Psychological Adjustment Among Chinese International Students During COVID-19: A
Network Analysis

Kaiwen Bi^{1,2}, Qiwenjing Jiang³, Shuquan Chen¹

¹Columbia University

²Tsinghua University

³Vanderbilt University

Correspondence concerning this article should be addressed to Shuquan Chen,
Department of Clinical and Counseling Psychology, Teachers College, Columbia University at
sc4173@columbia.edu, or Kaiwen Bi, Department of Psychology, Columbia University at
kb3158@columbia.edu

Abstract

A particularly vulnerable yet often-ignored subpopulation during the pandemic is Chinese international students (CIS). Literature suggests CIS suffer from a high prevalence of common mental health issues. Recent advances enable the use of network analysis on psychological data. Our study ($N = 421$) is the first to investigate depressive and anxiety symptoms simultaneously from a network perspective in CIS. Results of the Gaussian graphical model (GGM) suggested that: (1) central symptoms identified via the centrality index of strength included depressive symptoms of “anhedonia” and anxiety symptoms of “restlessness” and “tense”; (2) bridge symptoms identified via the bridge expected influence index included depressive symptom of “psychomotor agitation/retardation” and anxiety symptoms of “afraid” and “restlessness”. Results of the Bayesian directed acyclic graph (DAG) demonstrated the predictive priority of depressive symptoms of “anhedonia” and “sadness” in driving a co-existing state. The network analyses highlight the node of “anhedonia” (a central node in GGM and the top node in DAG) and several other mostly physical symptoms including “restlessness”, “tense”, “psychomotor agitation/retardation”, and “afraid” as candidates for intervention efforts and show great potential in generating actionable insights beyond western samples. Future directions for researchers, implications for counsellors and limitations are discussed.

Keywords: network analysis; depressive symptoms; anxiety symptoms; Chinese international students; directed acyclic graph

Public Significance Statement

As COVID-19 continues to exert differential adverse impacts depending on who one is, it is of great value to apply network analysis to investigate subpopulations that have often been ignored both in counseling services and research, as it holds promise to reveal symptoms that may play important roles in the development and maintenance of psychological symptoms. This article is the first to apply network analysis on Chinese international students and identifies several important nodes that could serve as intervention targets in this vulnerable subpopulation during the pandemic and long after.

Popular models assume that a latent underlying entity of psychopathology exists and leads to various manifest symptoms (e.g., Guze, 1992; Helzer et al., 2008). An alternative model—the network perspective—is gaining traction, positing that psychopathology (e.g., depression) amounts to the complex and dynamic interactions among individual symptoms (Borsboom, 2017; Borsboom & Cramer, 2013). To date, network analysis—a tool not only suitable for conceptualizing single mental health disorders but also comorbidity (Cramer et al., 2010)—were used to investigate individual mental disorders (for reviews, see Malgaroli et al., 2021; Robinaugh et al. 2019) as well as comorbidity between PTSD and depression, and between depression and anxiety (e.g., Konac et al., 2021; Malgaroli et al., 2018). Despite increasing recognition of its value, most network studies sampled western participants.

While not many, the existing studies on CIS suggested that there is a high prevalence of mental health issues (e.g., Han et al., 2012; Lian & Wallace, 2018; Redfern, 2016). Of note is the study of Han et al. (2012), revealing that 45% and 29% of participants reported at least mild depression and generalized anxiety symptoms assessed by Patient Health Questionnaire 9 and Generalized Anxiety Disorder (GAD-7), respectively. Using self-designed measures, Lian and Wallace (2018) suggested that 77.9% and 74.3% CIS suffered from past-year depressive and anxiety symptoms. COVID-19 studies found similar worrisome trends (e.g., Ma & Miller, 2020). Song and colleagues (2020) also found that more than a third of the CIS sample showed moderate-to-severe PTSD symptoms. While of great value and awareness-raising, these studies are limited in that they provided fewer direct clinical implications compared to network studies.

Using different samples, several studies examined depressive and anxiety symptoms simultaneously from a network perspective and found important symptoms. For example, applying both PHQ-9 and GAD-7/GAD-2, several recent studies generated critical insights.

Depressive symptoms of “sadness”, anxiety symptoms of “unstoppable worry” and “irritability” were found to be highly central symptoms twice among three such studies (Bai et al., 2021; Kaiser et al., 2020; Ren et al., 2021). With advances in network analysis (Jones et al., 2019), these studies also identified bridge nodes (nodes most connected to nodes from a different community) with depressive symptom of “sadness” identified in two studies; other bridge nodes identified included anxiety symptoms of “anxious mood”, “restlessness”, and “irritability”, and depressive symptoms of “anhedonia”, “psychomotor agitation/retardation”, and “inattention”.

The Current Investigation

The current study has two goals. First, we constructed a Gaussian graphical model (GGM; Costantini et al., 2015) using data from a sample of Chinese international students. GGM allowed us to identify both the strongest central nodes and bridge nodes. Second, to further elucidate the causal mechanisms among symptoms, we generated a directed acyclic graph (DAG) to map the dominant pathways of symptom activations leading to co-existing symptoms.

Our research advances previous research in two important ways. First, unlike many network studies that exclusively sampled western participants, our network study sampled a rarely investigated subpopulation (i.e., CIS) of a non-western population (i.e., Chinese). Given the lack of attention paid to the prevalence and treatment of mental health disorders among Chinese international students, our research may reveal important symptoms relevant to depressive and anxiety symptoms in this subpopulation and directly inform prevention and intervention efforts. Second, unlike most network studies, our study further examined the interrelationships among depressive and anxiety symptoms via DAG. While DAG was applied to investigate mental disorder comorbid symptoms (e.g., McNally et al., 2017; Jones et al., 2017), few studies took this approach to investigate depressive and anxiety symptoms together.

Methods

Participants and procedure

We drew the data from a project that sampled CIS in March 2021 (Bi et al., 2021). Participants ($N = 421$) were recruited from Chinese online platforms such as Wechat and Weibo and completed a survey including demographics, measures of depressive and anxiety symptoms and risk/protective factors. The present study has two inclusion criteria: (1) current registration in a foreign university; (2) no missing data on depressive and anxiety symptom measures. Participants' age ranged from 18 to 38 ($M = 22.30$, $SD = 2.67$), and 57.00% were female. 69.12% of participants were undergraduate students, and 30.88% were graduate students. 63.18% studied in the US, 10.21% in Australia, 5.93% in Canada, 5.46% in the UK, and 15.20% in other foreign countries. The original study was approved by the Institutional Review Board of Tsinghua University, and informed consent was provided by the participants before participation.

Measures

Depressive symptoms were measured using the Patient Health Questionnaire 9 (PHQ-9; Spitzer et al., 1999), a scale that assesses an individual's depressive thoughts and behaviors during the past two weeks on a 4-point scale from 0 (not at all) to 3 (nearly every day). Example items are "Poor appetite or overeating?" and "Feeling tired or having little energy?". Internal consistency was excellent ($\alpha = .90$), and the validity of the scale was previously validated in Chinese samples (Lin et al., 2021; Liu et al., 2011).

Anxiety symptoms was assessed via the Generalized Anxiety Disorder 7 (GAD-7; Spitzer et al., 2006), a 7-item scale that assesses symptoms of generalized anxiety using items including "Becoming easily annoyed or irritable" and "Trouble relaxing". The scale is on a 4-

point scale from 0 (*not at all*) to 3 (*nearly every day*). Prior research demonstrated its validity in a Chinese sample (Lin et al., 2021). Internal consistency was excellent ($\alpha = .92$).

Statistical analyses

Statistical analyses were performed in R Version 4.0.4 via *Bootnet*, *graph*, and *networktools* packages (R Core Team, 2021). R scripts and data are available on reasonable request.

To identify central nodes and bridge nodes, we first built an undirected network with two pre-specified communities (depressive and anxiety symptoms) using GGM. To produce a more parsimonious model with fewer spurious edges, the GGM network was combined with graphical LASSO penalties (Friedman et al., 2008) with model selected based on extended Bayesian information criterion (EBIC; Foygel and Drton, 2010). The EBIC γ hyperparameter was set to 0.5, which strictly controls for spurious edges. To relax the multivariate normal distribution assumption of GGM, a nonparanormal transformation was done using the `huge.npn()` function of the *huge* package (Zhao et al., 2012). For the undirected network model, a correlation matrix was calculated and partial correlations—the relationships between two nodes after controlling for the influence of other nodes within the network—were estimated based on the correlation matrix. To assess network parameter stability and accuracy of edge-weights, we ran 2,500 nonparametric bootstraps and constructed 95% confidence intervals (CI) on each edge using the *bootnet* package (Epskamp et al., 2016) with significance tests on differences in edge-weights also calculated.

To assess symptom importance, we used the strength centrality index, or the sum of absolute edge-weights connected to the focal node, as it was found to be the most robust (Epskamp et al., 2018). To assess bridge centrality, we used bridge expected influence (1-step)

(BEI). Compared to other bridge centrality indices, BEI has the advantage of distinguishing positive edges from negative ones and sums up the edge-weights from one node to all the nodes of a different network community (Jones et al., 2019). While there exists no consensus on selecting bridge nodes, researchers recommend that the top 20% with the highest BEI be labeled as bridge nodes (Jones et al., 2019). To assess the stability of centrality indices, we reported their corresponding correlation stability coefficients (CS-coefficients) using the *bootnet* package. Specifically, we ran 2,500 case-dropping subset bootstraps to calculate the CS-coefficients, which represent the proportion of participants who can be dropped from analysis while the correlation between the initial centrality indices and the new ones can remain 0.7 or above. For an index to be meaningful, the CS-coefficient needs to be above 0.25, meaning that more than 25% of the participants can be dropped while the correlation between original indices and new ones is still above 0.7. (Epskmap et al., 2018).

To further elucidate the causal relationships between depressive and anxiety symptoms, we applied directed acyclic graph (DAG), a Bayesian network approach that enables information not only regarding strength but also direction of connections between nodes (Scutari & Denis, 2014). The acyclic (i.e., no feedback loop) nature of DAG provides preliminary causal inference that could inform intervention targets in clinical experiments by revealing symptoms that potentially play a causal role in leading to other (comorbid) symptoms (Pearl, 2009). In DAG, upstream nodes are viewed as causes of downstream nodes (Moffa et al., 2017).

The DAG was modeled by a Hill-Climbing algorithm using the *hc()* function of the *bnlearn* package (Daly & Shen, 2007; Scutari, 2010). Three steps were taken to ensure the stability of DAG (Scutari & Nagarajan, 2013). First, using 50 random re-starts and 100

perturbations for each re-start, an iterative procedure that determined whether a connection exists between nodes based on BIC values, we generated an initial DAG with our data. Second, we bootstrapped 10000 DAGs to obtain edge frequency and calculate the significance, direction, and strength of the edges (McNally et al., 2017). Specifically, edges are considered statistically significant and thus retained, if they pass an empirical threshold that is estimated using the bootstrapped networks (Scutari and Nagarajan, 2013). The final direction of the retained edges was determined by a majority vote (i.e., the direction of the arrow that appeared above 50% of the bootstrapped networks). Averaged BIC values were used to represent the strength of each edge.

Results

Undirected network

Full descriptions of symptoms items and corresponding abbreviations and the partial correlation matrix after nonparanormal transformation were shown in Tables 1-2. We depicted the undirected network in Figure 1. Stability tests revealed that there was a degree of overlap between edge CIs, suggesting caution in interpreting edge-weight differences (see Figure S1-2). Node strength centrality and BEI were reported in Figure 2 with difference test results reported in Figure S3. The CS-coefficients of the strength centrality index and BEI exhibited excellent stability and were .59 and .67, respectively.

The most central node was depressive symptom of “anhedonia”. Other highly central nodes included anxiety symptoms of “restlessness” and “tense”. The strongest bridge node was anxiety symptom of “afraid”. Other bridge nodes were depressive symptom of “psychomotor agitation/retardation” and anxiety symptom of “restlessness”.

Directed network

The DAG generated from depressive and anxiety symptoms was depicted in Figure 3. The presence of arrows indicated significant predictive relationships, while the thickness of these arrows reflects the importance to the network structures. The higher the position of a node was estimated to be, the higher predictive priority it had.

The positioning of the nodes suggested that some depressive symptoms may be the primary drivers of comorbidity in the sample. Specifically, depressive symptom of “anhedonia” was the most salient. This node then activated two branches consisting of mostly symptoms of a distinct disorder, except for depressive symptoms of “inattention” and “psychomotor agitation/retardation”, which were found downstream of the anxiety branch. Specifically, “anhedonia” predicted the activation of anxiety symptoms of “anxious mood”—the top anxiety symptom—and “irritability”, and depressive symptoms of “sadness”, “fatigue”, “worthlessness”, and “inattention”. In terms of subsequent activations, anxiety symptom of “anxious mood” then predicted the activation of mostly anxiety symptoms including “unstoppable worry”, “frequent worry”, and “tense”. Meanwhile, depressive symptom of “sadness” also predicted anxiety symptoms of “anxious mood” and “unstoppable worry”, and depressive symptoms of “worthlessness” and “suicide”.

Discussion

Our study is the first to investigate the network of depressive and anxiety symptoms in Chinese international students. We find several central nodes and bridge nodes in the undirected network, many of which are physical in nature. In addition, the DAG enables preliminary inference about the causal mechanisms driving comorbidity of depressive and anxiety symptoms in this subpopulation. We find that depressive symptoms may directionally precede anxiety symptoms and that “anhedonia”—the most central node in the undirected network—activates a

cascade of both anxiety and depressive symptoms. These findings may inform prevention and intervention efforts for Chinese international students.

We first identify important nodes in the undirected network. Three central nodes including “anhedonia”, “restlessness”, and “tense” are identified; two of three are physical in nature. Central nodes likely instigate and/or maintain symptom networks and are therefore ideal targets for intervention efforts. Our findings are both consistent with and different from previous literature using PHQ-9 and GAD-7/GAD-2. For example, Bai et al. (2021) also found “tense” a central symptom. Liang et al. (2020) also identified “tense” or “I found it difficult to relax” in a Chinese population, although they used DASS-21 to assess symptoms. Nevertheless, while symptoms like “sadness”, “unstoppable worry”, and “irritability” were identified in other studies (e.g., Bai et al., 2021; Kaiser et al., 2020; Ren et al., 2021), our study did not. Regarding bridge nodes that may play important roles in the development and maintenance of comorbidity, perhaps our biggest novel finding is anxiety symptom of “afraid” being the strongest bridge symptom. This finding generates the hypothesis that alleviating this symptom in students suffering from anxiety may reduce the likelihood of their developing comorbid depressive symptoms. A closer examination reveals that except for anxiety nodes, “afraid” is most strongly connected to depressive symptom of “worthlessness”, which was the most strongly connected node to “suicide”, a finding similar to Bai et al. (2021). In other words, feeling afraid or fearful when anticipating the future is tied to worthlessness and suicidal ideation. This again highlights the value of targeting fear given the burden that suicide has caused to individuals, families, and society. In line with our findings of central nodes, the other two bridge symptoms—restlessness and psychomotor agitation/retardation—are physical in nature, both of which were also identified in Kaiser et al. (2020) despite sampling very different populations (German inpatients).

Coupled with our finding on central symptoms, this suggests the critical role physical symptoms may play in symptom networks in CIS and the need to incorporate physiological measures into the networks (Kaiser et al., 2020). In addition, while “irritability” was identified in other studies (Wang et al., 2020; Ren et al., 2021), it ranks lower in our study (6th by BEI).

Our second goal is to construct a DAG mapping the dominant pathways in which depressive and anxiety symptoms led to a comorbid state. The results suggest that depressive symptom of “anhedonia” may serve as the starting point of a comorbid system and that increased feelings of anhedonia activated other symptoms and led the system into a comorbid state. While exploratory, DAG provides preliminary evidence that by targeting the top nodes such as CIS’ depressive symptoms of “anhedonia” and “sadness” and anxiety symptom of “anxious mood”, the spread of symptoms may be interrupted (McNally et al., 2014). A degree of coherence exists between the findings of the DAG and those of the GGM: 1) “anhedonia” is also the most central node in the GGM. Coupled with our finding in DAG, this suggests that “anhedonia” may play an important role in the activation/development of co-occurring depressive and anxiety symptoms in CIS. This finding is partially consistent with Winer et al. (2017), who found that anhedonia led to anxiety, which in turn caused depression and that anxiety caused anhedonia and then depression over time. Such convergent evidence again suggests that decreasing feelings of “anhedonia” may lead to at least improvement in symptoms, if not remission; 2) Being relatively crucial in the DAG and activating a cascade of both depressive and anxiety symptoms, “tense” is also a central node in the GGM, again indicating the value of targeting this symptom.

Our study has several limitations. First, generalizability is limited by the snowballing sampling method. Future studies are encouraged to recruit more representative samples from this

subpopulation. Relatedly, the participants were assessed during the pandemic, network studies on Chinese international students are thus urgently needed to see if the same findings replicate and therefore provide convergent evidence for important targetable depressive and anxiety symptoms in this vulnerable and yet often-ignored subpopulation who may suffer disproportionately both during and after the COVID-19 pandemic. Second, while the DAG maps the dominant causal pathways of symptoms, it is exploratory and limited by the cross-sectional design. Future studies should adopt more advanced design (e.g., multilevel modeling/longitudinal). Likewise, our findings from both networks should be tested experimentally. Finally, because our study examined a subpopulation of Chinese, findings' generalizability to other Chinese may be limited. An obvious future direction in the network perspective is to examine the variations of findings across different samples with as many participants as possible.

To conclude, our study identified several clinically relevant nodes—many of which are physical in nature—in Chinese international students. Of note, “anhedonia” is both the most central node and exhibited the highest predictive (and potentially causal) priority in DAG, making it a prime intervention target, while “restlessness” is both a central and bridge node. Additionally, “tense” is both a central node and an important node in the DAG. Our findings on bridge nodes also suggest that apart from the symptoms identified by strength index and the DAG, alleviating symptoms of “afraid”, “restlessness”, and “psychomotor agitation/retardation” may yield promising results when serving CIS exhibiting depressive and/or anxiety symptoms.

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Figure 1. The Gaussian Graphic Model (GGM) of Depression and Anxiety

Note. Psychomotor = psychomotor agitation/retardation. Selected bridge nodes based on the 80th percentile rule are colored in light blue.

Figure 2. Plots of (z-score) Node Strength Index Scores (left) and Bridge Expected Influence Scores (right)

Note. Psychomotor = psychomotor agitation/retardation.

Figure 3. The Directed Acyclic Graph (DAG) of Depression and Anxiety Network

Note. Red-circled symptoms are individual items of the Generalized Anxiety Disorder-7 (GAD-7), a commonly used tool measuring generalized anxiety symptoms and severity. Black-circled symptoms are individual items of Patient Health Questionnaire-9 (PHQ-9), a commonly used tool measuring depressive symptoms and severity.

Table 1. Individual Items of PHQ-9 and GAD-7 and Corresponding Abbreviations

Measure	Abbreviation	<i>M</i> <i>SD</i>
Depression (PHQ 9)		9.09 6.28
Little interest or pleasure in doing things?	Anhedonia	1.25 0.89
Feeling down, depressed, or hopeless?	Sadness	1.10 0.86
Trouble falling or staying asleep, or sleeping too much?	Sleep	1.29 1.07
Feeling tired or having little energy?	Fatigue	1.49 1.00
Poor appetite or overeating?	Appetite	1.02 1.06
Feeling bad about yourself—or that you are a failure or have let yourself or your family down?	Worthlessness	0.97 0.99
Trouble concentrating on things, such as reading the newspaper or watching television?	Inattention	0.99 0.97
Moving or speaking so slowly that other people could have noticed? Or so fidgety or restless that you have been moving a lot more than usual?	Psychomotor	0.58 0.85
Thoughts that you would be better off dead, or thoughts of hurting yourself in some way?	Suicide	0.41 0.73
Anxiety (GAD-7)		7.47 5.20
Feeling nervous, anxious, or on edge	Anxious mood	1.39 0.84
Not being able to stop or control worrying	Unstoppable worry	1.18 0.94
Worrying too much about different things	Frequent worry	1.37 0.93
Trouble relaxing	Tense	1.20 0.94
Being so restless that it's hard to sit still	Restlessness	0.73 0.87
Becoming easily annoyed or irritable	Irritability	0.90 0.90
Feeling afraid as if something awful might happen	Afraid	0.70 0.87

Table 2. Partial Correlation Matrix

	Anxious Mood	Unstoppable Worry	Frequent Worry	Tense	Restlessness	Irritability	Afraid	Anhedonia	Sadness	Sleep	Fatigue	Appetite	Worthlessness	Inattention	Psychomotor	Suicide
Anxious Mood	1	0.723341133	0.718586173	0.699121635	0.521400595	0.546388432	0.504927115	0.547007348	0.617247427	0.508267344	0.553707791	0.506789645	0.544350606	0.38894532	0.343064435	0.416651613
Unstoppable Worry	0.723341133	1	0.733213166	0.727544229	0.580459209	0.581758361	0.62074027	0.486889938	0.597287426	0.523198745	0.489250329	0.50482022	0.545148099	0.398013013	0.404459823	0.473248123
Frequent Worry	0.718586173	0.733213166	1	0.758802609	0.589941547	0.573664658	0.538530723	0.504094384	0.578557199	0.462662092	0.501756848	0.454898467	0.506316512	0.381666988	0.376221029	0.428790598
Tense	0.699121635	0.727544229	0.758802609	1	0.674982592	0.641734758	0.573350826	0.436903899	0.561746226	0.497262679	0.531931608	0.471149233	0.52063013	0.371309906	0.420886974	0.459997823
Restlessness	0.521400595	0.580459209	0.589941547	0.674982592	1	0.68166202	0.572220682	0.39642165	0.508636199	0.463007362	0.459729275	0.495209351	0.504172994	0.492024169	0.543570282	0.44232107
Irritability	0.546388432	0.581758361	0.573664658	0.641734758	0.68166202	1	0.55658996	0.496403498	0.534608654	0.43429636	0.500720953	0.463669008	0.550876776	0.417724721	0.424392447	0.462174514
Afraid	0.504927115	0.62074027	0.538530723	0.573350826	0.572220682	0.55658996	1	0.477834348	0.517724367	0.477664538	0.432660976	0.470168082	0.535933849	0.408550971	0.493821745	0.446949557
Anhedonia	0.547007348	0.486889938	0.504094384	0.436903899	0.39642165	0.496403498	0.477834348	1	0.66057148	0.516561904	0.678209322	0.491453965	0.581530638	0.537720828	0.378251521	0.440122284
Sadness	0.617247427	0.597287426	0.578557199	0.561746226	0.508636199	0.534608654	0.517724367	0.66057148	1	0.480399781	0.567440476	0.492359547	0.607027013	0.452554313	0.391472356	0.52062266
Sleep	0.508267344	0.523198745	0.462662092	0.497262679	0.463007362	0.43429636	0.477664538	0.516561904	0.480399781	1	0.653054765	0.550350367	0.428721385	0.407953527	0.38535828	0.382772523
Fatigue	0.553707791	0.489250329	0.501756848	0.531931608	0.459729275	0.500720953	0.432660976	0.678209322	0.567440476	0.653054765	1	0.587698079	0.512378124	0.460942103	0.349386035	0.410010955
Appetite	0.506789645	0.50482022	0.454898467	0.471149233	0.495209351	0.463669008	0.470168082	0.491453965	0.492359547	0.550350367	0.587698079	1	0.530699411	0.399459678	0.362392012	0.408824571
Worthlessness	0.544350606	0.545148099	0.506316512	0.52063013	0.504172994	0.550876776	0.535933849	0.581530638	0.607027013	0.428721385	0.512378124	0.530699411	1	0.468594746	0.383021654	0.542304184
Inattention	0.38894532	0.398013013	0.381666988	0.371309906	0.492024169	0.417724721	0.408550971	0.537720828	0.452554313	0.407953527	0.460942103	0.399459678	0.468594746	1	0.492080097	0.354275848
Psychomotor	0.343064435	0.404459823	0.376221029	0.420886974	0.543570282	0.424392447	0.493821745	0.378251521	0.391472356	0.38535828	0.349386035	0.362392012	0.383021654	0.492080097	1	0.363341225
Suicide	0.416651613	0.473248123	0.428790598	0.459997823	0.44232107	0.462174514	0.446949557	0.440122284	0.52062266	0.382772523	0.410010955	0.408824571	0.542304184	0.354275848	0.363341225	1

Note. The partial matrix was calculated after nonparanormal transformation using the `huge.npn()` function of the *huge* package; Psychomotor = psychomotor agitation/retardation.