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ORIGINAL RESEARCH

The Symptom Structure and Causal Relationships of Comorbid Anxiety and Depression Among Chinese Primary and Middle School Teachers: A Network Analysis

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Background: In China, as educational reforms progress, the characteristics of teachers' work have undergone significant changes, resulting in extremely high levels of stress that can trigger anxiety and depression. Anxiety and depression often co-occur, with two mainstream theories explaining this co-existence: the tripartite model and the diathesis-stress model. However, systematic research focusing on this population is relatively scarce, and the applicability of these models has not been thoroughly tested. This study aims to use network analysis methods to examine the interactions between symptoms and analyze the co-existence of anxiety and depression, thereby expanding the research on teachers.

Methods: Data were provided by the Science Database of People Mental Health, which includes 1670 teachers with a mean age of 30.01. The Self-Rating Anxiety Scale and Self-Rating Depression Scale were used to estimate the network structures of anxiety and depression, respectively. Shared symptoms between depression and anxiety were identified using network analysis and clique percolation methods. Bayesian Networks was used to estimate causal relationships between symptoms. Data were analyzed using R packages. Network structure was constructed with the qgraph package, node centrality and bridge symptoms were evaluated using the networktools package, and network stability was measured via the bootnet package. The Clique Percolation method was implemented with the CliqurPercolation package, and Bayesian network modeling was performed via the Bnlearn package.

Results: Dizziness and Easy Fatigability & Weakness were central symptoms in the network. Bridging strength results showed that, the important bridging symptoms included Tachycardia, Depressed Affect, Fatigue, Crying Spell, Easy Fatigability & Weakness, Nightmares, Face Flushing, and Sweating were the strong bridging symptoms. Additionally, Sleep Disturbance played a key mediating role. Depressed Affect and Dissatisfaction were activation symptoms for anxiety-depression co-existence.

Conclusion: Using network analysis, this study elucidated core, bridging, and shared symptoms, as well as potential causal pathways between anxiety and depression. Specifically, somatic symptoms are crucial in maintaining and developing the anxiety-depression network among teachers. Sleep disturbance serves as the sole gateway for mild symptoms to develop into other communities. The Bayesian network identified two key activating symptoms within the teacher anxiety-depression network, validating the applicability of the tripartite model among teachers.

Keywords: network analysis, teachers, depression, anxiety, co-existence

Introduction

Teaching has always been a highly meaningful profession,[1] influencing the development of a country's new generation. However, it is also a highly demanding and challenging job.[2] In a qualitative analysis, one teacher noted, "For years, teaching and stress have gone hand in hand for many years. Because things are constantly changing in education, and expectations are continuously rising, teaching has become increasingly stressful".[3] In fact, teachers often find themselves under prolonged stress.[4,5] Moreover, stress is a significant factor contributing to increased anxiety and depression among teachers.[6,7] In recent years, to advance education and better promote the comprehensive development of the new

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generation, the education sector has implemented various reforms and initiatives, which can significantly impact teachers' psychological states. Taking China as an example, the General Office of the Central Committee of the Communist Party of China and the General Office of the State Council jointly issued the "Guidelines on Deepening the Development and Reform of the Teaching Workforce in the New Era" (hereinafter referred to as the "Guidelines"). The "Guidelines" state that teachers must diligently study to improve their teaching skills, and specifically strengthen their ideological and political education, thereby placing higher demands on their teaching abilities and political awareness. As a result, teachers are required to dedicate more time outside their regular work to additional learning. Furthermore, the "Guidelines" emphasize organizing high-quality teacher training programs and implementing credit-based training management, indicating increased training requirements for teachers. Overall, the Guidelines propose a comprehensive improvement in the quality of primary and secondary school teachers, setting higher requirements for their professional skills and ethics. The implementation of this policy has imposed higher demands and greater challenges on teachers, leading to drastic changes in their work characteristics.[8] Teachers need to spend more time and energy improving the quality of teaching and extending their working hours to participate in more training and professional development. These requirements set higher professional standards for teachers' subject knowledge and professional capabilities. All these factors contribute to their psychological state in various ways.

In the teacher population, the prevalence of anxiety and depression is notably high,[9] primarily due to the high occupational stress that teachers commonly face.[6] A study assessing occupational stress across 26 professions found teaching to be one of the most stressful jobs, posing significant physical and mental challenges. Factors such as increasing student numbers, stringent teacher evaluation systems, public misconceptions about teachers, and the expanding non-teaching responsibilities within the teacher role unsurprisingly contribute to increased teacher stress.[10] In China, due to decades of personnel system reforms in schools and various educational reforms, Chinese teachers face a broader range of risks.[11,12] In China, influenced by Confucian thought, education is especially important. Coupled with frequent educational reforms in recent years, the pressure faced by teachers may be even more severe.[13] This pressure stems not only from high expectations and demands but also from changes in the educational system and society's continuous focus on educational quality. More importantly, compared to other groups, teachers seem to be more susceptible to environmental stress.[14,15] Therefore, teachers are more likely to suffer from anxiety and depression. Multiple meta-analyses on the mental health of mainland Chinese teachers have found that the prevalence of depression among primary school teachers was 18.3%, while that of anxiety was 14.7%.[16] Among secondary school teachers, the prevalence of depression reached 20.1%, while that of anxiety was 18.9%.[17] Moreover, anxiety and depression among teachers may form a cycle with other adverse factors, further exacerbating their symptoms. For instance, research has found that higher levels of depression and anxiety in teachers lead to more negative emotions, which in turn raises their anxiety and depression levels.[18] As a result, co-existence of anxiety and depression may be more prevalent among teachers.

Numerous studies have examined the changes and impacts from the perspective of students in response to the policy, such as issues related to students' mental health and learning psychology.[19,20] However, research on teachers has lagged far behind other work conducted based on the policy.[13] This study aims to advance this research direction. Among various mental symptoms, anxiety and depression are common concerns faced by teachers, affecting not only the teachers themselves but also the psychological state of their students.

Given that anxiety and depression often coexist,[21] studying either anxiety or depression in isolation may overlook the interactions and connections between the two. Therefore, this study will explore the co-existence of anxiety and depression in the teacher population.

Co-Existence of Anxiety and Depression

Depression and anxiety are the two most prevalent mental health disorders globally, causing significant damage to individuals' mental and physical health, as well as their social functioning. For example, studies have found that depression and anxiety symptoms are closely related to social dysfunction.[22] Additionally, anxiety and depression can lead to various other health issues, such as coronary heart disease[23] and sleep disorders.[24] Although anxiety and depression are categorized as two distinct disorders in the International Classification of Diseases (ICD), the two disorder often coexist.[25,26] Compared to individuals with either anxiety or depression alone, those suffering from both disorders exhibit a higher rate of functional impairments[27] and present more challenges in treatment.[28] Given the complex and close interactions between anxiety and depression, exploring these mental health issues from the perspective of co-existence is more meaningful for alleviating and treating both conditions. The concept of "co-existence" is used to explain complex clinical phenomena, referring to the occurrence of two or more disorders simultaneously in the same individual. Anxiety and depression are two psychological outcomes with a high degree of co-existence, exceeding 60%.[21,29]

Theoretical Basis of Co-Existence of Anxiety and Depression

Currently, there are two main theoretical models to explain the co-existence of anxiety and depression: one is the tripartite model of anxiety and depression[30] and the other model is the diathesis-stress model.

The tripartite model of anxiety and depression is a correlated liabilities model that assumes a set of common risk factors contribute to the development of both depression and anxiety. This model is based on the structure of positive and negative emotions and posits that the basis for the co-existence of anxiety and depression is a pervasive negative affect factor. From the perspective of the tripartite model, studying the co-existence of anxiety and depression involves understanding three types of symptoms: specific anxiety, specific depression, and general symptoms. According to the tripartite model, specific anxiety refers to physiological hyperarousal (such as feeling scared or tense), specific depression refers to a lack of pleasure (such as feeling down or sad), and general symptoms refer to subjective distress or various aversive states.[30] Research has identified common and specific dimensions of anxiety and depression, validating this model.[31]

The diathesis-stress model is a causal model that largely assumes cognitive vulnerability interacts with anxiety disorders, which further predicts prospective depressive symptoms.[32] This model has been validated in samples from both China and the United States.[33,34]

Although both models contribute to our understanding of the co-existence of depression and anxiety, they focus on different aspects. The tripartite model emphasizes the interaction between symptoms, providing a framework for the co-existence of anxiety and depression, including unique and associated characteristics of both disorders. This model reveals the underlying mechanisms of how anxiety-depression co-existence develops and is maintained. In contrast, the diathesis-stress model highlights the interaction between environmental stressors and individual cognition, focusing more on how anxiety-depression co-existence is triggered. These models complement each other, each shedding light on different facets, and together help deepen our understanding of the co-existence of anxiety and depression.

To determine the most parsimonious explanation for the co-existence of anxiety and depression, researchers have tested both the tripartite model and the diathesis-stress model. These studies found that when anxiety precedes depression, co-existence is best explained by the diathesis-stress model (causal model).[35] Conversely, when depression precedes anxiety, the tripartite model (relational responsibility model) provides the best explanation.[34] However, no studies have yet tested the applicability of these models within the teacher population.

Application of Network Analysis in Co-Existence Research

In classic theories of psychopathology, the severity of mental symptoms is typically reflected by the total score on standardized tests. Based on classic theory, the traditional approach to conceptualizing co-existence often relies on structural equation modeling and uses standardized test total scores to reflect the severity of mental symptoms.[36] However, this strategy does not account for the distinctions and connections between different symptoms.[37] The network theory of mental disorders (NTMD) fills this gap. In NTMD, the development and persistence of mental illness are driven by the causal interactions between its symptoms. If these interaction is sufficiently strong, it will result in a feedback loop that will empower the illness to continue to progress.[38] The method that corresponds to the NTMD is network analysis method, which puts symptoms into an inter-connected network between nodes and describes the relationship between symptoms.[39] In network analysis, each symptom is considered a "node", and the connections between them are referred to as "edges". Using centrality metrics, network analysis identifies central symptoms within the network structure, representing symptoms that are closely connected to others.[38] Additionally, bridge symptoms represent another key concept in network analysis. Bridge symptoms connect symptoms between two different disorders,[40] playing a crucial role in explaining the co-existence and transmission between different symptoms. There are two mainstream ways to conceptualize bridge symptoms. One way is that bridge symptoms represent overlapping symptoms between two conditions.[40] The other conceptualization posits that bridge symptoms are specific to a cluster that plays a significant role in connecting two clusters.[41]

Clique Percolation (CP) is a network community method used to define groups of nodes where the connections among nodes within the same group are stronger than with other nodes.[42] CP is commonly used to explore the underlying factors behind symptoms and comorbidities.[42,43] A notable feature of CP is its ability to identify nodes that belong to multiple communities (shared nodes) or nodes that do not belong to any community (isolated nodes). Previous research has utilized the CP method to discover the bridging role of "sadness" in an anxiety-depression network.[44]

However, the aforementioned network analysis method relies on partial correlations, which limits its ability to explore causal relationships. Bayesian Networks (BN) address this limitation by providing an innovative approach to model causal relationships, overcoming the challenges posed by partial correlation networks in cross-sectional data. This method allows for a more nuanced understanding of how different symptoms may influence each other within a network, thereby offering insights into potential causal pathways in the data. Directed Acyclic Graphs (DAG) within Bayesian Networks (BN) allow us to reveal causal relationships between symptoms in a network. BN measure the probability of one event occurring after another through conditional probabilities. This method is crucial for understanding the complex relationships between different variables. Another key concept in BN is conditional independence, which indicates that the probability of one node is independent of another, given the control of other variables. This helps to isolate the impact of individual variables in a complex network. BN also incorporate prior probabilities and joint probabilities. Prior probabilities represent the initial beliefs about the states of each variable before any data is observed. These priors are updated through Bayesian inference with observed data, refining our understanding of the network's variables. Joint probabilities specify the likelihood of various combinations of observed variable states and quantify the potential causal effects between variables, even within cross-sectional data. The network encodes the joint probability distribution, providing a probabilistic framework for representing and reasoning about causal relationships. Furthermore, BN can identify activating symptoms—those more likely to affect all other symptoms—and receptive symptoms—those more likely to be influenced by other symptoms. In network analysis, central symptoms have always been a focal point. However, there remains a gap in the analysis regarding central symptoms: Do central symptoms drive other symptoms in the network, or do changes in other symptoms drive the expressions of these central symptoms? This is a question of causality, and BN are designed to address such questions. Additionally, BN can identify symptoms that activate bridging symptoms, enhancing our understanding of co-existence. For example, studies using network analysis and BN methods have explored the co-existence between obsessive-compulsive disorder and depression, not only identifying bridging symptoms but also revealing the symptoms that activate these bridges, thereby uncovering potential mechanisms of co-existence.[45]

Network analysis has been widely applied to the studies of depression and anxiety symptoms in different populations, such as adolescents,[46] college students,[47,48] disabled elderly individuals,[49] patients with chronic diseases,[50,51] war survivors,[52] and healthcare workers.[53] These studies have all demonstrated that depression and anxiety symptoms are highly correlated, and certain symptoms play key roles in the network structure. Addressing these central symptoms can have a stronger impact on improving the overall network.[54,55] Therefore, utilizing network analysis to study the primary symptoms of mental disorders and identify more effective intervention targets is highly meaningful and has important practical value.[49] Furthermore, the aforementioned studies also found that the network structures and central symptoms vary across different populations due to the influence of age differences,[46] gender differences,[47,48] and cultural differences.[52] As for the teacher population, no studies utilizing network analysis have yet been conducted on this group. Previous research has analyzed the co-existence of anxiety and depression using the Least Absolute Shrinkage and Selection Operator (LASSO) model.[56] However, the lack of exploration into causal relationships limited the depth of these studies. In contrast, our study utilizes Directed Acyclic Graphs (DAG) in Bayesian Networks to overcome this limitation. This approach helps reveal the potential directions of symptom associations within the anxiety-depression network, enabling the visual identification of the sources or recipients of the activating effects exhibited by central and bridging symptoms. This provides further insights into the potential structure of the anxiety and depression network, enriching our understanding of the co-existence of anxiety and depression among teachers.

The Current Study

In this study, we employed three network analysis methods, LASSO network, CP network, and BN, to investigate the co-existence of anxiety and depression in a teacher population. Network analysis methods allow us to examine the interactions between individual symptoms of depression and anxiety. Specifically, the LASSO network enables us to identify central symptoms and bridge symptoms in the anxiety-depression network. Additionally, we used the CP method to reveal the community structure of symptoms, allowing the same symptom to belong to multiple communities, thus facilitating the study of shared symptoms. In our study, symptom clusters were not organized based on traditional categories of depression and anxiety symptoms. Instead, these clusters were organized based on the functional impact of the symptoms. To address the limitation of the above methods in determining causal relationships between symptoms, this study introduced the BN's DAG (Directed Acyclic Graph) method. The DAG results indicated that Depressed Affect and Dissatisfaction are two activating symptoms.

This study has three primary objectives. First, we aim to conceptualize central and bridging symptoms through network analysis. The LASSO network and the CP method enable us to explore the structure and relationships between anxiety and depression symptoms. Moreover, given the sensitivity of networks to the samples used, it is valuable to recapture central and bridging symptoms within the teacher population and compare these results with previous studies. Second, we seek to assess the causal relationships between symptoms. Using Directed Acyclic Graphs (DAG) in Bayesian analysis, our study endeavors to reveal the potential causal relationships between symptoms in the network, thereby enhancing our understanding of the co-existence of the anxiety-depression network. Through this approach, we can identify the activating or receptive roles of central and bridging symptoms, elucidating the critical role of specific symptoms as links between anxiety and depression. Finally, we attempted to validate the applicability of the tripartite model and the diathesis-stress model in the teacher population using the CP method and Bayesian Networks.

Methods

Sample and Procedure

The data used in this study were obtained from the Science Database of People Mental Health (SDPMH) of the Population Health Data Archive (PHDA). SDPMH is a comprehensive study conducted across China by the National Research Institute for Family Planning, surveying children, adolescents, adults, and occupational groups, and encompassing seven major demographic segments. The survey period spanned from March 2017 to December 2022. It follows standards of the psychological industry, expert consensus, guidelines, and regulations, and uses widely accepted international and domestic standard scales suitable for Chinese norms. Data collection involved validity and reliability evaluations, and was performed following standardized procedures for both offline and online data collection (eg, organization, training, and management) using surveys and assessments in mental health contexts. Furthermore, in 2021, the PHDA received the CoreTrustSeal global certification for trusted data repositories. This study analyzed teacher-related data. A total of 1670 teachers were randomly selected from primary and secondary schools in Sichuan Province, China (40.42% male, 59.58% female). They completed the relevant survey based on their actual conditions over the past week. Because network analysis models do not allow for missing values and to improve data quality, we applied the following inclusion criteria: (1) no missing or incomplete data, and (2) no random responses (eg, choosing the same answer for all questions). All samples met these criteria. Therefore, a total of 1670 participants were included in the analysis, with an average age of 37.01 years (min:18; max: 65). Participants included 820 primary school teachers (49.10%, M_{age} = 36.44 years, SD = 10.59), 625 middle school teachers (37.43%, M_{age} = 37.70 years, SD = 9.90), and 225 high school teachers (13.47%, M_{age} = 37.16 years, SD = 9.65). All analyses were conducted on the entire teacher sample.

Ethical Statement

The study was approved by the Biomedical Ethics Committee of Hebei Normal University of the People's Republic of China (LLSC2024060). The design of SDPMH was approved by the Ethics Committee of the Cancer Hospital, Chinese Academy of Medical Sciences. The study was conducted in accordance with the Declaration of Helsinki, and informed consent was obtained from all participants during the survey.

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Measure

The Self-Rating Anxiety Scale (SAS) and the Self-Rating Depression Scale (SDS), developed by Zung, each consist of 20 items scored on a scale from 1 (never) to 4 (always).[57,58] The scores for the 20 items are summed to obtain a raw score, which is then multiplied by 1.25 and rounded to the nearest whole number to derive the standard score. A higher total score indicates a greater tendency towards anxiety or depression. The SAS scale covers both psychological and somatic symptoms,[57] while the SDS scale includes affective, physiological, psychomotor, and psychological symptoms.[58] The SAS and SDS scales have been widely used in various populations in China, such as adolescents,[59] college students,[60] graduate students,[61] nurses,[62] and firefighters,[63] all demonstrating good reliability and validity. In this study, the internal consistency of the SAS was 0.88, and SDS was 0.90.

Statistical Analysis

Average scores and standard deviations for each item of the SDS and SAS were calculated using SPSS (v26.0), as well as the Cronbach's alpha coefficient for the instruments. Network analysis, CP analysis, and BN analysis were all conducted in R (version 4.3.3).

First, utilizing the "qgraph" and "bootnet" packages in R, network estimation and visualization were conducted. The network model was constructed using the 40 items from the SAS and SDS as nodes in a Gaussian Graphical Model (GGM). In a GGM, edges represent partial correlations between nodes, controlling for the influence of all other nodes in the network. Line thickness in our study indicates the strength of association between two nodes, with green denoting positive associations and red indicating negative associations. To simplify the model and emphasize significant connections by removing spurious edges, the graphical least absolute shrinkage and selection operator (LASSO) technique was applied to regularize the GGM. The final model was selected based on the lowest Extended Bayesian Information Criterion (EBIC),[64] with the EBIC hyperparameter gamma (γ) set at 0.5 to control false positives. Additionally, for identifying central and bridge symptoms, the R package "networktools" was used to calculate each node's expected influence (EI) and bridge expected influence (BEI). Centrality encompasses five metrics: degree, strength, betweenness, closeness, and EI.[44] EI, considered a more reliable measure of centrality compared to other methods like the strength method, accounts for both negative and positive edges, overcoming inaccuracies in edge impact estimation.[65,66] BEI, similar to expected influence, sums the edge weights connecting a node from one community to another, predicting the node's impact on the opposing community.[67] A node with higher BEI is more likely to activate the opposing community. Following recommendations for bridge node selection, we applied an 80th percentile cutoff to the BEI values to select bridge nodes.[67] The network consists of two nodal communities: one for anxiety (20 items from SAS) and another for depression (20 items from SDS).

The "bootnet" package was utilized to compute the case-dropping subset bootstrap stability coefficients (CS coefficients) for assessing the stability of strength centrality. Specifically, we conducted 5000 case-dropping subset bootstrap samples to calculate the CS coefficients. These coefficients indicate the maximum proportion of participants that can be omitted while still maintaining a high correlation (greater than 0.7) between the original strengths and the new strengths based on the subsets. Ideally, the CS coefficient should exceed 0.5, with a minimum threshold of above 0.25. This signifies that even after removing at least 25% of participants, the correlation between the original and new strengths remains above 0.7.[68]

Secondly, regarding the Clique Percolation (CP) method, we employed the "CliqurPercolation" package in R.[35] Specifically, we first used the function "cpThreshold()" to determine two important parameters of the CP method: I and k. I represents the strength of connection required to be considered part of a community, while k indicates the size of the community. In our study, k varied from 3 to 8, and I was allowed to range from 0.8 to 0.01.

Finally, to estimate the directed structure, we applied the Directed Acyclic Graph (DAG) within the Bayesian Networks (BN) framework. DAG, a Bayesian network approach, provides insights into the strength and direction of connections between nodes.[69] They offer initial insights into causal relationships between nodes, prioritizing predictive priority from upstream to downstream nodes.[70,71] Initially, the DAG was constructed using the hill-climbing algorithm via the "hc()" function in the "bnlearn" package.[72] To ensure model stability, the construction of the network model proceeded in three steps.[73] First, we conducted 50 random re-starts, with 100 perturbations for each re-start. These multiple re-starts aimed to evade local maxima, while perturbations iteratively altered edges to optimize fit indices like BIC value, generating an initial DAG. Subsequently, we bootstrapped 10,000 DAG to determine edge frequencies and assess significance, direction, and strength of edges.[74] A statistically significant edge was retained if its frequency surpassed the empirical threshold estimated from bootstrapped networks,[73] balancing sensitivity and specificity. Finally, the direction of retained edges was determined via majority voting, where the direction appearing in at least 51% of the 10,000 bootstrapped networks was chosen as the final direction.

Results

For all the teachers, the mean score for SAS is 1.808 with a standard deviation of 0.769, while the mean score for SDS was 2.194 with a standard deviation of 0.841. Descriptive statistics for individual items of both SAS and SDS are presented in the supplementary materials (Table S1).

Figure 1 illustrates the undirected network of anxiety and depression among primary and secondary school teachers. Blue edges indicate positive associations between nodes, while red edges indicate negative associations. The thickness of edges indicates their strength.

The centrality plot (Figure 2) depicts SAS11 (Dizziness) as the highest anxiety symptom, and SDS9 (Tachycardia) as the highest depression symptom. The bridge expected influence index (Figure 3) reveals that SDS9 (Tachycardia), SDS1 (Depressed Affect), SDS10 (Fatigue), SDS3 (Crying spell), SAS8 (Easy fatigability and weakness), SAS20 (Nightmares), SAS18 (Face flushing), and SAS17 (Sweating) are bridge nodes. The network stability plot of centrality and bridge indices (Figure 4) demonstrates that according to the case-dropping method, the correlation coefficient between EI and BEI is 0.75, indicating ideal stability. More information about the edge weight confidence intervals (CIs) for each cross-sectional undirected network, as well as the differences in node strength, can be found in the supplementary materials (Figures S1 and S2).

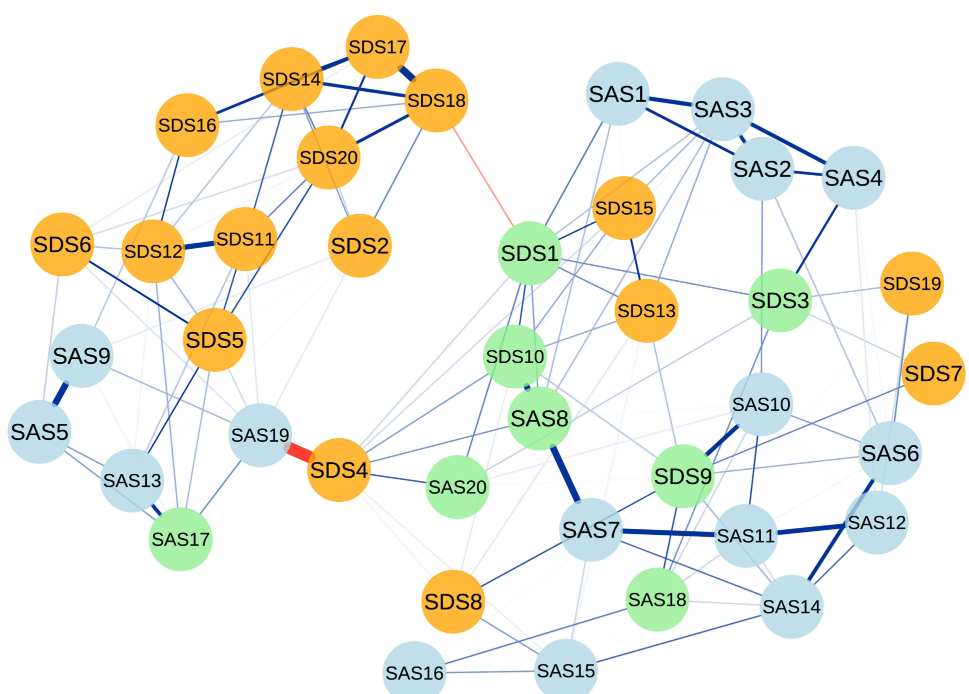

Figure 1 Network structure of anxiety and depression.
Notes: Green nodes represent bridge nodes identified through bridge expected influence (BEI) scores. Orange nodes represent individual items of SDS not identified as bridge nodes. Light-blue nodes represent individual items of SAS not identified as bridge nodes.

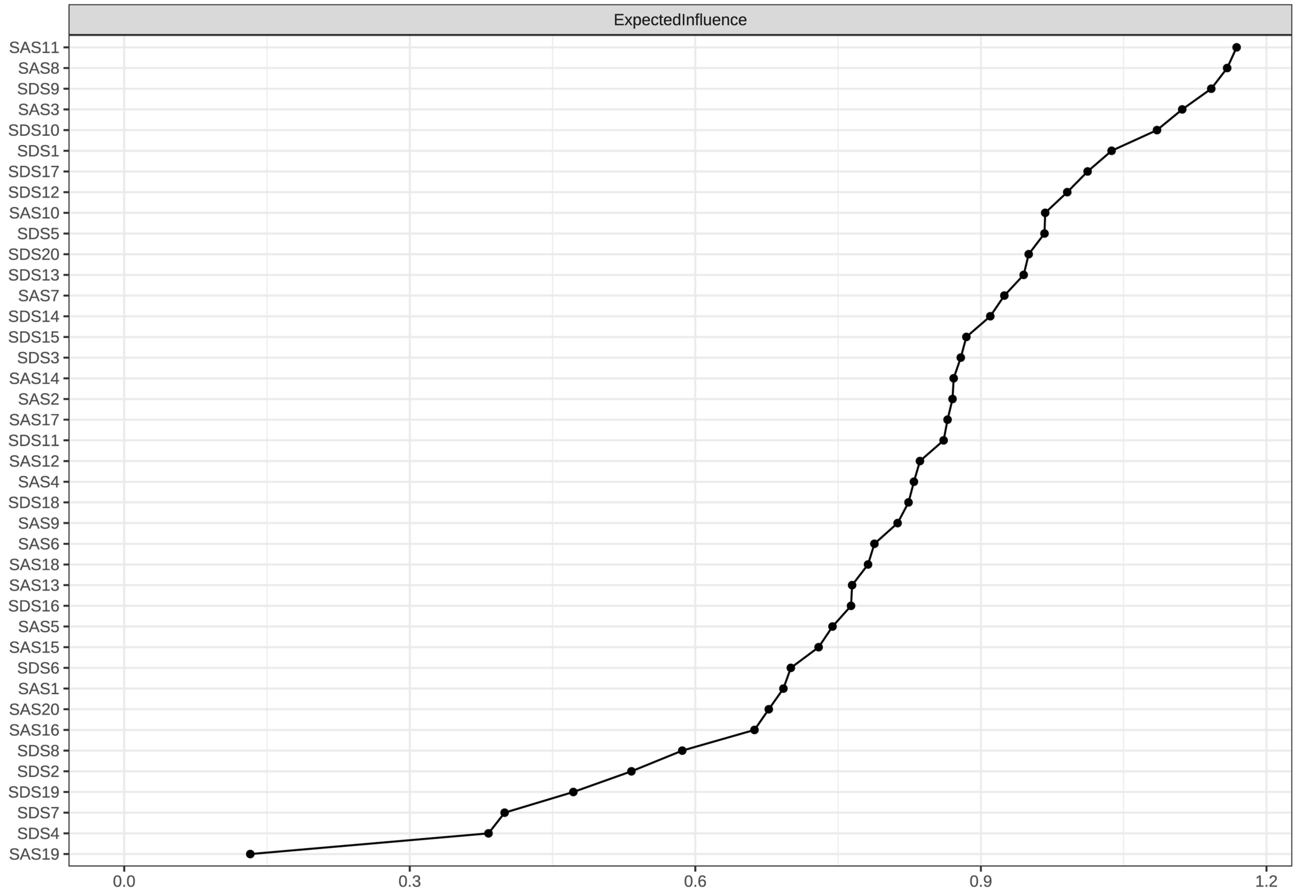

Figure 2 Centrality plot depicted the expected influence (z-score).

For primary and secondary school teachers, the results of the CP method and DAG are depicted in Figure 5. In this particular CP study, parameter I is set to 7, and parameter k is set to 0.04. Community detection results reveal four distinct communities.

The first community comprises emotional and physiological tension symptoms, including Apprehension (SAS5), Restlessness (SAS9), Dyspnea (SAS13), Sweating (SAS17), Insomnia (SAS19), Diurnal variation (SDS2), Sleep disturbance (SDS4), Decreased appetite (SDS5), Decreased libido (SDS6), Confusion (SDS11), Psychomotor retardation (SDS12), Hopelessness (SDS14), Indecisiveness (SDS16), Personal devaluation (SDS17), Emptiness (SDS18), and Dissatisfaction (SDS20). The second community comprises emotional and physiological stress symptoms, including Tremors (SAS6), Palpitation (SAS10), Dizziness (SAS11), Faintness (SAS12), Paresthesias (SAS14), Face flushing (SAS18), Nightmares (SAS20), Crying spells (SDS3), Tachycardia (SDS9), Psychomotor agitation (SDS13), and Suicidal rumination (SDS19). The third community comprises emotional and physiological fatigue symptoms, including Anxiousness (SAS1), Panic (SAS3), Easy fatigability and weakness (SAS8), Nausea & vomiting (SAS15), Urinary frequency (SAS16), Face flushing (SAS18), Nightmares (SAS20), Depressed affect (SDS1), Sleep disturbance (SDS4), Constipation (SDS8), Tachycardia (SDS9), Fatigue (SDS10), Psychomotor agitation (SDS13), and Irritability (SDS15). The fourth community comprises emotional and physiological crisis symptoms, including Fear (SAS2), Mental disintegration (SAS4), Tremors (SAS6), Palpitation (SAS10), Dizziness (SAS11), Faintness (SAS12), and Suicidal rumination (SDS19). The CP method identified 10 shared nodes: Tremors (SAS6), Palpitation (SAS10), Dizziness (SAS11), Faintness (SAS12), Face flushing (SAS18), Nightmares (SAS20), Sleep disturbance (SDS4), Tachycardia (SDS9), Psychomotor agitation (SDS13), and Suicidal rumination (SDS19). Body aches and pains (SAS7) and Weight loss (SDS7) do not belong to any community and are isolated nodes. The community of emotional and physiological fatigue symptoms encompasses most of the bridge symptoms, including Easy fatigability and weakness, Face flushing, Nightmares, Depressed Affect, Tachycardia, and Fatigue.

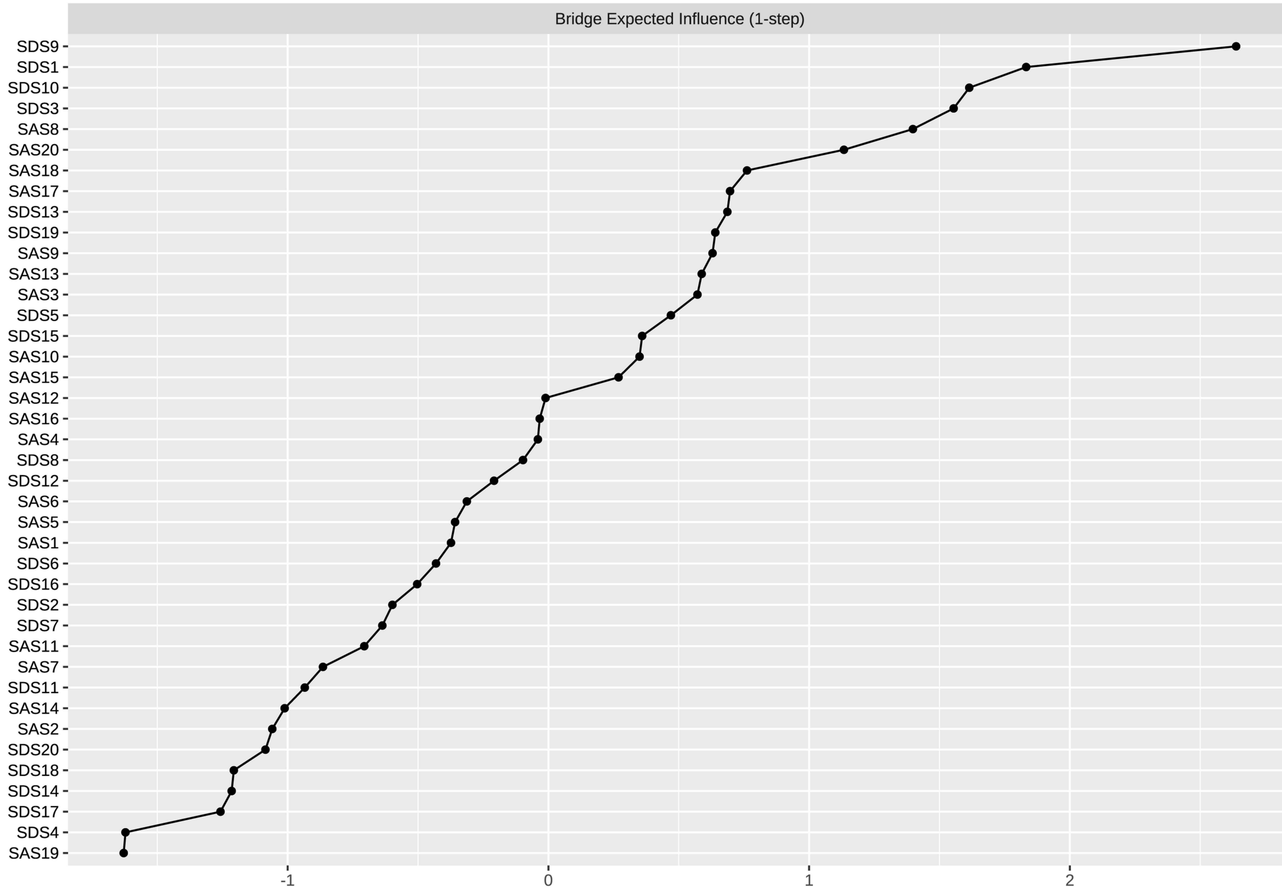

Figure 3 Centrality plot depicted the bridge expected influence (z-score).

The results of the DAG reveal two key activating symptoms at the top of the network, leading to the co-existence of anxiety and depression: Depressed affect and Dissatisfaction. The LASSO model confirms that Depressed affect (SDS1) occupies a central position in the network, serving as both a bridge and a central symptom. Dissatisfaction also exhibits high centrality but has a lower bridge expected influence, indicating it is not a bridge symptom.

Combining the results of the CP method and DAG, symptoms activated by Dissatisfaction primarily exist within the community of emotional and physiological tension symptoms. On the other hand, symptoms activated by Depressed affect belong to a more complex community structure.

Discussion

To gain a deeper understanding of how anxiety and depression develop and persist among Chinese primary and middle school teachers, the present study employed three network analysis methods to investigate the co-existence of anxiety and depression in the teacher population. The LASSO network revealed central and bridging symptoms within the anxiety-depression network, while the CP method categorized symptoms into different communities. Additionally, BN visualized the causal relationships between symptoms. More specifically, we first used the LASSO model to provide centrality indices for central and bridging symptoms. Then, the CP method was employed to classify anxiety and depression symptoms into different communities, allowing symptoms to belong to multiple communities, which offers a deeper understanding of shared symptoms. Finally, we used Directed Acyclic Graphs (DAG) to identify activating symptoms and uncover the potential causal pathways between anxiety and depression symptoms.

The first objective of this study was to identify the central and bridge symptoms of comorbid anxiety and depression in the teacher population. The LASSO model and CP method facilitated this objective. We identified the network structure of anxiety and depression co-existence. Specifically, we examined the most central nodes, which may drive the

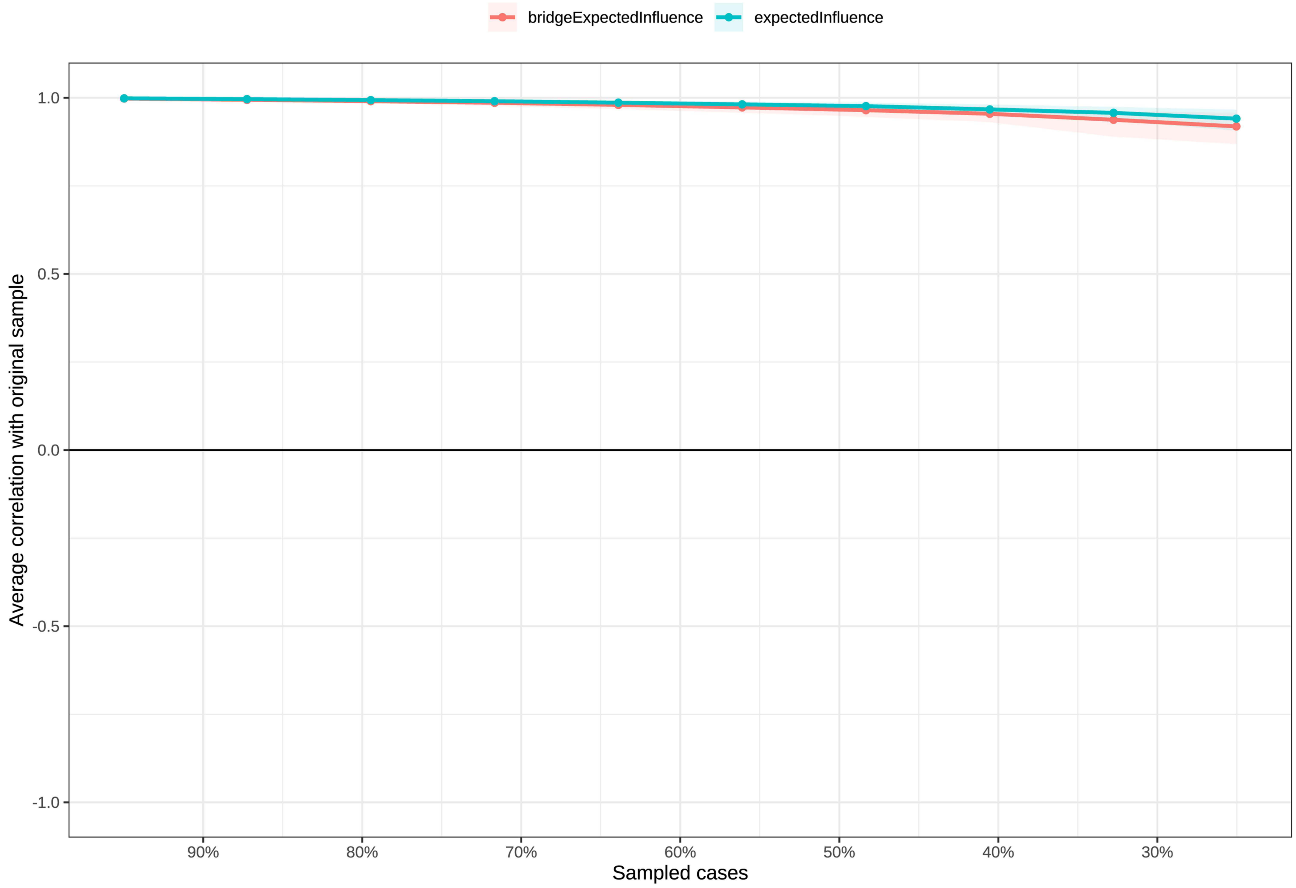

Figure 4 Stability and accuracy of centrality and bridge indices.

highest number of other symptoms, and the most influential bridges, which may explain the co-existence. According to the LASSO model, the most prominent central symptoms in the network are Dizziness (SAS11) and Easy Fatiguability & Weakness (SAS8), with Tachycardia (SDS9) being the most central depression symptom. These symptoms significantly impact the maintenance and development of anxiety and depression symptoms, playing a crucial role in the network. Prioritizing these symptoms in clinical practice can effectively alleviate the symptoms of teacher patients.[32]

Bridge symptoms are key to understanding co-existence.[67] In this study, Tachycardia (SDS9) was identified as the strongest bridge node, followed by Depressed Affect (SDS1) and Fatigue (SDS10). These symptoms increase the risk of symptom transfer from one mental disorder to another.[34] Our findings differ from previous studies, where central and bridge symptoms identified in anxiety-depression research mainly focused on emotional aspects. For example, a study on disabled elderly individuals found that sadness, worry, and difficulty relaxing were the primary symptoms in the anxiety-depression network.[49] Our study found that in the anxiety-depression network of the teacher population, central and bridge symptoms are mainly centered on somatic symptoms. Compared to other interpersonal-oriented professions, teaching is a physically demanding job. Teaching involves prolonged standing, blackboard activities, talking, guiding, and other tasks, requiring teachers to stand for extended periods.[75] While much research has focused on the emotional labor of teachers,[19,76,77] our findings emphasize that the physical labor of teachers and the resulting somatic symptoms (such as dizziness and tachycardia) also deserve attention. Some studies now focus on the physical labor of teachers. For example, Pen pointed out that teachers need to stand for long periods during lessons, along with preparing lessons and grading assignments, involving prolonged desk work and extensive computer use.[78] Prolonged loud speaking also strains physical endurance, which may lead to mental health issues such as irritability and depression. Thus, targeting somatic symptoms to improve teachers' mental health might be an effective approach. Research shows that leisure-time physical exercise improves both the physical and mental health of teachers.[79] Findings from this study indicate that somatic

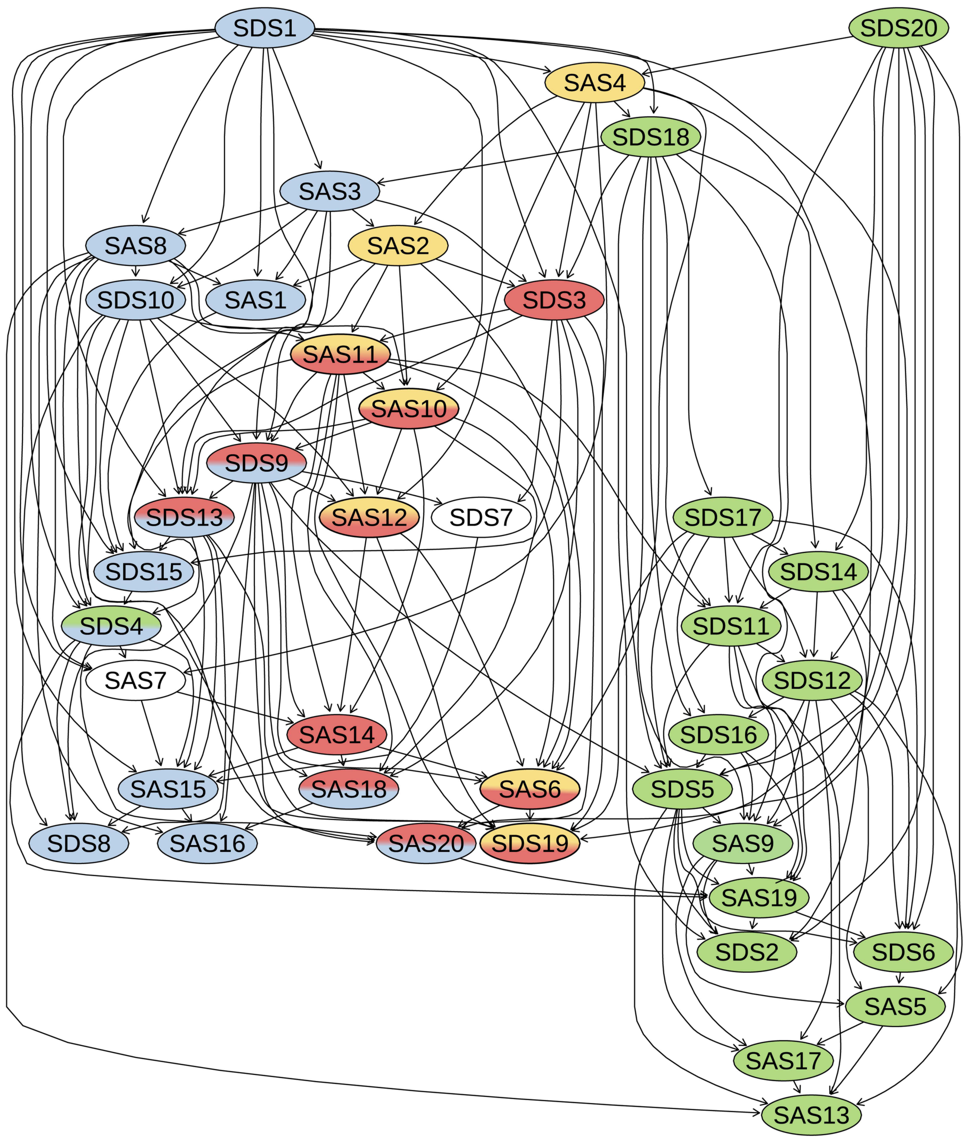

Figure 5 Community structure and Bayesian network (directed acyclic graph) of depression and anxiety.
Notes: Green community: emotional and physiological tension symptoms; red community: emotional and physiological stress symptoms; blue community: emotional and physiological fatigue symptoms; orange: emotional and physiological crisis symptoms.

symptoms play a crucial role in teachers' anxiety and depression. Physical exercise effectively alleviates central and bridging symptoms within the anxiety-depression network, leading to overall improvements in anxiety and depression among teachers.

The application of the CP method is the first innovative aspect of our study. The CP method identified four distinct communities: Emotional and Physiological Tension Symptoms, Emotional and Physiological Stress Symptoms, Emotional and Physiological Fatigue Symptoms, and Emotional and Physiological Crisis Symptoms. Consistent with previous research, most bridge symptoms were included in the same community.[44] In our study, bridge symptoms were concentrated in the Emotional and Physiological Fatigue community. The DSM-5 criteria suggest that fatigue is a key identifier for both anxiety and depression.[80] Fatigue can alter an individual's coping style, shifting from problem-solving to avoidance and emotion-focused strategies, potentially exacerbating the transition from anxiety to depression or vice versa.[81] To our surprise, in our study, symptom clustering was not based on the traditional categorization of depression and anxiety symptoms. Instead, these clusters were organized based on the functional impact of the symptoms. Thus, using the CP method to identify overlapping symptoms is meaningful. Overlapping symptoms were primarily concentrated in the Emotional and Physiological Stress community. This finding aligns with the stress causality hypothesis, which posits that stress is an intrinsic mechanism underlying changes in depression and anxiety. Stress can explain the fluctuations in anxiety and depression over time.[82] Our study further reveals that this intrinsic mechanism may operate through the evolution of one anxiety-depression symptom cluster into another.

The second innovative aspect of this study is the use of Bayesian networks to effectively capture the potential causal relationships between symptoms, which is also the second objective of our research. In this study, we identified two major activating symptoms: Depressed Affect and Dissatisfaction. Previous studies have identified depressed affect as a central node.[36,53] In our study, Depressed Affect was also an important symptom, serving as a significant activating symptom rather than a central one. Depressed affect, a typical feature of depression, refers to a range of negative emotional experiences, including sadness, low mood, and feelings of personal failure.[83] Due to increasing enrollment and expanding student populations, teachers face heavier workloads and fewer rest opportunities, heightening the likelihood of negative emotions.[84] Additionally, as educational standards advance, teachers encounter higher expectations and demands, potentially increasing stress and negative emotional risks.[85] Previous research has found that depressed affect is a common risk factor for comorbid emotional disorders, including anxiety and depression.[86–88] This evidence helps explain why depressed affect a prominent activating symptom for anxiety and depression in our study. Furthermore, prior network analysis studies have identified Interest Loss as one of the central symptoms in the anxiety-depression network.[89] In our study, Interest Loss was the second activating symptom. Previous research using the DAG model on the CESD-20-R scale found Anhedonia (loss of interest or pleasure) at the highest position,[90] which is consistent with our findings. "Interest Loss" plays a crucial role not only in the depression network but also as a gateway activating many symptoms in the comorbid anxiety-depression network. One study even found that Interest Loss predicts suicidal behavior.[91] In our DAG, we also found a direct path from Interest Loss to Suicidal Rumination. This pathway has been validated in students with poor academic performance.[92] Our study extends the applicability of this predictive pathway to the teacher population. In fact, teachers' work involves significant teaching and daily pressures. When teaching is unsuccessful and student performance fails to improve, teachers are prone to experiencing Interest Loss. This can lead to self-blame and self-doubt, and even suicidal thoughts. According to the activating symptoms identified in this study, emotional, satisfaction, and interest-related issues are primary drivers of anxiety and depression in teachers. Early attention to these issues is crucial for prevention, highlighting the importance of focusing on teachers' emotions and providing timely interventions. However, compared to improving somatic symptoms with physical exercise, mental health interventions often demand extra time and energy from teachers with busy schedules, such as participating in lengthy counseling or mindfulness exercises. This can be an additional burden for teachers already managing heavy workloads. For instance, high absenteeism was observed in a mental health training program for teachers.[93] Consequently, researchers have proposed a brief mindfulness intervention comprising four sessions over six hours, proven effective in reducing negative emotions, stress, depression, and other symptoms.[94] Future research could validate this intervention's effectiveness among Chinese primary and secondary school teachers and explore its practical application.

Combining the cluster results with the DAG results, we have several interesting findings. First, the two activation sources of comorbid anxiety and depression are both depressive symptoms. This does not support the significant distinction between anxiety and depression, which is inconsistent with previous studies.[44] The CP method results seem to confirm this, indicating that the co-existence of anxiety and depression in the teacher population is more complex. It is not simply a transition from anxiety to depression or vice versa, but rather an intricate mixture, forming multiple comorbid anxiety-depression communities. As a group with high occupational stress, teachers may exhibit a more complex anxiety-depression comorbidity pattern due to specific work stressors, such as educational reforms and classroom atmosphere.[95] For example, prolonged emotional exhaustion and occupational burnout may lead to both anxiety and depression, and the interaction between anxiety and depression is likely more pronounced among teachers.[96,97] Second, although both are activating symptoms, Interest Loss mainly activates the community of Emotional and Physiological Tension Symptoms, while Depressed Affect activates the other three clusters. Interest Loss is a more specific symptom linked to specific life experiences, often reflected in the loss of interest in activities, hobbies, and social interactions.[97] Therefore, its impact may be more narrowly scoped. Depressed Affect, on the other hand, is a broader and more pervasive fundamental negative emotional state. Studies have found that depressed affect is associated with neurotransmitter imbalances,[98] which may result in various depressive symptom clusters. Since depressed affect involves deeper psychological and physiological changes, it may link to diverse symptoms through complex mechanisms, thereby activating multiple symptom communities. This also explains why Interest Loss is not a bridge symptom. Third, compared to the other three clusters, the Emotional and Physiological Tension Symptoms community exhibits milder symptoms. The transition from this community to the other communities has only one gateway: Sleep Disturbance (SDS4). Although Sleep Disturbance is neither a central symptom nor a bridge symptom, it is still noteworthy as the only shared node in the mild symptom community. Sleep disturbance is one of the most common complaints among teachers. For example, a systematic review found that 36–61% of teachers reported sleep problems.[99] Multiple studies have confirmed the bidirectional relationship between sleep disturbances and anxiety and depression.[100,101] Our study highlights the importance of Sleep Disturbance in anxiety-depression co-existence from another perspective, serving as the only gateway connecting the mild symptom community to the other communities. Finally, our results indicate that in the teacher population, depressive symptoms tend to appear earlier and activate anxiety symptoms. This finding supports the tripartite model hypothesis, which posits that common risk factors lead to the development of both anxiety and depression. Furthermore, our results further suggest that there may be more than one common factor contributing to the co-existence of anxiety and depression, and different factors may trigger different co-existence communities. Future research could further analyze the different communities triggered by various factors.

To our knowledge, this is the first network analysis exploring the interactions between anxiety and depression symptoms in a large sample of Chinese teachers. The current use of Bayesian networks provides valuable insights into the potential causal relationships between depressive and anxiety symptoms. The results indicate that Depressed Affect and Dissatisfaction play crucial roles in activating other symptoms. At the same time, Tachycardia acts as an intermediary bridge, facilitating connections between symptoms. Additionally, the CP method identified four communities, and we consider Sleep Disturbance to be an important overlapping symptom. These findings illuminate the complex interactions and pathways between anxiety and depression symptoms, contributing to a better understanding of the underlying mechanisms between these two mental health conditions.

It must be acknowledged that this study has limitations. First, the sample used in this study may not be fully representative. Therefore, the generalizability of the findings may be limited to the teacher population. Additionally, the structure of symptom networks may be influenced by different samples. Future research should consider other populations to enhance the generalizability of the findings. Second, although Bayesian Network (BN) analysis can demonstrate potential causal relationships between symptoms through conditional probabilities, it cannot substitute for longitudinal study designs. BNs can identify possible causal relationships and suggest potential causal links in related data, but they do not inherently provide the temporal sequence of events. Future research could consider longitudinal network analyses. Third, this study used single-dimensional scales to assess depression and anxiety, specifically the SAS and SDS scales. While this approach is useful, it may oversimplify these complex mental health phenomena. Recognizing this limitation, future research should explore diverse dimensions and incorporate external factors such as biological vulnerabilities and environmental stressors. This approach could lead to more comprehensive models that better capture the complexity of comorbid depression and anxiety.

Conclusion

In summary, this study applied network analysis methods to identify the core symptoms, bridging symptoms, shared symptoms, and activating symptoms of anxiety and depression co-existence in the Chinese teacher population. Our findings suggest that somatic symptoms play a crucial role in maintaining and developing anxiety and depression among primary and secondary school teachers. Emotional, satisfaction, and other psychological symptoms serve as key activating factors. The results indicate the tripartite model is more applicable for explaining the co-existence of anxiety and depression in teachers. We identified multiple common factors that trigger the co-existence, with different factors playing roles in different communities. These findings reveal the characteristics of teachers' anxiety and depression amid heavy workloads and ongoing educational reforms. Based on the core symptoms, bridging symptoms, and activating symptoms identified in this study, several targeted interventions are proposed to reduce anxiety and depression in primary and secondary school teachers, such as leisure-time physical exercise and brief mindfulness interventions, which may significantly alleviate anxiety and depression among teachers.

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Author Contributions

All authors made substantial contributions to research design, acquisition of data, or analysis and interpretation of data; took part in drafting the article or revising it critically for important intellectual content; agreed to submit to the current journal; provided final approval of the version to be published; and agree to be accountable for all aspects of the work.

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Disclosure

The authors report no conflicts of interest in this work.

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