ORIGINAL RESEARCH

Network Analysis of Insomnia in Chinese Mental Health Professionals During the COVID-19 Pandemic: A Cross-Sectional Study

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Purpose: The coronavirus disease 2019 (COVID-19) pandemic is associated with increased risk of insomnia symptoms (insomnia hereafter) in health-care professionals. Network analysis is a novel approach in linking mechanisms at the symptom level. The aim of this study was to characterize the insomnia network structure in mental health professionals during the COVID-19 pandemic.

Patients and Methods: A total of 10,516 mental health professionals were recruited from psychiatric hospitals or psychiatric units of general hospitals nationwide between March 15 and March 20, 2020. Insomnia was assessed with the insomnia severity index (ISI). Centrality index (ie, strength) was used to identify symptoms central to the network. The stability of network was examined using a case-dropping bootstrap procedure. The network structures between different genders were also compared.

Results: The overall network model showed that the item ISI7 (interference with daytime functioning) was the most central symptom in mental health professionals with the highest strength. The network was robust in stability and accuracy tests. The item ISI4 (sleep dissatisfaction) was connected to the two main clusters of insomnia symptoms (ie, the cluster of nocturnal and daytime symptoms). No significant gender network difference was found.

Conclusion: Interference with daytime functioning was the most central symptom, suggesting that it may be an important treatment outcome measure for insomnia. Appropriate treatments, such as stimulus control techniques, cognitive behavioral therapy and relaxation training, could be developed. Moreover, addressing sleep satisfaction in treatment could simultaneously ameliorate daytime and nocturnal symptoms.

Keywords: sleep, insomnia, SARS-CoV-2, COVID-19, physicians

Introduction

Insomnia, characterized by dissatisfaction with sleep quantity or quality,[1] is a common sleep disorder.[2] Several factors, such as mental disorders,[3–5] emotional stress,[6,7] and working at night or in shifts,[8] are closely associated with insomnia. During the coronavirus disease 2019 (COVID-19) pandemic, health-care workers are confronted with the stress of high infection risk, heavy workload, long shift hours, and limited contact with their families, which can result in mental health issues, including stress, anxiety, depression, and insomnia.[9–11] A recent meta-analysis reported that the pooled prevalence of insomnia in health-care workers during the COVID-19 pandemic was 34.32%,[12] which was higher than the general population.[13] To reduce the risk of insomnia and develop effective measures to treat

insomnia in this population, it is vital to understand the symptom patterns of insomnia.

Network theory is a promising novel approach to studying psychopathology and understanding linking mechanisms at a symptom level,[14] in which the disorder is assumed to be constituted of co-occurring symptoms and that symptoms may trigger and accentuate each other.[15] Unlike traditional approaches, which implicitly reflect the underlying latent factor[16] or simply assume symptoms of disorders to be manifestations of an underlying disease,[17,18] symptoms and their mutual interactions are seen as the disorder itself in the network approach.[19] The network theory of psychopathology is flexible and dynamic and can explain the onset and maintenance of psychiatric symptoms.[20] Therefore, the perspective of network approach offers the opportunities to illustrate the structure and functioning of important psychological phenomena[16] such as the structure of insomnia symptoms. This theoretical framework can be statistically investigated via network analysis[21] to visualize the structure of symptoms[22] and to reveal information or key symptoms related to clinical status rather than relying on the summation of total scores from scales.[23]

In network analysis, each symptom is viewed as one node and the interaction between two nodes is represented as an edge. The value of each edge stands for the statistical association calculated between two nodes after controlling for other nodes in the network structure.[24] In the context of a strong edge in a network, the activation/deactivation of one symptom may predict the activation/deactivation of another symptom.[25] In addition, the node position in the network represents its relative importance, so the more the node is centrally placed, the more interconnected the node is. Central symptoms are more prone to activate other symptoms; thus, they may play a pivotal role in causing the onset and/or maintenance of the syndrome.[20] In theory, treatment targeting central symptoms are more effective than targeting peripheral symptoms.[22] Consequently, network analysis is a highly valuable approach for depicting the psychological constructs and generating testable hypotheses for further studies.[22,26]

Network analysis has been used in diverse clinical conditions among specific populations such as anxiety and depression in adolescents[27] and other psychiatric samples,[28] depressive symptoms in older people,[20] hopelessness in a community sample,[29] and post-traumatic stress disorder in earthquake survivors.[19] To provide targeted interventions and strategies that facilitate prevention and alleviation of clinically significant distress, it is

important to understand mechanisms that increase their risk for insomnia with sophisticated methods. A recent review[30] on the trends in insomnia research indicated research using network approach was warranted. To the best of our knowledge, only two studies[31,32] have examined insomnia using network analysis. One network analysis explored the effect of personality traits on insomnia in the Netherlands,[31] while the other network analysis explored the cognitive-behavioral therapy for insomnia (CBTI) induced effects on symptoms of insomnia and depression throughout the course of treatment.[32] To date, no network analysis on insomnia in mental health professionals has been published.

Therefore, we conducted an exploratory study using a network analysis to examine the associations of insomnia symptoms (insomnia hereafter) and identify the most central (influential) symptoms that could serve as intervention targets in mental health professionals during the COVID-19 pandemic.

Materials and Methods
Participants and Procedure

This study was based on a secondary analysis of a national mental health survey of mental health professionals in China during the COVID-19 pandemic.[33] To avoid the risk of contagion in population research,[34,35] we recruited and assessed participants using snow sampling method from March 15, 2020 to March 20, 2020. The link to the invitation and assessment forms of this survey was distributed by the panel members of the Psychiatric Branch of the Chinese Nursing Association and the Chinese Society of Psychiatry to all public psychiatric hospitals in China via a quick response (QR) code generated with the Questionnaire Star program embedded in WeChat. WeChat is a widely used communication application in China with around 1.2 billion users, including health-care professionals in clinical practice and continuing educational activities organized by the Chinese Nursing Association and the Chinese Society of Psychiatry. Therefore, nearly all mental health professionals working in psychiatric hospitals and psychiatric units of general hospitals in China were presumably WeChat users. The Psychiatry Branch, Chinese Nursing Association distributed the Quick Response Code (QR Code) linked to the assessment of this study to all psychiatric hospitals nationwide. Subsequently, mental health professionals working

in these hospitals were invited to participate in the survey on an anonymous and voluntary basis.

Inclusion criteria included: (1) 18 years old and above; (2) mental health professionals (eg, doctors, nurses and nursing assistants) working in psychiatric hospitals or units in China during the COVID-19 pandemic; (3) able to understand Chinese and provide electronic written informed consent. No specific exclusion criteria were used in this study. The study protocol was approved by the Institutional Review Board (IRB) of Beijing Anding Hospital, China (2020 – Keyan (No. 10)) based on the local ethical regulations and the Declaration of Helsinki.[36] All participants provided online written informed consent and the information collected were kept confidential.

Measures

Basic demographic information and clinical characteristics were collected, including age, gender, marital status, education level, living circumstances, type of hospital (tertiary or non-tertiary), and past experience combating Severe Acute Respiratory Syndrome (SARS) during the outbreak in 2003. Insomnia was measured by the 7-item Chinese version of the Insomnia Severity Index (ISI) questionnaire[37,38] which included 7 domains: 1) severity of sleep onset problem; 2) sleep maintenance problem; 3) early morning wakening problem; 4) sleep dissatisfaction; 5) interference of sleep difficulties with daytime functioning; 6) noticeability of sleep problems by others; and 7) distress caused by the sleep difficulties. Each item scored from 0 (no problem) to 4 (very severe problem); a higher score indicating more severe insomnia. The reliability and validity of the ISI has been well-documented in Chinese populations.[38–40]

Statistical Analysis

Network Estimation

The insomnia symptom network was estimated using the R program (Version 4.0.3).[41] Following previous studies,[25,29] item informativeness (ie, standard deviation (SD) of the item) was examined using the describe function in the R-package psych (Version 2.0.12),[42] and item redundancy (ie, < 25% of statistically different correlations) was measured using the goldbricker function in the R-package networktools (Version 1.2.3).[43] An item was regarded as having poor informativeness if its value is 2.5 times lower than the mean level of all items' informativeness in a scale;[29] in this case, this item should be excluded from the network analysis.

In network parlance, each symptom is considered as node, and the correlations between two individual symptoms were considered edges. A thicker edge represents a stronger correlation, while the green color edge indicates a positive correlation, and red color indicates a negative correlation.[44] The network structure of insomnia symptoms was estimated using the function estimateNetwork in the R-package bootnet (Version 1.4.3).[24] As recommended previously,[31] polychoric correlations were used to examine the correlations between ISI items, taking the Likert-scale type variables into account. To minimize spurious associations due to sampling error, the Extended Bayesian Information Criterion (EBIC) graphical least absolute shrinkage and selection operator (LASSO) model was adopted.[44] In this model, the LASSO algorithm is used to shrink all edges in the network and set small edges exactly to zero to make the network sparser and easier to interpret.[45] The EBIC model selection approach has been widely used to select related tuning parameters[24] (γ=0.5). To visualize the network, the R-package qgraph (Version 1.6.9)[44] was used.

Centrality indices including strength, closeness, and betweenness were calculated to explore the importance of individual symptoms in the network using the R-package bootnet (Version 1.4.3).[24] The default tuning parameter (alpha=1) was used. Following previous studies,[24,29] in tandem with lower stability of betweenness and closeness, this study only focused on the strength index. The node strength refers to the sum of absolute weights of edges (expressed by correlation coefficients) connected to a certain node, indicating how strongly a node was directly connected to other nodes in the network.[46] In addition, predictability was estimated using R-package mgm (Version 1.2–11),[47] indicating to what extent certain nodes were predicted by all its neighboring nodes.

Network Stability and Accuracy

The network stability and accuracy were assessed using the R-package bootnet (Version 1.4.3),[24] which reflected the robustness of the results. Based on a case-dropping subset bootstrap procedure, the correlation stability coefficient (CS-C) was calculated for centrality indices. The value of CS-C referred to the maximum proportion of dropped cases to maintain a correlation above 0.7 between the centrality indices of the original sample and those of subset samples with 95% of possibility.[24] As recommended previously,[24] CS-C value of above 0.25 is acceptable and preferably, above 0.5. A nonparametric

bootstrap procedure was then used to assess the accuracy of edge weights. Edge accuracy was assessed by 95% confidence intervals (CIs), with a narrower CI indicating a more trustworthy network and a larger CI suggesting a poorer accuracy.[24,29] In addition, bootstrapped tests were also conducted based on 95% CIs to evaluate the difference between two edges or between two nodes strength, with zero included in the CIs implying statistical differences.[24]

Network Comparisons

Considering the influence of gender on insomnia based on previous findings,[48] three invariance measures (network structure invariance, global strength invariance, and edge invariance) of the network were examined using the Network Comparison Test (NCT) in the R-package NetworkComparisonTest 2.2.1[49] to compare network measures between females and males. Network structure refers to the maximum difference of pairwise edges between female and male networks, global strength refers to the absolute sum of all edges of each network, and edge differences refer to the differences of individual edge weight between females and males networks. Holm-Bonferroni correction for multiple comparisons at the level of individual edge between gender was adopted. The three network comparison tests were conducted based on a similar permutation-based procedure.[49] First, 50% of the participants in female and male dataset were randomly switched 1000 times to form the permutated datasets, which was considered as the reference distribution in the null hypothesis. Second, the three invariance measures (eg, network structure invariance, global strength invariance, and edge invariance) were calculated in the network structure estimate based on the original dataset (ie, observed statistics). Finally, the observed statistics were compared with the reference distribution created with the permutated procedure.

Results

Descriptive Statistics

Table 1 presents the demographic characteristics of participants. Of the 10,516 mental health professionals included in this network analysis, the mean age was 33.2 years (SD=8.4), 1635 (15.5%) were males, 9635 (91.6%) had college education or above, 7273 (69.2%) were married, 8629 (82.1%) lived with family, 948 (9.0%) had past experiences combating SARS, and 6564 were working in tertiary hospitals. Information of the scale items are shown in the Supplementary Materials Table S1.

Table 1 Demographic Characteristics of Study Sample (N=10,516)

Variables	Mean (SD)	N (%)
Age	33.2 (8.4)	–
Male gender	–	1635 (15.5)
College education and above	–	9635 (91.6)
Married status		7273 (69.2)
Living with family		8629 (82.1)
Past experience of SARS	–	948 (9.0)
Working in tertiary hospital	–	6564 (62.4)

Abbreviation: SD, standard deviation.

Network Structure

Item informativeness was calculated (M_{SD}=0.8±0.1) and no item was found to be poorly informative. Additionally, analyses of item redundancy showed that no item was redundant with any other item in the ISI. Therefore, all the ISI items were included in the network analyses.

The network structure of insomnia is shown in Figure 1 and the corresponding correlation matric is presented in Table S2. All the connections showed positive associations between nodes. The edge ISI1 (severity of sleep onset) - ISI2 (sleep maintenance) has the strongest connection, followed by edge ISI2 (sleep maintenance) – ISI3 (early morning wakening problems), edge ISI5 (noticeability of sleep problems by others) – ISI6 (distress caused by the sleep difficulties), and the edge ISI6 (distress caused by the sleep difficulties) – ISI7 (interference with daytime functioning). Figure 1 shows two main clusters of insomnia, including the cluster of nocturnal symptoms (ISI1, ISI2, and ISI3), and the cluster of daytime symptoms (ISI5, ISI6, and ISI7), both of which were connected by the item ISI4 (sleep dissatisfaction).

In Figure 2, centrality indices of insomnia symptoms network show that ISI7 (interference with daytime functioning) was the most central symptom in mental health professionals with the highest strength. The item ISI3 (early morning wakening problems) was placed in the most peripheral area of the whole network with the lowest centrality indices. The predictability index shows that an average of 65.4% of variance could be potentially accounted by each node's neighboring nodes ($M_{predictabikity}$=0.654±0.071). ISI7 (interference with daytime functioning, 73.6%) had the highest predictability in the network shown in Table S1.

Network Stability and Accuracy

In terms of network stability shown in Figure S1, the CS-C of strength calculated by the case dropping bootstrap
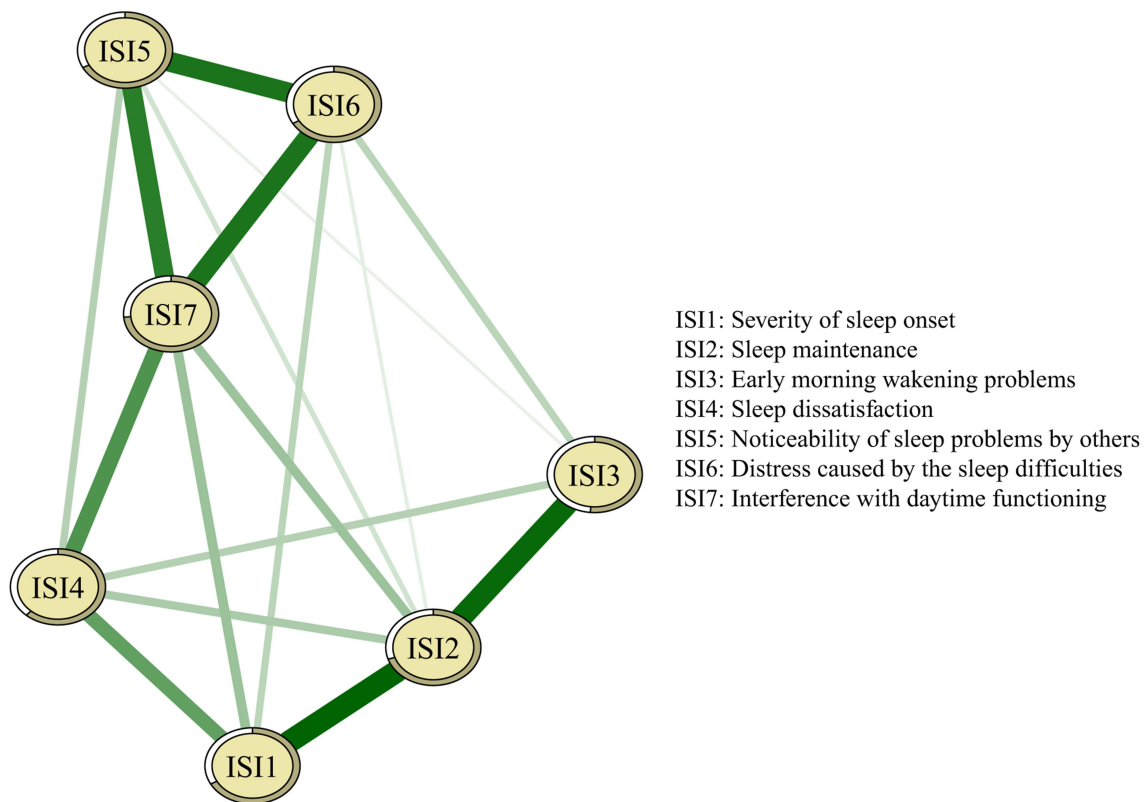
Figure 1 Estimated network model of insomnia symptoms in mental health professionals (N =10,516).

procedure was 0.75, which shows that the network remained stable, in that dropping 75% of sample would not change the primary results (r=0.7). Regarding the accuracy of the present network, the results of bootstrap 95% CI for edges show that 95% CIs were narrow, indicating edges are trustworthy shown in Figure 3. The bootstrapped difference tests revealed that most comparisons among edge weights and node strength were statistically significant shown in Figure S2 and S3.

Network Comparisons

The NCT results did not find significant differences in the network global strength (females: 3.27 vs males: 3.30; S=0.03, *p*=0.48), network structure (*M*=0.07, *p*=0.89), and individual edge weights (all *p* values >0.05 after Holm-Bonferroni correction), indicated that network characteristics did not differ between genders. Plots are shown in supplementary files Figure S4-S6.

Discussion

This network analysis was the first exploratory study that characterized the network structure of insomnia in Chinese mental health professionals during the COVID-19

pandemic. Our results revealed that the symptoms were separated into two clusters connected by ISI4 (sleep dissatisfaction), and ISI7 (interference with daytime functioning) was the most central symptom in this sample.

In this study, we found that sleep-related problems (ie, ISI1: severity of sleep onset; ISI2: sleep maintenance; and ISI3: early morning wakening problems), also known as nocturnal symptoms, were rounded up in one cluster. On the other hand, the daytime symptoms (ISI5: noticeability of sleep problems by others; ISI6: distress caused by the sleep difficulties; ISI7: interference with daytime functioning) were organized into another cluster. These two clusters both contributed to the node ISI4 (sleep dissatisfaction). Our findings are consistent with the previous findings[31] on the association of personality traits with different insomnia characteristics in the general population. These results suggest that the ISI total score may dilute the severity degree of nocturnal and daytime symptoms.[31] Our study findings may have clinical significance, particularly for the treatment of insomnia. For instance, cognitive behavioral treatment of insomnia (CBT-I) is the most widely used non-drug treatment[50] that encompasses techniques (ie, stimulus control
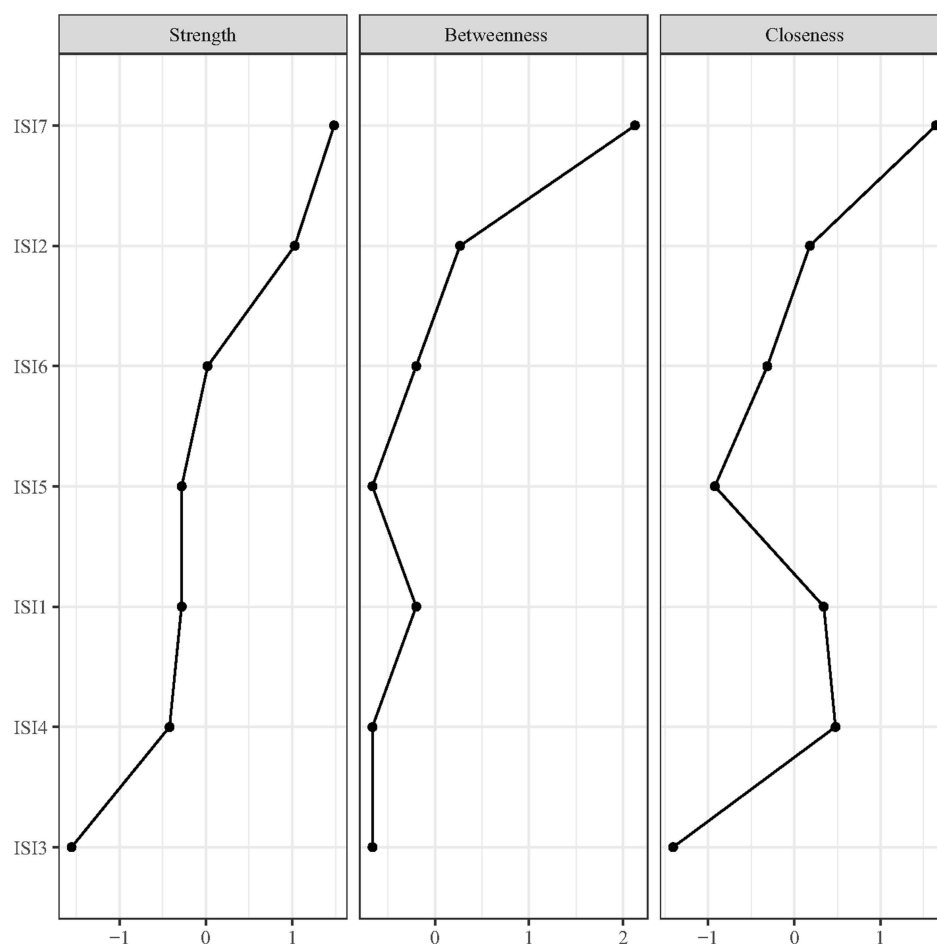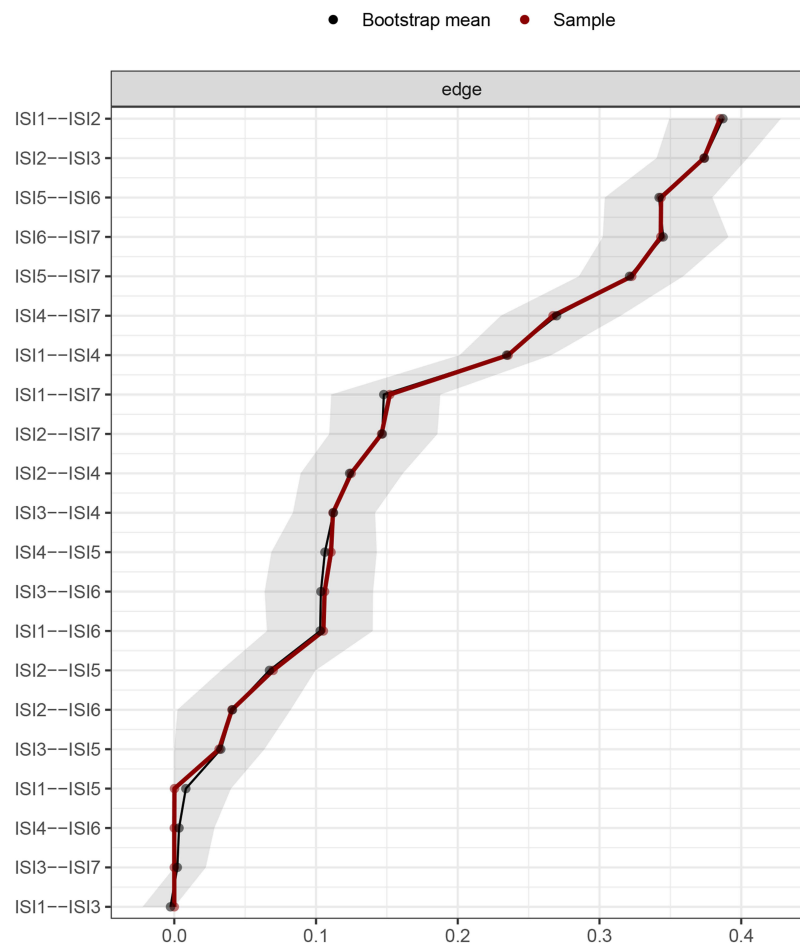
Figure 2 Centrality index of insomnia symptoms within the network.
Abbreviations: ISI1, severity of sleep onset; ISI2, sleep maintenance; ISI3, early morning wakening problems; ISI4, sleep dissatisfaction; ISI5, noticeability of sleep problems by others; ISI6, distress caused by the sleep difficulties; ISI7, interference with daytime functioning.

techniques, cognitive therapy techniques, relaxation training) on managing expectations and beliefs in relation to nocturnal sleep improvement and coping strategies for daytime insomnia complaints.[50,51] Hence, CBT-I could address both daytime and nocturnal symptoms.[31] Based on our findings, if interventions are specifically targeted to address ISI4 (sleep dissatisfaction), daytime and nocturnal complaints may be ameliorated concurrently.[31] Recent studies[32,52] have also supported that research regarding the dynamic effects of interventions on specific symptoms of insomnia is further warranted.

The item ISI7 (interference with daytime functioning) was the most central (influential) symptom in this study. This survey was conducted immediately after the WHO's declaration of COVID-19 as a global pandemic[53] when Chinese health-care workers were experiencing substantial stress due to the large number of COVID-19 cases and insufficient personal protective equipment.[54,55] The item

ISI7 assessed daytime functioning interference (ie, ability to function at work/daily chores) caused by insomnia. Given the moral responsibility[56] and strong sense of mission, health-care workers were likely concerned more about the negative consequences of insomnia problems, such as reduced work efficiency that may jeopardize patients' safety and medical service quality,[57] than their experience of insomnia itself. Moreover, the edges ISI7-ISI5 (ie, interference with daytime functioning-noticeability of sleep problems by others) and ISI7-ISI6 (ie, interference with daytime functioning-distress caused by the sleep difficulties) showed strong connections in this network model, indicating that interventions targeting the two daytime complaints (ISI5 and ISI6) may improve the symptom of "interference with daytime functioning" (ISI7); hence, "interference with daytime functioning" (ISI7) could also be an important treatment outcome measure of insomnia.

Figure 3 Bootstrapped confidence intervals of edge weights. The black dots indicate the values of each edge weight, ordered from the highest to the lowest value. The gray area represents the 95% confidence intervals of edge weights, estimated with the non-parametric bootstrap procedure.
Abbreviations: ISI1, severity of sleep onset; ISI2, sleep maintenance; ISI3, early morning wakening problems; ISI4, sleep dissatisfaction; ISI5, noticeability of sleep problems by others; ISI6, distress caused by the sleep difficulties; ISI7, interference with daytime functioning.

The average of predictability is 65.4%, indicating that most of the variance (ie, 65.4%) of individual symptoms of insomnia could be accounted for by this network model. The remaining (34.6%) variance could be attributed to other symptoms associated with insomnia, such as depressive and anxiety symptoms, fatigue, and perceived stress.[48,58] Moreover, as recommended previously,[29] the association of centrality index of strength and predictability with the item mean levels was examined, but no associations were found (node strength and item mean level: r_s=−0.487, p=0.268; predictability and item mean level: r_s=−0.179, p=0.702). This suggests that network analysis could gain insight into the influence of individual symptoms on the model, which is not possible for traditional statistical approach that only used total scale scores; for example, the ISI7 (interference with daytime functioning) had the highest predictability and node strength in the network model, but its mean score was the lowest among all ISI items.

The strengths of this study included the large sample size and use of network analysis. Some limitations should be acknowledged. First, this is a cross-sectional study, hence the risk factors, co-morbidities and causality of the symptoms of insomnia could not be established. Second, data were collected based on participants' self-report, and the possibility of recall bias could not be excluded. Third, this study focused on mental health professionals, therefore, the findings could not be generalized to other populations, such as other health or general population. Third, an online survey with snowball sampling method was used to avoid the risk of COVID-19 infection, and therefore, the selection bias was inevitable with limited representativeness. Fourth, for logistical reasons, certain associated factors of insomnia, such as the different mental health disciplines, presence and severity of physical diseases, and the influence of insomnia on daily life, were not analyzed.

Conclusion

The results of this network analysis may have treatment implications. As the symptom of interference with daytime functioning was the most central symptom in the insomnia model, it may be an important treatment outcome measure of insomnia in mental health professionals. Further, addressing sleep satisfaction in treatment could simultaneously improve daytime and nocturnal symptoms.

Abbreviations

CI, confidence interval; CS-C, correlation stability coefficient; COVID-19, the coronavirus disease 2019; EBIC, Extended Bayesian Information Criterion; ISI, Insomnia Severity Index; LASSO, least absolute shrinkage and selection operator; NCT, Network Comparison Test; QR, quick response; SARS, Severe Acute Respiratory Syndrome; SD, standard deviation.

Ethics Approval

The study protocol was approved by the Institutional Review Board (IRB) of Beijing Anding Hospital, China (Approval No.: (2020) Keyan (No. 10)).

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Disclosure

The authors report no conflicts of interest in this work.

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