Core and activating Symptoms of Depression in Chinese Teachers and Comparison between Different Gender and Stage of Teaching: A Network Analysis Approach

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Abstract

Background

Depression, increasingly recognized as a critical factor impacting mental health, notably affects various populations, including teachers. This study aimed to delineate the specific characteristics of depressive symptom networks among Chinese teachers, identify the core symptoms of depression within this demographic, and examine the variations in depressive symptom networks across different genders and teaching stages.

Method

The study encompassed 1,670 teachers. Depressive symptoms were assessed using the Self-Rating Depression Scale (SDS). Central symptoms were identified through centrality indices. Network stability was examined via a case-dropping procedure. Directed Acyclic Graphs (DAG) was used to identify the activating symptoms.

Results

“Personal devaluation” exhibited the highest and most stable centrality values in the network. “Depressed Affect” and “Emptiness of Life” were identified as the activating symptoms in the network. No significant differences were observed in the network structure and global strength of depression between teachers of different genders. However, significant differences in the network’s global strength were found between junior and senior high school teachers.

Conclusion

“Personal devaluation” emerged as the core depressive symptoms among teachers in China. “Depressed Affect” and “Emptiness of Life” serve as the gateways that activate the entire teacher depression network. Paying close attention to these symptoms could potentially alleviate the experiences of depression in this demographic.

Introduction

Depression, recognized globally as a significant mental disorder, has a reported prevalence of approximately 5% among adults worldwide according to the World Health Organization in 2023 [1]. Individuals suffering from depression are at a significantly higher risk of developing physical ailments, including type 2 diabetes [2], dementia [3], coronary heart disease [4], and even leads to an increased risk of premature death. Recognized as a significant risk factor for depression, work stress has been particularly noted in the teaching profession, a field marked by its high susceptibility [5,6]. The unique challenges faced by teachers, characterized by intense quantitative workload and substantial emotional demands, play a pivotal role in this increased vulnerability [7,8]. These combined pressures not only intensify the stress experienced by educators but also significantly elevate the risk of depression within this profession. The rising student enrollment numbers, stringent teacher evaluation systems, negative public perceptions, and expanding non-teaching responsibilities have collectively heightened stress and depression among educators [9]. Depression has been proven to be one of the most common mental health issues among teachers of compulsory education [10]. A research effort in Egypt revealed that 23.2% of teachers displayed depression symptoms, with 0.7% experiencing severe depression [11]. Similarly, in the United States, the United Kingdom, and other countries, the prevalence of depression among teachers is also high to varying degrees [10,12,13]. In China, teachers are potentially at an even greater risk due to the comprehensive implementation of school personnel system reforms and various educational reforms over recent decades, which have been linked to an increased risk of depression [14,15]. In several meta-analyses, teachers' depression scores were significantly higher than the national standards for Chinese adults [16]. In a survey of English teachers in secondary schools, it was found that 19.4% scored 10 or above on the Patient Health Questionnaire-9 (PHQ-9), indicating a moderate level of depression [12].

For teachers, experiencing psychological distress can have a particularly pronounced effect on both their personal and professional lives [17]. Such distress can significantly impact their health and productivity, leading to increased attrition rates

[10]. Individuals with depression often struggle with meeting interpersonal, time-management, and productivity demands. Additionally, they may face psychological issues, a decline in work quality, frequent absences due to illness, and heightened work disability. These factors collectively can have a profound impact on overall teacher productivity, affecting not only the individual teacher but also the educational environment they are part of [18,10,19]. The mental well-being of teachers plays a pivotal role in shaping students' learning outcomes [20]. Research has demonstrated a significant link between the mental health of educators and student behavior. Prolonged periods of poor mental health in teachers can adversely affect student academic performance and negatively impact the quality of teacher-student relationships [21].

Most quantitative studies on depression have traditionally viewed depressive symptoms as manifestations of a single underlying disorder, analogous to the relationship between a set of items and an underlying latent dimension (such as a factor or trait) in psychometric research. However, this approach has practical limitations, as it often overlooks key aspects like causality, symptom progression, symptom heterogeneity, and the interrelationships among symptoms [22,23,24] . Consequently, the intricate complexity of mental health issues is frequently oversimplified by the notion that all symptoms are merely external signs of a singular, underlying disorder [22,23].

The Network Theory of Mental Disorders (NTMD) posits that symptoms of psychological disorders are interconnected through various mechanisms [25]. When these causal connections strengthen, symptoms can form a self-sustaining feedback loop, potentially resulting in a persistent disorder state. NTMD posits that this interconnectedness is a fundamental characteristic of mental disorders. In the context of depression, NTMD views it as a network of interlinked depressive symptoms, arising from complex interactions among multiple risk factors and causal pathways [26,27]. Research in this area has revealed that changes in a single symptom may not directly alter the overall severity but can influence other associated symptoms [28]. Targeting a specific symptom could lead to improvements in others [29]. Hence, network theory has gained traction as an innovative approach to understanding and treating depression [30,31,32]. A key methodology in this framework is network analysis, a visualization tool adept at representing such intricate relationships [33,34]. Unlike traditional approaches that aggregate symptom scores to define disorders, network analysis focuses on individual symptoms, mapping the strength and nature of their interconnections [26,35]. Core symptoms, identified based on centrality metrics in the network (such as betweenness, closeness, and strength), are crucial. Interventions aimed at these core symptoms can significantly impact the network, alleviating the mental illness and benefiting peripheral symptoms [26,36]. Consistent with clinical practice, network analysis is used to examine symptom-symptom interactions [37], which is instrumental in identifying intervention priorities and enhancing treatment efficacy, thus offering substantial practical value [38].

Previous research has explored the network structure of depressive symptoms in diverse populations. A study constructing a network model of depression among Chinese adolescents found that the central symptoms included "depressed mood", "feelings of failure", "sadnes", and "fatigue" [38]. In contrast, for psychiatric inpatients, they found the core symptoms to be loss of interest, difficulty concentrating, and tiredness/fatigue [32]. In a cohort study by [39], it was observed that changes in core symptoms like a sad or depressed mood, diminished interest, and fluctuations in suicidal ideation were intricately connected to shifts in other symptoms. Clinical trials involving adults with major depression have indicated that depressed mood, insomnia, and suicidality are particularly pivotal in determining the effectiveness of antidepressant treatments in terms of remission and recovery [27]. Considering the sensitivity of network analyses to sample characteristics such as age, socioeconomic status, and specific stressors, it is crucial to recognize that the applicability of network results might vary across different populations. Therefore, depressive symptoms should be analyzed within the context of specific population groups.

However, the aforementioned network analysis method relies on partial correlations and cannot explore the underlying causal relationships between symptoms. Bayesian Networks (BNs) offer an innovative approach to model causal relationships, addressing the limitations of partial correlation networks in cross-sectional data. We used Directed Acyclic Graphs (DAG) in Bayesian Networks (BNs) to reveal the causal relationships between symptoms within the network. Bayesian Networks measure the likelihood of one event occurring after another through conditional probabilities. This approach allows us to understand the complex relationships between different variables. BNs also incorporate prior probabilities and joint probabilities. Prior probabilities represent the initial belief about the state of each variable before observing any data. These priors are updated with observed data through Bayesian inference, refining our understanding of the network variables. Joint probabilities specify the likelihood of various combinations of observed variable states and quantify the potential causal effects between variables, even in cross-sectional data. The network encodes the joint probability distribution, providing a probabilistic framework for representing and reasoning about causal relationships. Additionally, BNs can identify activating symptoms, which are more likely to influence all other symptoms, and receiving symptoms, which are more likely to be influenced by other symptoms. In network analysis, central symptoms have always been a focal point. However, there is still a gap in analyzing central symptoms: are central symptoms driving the other symptoms in the network, or are changes in other symptoms driving the manifestations of these central symptoms? This is a question of causality, and BNs are a tool that attempts to answer such questions. Previous studies have analyzed depression symptoms based on the Least Absolute Shrinkage and Selection Operator (LASSO) model [40]. However, the lack of exploration of causal relationships limited the depth of previous research. In contrast, our study uses DAG in Bayesian Networks to address this limitation. This approach helps reveal the potential directions of symptom associations in the anxiety-depression network, making it possible to visually identify whether central and bridging symptoms are sources or recipients of activation effects. It provides further insights into the underlying structure of anxiety and depression networks, enriching our understanding of teacher depression.

The prevalence of depression in female and male teachers often shows marked differences, with multiple studies indicating higher depression levels in female teachers compared to their male counterparts [41,42]. Additionally, research has demonstrated that high school teachers exhibit significantly higher depression scores than grade school teachers [43]. In a Chinese context, a study revealed a gradual but more rapid increase in depression levels among middle school teachers over time, compared to elementary school teachers [44]. This raises pertinent questions: Are there notable gender-based differences in the depression network among teachers? Does the depression network vary among primary, junior high, and senior high school teachers? To our knowledge, no prior research has applied network analysis to investigate the relationships among depression symptoms specifically in teachers. Hence, this study used the network analysis to explores the network structure and central symptoms of depression among Chinese teachers and assesses the differences across gender and teaching stages. Although this study focuses on Chinese teachers, high-stress teaching environments, cultural expectations regarding teachers' roles, and demands for academic achievement are common characteristics across the globe. Moreover, the network analytic approach adopted here is universally applicable and can be employed across diverse cultural contexts to uncover the structure of psychological symptoms [45,46,47].

The current study has three objectives. First, we aim to construct the network structure of depression among teachers and identify the central symptoms. Secondly, we compare the networks of male and female teachers to explore gender differences, and we also compare the networks of primary, middle, and high school teachers to investigate the differences among these three groups. Finally, we use Directed Acyclic Graphs (DAG) to reveal potential causal pathways in the depression networks of teachers and identify the activating symptoms.

Methods

Source of data and participants

The data for this study was sourced from the Science Database of People's Mental Health [48], established by the National Research Institute for Family Planning and managed by the National Population Health Data Center (China). It encompasses data on diverse demographic groups, including children, adolescents, adults, the elderly, individuals with disabilities, pregnant women, and specific occupational groups like teachers and civil servants. For this study, data specifically related to teachers" depression were selected. Analyzed demographic variables included gender and the educational stage taught by the participants. The final sample consisted of 1,670 participants with an average age of 37 years

(SD = 10.22 years) and the average length of service was 14 years (SD = 11.12 years), comprising 675 males (40.4%) and 995 females (59.6%). This included 820 primary school teachers

(49.1%), 625 middle school teachers (37.4%), and 225 high school teachers (13.5%). Further descriptive information about the samples can be found in the supplementary materials (Table S1).

Measurements

Depressive symptoms were assessed using the Self-Rating Depression Scale (SDS). This scale comprises twenty items, each rated on a scale ranging from 1 (never) to 4 (always). Of these items, 10 indicate negative experiences and 10 indicate positive experiences [49]. The total SDS score can range from a minimum of 20 to a maximum of 80. The total SDS scores were multiplied by 1.25, and the resulting integral part was used as the normal score. A higher normal score suggests a greater tendency towards depression. The SDS have been standardized and shown to be effective in China [50]. In this study, the Cronbach's α coefficient for the scale was 0.90.

Statistical analysis

Network estimation

For statistical analyses, network models were created using R software (Version 4.0.3) (R Team, 2021). In these models, each symptom of depression is represented as a node, and edges between nodes represent regularized partial correlations, reflecting the unique statistical association between two symptoms after controlling for all others [51]. The Extended Bayesian Information Criterion (EBIC) along with the graphical Least Absolute Shrinkage and Selection Operator (LASSO) were employed to establish the network of depression symptoms. Specifically, we constructed a network model using the 20 items of the Self-Rating Depression Scale (SDS) as nodes in a Gaussian Graphical Model (GGM) (Costantini et al., 2015). The teacher depression network was estimated using the EBICglasso method by specifying default = 'EBICglasso' in the 'estimate network()' function of the boot net package. GGM is an undirected network where the edges represent partial correlations between nodes, controlling for the influence of all other nodes in the same network. To eliminate spurious edges and make the model more parsimonious and prominent, the GGM was regularized using the graphical least absolute shrinkage and selection operator (LASSO) penalty, with the final model selected according to the extended Bayesian information criterion (EBIC) [22,23]. The EBIC hyperparameter gamma (γ), which typically ranges from 0 to 0.5 with higher values favoring more parsimonious models by reducing spurious edges [51], was set to 0.5 in this study. Considering that our analysis prioritized robustness of results and was supported by a large sample size (N = 1670), adopting this conservative setting was appropriate. The R packages qgraph (version 1.9.5) [52] and bootnet (version 1.5.6) [53] were utilized for estimating and visualizing the network. The associations between each pair of continuous variables, representing depression symptoms, were calculated using correlation analyses [53] . In the network diagrams, thicker edges indicate stronger associations between nodes. Red edges represent negative associations, while green edges signify positive relationships [52].

To explore the importance of each symptom in the network, previous studies have typically used the centrality index strength (i.e., the sum of the absolute edge weights connected to a specific node), which is considered the most reliable centrality index [54,55]. However, Robinaugh et al. (2016) argued that when a network contains both positive and negative edges, strength may not be a reliable indicator, and expected influence (EI) might be a more reliable metric. Therefore, we used EI in this study to measure the importance of each symptom in the network. Additionally, predictability was calculated using the R package mgm (Version 1.2-14). This measure evaluates how well a node is predicted by its neighboring nodes, serving as an index of the network model's controllability. Predictability is visually represented by the area within the rings surrounding each node in the network layout [56].

Network stability.

The stability of the network was assessed using the R package bootnet (Version 1.5.6) [53] Specifically, we ran 1,000 bootstraps using the `bootnet()` function in the bootnet package, and calculated the CS coefficient by specifying `type= 'nonparametric'` and `nBoot = 1000`. The confidence intervals were set at 95%.The CS-C values determine the maximum proportion of the sample that can be omitted while still maintaining correlations above 0.7 with a 95% probability in relation to the original centrality indices [53]. CS-C values above 0.5 are indicative of robust stability, whereas values below 0.25 suggest instability.

DAG

In the DAG, upstream nodes are prioritized as predictors and are considered the causes of downstream nodes [57]. Specifically, the construction of the DAG is based on the hillclimb algorithm, using the 'hc ()' function from the bnlearn package [58]. To ensure the stability of the model, the network model is established in three steps [59]. First, we performed 50 random starts, with each random start setting 100 perturbations. The purpose of performing 50 different random starts is to avoid local maxima, and the 100 perturbations involve iteratively inserting, removing, or reversing an edge to determine the best-fitting structure of the DAG based on the optimized fitness index (i.e., BIC value). This process allows us to generate an initial DAG based on the data. Next, we bootstrapped 10,000 DAGs to obtain edge frequencies and calculate the significance, direction, and strength of the edges [60]. Specifically, if the frequency of an edge exceeds the empirical threshold estimated using the bootstrap networks, it is considered statistically significant and thus retained [59]. This approach ensures a good balance between sensitivity and specificity. Finally, the final direction of the retained edges is determined using a majority voting method, where the direction that appears in at least 51% of the arrows in the 10,000 bootstrap networks is considered the final direction of the edge. The thickness of the edges represents the percentage of the final direction appearing in the visualized network.

Comparisons based on gender and educational stage of teaching

Differences in network characteristics based on gender and the educational stages taught were assessed using the Network Comparison Test (NCT) implemented in the R package Network Comparison Test [61]. The NCT was applied to subsamples, specifically male and female teachers, as well as primary, junior high, and senior high school teachers. A total of 5000 permutations were conducted to evaluate network invariance, global strength invariance, and centrality invariance across these groups. Due to the smaller number of high school teachers, we down sampled the primary and middle school teachers to match the number of high school teachers for comparison. Down sampling is a data processing method aimed at balancing the dataset by reducing the sample size of the categories with larger sample sizes to match those with smaller sample sizes. This method helps to mitigate bias caused by sample size differences, making the comparison fairer and more accurate [62]. Therefore, unlike the overall network estimation and gender-based comparisons that were conducted on the full dataset (N = 1,670), the comparisons across educational stages were performed on the down sampled subsample (675).

Table 1. Descriptive Statistics of the SDS

Labels	Symptoms	Mean	Standard deviation
1	Depressed affect	1.71	0.737
2	Diurnal variation	2.73	1
3	Crying spells	1.42	1
4	Sleep disturbance	1.98	0.896
5	Decreased appetite	3.01	0.932
6	Decreased libido	2.49	1.067
7	Weight loss	1.35	0.624
8	Constipation	1.55	0.8
9	Tachycardia	1.36	0.595
10	Fatigue	1.84	0.828
11	Confusion	2.93	0.962
12	Psychomotor retardation	2.72	0.978
13	Psychomotor agitation	1.56	0.719
14	Hopelessness	2.94	0.949
15	Irritability	1.81	0.815
16	Indecisiveness	2.52	0.925
17	Personal devaluation	2.92	0.915
18	Emptiness	2.84	0.929
19	Suicidal rumination	1.23	0.564
20	Interest loss	2.99	0.935

Results

Descriptive

The mean SDS score was 2.194 with a standard deviation of 0.841. Descriptive statistics for individual SDS items are shown in Table 1. The results of difference tests between male and female teachers, as well as among primary, middle, and high school teachers, can be found in the supplementary materials (Table S2).

Network structure

The structure of the depressive symptom network for teachers is depicted in the left side of Figure 1. Of the 190 edges, 110 (57.89%) were positive, demonstrating interconnectedness among the depression symptoms. The strongest connection was observed between “Sense of Futility” and “Emptiness of Life”, followed by the connections “Difficulty in Thinking - Decreased Ability” and “Depressed Affect - Fatigue Easily”. Additionally, node predictability values varied from 57.6% to 93.4%, with an average of 75.0%. This suggests that, on average, 75.0% of the variance in the network nodes could be accounted for by their adjacent nodes. Notably, “Weight Loss” and “Sense of Worthlessness” exhibited the highest predictability within the model, whereas “Emptiness of Life” displayed the lowest predictability.

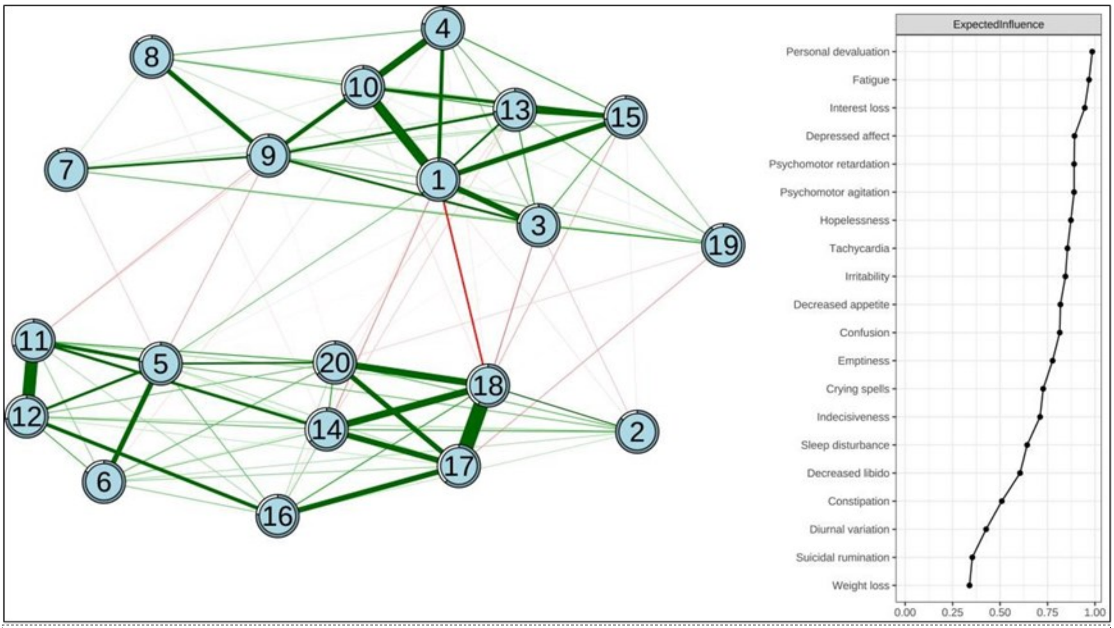

Figure 1. Network structure of depressive symptoms in teachers and expected influence (z-score) of each variable

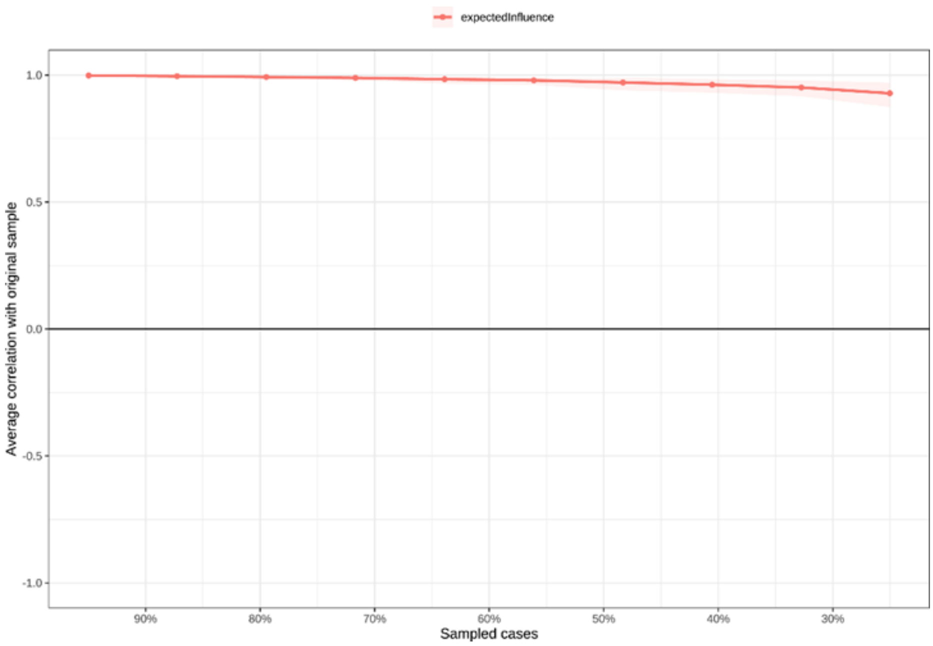

Figure 2. The stability of network structure by case dropping subset bootstrap

The significance of each node within the network is detailed in the right side of Figure 1. The most central symptoms of teacher depression identified were “Sense of futility” (EI = 0.986), “Fatigue” EI = 0.969), “Interest loss” (EI = 0.946), and “Depressed affect” (EI = 0.892). The depression network demonstrated good stability. The CS-C of EI was 0.75, indicating that the EI after discarding 75% of the data was still significantly correlated with the original data at the 95% confidence level (Figure 2). Further information on the edge weight confidence intervals (CI) and differences in node strength for each network can be found in the supplementary materials (Figure S1-S2).

Directed Acyclic Graphs

Figure 3 shows the DAG obtained through the hill-climbing algorithm. The symptoms at the top have higher predictability compared to other symptoms. In the DAG visualization, the depression symptoms “Depressed affect” and “Emptiness of life” occupy the highest and second-highest positions, respectively, influencing a large number of symptoms below them.

Network comparison

Comparisons based on gender

The network structures generated from the two genders are shown in Figure 4. There were no significant gender differences in network global strength (males: 8.79 vs females: 8.51; S = 0.28, p = 0.212) or network structure (M = 0.12, p = 0.717).

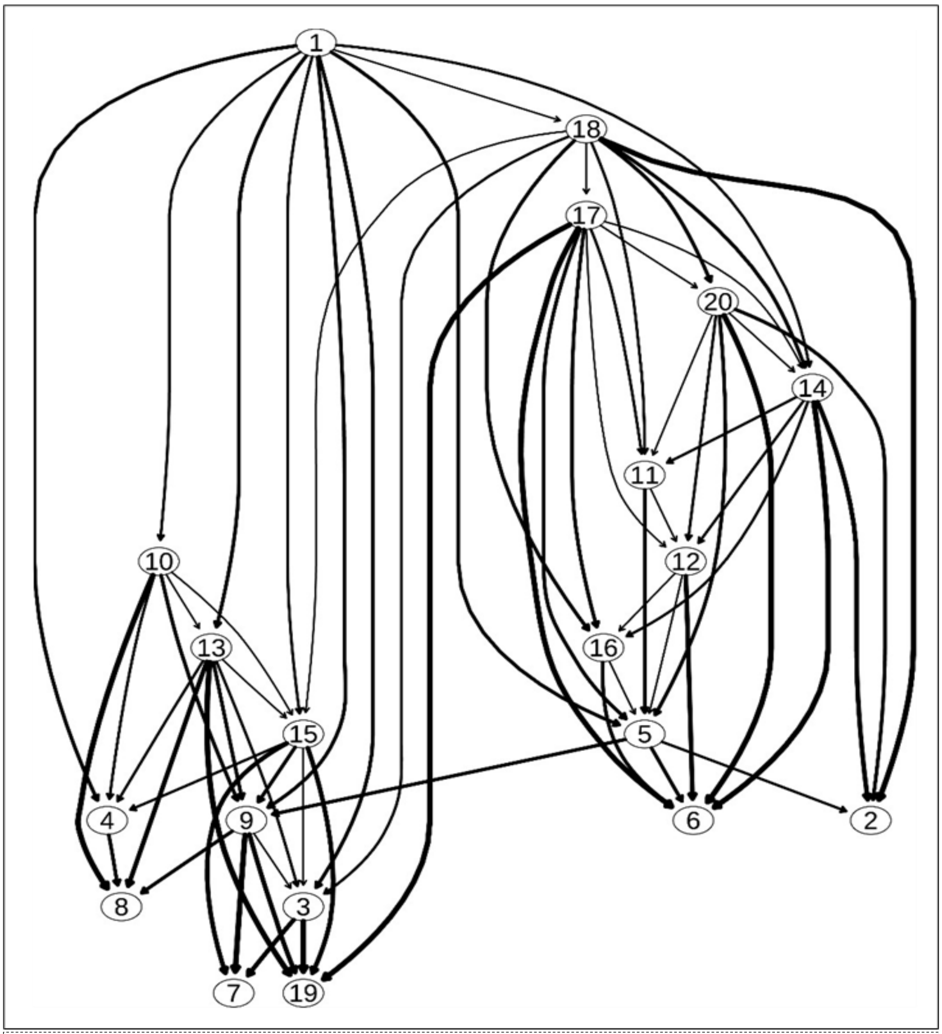

Figure 3. Bayesian network (directed acyclic graph) of depression

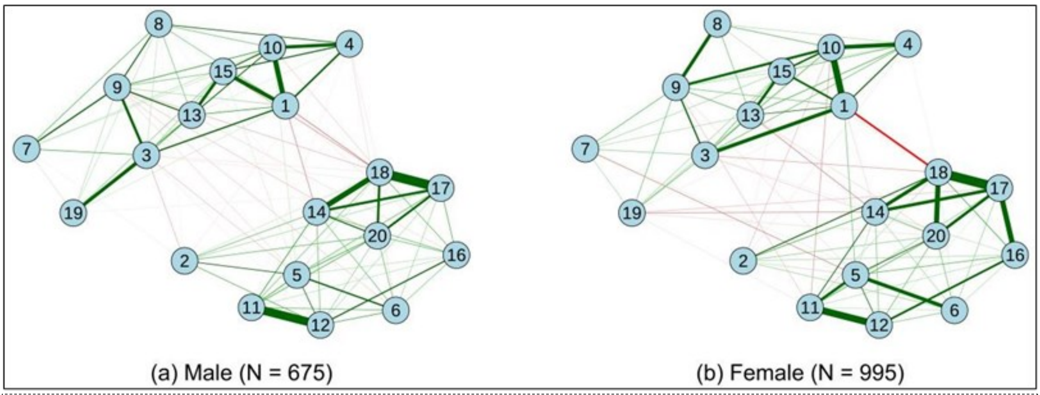

Figure 4. Estimated network of depressive in males and females participants.

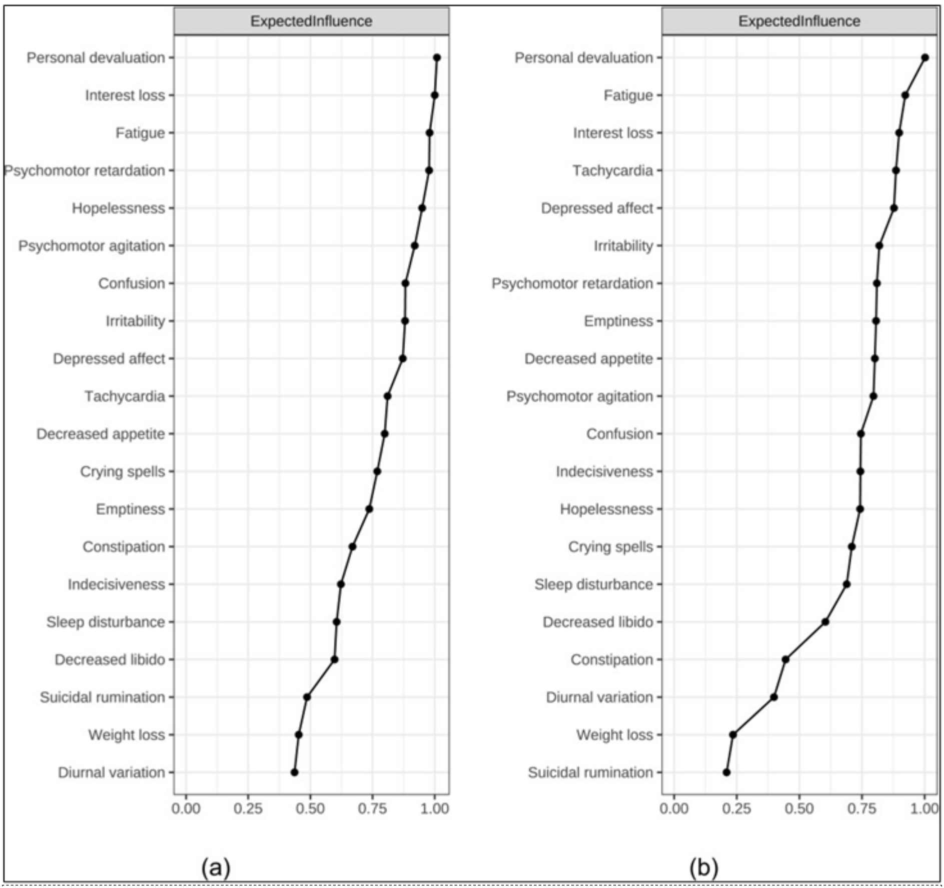

Figure 5. Centrality plot depicted the expected influence (z-score) of each variable chosen in the male and female teachers.

In the depression network of male teachers, the most central symptoms included “Sense of futility”, “Loss of interest”, “Fatigue easily”, and “Decreased ability” (Figure 5(a)). However, in female teachers, “Decreased ability” was not a central symptom; instead, “Palpitation of heart” was central (Figure 5(b)). Based on the network comparison, no significant differences were observed in the centrality indices of these core depressive symptoms across the groups (all p values > 0.05).

Comparisons based on education stages of teaching

Comparisons of network characteristics between primary and junior high school teachers showed no significant differences in global network strength (primary: 8.43 vs junior: 8.77; S = 0.34, p = 0.132) or network structure (M = 0.12, p = 0.794). Similarly, the comparison between primary and senior high school teachers did not reveal significant differences in either global strength (primary: 8.34 vs high: 7.99; S=0.35, p = 0.293) or network structure (M = 0.20, p = 0.680). However, the global network strength was significantly higher in junior high school teachers compared to senior high school teachers (junior: 8.62 vs senior: 7.89; S = 0.64, $p < 0.05$), although no significant differences were observed in

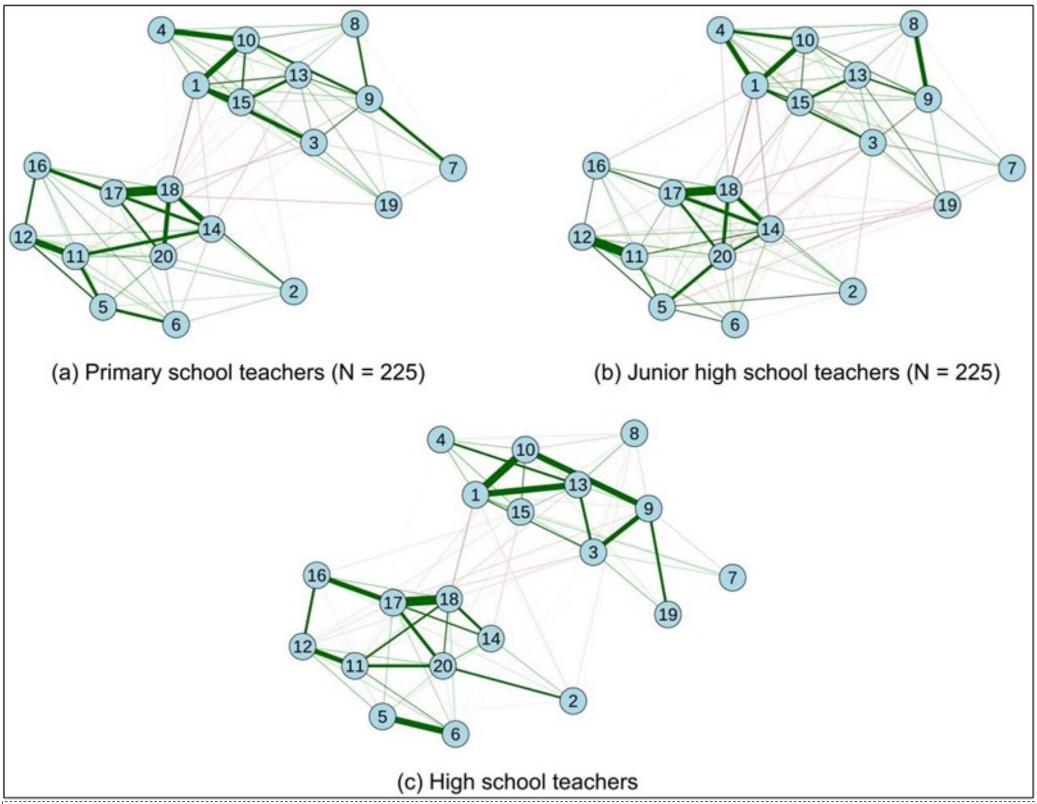

Figure 6. Estimated network of depressive and anxiety symptoms in primary, junior high and senior high school participants.

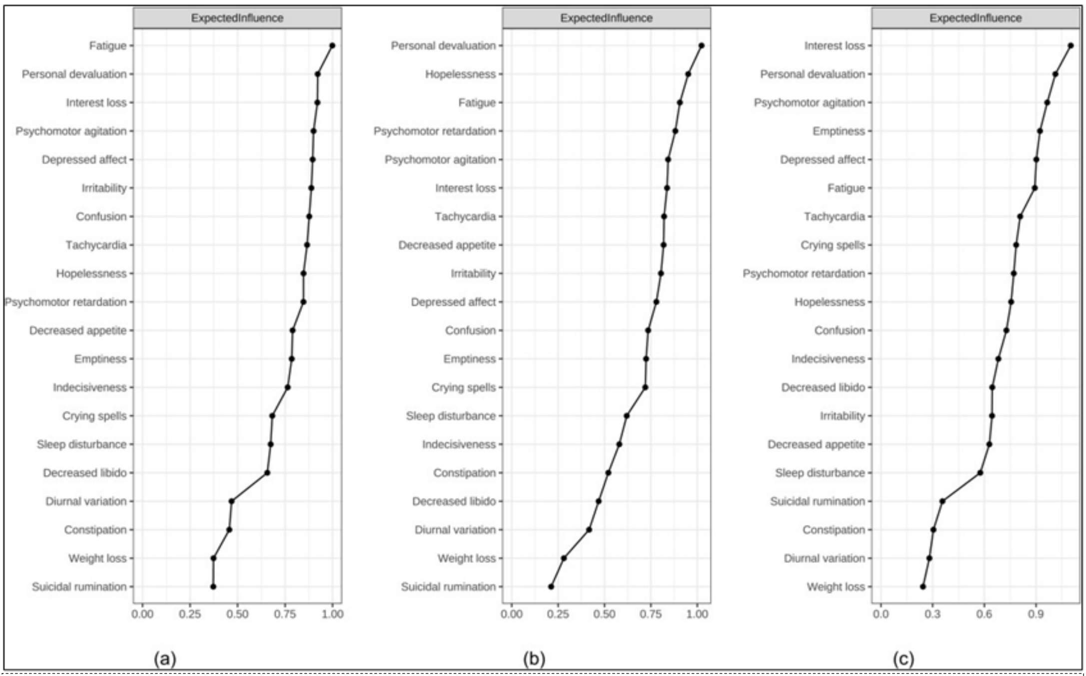

Figure 7. Centrality plot depicted the expected influence (z-score) of each variable chosen in the primary, middle and high school teachers

network structure between these two groups (M = 0.18, p = 0.832). No significant differences were observed in the centrality indices of these core depressive symptoms across the groups (all p values > 0.05). The corresponding plots are presented in the supplementary materials (Figure 6).

Figure 7 displays a comparative analysis of centrality indices among teachers at primary, junior high, and senior high school levels. For primary school teachers, the central symptoms of depression are identified as “Fatigue”, “Personal devaluation”, “Interest loss”, and “Psychomotor agitation” (Figure 7 (a)). In junior high school teachers, the core symptoms include “Personal devaluation”, “Hopelessness”, “Fatigue”, and “Psychomotor retardation” (Figure 7 (b)). Among senior high school teachers, the core symptoms are “Interest loss”, “Personal devaluation”, “Psychomotor agitation”, and “Emptiness” (Figure 7 (c)).

Discussion

Considering the increasing prevalence of depression among teachers and its adverse effects on their mental and physical well-being, which in turn may influence student behavior and achievement, this study employed network analysis. The aim was to investigate the core symptoms of depression in teachers, delving into how these symptoms manifest and interact within this specific professional group. Additionally, the study examined variations in the depression symptom network across different genders and stages of teaching, seeking to identify any distinct patterns or characteristics.

To evaluate the core symptoms of teacher depression, one key metrics were utilized: expected influence. The analysis revealed that the most central symptoms of depression among teachers include “Personal devaluation”, “Fatigue”, “Interest loss”, and “Depressed affect”. These symptoms emerged as critical indicators in the network analysis, highlighting their significance in the context of teacher depression.

The centrality indices within the teacher depression network exhibited high levels of stability. The Correlation Stability Coefficients (CS-C) demonstrated robustness, indicating reliable results in the network analysis. In our comparative analysis, it was found that the global strength of the depression network among junior high school teachers was significantly higher compared to their senior high school counterparts.

Core of teachers’ depression

To our knowledge, this study represents the first attempt to characterize the depressive symptom network specific to teachers. Our findings highlight “Personal devaluation” as the most central symptoms within the overall network, consistently emerging as core features across various teacher groups. Consequently, this symptom is the most likely candidates for triggering or maintaining remaining depressive symptoms. The important role of “Personal devaluation” in depression symptoms has been supported by numerous studies [63,64]. A network analysis study focusing on patients with major depressive disorder also confirmed the high centrality of “Personal devaluation”. Exploring “Personal devaluation” among teachers in the Chinese context is particularly meaningful when considering the unique aspects of Chinese culture. In terms of work, Confucian culture in China places a high value on education, with the saying “all trades and professions are inferior to being a scholar” reflecting the high expectations Chinese parents have for teachers and the great hopes society places on them. Additionally, Confucian thought emphasizes that teachers should “serve as a role model”, setting an example for students and nurturing talents that align with Confucian cultural values [65,66]. In the context of family, Confucian familism, a key aspect of Confucian thought, emphasizes the obligations of family members to their families. Under such multiple pressures, Chinese teachers often carry a heavy burden and frequently feel dissatisfied with their achievements, making them more prone to self-devaluation [67]. Moreover, the central role of "diminished self-worth" in the depression symptom network provides important insights into understanding depression and occupational burnout among teachers. "Diminished self-worth" reflects an internalized sense of low self-value and a tendency toward self-criticism. It is not only a core symptom of depression but also overlaps with reduced personal accomplishment [68]. Research on the mental health of Chinese teachers has shown that depressive symptoms and occupational burnout frequently co-occur at high rates [69,70]. Therefore, early screening and interventions targeting "diminished self-worth" may have particularly significant effects: alleviating this core symptom can help reduce the severity of other depressive symptoms and prevent teachers from falling into a vicious cycle of "worsening depression and progressively deepening occupational burnout."

Activating symptoms of teachers' depression

According to the results of the DAG, we identified that "Depressed Affect" and "Emptiness of Life" have significant activating roles in teacher depression symptoms.

"Depressed Affect", consistently identified as a central symptom of depression [26,71,72,73], has been shown to play a pivotal role across diverse populations and cultures within the core structure of depression networks [73]. In this study, "Depressed affect" is also identified as a significant symptom, serving as an important activating symptom rather. Teachers face multiple sources of stress from work, family, and personal life [74,75], and many are also responsible for administrative duties [76]. Excessive stress and heavy workloads exacerbate emotional exhaustion, leading to depressive mood [77] and potentially triggering additional depressive symptoms. Research has already confirmed the impact of depressed affect on the progression of depression symptoms [78], indicating that how individuals cope with depressed affect can significantly influence future psychological outcomes. As an important activating symptom, addressing depressed affect is crucial. In the teacher population, third-wave cognitive behavioral therapies such as Acceptance and Commitment Therapy (ACT) or mindfulness-based cognitive therapy (MBCT) are worth exploring. These therapies can guide teachers to bring more vitality, action, and positive experiences into their lives. Similarly, Behavioral Activation Therapy can help teachers engage in positive activities to counteract depressed affect. The preventive effects of cognitive-behavioral therapy on depression symptoms have received some validation in clinical settings [79]. However, their effectiveness in the teacher population has yet to be established.

"Emptiness of Life" emerged as another activating symptom in this study. The professional demands and societal expectations placed on teachers often require them to exercise restraint over their emotions. This includes occasions where they must disguise or conceal their true emotional responses and display emotions that align with their professional roles [80]. This disparity between experienced and expressed emotions is termed " surface acting " , a concept within the three-dimensional structure of emotional labor [81,82]. The conservation of resources theory posits that such continuous emotional regulation depletes personal affective or motivational resources [83]. Over time, this depletion can lead to emotional exhaustion [84,85], with 'Emptiness of Life' frequently manifesting as a key indicator of this state of exhaustion [86]. The findings of this study further emphasize the significant role of "Emptiness of Life" as an activating symptom in teacher depression. The activating role of emptiness identified in the teacher population may be related to the impairment of teachers' sense of well-being. Emptiness is typically associated with lower levels of well-being [87]. A study of primary and secondary school teachers found that the core of teachers' well-being lies in the quality of their interactions with students [88]. From this perspective, and in conjunction with our findings, the crucial role of teacher-student interaction offers new insights into the prevention of teacher depression and the construction of psychological health. Development and reform should fully consider the importance of interactions with students.

Depression networks among teachers of different genders

Furthermore, our findings indicate that the network connectivity and structure of depression among teachers are consistent across genders, aligning with previous studies [89]. While earlier research has often shown a higher prevalence and overall scores of depressions in females compared to males [90], our network analysis reveals no significant differences between genders in terms of network structure and global strength. This observation might suggest that the centrality of symptoms within the network is independent of the average levels of those symptoms [72]. Essentially, while the prevalence and severity of symptoms might differ between genders, the way symptoms are interconnected and influence each other within the network appears to be similar.

Depression networks among teachers of different stage of teaching

This study revealed no significant differences in the structure of depression symptom networks among teachers at various educational stages. This indicates a similarity in how depression symptoms interact and in the fundamental network structure across different groups of teachers, regardless of their teaching stage. Notably, middle school teachers exhibited a higher global strength in their depression symptom network compared to high school teachers. This suggests a more closely knit relationship between depression symptoms among middle school teachers. The junior high school stage, as a transitional period bridging primary and senior high school, places teachers under unique instructional pressures. Academic pressure also intensifies sharply as students begin preparing for competitive examinations, while teachers often face reduced professional autonomy in modifying curricula or pedagogical approaches [91]. Moreover, adolescents at this stage frequently experience emotional and behavioral fluctuations associated with puberty, which further complicates classroom management [92]. The unique role of the junior high school stage as a transitional period, coupled with the challenges of teaching adolescents, may contribute to a more interconnected network of depression symptoms in middle school teachers. This interconnectedness could lead to stronger feedback loops that sustain depressive symptoms [26,25,27]. Based on these findings, while similar intervention strategies can be applied to address depressive symptoms in teachers across various educational stages, a greater focus may be needed for interventions targeting middle school teachers, given their higher network global strength.

Strengths and limitation

Recent studies have increasingly focused on the mental health of teachers [93], uncovering that their mental health conditions are far from optimistic [94,95]. Compared to other professions, primary and secondary school teachers are subjected to higher levels of psychological risks [96], with notable concerns regarding the high prevalence and detection rates of depression [97]. Among teacher samples, various factors such as work-family conflicts and perceived stress have been identified as contributors to symptoms of depression [98,99]. Given the significance of high centrality symptoms within networks as reported in previous studies [100,101], our research could be instrumental in developing and testing targeted interventions to mitigate depression among teachers. For example, it would be beneficial to incorporate explicit measures and strategies within teacher management protocols, such as mandatory training and avenues for aligning with school culture and systems. These measures should focus on managing and appropriately expressing emotions, reducing the need for surface acting in emotional labor, thereby diminishing emotional exhaustion and the sense of emptiness in life [48].

Despite the potential applied implications of this study, several limitations must be acknowledged. First, the reliance on self-reported data introduces the possibility of response biases, including social desirability bias. Second, the cross-sectional design of this study limits our ability to infer causal relationships or track the dynamics of depression symptoms over time. Third, the generalizability of our findings may be primarily applicable to Chinese teachers, suggesting that studies in different countries or with different populations might yield varying network structures. Finally, although Bayesian Network (BN) analysis can demonstrate potential causal relationships between symptoms through conditional probabilities, it cannot replace longitudinal study designs. BNs can identify possible causal relationships and suggest potential causal links in correlated data, but they inherently do not provide the temporal order of events. Future research could consider longitudinal network analysis.

Conclusion

Our network analysis successfully identified the core symptoms in the depression network of Chinese teachers: “Personal devaluation”, and the activating symptoms: “Depressed Affect” and “Emptiness of Life”. The study revealed consistency in core symptoms, network connectivity strength, and structure across different genders. Regarding the stage of teaching, notable differences were observed in network global strength between junior and senior high school teachers, with junior high school teachers exhibiting higher network global strength. This suggests that depressive symptoms may be more entrenched and challenging to alleviate among junior high school teachers, highlighting the need for focused interventions in this group to prevent the exacerbation of depression. The study further identified activating symptoms of depression among teachers, namely depressed affect and emptiness of life, which offer a new perspective for the prevention of teacher depression. In clinical practice, timely interventions targeting core symptoms can effectively alleviate overall depression levels, while the early monitoring and management of activating symptoms are particularly crucial for prevention.

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Conceptualization: Shumeng Ma; Data curation: Shumeng Ma; Formal analysis: Shumeng Ma; Funding acquisition: Ning Jia; Methodology: Shumeng Ma, Ning Jia; Supervision: Ning Jia, Jinghua Dai; Visualization: Shumeng Ma; Writing - original draft: Shumeng Ma; Writing - review & editing: Ning Jia, Jinghua Dai. Approval of the final version for publication: all co-authors.

Ethics Statement

The database, approved by the Ethics Committee of the Cancer Hospital, Chinese Academy of Medical Sciences, ensures participant informed consent, with the latest ethics revision dated May 26, 2023.

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Data Availability Statement

The data that support the findings of this study are available from the Science Database of People"s Mental Health but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Science Database of People's Mental Health.

Preprint Disclosure

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Supplementary Material

Supplementary Material

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