections and network architecture, so their ability to describe comorbidity may be restricted. Network analysis has been utilized in recent times to identify and investigate statistical relationship patterns in multivariate psychological datasets. Using this approach, the variables in the dataset are represented by the nodes of the network, and the pairwise conditional relationships between these variables are shown by the edges.[18] Rather than attributing psychological occurrences to underlying latent causes, this strategy offers a unique viewpoint by concentrating on the direct links between visible symptoms or behaviors.[17] According to Borsboom and Cramer (2013), it makes it possible to analyze intricate relationships and maybe identify key or core symptoms inside a network that might be the focus of treatments.[19]

Currently, several studies have employed network analysis to investigate the relationship between emotion regulation and mental health. For instance, a clinical study focusing on adolescents identified emotion regulation strategies as intervention targets for treating anxiety and depression, but it did not specify which strategies were to be intervened upon.[20] Another study examined the network relationships between emotion regulation, depression, and anxiety during the COVID-19 pandemic, revealing that cognitive reappraisal strategies had negative bridge indices in the networks, while expressive suppression had positive bridge indices.[21] Additionally, one study explored the relationship between specific cognitive patterns and depression, discovering that rumination and catastrophizing exhibited high expected impact value. However, this study overlooked the application of bridge symptom analysis and neglected to explore other frequently encountered mental health concerns, including anxiety and somatization.[22] In summary, most current studies lack detailed distinctions among cognitive patterns,[20,23,24] making it difficult to pinpoint accurate intervention targets.

Hence, this study employs network analysis to delve into the intricate interplay between cognitive emotion regulation strategies and mental health among the general public during public health emergencies. Specifically, we collected questionnaires pertaining to depression, anxiety, somatization, and cognitive emotion regulation strategies among university students during the COVID-19 pandemic. By examining the network structure and identifying bridge symptoms, we aim to gain an insight into the relationship between emotion regulation and mental health during PHEs, providing a theoretical foundation for targeted prevention and intervention. Based on previous literature, we hypothesize that: (i) In the network structure of cognitive emotion regulation and mental health, maladaptive strategies are negatively correlated with mental health, while adaptive strategies are positively correlated with mental health. (ii) Maladaptive strategies, such as self-blame and catastrophizing, may be important bridge symptoms connecting cognitive emotion regulation and mental health.

Method

Participants

Participants were recruited through the University of Sussex's School of Psychology recruitment platform, Sona. The study's procedures received approval from the Science and Technology Research Ethics Committee at Sussex University and everyone gave their informed consent in line with the Declaration of Helsinki. All the participant receiving either 4 course credits or £4 as compensation for their involvement and time completing the survey. The research engaged a total of 1100 subjects, comprising 171 males (15.55%, mean age = 20.06, SD = 1.88), 901 females (81.91%, mean age = 19.86, SD = 3.13), and 28 individuals who preferred not to disclose their gender (2.54%, mean age = 19.46, SD = 1.78), with participant ages spanning from 17 to 57 years. Exclusion criteria included a personal or first-degree relative's history of developmental disorders, learning disabilities, autism spectrum conditions, mood disorders, or anxiety disorders. Data collection occurred from October 26, 2020, to November 30, 2021, amidst the COVID-19 pandemic within the United Kingdom.

Materials

Cognitive Emotion Regulation Questionnaire (CERQ)

The Cognitive Emotion Regulation Questionnaire (CERQ), developed by Garnefski et al (2001), is a psychometric tool intended to assess the cognitive coping strategies employed by individuals when confronted with adverse experiences.[25] This instrument comprises 36 items, each rated on a 5-point Likert scale that spans from 1 ("almost never") to 5 ("almost always"). Representative items include statements such as "I feel that I am the one to blame for it". The CERQ is organized into nine distinct sub-scales, namely self-blame, acceptance, rumination, positive refocusing, refocusing on planning, positive reappraisal, putting into perspective, catastrophizing, and other-blame, with each sub-scale encompassing four items. A higher score within a given sub-scale indicates a more frequent utilization of the corresponding cognitive coping strategy by the respondent. The Cronbach's alpha value was 0.84, indicating a reliable reliability. In previous studies, this questionnaire has demonstrated good applicability within university student populations.[26]

Patient Health Questionnaire-9 (PHQ-9): Depression

The Patient Health Questionnaire-9 (PHQ-9), conceptualized by Kroenke, Spitzer, and Williams (2001), is a diagnostic tool to evaluate the severity of depression in patients and to monitor symptom changes in response to therapeutic interventions. This instrument comprises nine items, and each assessed using a four-point Likert scale that extends from 0 ("not at all") to 3 ("nearly every day"). One example of an item is "Little interest or pleasure in doing things." A higher score on the PHQ-9 suggests an increased likelihood of depression. The Cronbach's alpha value was 0.89, indicating a reliable reliability. In previous studies, this questionnaire has demonstrated good applicability within university student populations.[27]

Generalized Anxiety Disorder (GAD-7)

The Generalized Anxiety Disorder 7-item scale (GAD-7), developed by Spitzer, Kroenke, Williams, and Löwe (2006), is a diagnostic tool to evaluate the severity of generalized anxiety disorder symptoms.[28] This instrument comprises seven items using a four-point Likert scale ranging from 0 ("not at all") to 3 ("nearly every day"). An example item includes "Not being able to stop or control worrying." Higher scores signify an increased likelihood of the presence of an anxiety disorder. The Cronbach's alpha value was 0.90, indicating a reliable reliability. In previous studies, this questionnaire has demonstrated good applicability within university student populations.[29]

Patient Health Questionnaire-15 (PHQ-15): Physical Symptoms

The Patient Health Questionnaire-15 (PHQ-15) is a diagnostic tool designed to quantify the severity of somatic symptoms in individuals.[30] This assessment comprises 15 items, each rated on a 3-point scale ranging from 0 ("not bothered at all") to 2 ("bothered a lot"). The items encapsulate a broad spectrum of somatic symptoms, such as pain, gastrointestinal issues, fatigue, and sleep disturbances. Higher scores on the PHQ-15 indicate greater somatic symptom severity. The Cronbach's alpha value was 0.81, indicating a reliable reliability. In previous studies, this questionnaire has demonstrated good applicability within university student populations.[31]

Statistical Analyses

We performed network analysis using R Studio software (Version 4.3.1), focusing on four domains: network estimation, centrality and bridge estimation, network visualization, and network accuracy and stability assessment.

Firstly, the network structure was inferred using the Gaussian Graphical Model (GGM), a method described by Epskamp (2018).[32] To get a sparse network representation, the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) regularization approach for partial correlations was utilized.[33] The estimation process was completed by the implementation of the "bootnet" package within the R computational environment. Within this network, nodes represented psychological symptoms, with the inter-symptom relationships illustrated as edges connecting these nodes. The quantification of the association strength between each pair of symptoms was conducted through generalized linear regression modeling, ensuring a rigorous statistical foundation for the network analysis.

Secondly, centrality delineates the extent, intensity, and coherence of a node's connections within the network, with alterations in highly central nodes will impacting the broader network structure. Traditionally, three primary centrality indices have been employed: 'strength', which denotes the direct connections of a node; 'closeness' and 'betweenness', which infer indirect relationships.[34] Notably, contemporary research underscores the superior stability and reliability of "strength" over "closeness" and "betweenness" for assessing node centrality within psychological networks, rendering the latter two less appropriate for this context.[35] Therefore, this study adopts "strength" as the pivotal centrality index. The "qgraph" package within the R statistical environment was utilized to calculate these centrality indices. Furthermore, "bridge strength" was calculated employing the "networktools" package in R,[36] to gauge the connectivity efficiency between symptoms across disparate disorders, providing insights into how symptoms from one disorder may influence or relate to symptoms of another, thereby disrupting pathways of comorbidity, offering targeted Interventions or maximizing treatment efficacy.

Thirdly, we visualized the network using Fruchterman-Reingold algorithm, which systematically positions nodes with stronger connections in closer proximity to each other.[37] This method helps provide a clearer understanding of the network structure by highlighting the density of connections between nodes. The network was built and displayed using the "qgraph" package.[38] To configure the network plot, specific parameters were selected: a tuning parameter (γ) set at 0.5, a threshold (cut-off) value of 0.1, and a stipulated minimum value of 0, ensuring an optimal balance between visibility and interpretability of the network connections.

Finally, the accuracy and stability of the network were evaluated using the "bootnet" package within the R statistical framework.[39] First, the accuracy of edge weights within the network was assessed by generating a 95% confidence interval (CI) for each edge through a bootstrap methodology, utilizing 1000 iterations, and then conducting bootstrapped differential analyses to determine the significance of variations in edge weights. The next step involved the assessment of the stability of node strength and bridge strength, which by calculating the correlation stability (CS) coefficient through case-dropping bootstrap with 1000 iterations. Based on prior research,[39] the CS coefficient should be above 0.50 but not lower than 0.25. To ensure the tests were reliable, 5000 permutations were carried out.

Results

Network Estimation

The network of emotion regulation and depression is presented in Figure 1 and shows several characteristics: (1) 88 edges are not zero (57.5%) among 153 possible edges and there exist both positive and negative edges. (2) Among the cognitive emotion regulation strategies, the strongest edge was C5 (Refocus on planning) and C6 (Positive reappraisal); Among the depressive symptoms, the strongest edge was D1 (Little interest) and D2 (Feeling down). (3) In this network, there are four bridge symptoms, which are C1 (Self-blame), C8 (Catastrophing), D6 (Feeling bad) and D9 (Suicide).

The network of emotion regulation and anxiety is presented in Figure 2 and shows several characteristics: (1) 73 edges are not zero (61.0%) among 120 possible edges and there exist both positive and negative edges. (2) Among the cognitive emotion regulation strategies, the strongest edge was C5 (Refocus on planning) and C6 (Positive reappraisal);

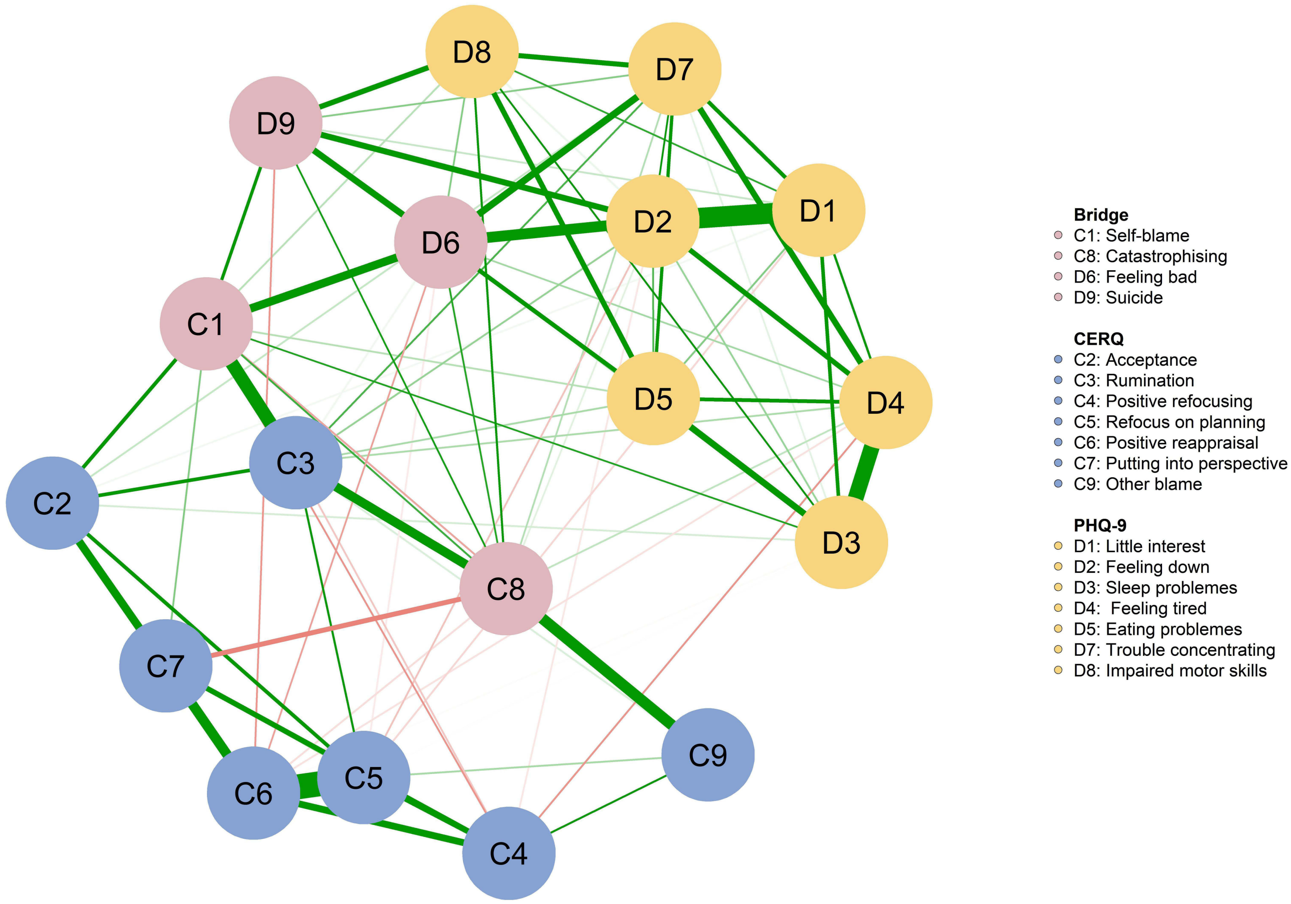

Figure 1 The network structure of cognitive emotion regulation and depression. Blue nodes indicate different cognitive emotion regulation strategies. Yellow nodes indicate depression symptoms. Pink nodes indicate bridge symptoms. Thicker edges between symptoms denote stronger associations. Green edges denote positive interconnections while red edges denote negative interconnections.

Among the anxiety symptoms, the strongest edge was A2 (Uncontrollable worrying) and A3 (Worrying too much). (3) In this network, there are three bridge symptoms, which are C1 (Self-blame), C8 (Catastrophing) and A6 (Easily annoyed).

The network of emotion regulation and somatization is presented in Figure 3 and shows several characteristics: (1) 140 edges are not zero (61.0%) among 276 possible edges and there exist both positive and negative edges. (2) Among the cognitive emotion regulation strategies, the strongest edge was C5 (Refocus on planning) and C6 (Positive reappraisal); Among the somatization symptoms, the strongest edge was S14 (Fatigue) and S15 (Trouble sleeping). (3) In this network, there are five bridge symptoms, which are C1 (Self-blame), C3 (Rumination), C8 (Catastrophing), S9 (Palpitations)and S14 (Fatigue).

Centrality Estimation

The plot of centrality indices is shown in Figure S1. For depression, the highest node strength is D2 (Feeling down), followed by C6 (Positive reappraisal) and D6 (Feeling bad). For anxiety, the highest node strength is A2 (Uncontrollable worrying), followed by C6 (Positive reappraisal) and A3 (Worrying too much). For somatization, the highest node strength is C6 (Positive reappraisal), followed by S6 (Chest pain) and S9 (Palpitations).

Accuracy and Stability Estimation

The accuracy results of edge weights using the bootstrapping approach reveal that the edge weights' confidence intervals are rather narrow for three networks. The relatively narrow CIs imply acceptable accuracy because of the huge number of subjects and small number of measurement variables in this study. The CS coefficients of strength and bridge strength are

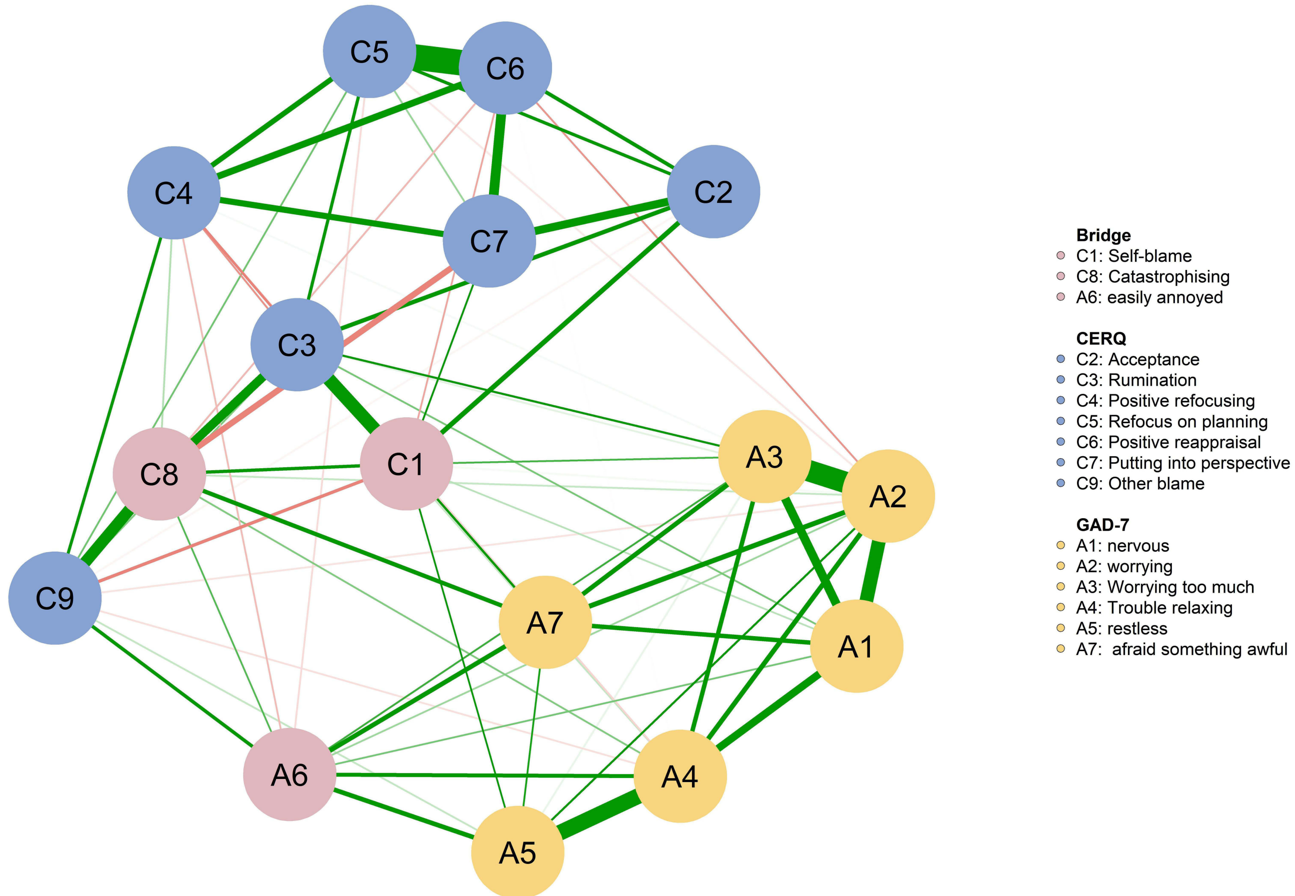

Figure 2 The network structure of cognitive emotion regulation and anxiety. Blue nodes indicate different cognitive emotion regulation strategies. Yellow nodes indicate anxiety symptoms. Pink nodes indicate bridge symptoms. Thicker edges between symptoms denote stronger associations. Green edges denote positive interconnections while red edges denote negative interconnections.

0.75 and 0.75 for depression network, 0.75 and 0.672 for anxiety network and 0.672 and 0.595 for somatization network. This indicate that they are reliable for measuring the characteristics of network nodes (Figure S2).

Discussion

In the context of public health emergencies such as the COVID-19 pandemic, the mental health of the public has been particularly vulnerable. Emotion regulation emerges as a critical factor influencing this vulnerability, given its direct implications for individuals' ability to manage stress and maintain psychological well-being. To gain a deeper understanding of this intricate relationship, our study employed symptom network analysis to explore the relationship between cognitive emotion regulation strategies and mental health.

The Network of Cognitive Emotion Regulation and Mental Health

In the three networks of cognitive emotion regulation and mental health, we found that the negative edges in the network are concentrated on adaptive cognitive strategies, such as positive reappraisal. The positive edges are concentrated on maladaptive cognitive strategies, such as rumination and self-blame. This is reasonable, consistent with previous research, and also confirms our first hypothesis. Below is a detailed discussion of each network's structure.

In the depression and emotion regulation network, the strongest edge is D1 (Little interest) and D2 (Feeling down), while D2 emerged as the node with the highest centrality. These findings align with many previous research.[40,41] Additionally, Our results also support that "Feeling down" is core symptom for the diagnosis of major depressive disorder (MDD), which is consistent with the provisions in the Diagnostic and Statistical Manual of Mental Disorders-5

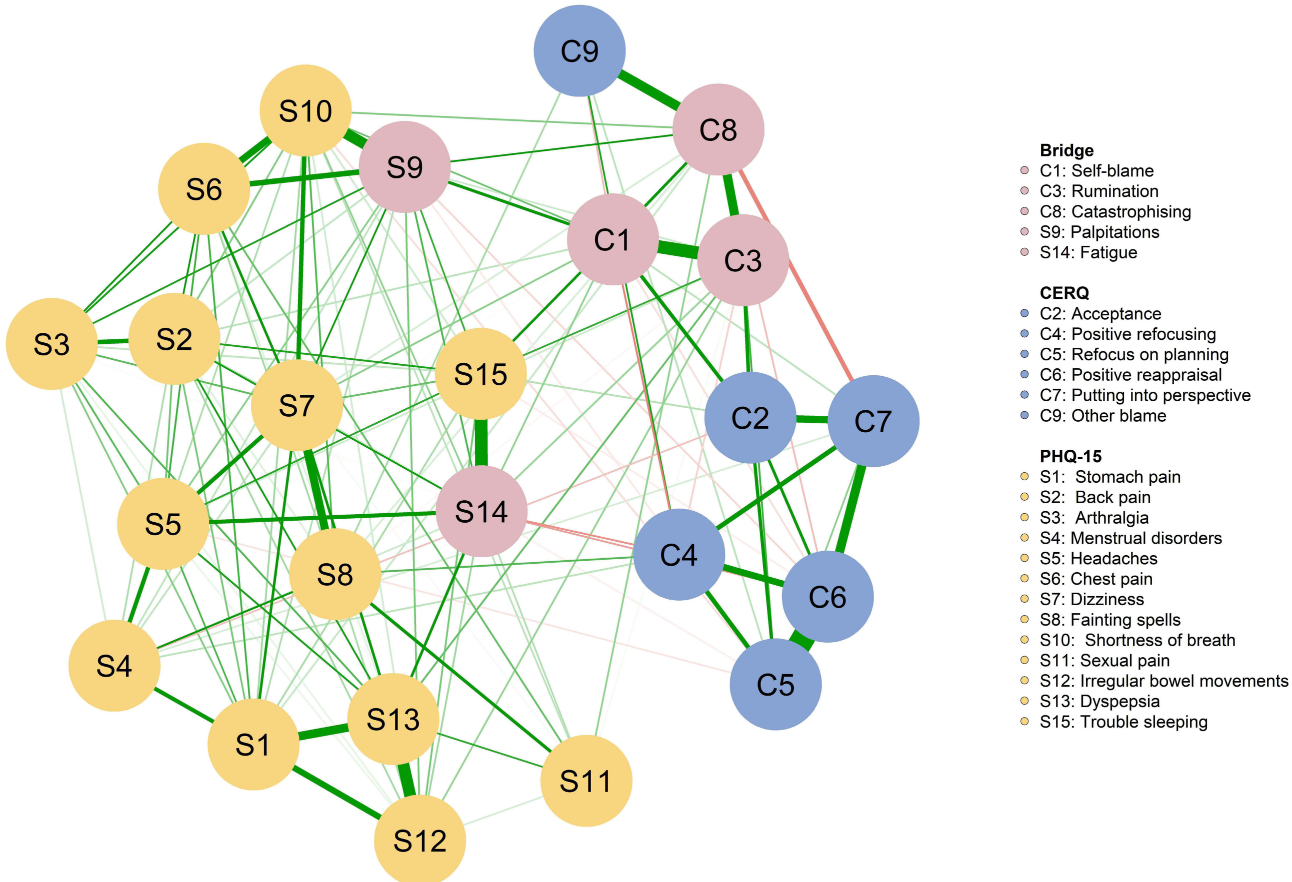

Figure 3 The network structure of cognitive emotion regulation and somatization. Blue nodes indicate different cognitive emotion regulation strategies. Yellow nodes indicate somatization symptoms. Pink nodes indicate bridge symptoms. Thicker edges between symptoms denote stronger associations. Green edges denote positive interconnections while red edges denote negative interconnections.

(DSM-5).[42] Our study, for the first time, identified C1 (Self-blame), C8 (Catastrophizing), D6 (Feeling bad), and D9 (Suicide) as bridge symptoms in this network. This suggests that the cognitive style of self-blame and catastrophizing contribute to the spread and aggravation of the pathological process of depression.[43] For example, Self-blame (C1) tends to lead people to pay excessive attention to their own faults and shortcomings, and then triggers catastrophic thinking (C8), that is, extremely pessimistic expectations for the future.[44] This negative thinking mode further aggravates negative emotions, such as continuous sadness, despair, and hopelessness, and may ultimately trigger suicidal thoughts.[45]

In the anxiety and emotion regulation network, uncontrollable worrying (A2) and excessive worrying (A3) were identified as the strongest edge, and uncontrollable worrying (A2) exhibiting the highest centrality. These findings align with previous research.[41] This verifies that uncontrollable and excessive anxiety is the core symptom of Generalized Anxiety Disorder according to DSM-5.[42] Notably, our research sheds new light on the role of C1 (Self-blame), C8 (Catastrophizing), and A6 (Easy annoyance) as bridge symptoms in this network. This reminds us that self-blame and catastrophizing, as a kind of negative self-evaluation tendency, are prone to make individuals fall into a state of self-denial. Individuals who are in a state of self-blame for a long time tend to be more sensitive to external stimuli and are prone to feel dissatisfied or angry about trifles, that is, they are irritable.

Lastly, in the somatization and emotion regulation network, the strongest connection was detected between S14 (Fatigue) and S15 (Sleep disturbances). This means that during the covid-19, fatigue may make it difficult for individuals to fall asleep or stay asleep, and sleep disorders may further aggravate the sense of fatigue, forming a vicious circle. We also find S9 (Palpitations) exhibited the highest centrality, which is in line with previous study.[46] Palpitation refers to a sense of discomfort caused by the subjective awareness of one's heartbeat and may feel that their heart beats too fast, too slow, irregularly, or forcefully, and sometimes accompanied by symptoms such as chest tightness and shortness of breath.[47] Numerous studies have proven that palpitation is the most common symptom in mental illnesses such as anxiety disorders and somatization disorders.[48,49] Importantly, our research reveals C1 (Self-blame), C3 (Rumination), C8 (Catastrophizing), S9 (Palpitations), and S14 (Fatigue) as bridge symptoms in this network, representing a novel contribution to the field.

Self-Blame, Catastrophing and Mental Health

Among the nine emotion regulation strategies, we found that C1 (Self-blame) and C8 (Catastrophizing) are the main bridge symptoms that link mental health symptoms. This is consistent with our second hypothesis. This finding implies that during the COVID-19 pandemic, resorting excessively to cognitive patterns of self-blame and catastrophizing to cope with emotional issues can lead to more mental health problems, such as depression, anxiety, and somatization. Bridge symptoms play a significant role in symptom network analysis. They not only connect different symptom clusters but also reveal potential relationships between symptoms, providing crucial targets and foundations for precise interventions.

Self-blame refers to the individual attributing problems to their own deficiencies or faults.[50] It is divided into Characterological Self-blame and Behavioral Self-blame, with the former blaming one's character or identity, and the latter blaming specific behaviors.[51] This study reconfirmed that both forms of self-blame significantly impact individuals' depression and anxiety levels. This effect can be attributed to self-blame being a negative attribution style, where individuals tend to attribute negative events to internal, stable, and uncontrollable factors.[52,53] Such an attribution style leads to feelings of helplessness and despair, increasing the risk of depression.[52] Research indicates a significant correlation between self-blame and depressive symptoms.[54] Self-blame is also associated with anxiety symptoms. The core of anxiety lies in the worry about future uncertainties and the lack of confidence in one's own abilities.[55] Self-blame reinforces the negative evaluation of one's capabilities, thereby increasing concerns about the future and anxiety.[56] Self-blame may also lead to somatization, where psychological distress is converted into physical symptoms, and when individuals attribute responsibility for negative events to themselves, it can increase the frequency and severity of physical symptoms.[57,58]

Catastrophizing is a cognitive distortion where individuals tend to exaggerate the negative impact of events. Previous research has found that catastrophizing is associated with maladjustment, emotional distress, and depression.[59,60] This may be because catastrophizing leads to a highly pessimistic outlook on the future, resulting in persistent negative emotions that can trigger and maintain depressive symptoms.[61] Catastrophizing is also closely related to anxiety, as this strategy amplifies perceptions of future uncertainty and potential threats.[62] Research has found that catastrophizing increases anxiety levels in individuals, as they constantly worry about the worst-case scenarios occurring.[63,64] Catastrophizing not only affects emotions but also induces somatization symptoms through psycho-physiological mechanisms.[65] In the field of pain research, numerous studies have found that catastrophizing leads to increased attention and perception of pain, making the pain experience more intense and persistent and enhances the somatization of pain symptoms.[66,67]

According to Cognitive Behavioral Theory, an individual's cognitive patterns influence their emotions and behaviors.[68] If cognitive processes are distorted, such as with catastrophic thinking, this can lead to negative emotions, which in turn can result in psychological issues like depression and anxiety. Correspondingly, Cognitive Behavioral Therapy (CBT) can effectively improve mental health by addressing maladaptive cognitive patterns.[69,70] Therefore, identifying the key cognitive patterns that impact mental health is crucial. Future research could use CBT focused on self-blame and catastrophizing to alleviate symptoms of depression, anxiety, and somatization.

Conclusion

The study emphasizes how important cognitive emotion regulation strategies are in influencing mental health symptoms in times of public health emergencies, like the COVID-19 pandemic. Through network analysis, it was evident that certain cognitive strategies, notably self-blame and catastrophizing, serve as bridge symptoms linking cognitive pattern and mental health like depression, anxiety, and somatization. Therefore, cognitive behavioral therapy that focuses on addressing self-blame and catastrophizing as primary intervention targets, might be particularly effective in improving mental health levels during public health emergencies.

Limitations and Future Directions

Notwithstanding the robust results, this investigation has some limitations: Firstly, the cross-sectional methodology limits the capacity to infer causal relationships. Longitudinal studies are needed to establish temporal causality. Secondly, because individuals may underreport or fail to recall their cognitive and emotional states, the use of self-reported measures may introduce bias. Thirdly, the sample consisted of university students, which may restrict the findings' applicability to other populations. The focus on a single public health emergency (COVID-19) may not fully capture the variability in emotional regulation and mental health impacts across different types of public health emergencies. Fourthly, the exploration of mental health intervention targets in this study has primarily been confined to the framework established by this research itself. However, there exist other forms of coping strategies that can serve as intervention targets, such as proactive behavior and problem-solving strategies. Furthermore, we have defined the framework of mental health as encompassing symptoms of depression, anxiety, and somatization. Yet, there are other types of mental health symptoms, such as anorexia nervosa and obsessive-compulsive disorder, among others. Future research should strive to adopt a broader or different research framework in order to identify better intervention targets.

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Disclosure

The authors have no conflicts of interest to declare.

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