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Utilizing network analysis to understand the structure of depression in Chinese adolescents: Replication with three depression scales

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Abstract

Depression involves a heterogenous collection of symptoms. Network perspective views depressive symptoms as an interrelated network. The current study aimed to replicate network analyses on adolescent depression in three samples assessed with three instruments to examine the consistency of network structures and also examine the variance of networks between genders. Three samples of adolescents (total $N = 4375$, mean age = 15, 49.1% boys) were assessed with PHQ-9, SMFQ and CDI, respectively. Network analyses were carried out on depression symptoms. Network stability, node centrality and network comparisons between genders were examined. Three networks were reliably stable. Sadness and self-hatred were unanimously identified to be central symptoms of adolescent depression in three networks. In addition, fatigue, no good, everything wrong and loneliness also appeared to be central in specific networks. Among three depression networks, PHQ-9 network demonstrated gender difference in network structure. The current study is exploratory in nature. The differences in three networks can be due to various samples or different node inclusions. Further, the study is cross-sectional precluding causal interpretation and the samples are nonclinical. Besides "hallmark" symptom sadness, self-hatred was also identified unanimously in three networks, which demonstrated the significant role self-worth played in adolescent depression. The results also suggested that differences in node inclusion may have influence on the network structure.

Keywords Depression · Network analysis · Adolescent · Depression scales

Introduction

Depression is one of the most prevalent mental health problems occurred among adolescents in China as well as worldwide (Avenevoli et al., 2015; Tang et al., 2019). As a challenging developmental phase with physical and psychological changes and school transition, adolescence is marked with drastic increase in depression incidence (Benner, 2011; Costello et al., 2011). Epidemiological studies done in mainland China suggested that among children and adolescents aged 5–19, approximately 1.3% have experienced major depressive disorder (MDD; Xu et al., 2018) and the prevalence of depressive symptoms was 24.3% among adolescents attending secondary schools (Tang et al., 2019). Adolescent depression is demonstrated to be associated with a myriad of disrupting psychosocial consequences that can expand across the lifespan, including compromised educational attainment and employment opportunities, impaired intimate relationships and social networks (Clayborne et al., 2019).

Since depression is pervasive and debilitating, it's been extensively researched. In regard to assessment, more than 280 various depression instruments have been developed and published over the past century to measure depression severity (Santor et al., 2006). These scales were developed with different theoretical conceptualizations in mind and to serve different purposes so their content also varied vastly (Fried, 2017). For example, Patient Health Questionnaire (PHQ-9) was developed for criteria-based diagnoses of depression, and thus includes nine items directly corresponding to the nine DSM-5 criteria symptoms for MDD (Kroenke et al., 2001).

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Beck Depression Inventory (BDI) was developed based on Beck's conceptualization of depression and accordingly characterizes several cognitive symptoms central to Beck's theory (Beck, 2002). Fried (2017) compared seven frequently used depression scales (encompassing a total of 125 items) and found that the content overlap among the scales was low.

Depression studies routinely employed particular scales and used total scores of all items to measure depression severity, without specifically demonstrating the rationale for scale selection. This practice was suggestive of the traditional entity perspective on psychopathology, which emphasizes on the underlying depression entity, and views depressive symptoms only as equivalent and interchangeable indicators of the depression entity (Brown & Barlow, 2005; Schmittmann et al., 2013). Inspired by this perspective, various studies revolving depression used the sum scores of certain depression instruments as the assessment of depression severity in a general sense, without delving into the symptom-level differences or explaining the rationale for scale selection (Fried, 2017; Fried & Nesse, 2015).

In fact, individual depressive symptoms varies in important properties such as risk factors (Lux & Kendler, 2010), predictive value (McKenzie et al., 2011) and impairment of functioning (Fried & Nesse, 2014; Tweed, 1993). Furthermore, both clinical theory (Beck, 2002) and empirical research (e.g., Bringmann et al., 2015) provided substantial evidence that depressive symptoms influence each other. For example, in Beck's descriptive model of depression, negative beliefs about the self, the world and the future serves to exacerbate negative mood and in turn maintain depression (Beck, 2002). Studies conducted in the U.S. healthy adult samples demonstrated that hopelessness predicts suicidal ideation over time (Kuo et al., 2004). This suggested that various symptoms of depression are not equivalent and interchangeable and it may be beneficial to study depression at the symptom level (Fried & Nesse, 2015). Also, it may be advantageous to be more aware of the symptoms included in the instruments in use.

The recently proposed network perspective of psychopathology views disorders as constituted by the causal interplay between specific symptoms (Wasil et al., 2020). The network perspective focuses on symptom-level associations that form a complex system described as depression (Beard et al., 2016). Developed under this perspective, network analysis helps to visualize the interrelated system of depression. In depression networks, symptoms are represented as "nodes" and relationships between them are represented as "edges". Central nodes which share stronger relationships with other nodes are integral to the network structure and play a crucial role in the development and maintenance of mental disorders (Barrat et al., 2007).

Burgeoning studies have been conducted using network analysis to understand symptom-level structure of psychopathology. Previous research of depression networks primarily revolved around depression in clinical samples of adults. Among adult samples diagnosed with MDD and other psychiatric conditions, sad mood, low energy, and anhedonia were identified to be highly central symptoms of depression networks measured with PHQ-9, BDI-II and QIDS-SR, respectively (Beard et al., 2016; Bos et al., 2018; McNally et al., 2017). Several studies have also explored the network structure of depressive symptoms in adolescent samples. In a study conducted in an American community sample of adolescents, sadness, pessimism, self-hatred and loneliness were identified as the central symptoms of depression measured with CDI (Mullarkey et al., 2019). Feeling like a failure and depressed mood were indicated to be the most central depressive symptoms in the depression network assessed with PHQ-9 among non-clinical adolescents from Sub-Sahara Africa and India (Osborn et al., 2020; Wasil et al., 2020). In summary, among nonclinical adolescents, in addition to sad mood, feeling like a failure (or self-hatred and self-blame) was also central in the depression network, which is consistent with the cognitive features associated with developmental period of adolescence (Carlson, 2000). Above-mentioned studies all used single instruments to investigate interrelations between depressive symptoms without specifying the rationale for scale selection. Though network approach performs on symptom-level and is supposed to be less susceptible to the bias resulted from using various measures, the inclusion of different symptoms in the network still has substantial impact on the network structure (Fried & Cramer, 2017; Jones et al., 2017). Network structure is determined based on the partial correlations between nodes included in the network. Thus, the inclusion of redundant nodes and even more so the exclusion of relevant variables that are strongly associated with other nodes pose serious challenge to network accuracy and interpretation (Fried & Cramer, 2017). Since depression involves heterogenous symptoms as well as numerous related cognitive and behavioral factors, it's impractical to create a depression network with all-inclusive variables. Therefore, the current study chose to select three widely-used depression measures to replicate the network estimation and examine if important network properties (e.g., node centrality) hold across three networks.

The present study sought to expand on the existing literature by pursuing three primary goals. Firstly, this study intended to estimate the depression network in a sample of Chinese adolescents. It has long been recognized that mental disorders are expressed, perceived and described quite differently across different age groups (Nardi et al., 2013) and among diverse cultures (Wilk & Bolton, 2002). For instance, as a turbulent period of life, adolescence appears to be associated with specific features of depression such as low self-esteem (Carlson, 2000). In addition, Chinese individuals tend to report more somatic symptoms of depression than their western counterparts (Ryder et al., 2008). Also, depression

Table 1 Participant demographic information ($N = 4375$)

	Grades		Parents' marital status		Place of residence	
	Middle school	High school	Married	Other[a]	Village	City
Sample 1	605	1005	1468	142	1059	551
Sample 2	1062	1132	1950	244	77	2117
Sample 3	284	287	510	61	283	288
Total	1951	2424	3928	447	1419	2956

[a] The Other category includes separated, divorced and widowed status

was more closely associated with peer problems among western adolescents and more strongly linked with academic difficulties in Chinese adolescents (Ryder et al., 2012). Therefore, applying network analyses to different age groups in different cultures has the potential to deepen our understanding of the patterns of depression networks. Secondly, the current study aimed to replicate the network analyses with three different depression instruments in three samples. Symptoms with high centrality would be identified in each network. Since node inclusion has significant influence on the network model, the current study would estimate depression networks using different scales and samples to examine if centrality of nodes remains relatively invariable across three networks. Thirdly, the present study proposed to investigate the differences of depression networks between genders. Gender differences in depression severity becomes evident since adolescence (e.g., Hankin & Abramson, 2001). Epidemiological studies conducted in the U.S. reported that MDD is nearly twice as prevalent in girls than in boys (Merikangas et al., 2010). Previous network analyses found differences in both network structure (Mullarkey et al., 2019) and network connectivity (Kim et al., 2021) between genders in samples of children and adolescents. The present study aimed to replicate network comparisons between genders in three Chinese adolescent samples with three depression instruments.

Methods

Participants and Procedures

Data from three samples of Chinese adolescents were utilized in the current study. Sample 1 ($N = 1610$, age $= 16.03 \pm 1.72$, 46.5% girls and 53.4% boys) was a convenience sample of adolescents from three public secondary schools in Henan, Sichuan and Shaanxi Provinces in China. Sample 2 ($N = 2194$, age $= 14.33 \pm 3.60$, 47.0% girls, 47.5% boys and 5.5% not reported) was recruited in three secondary schools in Beijing. Sample 3 ($N = 571$, 14.70 ± 1.72, 56.7% girls and 43.3% boys) consisted of adolescents from two secondary schools in Shanxi Province. The data collection of the three samples were carried out before the COVID-19 pandemic. Demographic information is provided in Table 1.

The present study was approved by the local Ethics Committee and the process of data collection was conducted with the permission of the principals of the participating schools. Questionnaires were handed out on school days in classes and completed in paper–pencil format. After explaining the purpose and the nature of the study, informed consent was obtained from classroom teachers and participants. The present researchers provided clarification and ensured independent response from participants.

Measures

Depressive symptoms were assessed with three scales in three samples. Sample 1 was measured with PHQ-9, Sample 2 with SMFQ and Sample 3 with CDI.

Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) is a self-report measure designed for criteria-based diagnoses of depression in primary care. It consists of 9 items that are rated on a 4-point scale (0 = not at all to 3 = nearly every day). The original and Chinese version of PHQ-9 have been shown to be well-validated in previous research (Kroenke et al., 2001; Yu et al., 2012). In our present study, Cronbach's alpha was 0.84.

Short Mood and Feelings Questionnaire (SMFQ; Angold et al., 1995) was developed for the purpose of rapid evaluation of depressive symptoms in youths aged 8–16 years old. The scale mainly revolves around affective and cognitive symptoms. It comprises 13 items, each rated on a 3-point scale (0 = never, 1 = sometimes, 2 = always). The Chinese version of SMFQ demonstrated good internal consistency and test–retest reliability (Cheng et al., 2009). In the present study, Cronbach's alpha was 0.88.

Children's Depression Inventory, (CDI; Kovacs, 1992) was adapted from Beck's Depression Inventory to assess depression in children and adolescents aged 7–17. It includes 27 items measuring cognitive, affective and behavioral symptoms, respectively. The participants were asked to select one out of three statements for each item (0 = absence of symptoms, 1 = mild presence of symptoms, 2 = definite presence of symptoms). The Chinese version of the CDI has evidenced good internal consistency (Wu et al., 2010). In the current study, Cronbach's alpha was 0.83.

Data Analysis Plan

Descriptive analyses of variables were performed in SPSS version 26 and R version 4.0.2. Missing data accounted for 0.36% of the data, with 213 missing values out of 58,429 possible values. The Full Information Maximum Likelihood (FIML) estimation via the Expectation Maximization (EM) algorithm was used to impute the missing values (Dempster et al., 1977; Wang & Deng, 2016).

Item Selection

It's suggested that if redundant nodes were included in the network at the same time, it will obscure the real relationships between nodes (Levinson et al., 2018). To address that concern, the goldbricker function in the R package *networktools* (Jones, 2020) was used to detect each pair of nodes for high correlation between them and compare their correlation pattern with the remaining nodes. The results indicated that there were no redundant nodes in three node collections and thus all items were included in the corresponding networks.

Network Estimation

Network analysis and visualization were conducted in R using the *bootnet* and *qgraph* packages (Epskamp et al., 2012, 2017). The networks were estimated using a Gaussian Graphical Model (GGM; Costantini et al., 2015) regularized by glasso algorithm, creating a sparse graph containing significant partial correlations between nodes (Epskamp & Fried, 2018; Simon et al., 2011). Spearman correlation was used to account for the ordinal data and the dense networks. Glasso algorithm was implemented in combination with Extended Bayesian Information Criterion (EBIC) to select the optimal degree of shrinkage (Chen & Chen, 2008). The default hyperparameter value ($\gamma = 0.5$)[1] was used in the networks (Epskamp & Fried, 2018).

Network Stability

The stability of the network was examined with the *bootnet* package using both nonparametric bootstrapping and case-dropping bootstrapping (Epskamp et al., 2017). The nonparametric bootstrapping repeatedly resamples subsets of the data to construct bootstrapped confidence intervals (CI) around edge estimates. Wider CIs indicates lower accuracy of the edge values. To test the stability of centrality indices, case-dropping bootstrapping was employed to calculate a correlation-stability (CS) coefficient.

[1] $\gamma = 0.25$ was used in Network 3 for the sparsity of the network, following the suggestion by Epskamp and Fried (2017).

Centrality and Difference Test

In addition to visual inspection, the centrality indices were computed in the *qgraph* package to infer the structural importance of nodes in the network (Opsahl et al., 2010). There're three centrality indices that have been used in previous research employing network analysis (e.g., Olatunji et al., 2018). The current study didn't examine betweenness and closeness indices as they demonstrated poor replicability (Epskamp et al., 2017) and appeared to be not suitable in psychopathology networks (Bringmann et al., 2019). Hence, the analyses and interpretations of centrality would focus on strength index. Strength refers to the sum of the absolute edge values between a given node and all other nodes to which the node is connected (McNally, 2016).

The node centrality difference tests were also employed to determine which nodes were significantly more central than other nodes (Levinson et al., 2018).

Network Comparison Tests by Genders

We also tested whether three depression networks varied with genders. First, t-tests were performed on the mean sum scores of depression measures between genders. Then the network comparison tests (NCT) were conducted with the R package *NetworkComparisonTest* (van Borkulo et al., 2017) to determine whether significant gender differences existed in global strength and network structure. Global strength referred to the overall network connectivity and can be calculated as the weighted absolute sum of all edges. The calculation of differences in network structure involved absolute maximum differences among all edge strengths.

Results

Participant Characteristics and Descriptive Statistics

The complete sample included three datasets totaling 4375 adolescents, aged 11–18 years old (mean age = 15), with approximately even gender proportion (48.1% girls, 49.1% boys and 2.8% not reported).

The mean sum scores on the PHQ-9, SMFQ and CDI were 8.27, 6.28 and 16.69, respectively. According to the cut-off values of the three depression instruments (Kroenke et al., 2001; McKenzie et al., 2011; Bang et al., 2015), approximately 32.8% of Sample 1, 19.55% of Sample 2 and 31.9% of Sample 3 were above the clinical threshold of depression.

Descriptive information for each item in the three depression scales are provided in Table 2.

Network Stability

The three depression networks all robust to stability tests. Centrality stability coefficients for strength were investigated for three networks. CS coefficients were excellent for Network 1(CS coefficient = 0.75) and Network 2(CS coefficient = 0.75) and acceptable for Network 3(CS coefficient = 0.36) based on the values suggested by Epskamp et al. (2017) (See Fig. S1-S3). Edges values were estimated to be with moderate confidence intervals (Fig. S4-S6). The strength indices of central nodes were estimated to be significantly higher than other nodes in a bootstrapped difference test which aids in demonstrating stability and accuracy in network interpretation (Fig. S7-S9; Epskamp et al., 2017).

Network Visualization and Interpretation

Network 1 (PHQ-9)

The resultant network with 9 nodes and the strength centrality plot of all nodes were presented in Fig. 1. Nodes that appeared central in the network were *fatigue* (Strength = 1.47), *depressed* (Strength = 1.23) and *self-blame* (Strength = 0.88), which, as stated above, appeared to be significantly more central than 62.5% of the other nodes. There have been suggestions that differential variability of symptom severity could distort the results about node centrality (Terluin et al., 2016). Following prior research (Heeren et al., 2018), the correlation between strength of nodes and variance of symptom severity ratings was calculated. In this network, the strength of the nodes was not significantly related to the variance ($r_s = 0.82$, $p = 0.835$). Hence, the differential variability didn't present a problem for interpreting the centrality indices in this network. Some pairwise associations that stood out were *anhedonia—feeling fatigued*, *feeling fatigued—sleep problems*, and *depressed mood—suicidal ideation*.

Network 2 (SMFQ)

The estimated depression network measured with SMFQ and the corresponding plot of strength index was shown in Fig. 2. *No good* (Strength = 1.23) stood out to be the most central symptom in the network, with its strength significantly higher than 75% of other symptoms. *Self-hatred* (Strength = 0.91), *Everything wrong* (Strength = 0.77) and *Miserable* (Strength = 0.72) appeared as relatively central in the network. The correlation between strength and variance of symptom severity was $r_s = 0.30$ ($p = 0.33$), ruling out the influence of differential variability on centrality estimation. There existed strong associations between *self-hatred—bad person*, *never as good—everything wrong*, and *not enjoy—tired* symptom pairs.

Network 3 (CDI)

Network 3 was relatively sparse compared to the previous two networks due to more nodes and smaller sample size (see Fig. 3). *Self-hatred* (Strength = 2.24), *loneliness* (Strength = 1.96), and *sadness* (Strength = 1.54) were highly central symptoms in the network, significantly more central than 76% of other symptoms as indicated by strength. Strength scores and variance of the symptoms weren't significantly correlated ($r_s = 0.23$, $p = 0.26$), so centrality calculation wasn't biased by variability differences. Strong partial correlations existed between *crying—sadness*, *sadness—loneliness*, *loneliness—lack of friends*.

Network Comparison Between Genders

Differences between genders in the three depression networks were investigated with t-tests and NCTs. According to the results of t-tests, whereas the mean levels of depression in Sample 1 (measured with PHQ-9; t = -3.43, $p = 0.001$) and Sample 2 (measured with SMFQ; t = -2.31, $p = 0.021$) showed significant differences between boys and girls, depression level didn't significantly differ between genders in Sample 3 (measured with CDI; t = 0.30, $p = 0.77$). In both Sample 1 and Sample 2, girls reported higher level of depressive symptoms than boys. Whereas the results of network comparison tests indicated no significant differences between gender in global strength in Network 1 ($p = 0.85$), Network 2 ($p = 0.13$), and Network 3 ($p = 0.08$), the network structures appeared to be significantly different between boys and girls for Network 1 ($p = 0.005$), but not for Network 2 ($p = 0.06$) and Network 3 ($p = 0.73$). Since Network 1 demonstrated significant difference in network structure between boys and girls, specific edges were further compared to elucidate gender differences. Four edges turned out to be significantly different. *Fatigue—poor appetite* ($p = 0.00$) and *depressed—suicidal* ($p = 0.001$) appeared to be more strongly connected in girls than in boys, whereas *fatigue—poor concentration* ($p = 0.02$) and *depressed—motor problems* ($p = 0.05$) were more closely related in boys than in girls (Fig. 4).

Discussion

The present study replicated network analyses on adolescent depression in three samples measured with three different depression instruments.

Our results revealed that *sadness* (*depressed* or *miserable*) and *self-hatred* were unanimously identified to be two of the most central symptoms of depression in the three networks among three samples of Chinese adolescents.

Table 2 Items included in three networks

Node	Mean	SD	Presence in % of participants[a]	Skewness	Kurtosis
PHQ-9 (Sample 1)					
Anhedonia	1.16	0.76	85.8%	0.77	0.68
Depressed	0.94	0.73	74.7%	0.75	0.91
Sleep problems	1.07	0.97	67.6%	0.63	-0.56
Fatigue	1.15	0.81	81.2%	0.61	0.12
Poor Appetite	0.89	0.88	62.5%	0.83	0.06
Self-blame	1.15	0.90	75.9%	0.53	-0.40
Poor concentration	0.96	0.94	62.8%	0.74	-0.34
Motor problems	0.57	0.80	41.2%	1.40	1.34
Suicidal ideation	0.39	0.68	29.6%	1.94	3.68
SMFQ (Sample 2)					
Miserable	0.91	0.64	74.4%	0.09	-0.58
Not enjoy	0.50	0.66	40.3%	0.98	-0.20
Tired	0.91	0.72	69.7%	0.13	-1.05
Restless	0.45	0.65	36%	1.15	0.13
No good	0.36	0.61	29.3%	1.52	1.14
Cried a lot	0.24	0.53	19.3%	2.13	3.55
Poor concentration	0.61	0.67	50.1%	0.66	-0.66
Self-hatred	0.28	0.57	22.3%	1.89	2.50
Bad person	0.22	0.51	17%	2.34	4.54
Loneliness	0.62	0.74	46.1%	0.75	-0.81
Unloved	0.30	0.59	22.8%	1.84	2.19
Never as good	0.52	0.69	40.5%	0.97	-0.31
Everything wrong	0.38	0.62	30.8%	1.39	0.76
CDI (Sample 3)					
Sadness	0.32	0.58	25.7%	1.67	1.7
Pessimism	0.99	0.28	95.8%	-0.25	10.06
Self-deprecation	1.22	0.45	98.8%	0.90	-0.07
Anhedonia	0.67	0.56	62.2%	0.10	-0.69
Misbehavior	0.26	0.55	20.5%	2.03	3.07
Worry	0.48	0.70	35.9%	1.13	-0.09
Self-hatred	0.45	0.62	38.5%	1.04	0.02
Self-blame	0.42	0.60	35.7%	1.15	0.28
Suicidal	0.56	0.57	52.7%	0.36	-0.82
Crying	0.26	0.55	20.7%	2.02	3.07
Irritable	0.56	0.71	43.6%	0.86	-0.56
Withdrawal	0.35	0.60	28.2%	1.53	1.20
Indecisiveness	0.97	0.71	73.2%	0.04	-1.03
Negative body image	0.77	0.61	67.3%	0.17	–0.54
School difficulty	1.00	0.69	76.2%	0.00	-0.90
Sleep problems	0.49	0.73	34.9%	1.14	-0.19
Fatigue	0.64	0.74	48.5%	0.68	-0.88
Poor appetite	0.43	0.64	34.9%	1.20	0.27
Somatic concern	0.44	0.62	36.8%	1.11	0.17
Loneliness	0.64	0.72	49.6%	0.66	-0.83
School dislike	0.81	0.66	67.3%	0.22	-0.74
Lack of friends	0.68	0.53	64.4%	-0.11	-0.76
School performance	0.90	0.74	67.6%	0.16	-1.14
Low self-esteem	1.04	0.46	91.4%	0.16	1.64
Unloved	0.46	0.63	38.9%	1.03	-0.02

Table 2 (continued)

Node	Mean	SD	Presence in % of participants[a]	Skewness	Kurtosis
Disobedience	0.68	0.50	66.0%	-0.34	-0.94
Fights	0.18	0.42	17.0%	2.18	4.06

[a] Presence of symptoms was indicated if participants responded with "1" or greater on the item

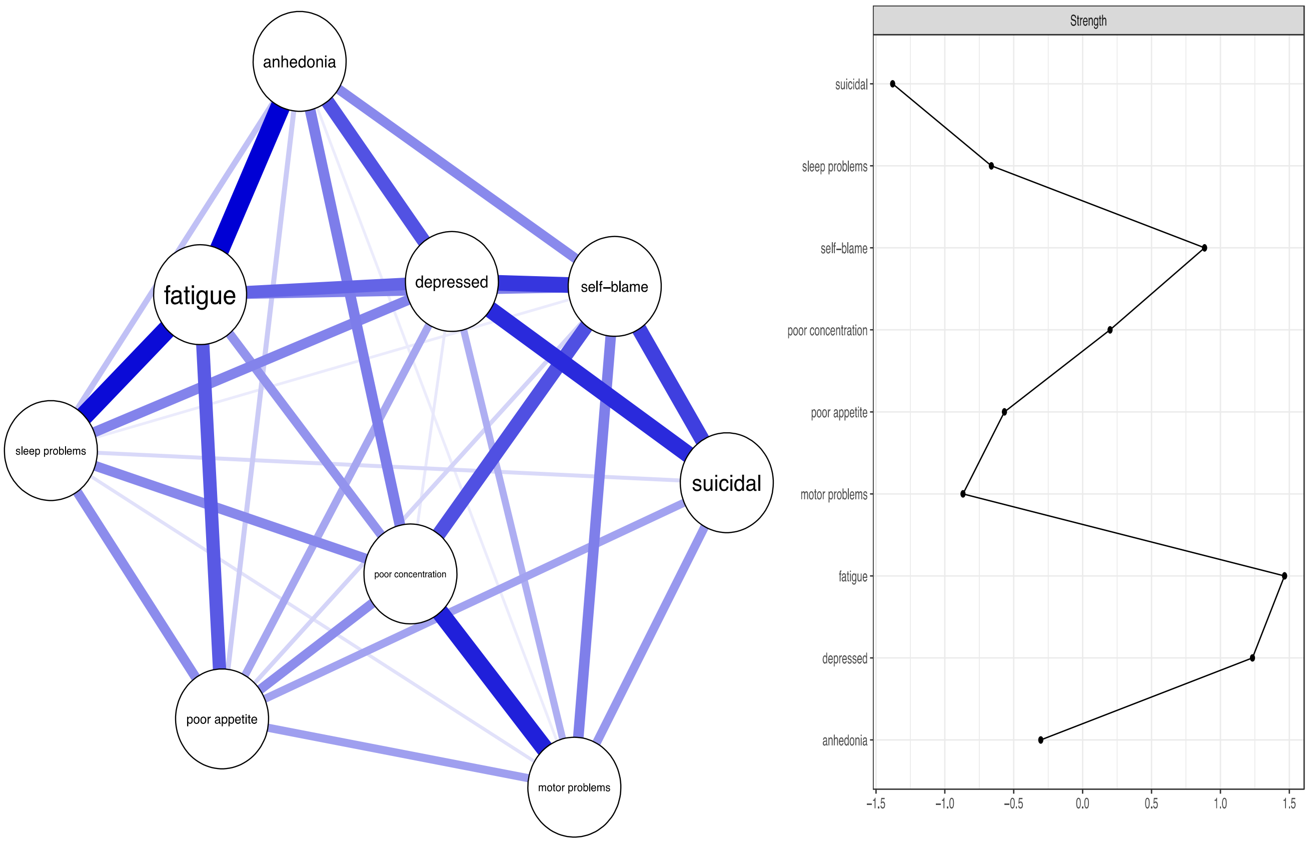

Fig. 1 The left part shows the estimated network of depression (measured by PHQ-9) and the right panel shows the strength scores (centrality indices) of Network 1, shown as z scores

Consistent with the results of previous network analyses (Mullarkey et al., 2019; Osborn et al., 2020; Wasil et al., 2020), this finding spoke to the stability and generalizability of the centrality of sadness and self-hatred in adolescent depression. Sad mood is usually recognized as the "hallmark" symptom of depression (American Psychiatric Association, 2013), and the centrality of sad mood is in line with the theoretical conceptualization of depression (Beck, 2002) as well as previous research of depression network in both adults and adolescents (Beard et al., 2016; Wasil et al., 2020). It's notable that *self-hatred* (*self-blame*) was also identified as a central symptom, which was found before in adolescent samples (e.g., Wasil et al., 2020) but not in adult samples (e.g., Beard et al., 2016). During adolescence, individuals are prompted to introspect who they are and how they are perceived by others (Steinberg, 2005) and are in turn vulnerable to develop low self-esteem and form negative self-referent thinking style (Neff & Mcgehee, 2010). According to Beck's cognitive theory of depression (Beck, 2002), negative self-referent thinking puts individuals at greater risk for developing depression, as corroborated by substantial empirical evidence (e.g., Franck et al., 2007; Orth et al., 2009). Low self-worth was also found to have high predictive value for adolescent depression (McKenzie et al., 2011). Along with previous network analyses (e.g., Mullarkey et al., 2019), our research supported self-hatred as a central symptom in depression among adolescents in diverse cultural backgrounds.

Apart from shared central symptoms (i.e., *sadness* and *self-hatred*), network analyses of three depression

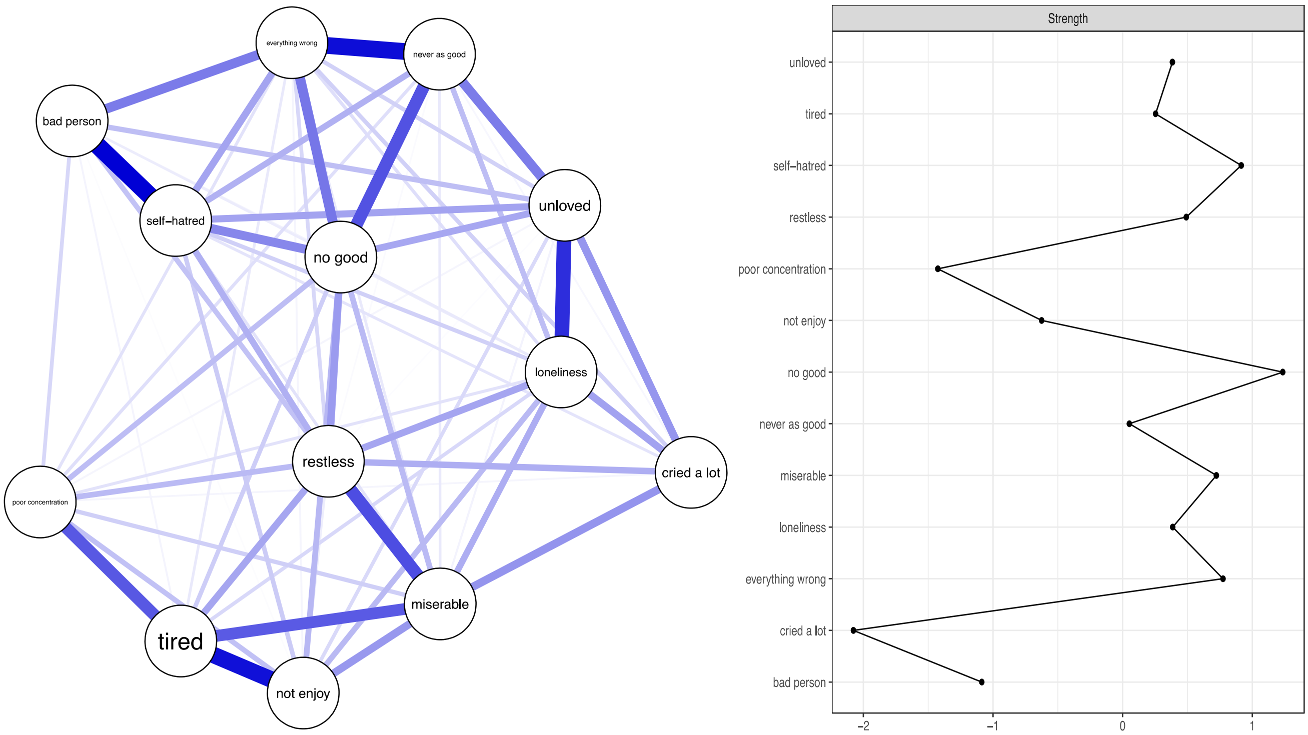

Fig. 2 The left part depicts the estimated network of depression (measured by SMFQ) and the right panel presents the strength scores (centrality indices) of Network 2, shown as z scores

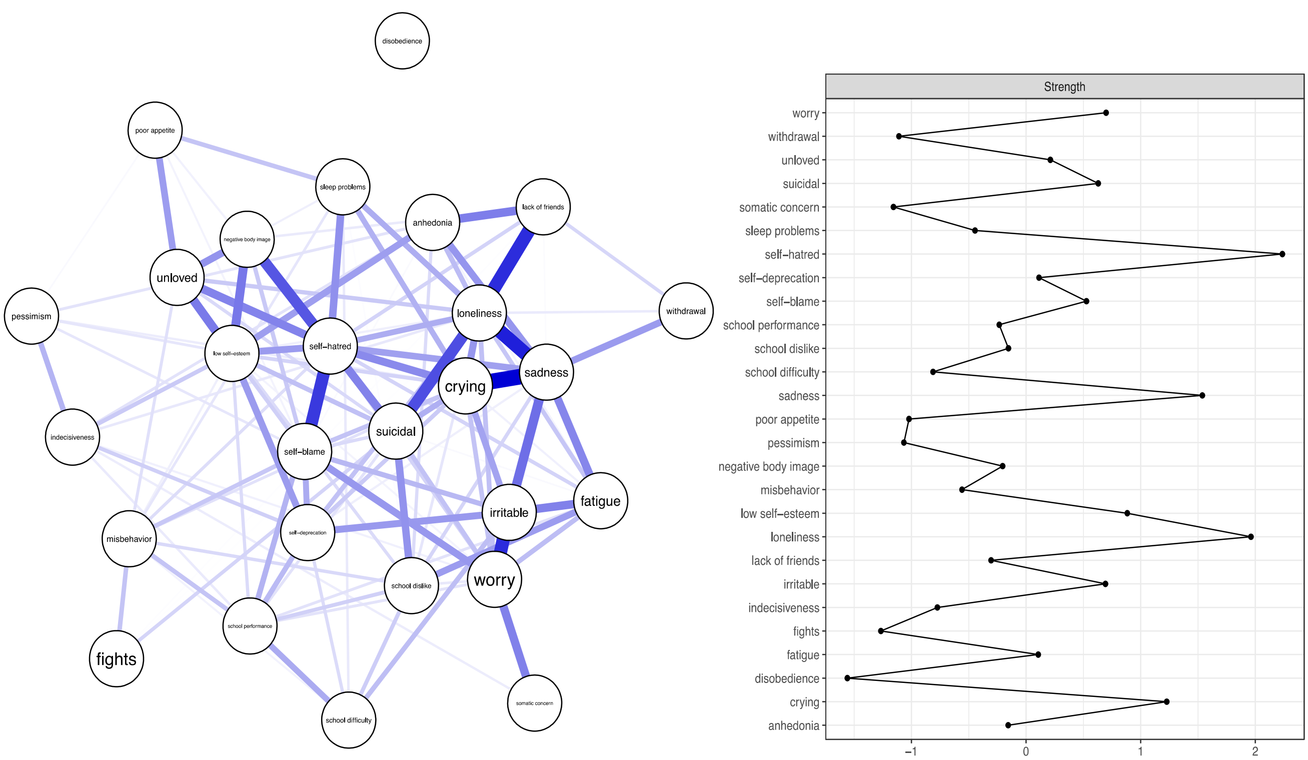

Fig. 3 The left part presents the estimated network of depression (measured by SMFQ) and the right panel shows the strength scores (centrality indices) of Network 3, shown as z scores

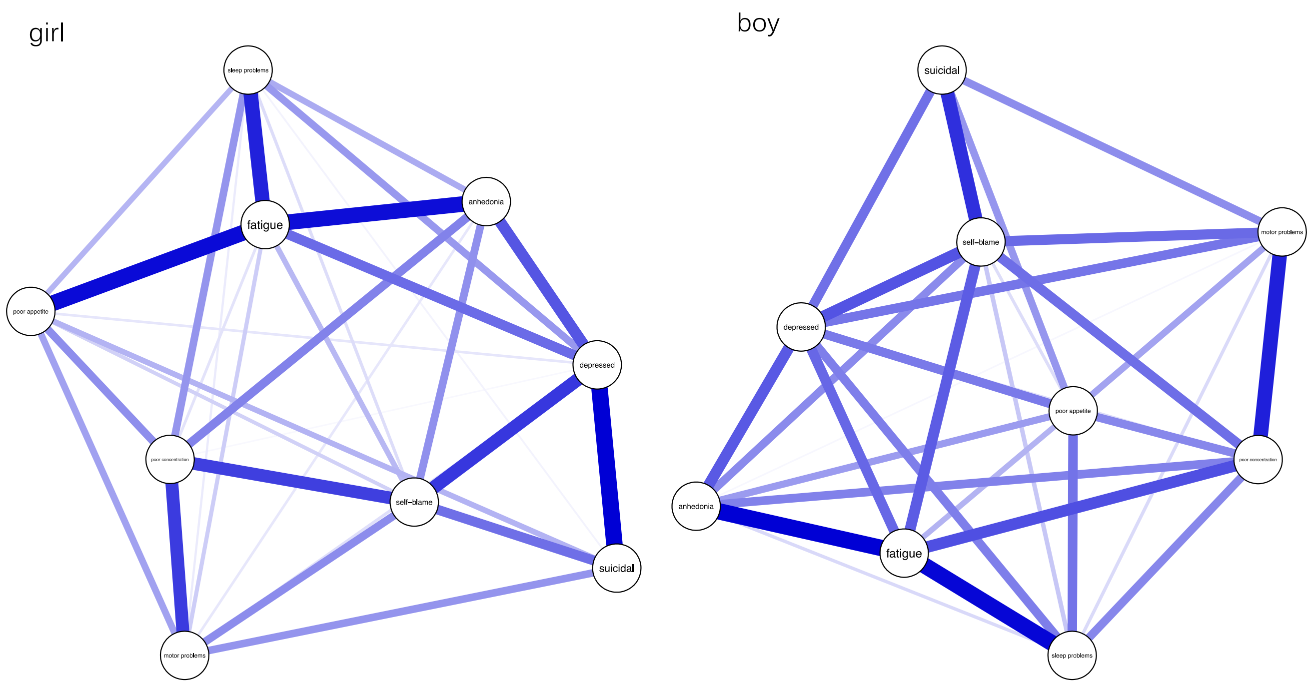

Fig. 4 Estimated Network 1 (PHQ-9) in girl ($n=749$) and boy ($n=861$) participants

instruments also identified unique central nodes in their respective networks. *Fatigue* emerged as a central symptom in Network 1 (measured with PHQ-9), *no good* and *everything wrong* appeared to be central in Network 2 (measured with SMFQ) and Network 3 (measured with CDI) features *loneliness* as a central symptom. Fatigue as a central node was previously found in clinical adult samples but not in nonclinical adolescent samples (Fried et al., 2016). A probable explanation is that, somatic symptoms such as fatigue or headache are characteristic of Chinese presentation of depression (Ryder et al., 2008). Secondary school students in China are faced with exhausting academic pressure that could add to the symptom of fatigue. These contextual factors may partially account for the high centrality of fatigue in the current study. It's also noticeable that *fatigue* was identified in the PHQ-9 network but not in the CDI network which also included *tired* as a symptom. It could be due to that PHQ-9 composed of a variety of physical behavioral symptoms such as *motor problems*, *poor appetite* and *sleep problems*, which had closer relationship with *fatigue* and increased the connectivity and strength of *fatigue* in the network. Cognitive characteristics common for adolescent depression, such as *everything wrong* and *no good*, emerged as central nodes in SMFQ network. This could be attributed to the focus on cognitive factors in the SMFQ and its close relationship with negative self-referent thinking style and low self-worth, which was integral to adolescent depression (McKenzie et al., 2011). *Loneliness* appeared to be central in the CDI network rather than in the SMFQ network. It could partially be explained by the emphasis of CDI on school life and interpersonal relationships with the inclusion of items such as *lack of friends* and *withdrawal*.

The t-test results showed that the mean scores of PHQ-9 and SMFQ showed significant gender differences, which was supportive of the widely recognized findings that girls experienced higher level of depression than boys (e.g., Hankin & Abramson, 2001). The NCT results revealed that only PHQ-9 network demonstrated significant network structure difference between boys and girls. *Fatigue* was more strongly related with *poor appetite* in girls and more closely associated with *poor concentration* in boys. *Depressed* shared stronger relationships with *motor problems* in boys and with *suicidal ideation* in girls. These results suggested that gender differences in adolescent depression may be more manifest in somatic and behavioral aspects, which was consistent with previous findings in adults (e.g., Silverstein et al., 2013).

Study Limitations and Strengths

The present study has several limitations. First, the current study raised no formal hypotheses and was exploratory in nature. Network analysis of psychopathology was a strongly exploratory and data-driven field. Especially, no study that we know has compared network models with nodes from different measuring instruments. Second, the three network analyses were conducted in three different samples varying in demographic characteristics, depression levels. Also, the sample sizes of the three studies varied considerably. Though we tried to control for the differences in sample sizes by statistical methods (i.e., using different γ), it still had the potential to skew the results. Therefore, the differences in network structure could be argued to result from differences in samples rather than node inclusions. However, for the very reason of the heterogenous samples, the results indicated the generalizability of the central role that sadness and self-hatred played in the development and maintenance of adolescent depression. Third, given the cross-sectional nature of the data, the present study can only draw conclusions about simultaneous associations among symptoms, precluding strong inference of causal interplay. Fourth, the sample of this study were nonclinical and convenient, so the structure of the present network analyses may not be completely generalizable to clinical adolescent samples. Previous research suggested that the connectivity among symptoms within the network is likely to differ between clinical and nonclinical samples (Santos et al., 2017). Future studies could examine the depression network in clinically diagnosed adolescents and compare the networks of clinical and nonclinical groups. Fifth, the current study only investigated the general network structure of depression in common samples of Chinese adolescents. However, the structures of depression can be different for adolescents faced with specific risk factors (e.g., sexual minority) (Forbes et al., 2021; Lucassen et al., 2017). Future research examining the network structures of depression in relation to different predisposing factors would broaden our understanding of the relationships within symptoms of depression as well as with other correlates (e.g., Choi et al., 2017).

These limitations notwithstanding, the current study helped to deepen our understanding of the structure of depression network in adolescent in the background of Chinese culture. In combination of previous studies (McKenzie et al., 2011), sad mood and self-hatred demonstrated to be significant in adolescent depression. Targeting self-worth in adolescents with elevated level of depression may have beneficial cascading effects on the depression network (McNally, 2016; Valente, 2012). Network structure differences in three networks indicated that researchers should be more aware of the generalizability challenge of psychopathology network derived from single scales. The network comparison tests implied that gender differences in adolescent depression was more evident in somatic and behavioral aspects.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12144-022-03201-z.

Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval The present study was approved by the relevant Ethics Committee.

Conflict of interest The authors declare they have no financial interests.

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