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Highlight

- Cynicism symptom "less interest in studies" played the most central role in the burnout network.
- Depressive symptoms "anhedonia" and "fatigue" and burnout symptom "doubting the significance of studies" exhibited the most bridging effect to maintain burnout-depression comorbidity.
- Community detection indicated three communities within burnout symptoms, which corresponded to the three dimensions identified via factor analysis, and there was no overlap between burnout and depression symptoms.
- These findings substantiate the multidimensional structure of burnout and underscore burnout as a distinct concept separate from depression.

Burnout and depression in college students

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Abstract

Research on burnout has garnered considerable attention since its inception. However, the ongoing debate persists regarding the conceptual model of burnout and its relationship with depression. Thus, we conducted a network analysis to determine the dimensional structure of burnout and the burnout-depression overlap. The Maslach Burnout Inventory-Student Survey and Patient Health Questionnaire-9 were used to measure burnout and depression among 1096 college students. We constructed networks for burnout, depression, and a burnout-depression co-occurrence network. The results showed that cynicism symptom was the most central to the burnout network. In the co-occurrence network, depressive symptoms ("anhedonia", "fatigue") and burnout symptom ("doubting the significance of studies") were the most significant in causing burnout-depression comorbidity. Community detection revealed three communities within burnout symptoms, aligning closely with their three dimensions identified through factor analysis. Additionally, there was no overlap between burnout and depression. In conclusion, our findings support a multidimensional structure of burnout, affirming it as a distinct concept separate from depression. Cynicism, rather than exhaustion, played the most important role in burnout and the burnout-depression comorbidity.

Keywords: burnout; depression; network analysis; comorbidity.

1. Introduction

Burnout has long been recognized as an occupational hazard in various human service occupations (Lacy and Chan, 2018; Maslach and Leiter, 2016; Sullivan et al., 2022; Weigl, 2022). Since its emergence, the concept of burnout has attracted increasing attention worldwide and has gradually expanded to include a more general range of occupations (Aronsson et al., 2017; Embriaco et al., 2007; Shanafelt et al., 2019).

Burnout is now defined as a psychological syndrome, caused by prolonged occupational stressors. Additionally, personality traits, particularly neuroticism, play an important role in the development of burnout (Angelini, 2023). People with high levels of neuroticism may adopt maladaptive coping strategies that magnify the impact of adverse events in the workplace, leading to greater anxiety and exhaustion from work. In summary, both external and internal factors influence the development of burnout.

The widely accepted conceptual model of burnout is a multidimensional model that stratifies burnout into three dimensions: exhaustion, cynicism or depersonalization, and a lack of professional efficacy (Maslach and Leiter, 2016). However, in contrast to the increasing research on burnout, minimal advances have been made in the establishment of clinical diagnoses. An undetermined definition of burnout is reportedly the primary issue for a diagnostic consensus (Rotenstein et al., 2018). The evolving definitions of burnout contribute to variability in estimating its prevalence, posing challenges in policy development. Initially, exhaustion was identified as the most central and obvious manifestation of burnout (Maslach et al., 2001). Accordingly, in a few northern European countries, the diagnosis of burnout has been simplified to exhaustion; consequently, the focus of the public and policy has been limited to exhaustion alone. Meanwhile, some argued that despite the importance of exhaustion, it was not the most central component of burnout (Maslach and Leiter, 2008) and that focusing on exhaustion devalued the significance of burnout as a distinct construct. A recent study on the relationship between the three dimensions of burnout suggested that exhaustion is not the most closely associated dimension (Wu et al., 2021). Measurements using an alternative burnout structure exhibit better validity (Shoman et al., 2021). To date, there has been minimal consensus on the definition or dimensional structure of burnout, as well as the most important symptoms of burnout (Tavella et al., 2021).

The association and distinction between burnout and mental illness have been another issue since burnout was first proposed. Much of the related work has focused on depression (Meier and Kim, 2022; Schonfeld and Bianchi, 2021; Schonfeld et al., 2019; Verkuilen et al., 2021). On the one hand, burnout is considered as a gradation or a prodromal stage of depression under the same construct (Bianchi, 2020; Bianchi et al., 2015). Supporting this hypothesis, evidence has indicated a high rate of comorbidity between burnout and depression (Youssef, 2016), particularly demonstrating a positive correlation, especially between the exhaustion dimension and depression (Chen and Meier, 2021; Dyrbye et al., 2014; Ma et al., 2022; Sun et al., 2022). Some studies have suggested that burnout and depression influence and predict each other through circular effects (Ahola and Hakanen, 2007; Toker and Biron, 2012). A growing body of empirical evidence recognizes burnout as a concept that largely overlaps with depression (Schonfeld and Bianchi, 2021). On the other hand, burnout represents a quality distinct from depression (Koutsimani et al., 2019). Studies supporting this idea suggest that exhaustion-related items inflate the association between burnout and depression (Koutsimani et al., 2019; Maslach and Leiter, 2016) and that the high correspondence between burnout and depression reflects only the conceptual redundancy of the measures (Maslach and Leiter, 2016). In fact, the cynicism and professional efficacy dimensions of burnout do not show a strong link with depression (Hakanen and Schaufeli, 2012; Steinhardt et al., 2011). Therefore, as a distinct variable, burnout involves content that does not overlap with depression. Burnout is thought to be job- and situation-specific, whereas depression is more general and independent of context (Maslach and Leiter, 2016). In conclusion, the debate on whether burnout is theoretically and empirically distinct from depression has gained prominence with evidence from both sides.

Previous research on burnout-depression relationships has been based mainly on the latent variable theory, which assumes that a genuine cause of a mental disorder and its symptoms exist. Network analysis has recently emerged as an alternative way of conceptualization (Borsboom, 2017). In the network model, a mental disorder is characterized as a cluster of symptoms that directly relate to each other, with no prior assumption of a common cause. The network comprises symptoms (nodes) and their causal relationships (edges). Given that mental disorders are empirically diagnosed without hard boundaries, network analysis allows for a more comprehensive conceptualization of mental disorders and their symptoms. Thus, we can observe the symptoms with the highest centrality in one disorder and verify the dimensional model of one concept (Christensen et al., 2023). More importantly, in the study of comorbidities, we can identify the symptoms that bridge the two disorders and maintain the comorbidity (Cramer et al., 2010). Thus, network analysis provides valid supporting evidence for the latent variable model. Therefore, to identify the central symptoms of burnout, provide evidence for a conceptual model of burnout, and distinguish burnout from depression, it is necessary to establish a network structure at the symptom level.

Burnout has been studied mainly in health-service occupations; however, academic burnout among college students has been a growing concern (Frajerman et al., 2019; Rotenstein et al., 2016). Although students are not employed in a traditional work setting, the structured and mandatory activities they engage in, such as attending classes and completing assignments, can be considered as a form of "work". Moreover, the academic pressure associated with passing exams can act as a chronic stressor. Academic burnout can persist through college and predict negative outcomes such as alcohol abuse (Jackson et al., 2016) and suicidal ideation (Rotenstein et al., 2016). However, despite the high prevalence of academic burnout among college students and its coexistence with depression (Dyrbye et al., 2014; Paro et al., 2014), limited studies have focused on the burnout-depression relationship using network analysis.

Therefore, to explore the conceptual model of burnout and its overlap with depression in college students, we constructed three networks (burnout, depression, and their co-occurrence) using network analysis. The aims of our study were threefold: 1) to demonstrate the central symptoms of burnout; 2) to identify the association and distinction between burnout and depression; and 3) to provide evidence of a single- or multiple-dimensional structure of burnout.

2. Methods

2.1 Participants

This study was conducted on college students in Xi'an City from February 6th to February 20th, 2023. Given that WeChat has the widest range of users in China and is used by almost every college student, we distributed and collected questionnaires online via the WeChat platform. Snowball sampling, a non-probability sampling method, was adopted to optimize the number and variety of study participants. We used a respondent-driven sampling method that relied on initial respondent referrals to generate additional respondents. First, we randomly selected college students to participate in the survey and anticipated that they would forward the questionnaire to as many students as possible. Since our questionnaire evaluation was completed online, we designed and included two attention checking items in the questionnaire to better ensure the quality of the measure (for example, "Please choose the first option in this question"). Current college students with no self-reported history of neurological or mental illness and who volunteered to participate were included in this study. Participants were excluded if they failed to provide the required information in the questionnaire or if they failed to correctly answer the checking items. Consequently, 1096 college students participated in this survey, and seven questionnaires were excluded because of incomplete basic information or questionnaire content. Ultimately, 1089 valid questionnaires were collected for the analysis. This study was approved by the Ethics Committee of the First Affiliated Hospital of the Fourth Military Medical University (No.KY20234188-1) and complied with the Declaration of Helsinki. Informed consent was obtained from all the participants at the beginning of the online questionnaire.

2.2 Measures

Burnout was assessed using the Maslach Burnout Inventory (MBI)-Student Survey. The MBI was the first standardized tool developed to assess burnout, exerting a pivotal influence on burnout research (Bianchi et al., 2015). Other instruments developed for burnout measures have also shown better validity than the MBI (Shoman et al., 2021). However, because the MBI was based on the dimensional structure proposed by Maslach, it was the most suitable measure for the purpose of our study and for comparing our results from a network perspective with those of other studies using the MBI. For application to a variety of occupations and groups of people, the MBI has been divided into several subtypes, one of which is a Student Survey version for college students. Its validity and reliability were recently verified (Portoghese et al., 2018). Consistent with the MBI, the MBI-Student Survey has a three-dimensional structure that includes exhaustion, cynicism, and professional efficacy, with 15 items scored on a 7-point scale. The reliability and validity of the MBI-Student Survey for Chinese students have also been confirmed (Hu and Schaufeli, 2009; Liu and Cao, 2022).

Depression symptom severity was measured using the Patient Health Questionnaire-9 (PHQ-9). The PHQ-9 is one of the most commonly used questionnaires in depression research and measures the frequency of depression symptoms over the prior two weeks. It contains nine items and adopts a 4-point scoring (from “not at all” to “almost every day”). Previous studies have confirmed the reliability and validity of the PHQ-9 in the Chinese population (Du et al., 2017; Wang et al., 2014). Higher scores indicate more severe symptoms of depression.

2.3 Network analysis

2.3.1 Network estimation and visualization

The R package “qgraph” was used to compute networks, based on Spearman rho correlations (Epskamp and Fried, 2018; Isvoranu and Epskamp, 2023). The Graphical Least Absolute Shrinkage and Selection Operator technique was used to regularize the partial correlations in the networks (Friedman et al., 2008). By shrinking all edges and penalizing edges with trivially small partial correlation coefficients to zero, this regularization process aided in eliminating spurious edges, resulting in a more stable, sparse, and interpretable network (Epskamp and Fried, 2018; Friedman et al., 2008). In addition, the Extended Bayesian Information Criterion hyperparameter γ was set to 0.5 to balance sensitivity and specificity (Epskamp and Fried, 2018; Foygel and Drton, 2010). The visualization of networks was based on the Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991).

2.3.2 Central and bridging symptoms

Network centrality is calculated to quantify the extent to which a node is directly connected to other nodes in the network. Expected influence (EI), defined as the sum of all edges extending from one given node to the remaining nodes in the network, is one of the most commonly used indices of centrality. This indicates greater stability, because it considers the presence of negative associations (Robinaugh et al., 2016). Higher EI values indicate greater centrality or importance of the symptoms. Thus, we computed the EI for burnout network and depression network using the R package "qgraph" (Epskamp et al., 2012).

A co-occurrence network was constructed to explore the association between academic burnout and depression. In this network, the bridge expected influence (BEI) was calculated to evaluate the bridging symptoms linking depression and academic burnout. The BEI is the aggregate of edge weights connecting a single node to all nodes in the other community of the co-occurrence network. A higher BEI value indicates a greater likelihood of one symptom activating symptoms in another community. The BEI values were calculated using the R package "networktools" (Jones et al., 2021).

2.3.3 Network stability and accuracy

To determine the robustness of the centrality indices, we applied a case-dropping bootstrap method (with 2,000 bootstrap samples) and computed the correlation stability (CS) coefficient. The CS coefficient represents the maximum percentage of sample cases that can be dropped from the original full cases while retaining a correlation of 0.7 in at least 95% of the samples (Yang et al., 2022). A CS coefficient should not be less than 0.25, and a CS coefficient above 0.5 indicates decent network stability (Epskamp et al., 2018). The accuracy of the edge weights was assessed using a 95% confidence interval (with 2,000 bootstrap samples) for each edge within the network. A narrower 95% confidence interval indicates a more reliable network. Moreover, we conducted bootstrap difference tests (with 2,000 bootstrap samples) on edge weights, EI, and BEI. The aforementioned procedures were conducted using the R package "bootnet" (Epskamp et al., 2018).

2.3.4 Exploratory graph analysis

To explore the dimensional structure of burnout generated by factor analysis and to test for the burnout-depression overlap, we performed exploratory graph analysis (EGA) on the burnout network and burnout-depression co-occurrence network. The Walktrap algorithm (Pons and Latapy, 2006) was used to detect communities of burnout and depression symptom nodes. It is designed to identify densely connected subgraphs, also called communities, in a graph using random walks. The principal concept is that short random walks tend to remain in the same community. The EGA has proven to be as accurate or even more accurate than factor analysis (Golino and Epskamp, 2017). A bootstrap EGA with 2,000 iterations was used to examine the stability of the identified dimensions and items (Christensen and Golino, 2021). Dimensional stability was estimated using structural consistency, which was the proportion of times that the initial EGA-derived dimensions were recovered from the replicate bootstrap samples. Item stability was estimated as a measure complementary to structural consistency, which is the proportion of times each item was placed in each EGA-derived dimension. EGA was performed using the EGAnet R package.

3. Results

3.1 Sample description

Descriptive demographic information of the sample population is shown in Table 1. In general, most participants were young adults (aged 17-24 years), and more than half were not the only children in their families. Moreover, most were raised in a non-single-parent family.

3.2 Descriptive analysis and reliability test

Descriptive statistics and burnout and depression symptoms assigned to the respective items are presented in Table 2. The internal consistencies of the MBI-Student Survey ($\alpha = 0.929$) and its three dimensions were excellent (exhaustion [$\alpha = 0.945$], cynicism [$\alpha = 0.884$], and professional efficacy [$\alpha = 0.952$]). The PHQ-9 also demonstrated high internal consistency ($\alpha = 0.865$).

3.3 Burnout network

The burnout network and EI values for each node are shown in Figure 1 and Table 2. Symptoms representing higher EI values played a central role in the network. Among all burnout symptoms, the node “I have become less interested in my studies since enrolling at the university” (CY1, EI = 1.255) had the highest EI value within the network, followed by “I have learned many interesting things during the course of my studies” (EF5, EI = 1.101) and “I believe that I contribute effectively in the classes I attend” (EF2, EI = 1.095). While “I doubt the significance of my studies” (CY4, EI = 0.612) and “I can effectively solve study-related problems” (EF1, EI = 0.614) had the lowest EI values. The CS coefficient of the node EI values was 0.75, indicating that the estimated EI values in the network were adequately stable (Figure S1). Additionally, bootstrap difference tests on the EI values showed that the three nodes with the highest EI values were significantly different from approximately 57%-100% of the other symptom nodes in the network (Figure S2).

The strongest edges in the burnout network arose between “I have learned many interesting things during the course of my studies” and “In class, I feel confident in my ability to get things done” (EF5-EF6, weight = 0.514); between “I have become less interested in my studies since enrolling at the university” and “I have become less enthusiastic about my studies” (CY1-CY2, weight = 0.474); and between “I believe that I contribute effectively in the classes that I attend” and “In my opinion, I am a good student” (EF2-EF3, weight = 0.442). The 95% bootstrap confidence intervals of the edge weights are shown in Figure S3 and indicate that the edge weights were relatively stable and accurate. Moreover, a bootstrap difference test indicated that the three strongest edge weights were significantly different from most other edge weights (Figure S4).

3.4 Depression network

The depression community structure and EI values for each node are shown in Figure 2 and Table 2. The higher the value, the stronger is the association of that symptom in the network. Among all depressive symptoms, the symptom node “fatigue” (D4, EI = 1.079) had the highest EI value in the network, followed by “depressed mood” (D2, EI = 0.993) and “hopelessness” (D6, EI = 0.975). In contrast, “suicidal ideation” (D9, EI = 0.441) and “sleep-related problems” (D3, EI = 0.735) had the lowest EI values within the network. The CS coefficient of the node EI values was 0.75, suggesting a sufficiently stable estimation of EI values in this network (Figure S5). Moreover, bootstrap difference tests showed that the three nodes with the highest EI values were significantly different from approximately 62.5%-75% of the other symptom nodes in the network (Figure S6).

The strongest edges in the depression network emerged between “anhedonia” and “depressed mood” (D1-D2, weight = 0.326); between “sleep-related problems” and “fatigue” (D3-D4, weight = 0.262); and between “anhedonia” and “fatigue” (D1-D4, weight = 0.220). The bootstrap 95% confidence intervals of the edge weights are shown in Figure S7 and indicate that the estimates of the edge weights were stable and accurate. The bootstrap difference test results are shown in Figure S8.

3.5 Co-occurrence network of burnout and depression

The structure of the co-occurrence network is shown in Figure 3. In the co-occurrence network, we mainly focused on symptom nodes that bridge burnout and depression, as indicated by their BEI values (Table 2). The node “anhedonia” (D1, BEI = 0.161) had the highest BEI value, followed by “fatigue” (D4, BEI = 0.109) and “I doubt the significance of my studies” (CY4, BEI = 0.0.107). The findings indicated that “anhedonia” (D1) and “fatigue” (D4) had the strongest contagion for the onset of burnout symptoms and that “I doubt the significance of my studies” (CY4) had the strongest contagion for the onset of depression symptoms. The CS coefficient of node BEI was 0.52, suggesting that the estimates of the node BEI values were sufficiently stable (Figure S9). The bootstrap difference test results for the BEI values are presented in Figure S10.

The network edges with the largest edge weights occurred within the burnout community. The edge between “I have learned many interesting things during the course of my studies” and “In class, I feel confident in my ability to get things done” (EF5-EF6, weight = 0.496); between “I have become less interested in my studies since enrolling at the university” and “I have become less enthusiastic about my studies” (CY1-CY2, weight = 0.459); and between “I believe that I contribute effectively in the classes that I attend" and "In my opinion, I am a good student" (EF2-EF3, weight = 0.427) had the largest weights. While, "I feel used up at the end of a day at university" and "fatigue" (EX2-D4, weight = 0.044) was the strongest edge connecting the burnout-depression community. The bootstrap 95% confidence intervals of the edge weights (Figure S11) indicated that the edge weights were relatively stable and accurate. Bootstrap difference tests showed that the edges with the strongest weights were significantly different from most of the edges (Figure S12).

3.6 Community detection

Three communities were found in the burnout network (Figure S13): an exhaustion community (from EX1 to EX4), a cynicism community (from CY1 to CY4, plus EX5), and a professional efficacy community (from EF1 to EF6). These corresponded to the three dimensions of burnout, except for EX5, which was included in the cynicism community. In the co-occurrence network, four communities were identified (Figure S14): a depression community (from D1 to D9), an exhaustion community (from EX1 to EX4), a cynicism community (from CY1 to CY4, plus EX5), and a professional efficacy community (from EF1 to EF6). The communities within which burnout symptoms occurred were consistent between the two networks, and no overlapping symptoms were observed between the burnout and depression communities. Bootstrap EGA validated the above results (Figure S15 and S16), showing excellent dimension (Table S1) and item stabilities (Figure S17 and S18). Specifically, the dimension stability was 1.000, 1.000, and 1.000 in the burnout network and 1.000, 1.000, 1.000 and 0.962 in the co-occurrence network, respectively.

4. Discussion

In this study, we examined a conceptual model of burnout and investigated its overlap with depression among college students. Unlike the previous research that primarily focused on exhaustion, we found that symptoms of cynicism and professional efficacy had a more central role in burnout, highlighting the importance of "interest in studies" and "sense of contribution". According to the burnout-depression co-occurrence network, depressive symptoms “anhedonia” and “fatigue” had the strongest contagion for the onset of burnout. Similarly, the symptom of burnout most likely to trigger depression was also from the cynicism dimension “I doubt the significance of my studies”. In addition, community detection revealed three communities of burnout as established by factor analysis, with no overlap between burnout and depression. Taken together, the findings supported the multidimensional structure of burnout and suggested that it was a concept distinct from that of depression. Additionally, cynicism, rather than exhaustion, was the key component of burnout and the burnout-depression comorbidity.

In the burnout network, we explored the symptoms that were most associated with the pathogenicity and maintenance of burnout. The most central symptoms emerged at nodes CY1, EF5, and EF2. Consistent with a previous network analysis of depression and burnout in Chinese nurses (Wu et al., 2021), we found that the most associated symptom was cynicism (CY1) rather than exhaustion. These results consistently indicate the overlooked value of cynicism in causing and maintaining overall burnout symptoms. In other words, apart from emotional exhaustion, the lack of motivation, diminished empathy, and a passive approach to studying may be more crucial factors contributing to burnout in students. Additionally, symptoms related to professional efficacy (EF2 and EF5) were among the most central symptoms, emphasizing the significance of academic achievement in burnout among college students. These results indicated that students’ interest in their studies or work (CY1 and EF5) and their sense of contribution (EF2) was essential. Hence, the symptoms that played the most central role were potential treatment targets. Based on the network model, stimulating interest and increasing one’s sense of contribution may be effective interventions to alleviate burnout among college students. Moreover, “fatigue” (D4) was the most central symptom of depression, which underscored the importance of fatigue-related symptoms in depression, whereas exhaustion symptoms did not hold the same level of significance in the burnout network.

In the burnout-depression co-occurrence network, we examined the bridging symptoms that directly communicated between burnout and depression. We found that fatigue-related symptoms "anhedonia" and "fatigue" in the depression community had the strongest connection with burnout symptoms. This is in accordance with previous results showing that exhaustion- or fatigue-related symptoms are closely correlated with depression and burnout (Bianchi et al., 2015; Chen and Meier, 2021). Surprisingly, in the burnout community, symptoms that directly communicated with depression did not arise from exhaustion. Instead, cynicism symptom "I doubt the significance of my studies" (CY4) had the closest connection with depressive symptoms. This finding also contradicts the previous consensus that the conceptual overlap between burnout and depression lies primarily in the exhaustion dimension. Therefore, among students, the most significant causal relationship between burnout and depression was the loss of meaning in studies, rather than feeling exhausted. Additionally, the loss of meaning in studies aligned with one of the core depressive symptoms, the loss of meaning in life. Furthermore, item CY4 had the lowest EI value in the burnout network but one of the highest BEI values in the co-occurrence network. This indicated that the most central component of burnout symptoms and the bridging symptoms between burnout and depression did not overlap.

One of the crucial questions we attempted to resolve was the relationship between burnout and depression. By combining the aforementioned results and analyses, we concluded that burnout was a distinct construct rather than a largely overlapping concept with depression. In addition to the finding that there was no overlap in symptoms between burnout and depression communities, three reasons support this conclusion. First, most central and bridging burnout symptoms were not related to exhaustion or fatigue. Based on empirical evidence, redundancies or overlaps between burnout and depression mainly occur in the exhaustion dimension (Maslach and Leiter, 2016). Additionally, the most central and bridging symptoms of depression observed in this study were related to fatigue. However, our results emphasize the importance of cynicism symptoms in burnout and the burnout-depression comorbidity, which is not consistent with previous assumptions. Second, the symptom that most closely connected burnout to depression (CY4) in the co-occurrence network had the lowest centrality in the burnout network. It was assumed that burnout and depression overlapped excessively and that burnout symptoms influencing depression would at least have decent centrality in the burnout network. In contrast, the most connecting symptom in the co-occurrence network was the most marginalized symptom in the burnout network, which did not support this assumption. Finally, in the co-occurrence network, the strongest edges occurred within the burnout community, while the edge weights between the burnout and depression communities were considerably lower. If a large overlap existed between burnout and depression, the edges between burnout and depressive symptoms, which represent direct correlations, should have demonstrated notable. Instead, the strongest and most distinguishable edges emerged in the burnout community. In summary, the correlation between burnout and depression was not as strong as expected.

Finally, the third question this study aimed to answer was whether a single- or multidimensional structure for burnout should be applied. The findings of the present study suggest that a multidimensional burnout structure is appropriate. The main reason for this conclusion was that community detection revealed three separate communities under the burnout construct, which coincided with the three dimensions proposed by the factor analysis. Although EX5 was included in the cynicism community, which may be owing to the characteristics of college students, the remaining symptom nodes remained in the communities to which their original dimensions belonged. Additionally, in the co-occurrence network, symptoms from the three burnout dimensions had different bridging correlations with depression symptoms, suggesting that their different comorbidity mechanisms underlie these three dimensions. For example, the strongest bridging connection between exhaustion and depression symptoms was EX2-D4, whereas in the cynicism and professional efficacy communities, the strongest connections emerged in CY3-D7 and EF6-D7. The presence of different cross-community edges indicated that symptoms of different dimensions had different pathways for influencing depression, which also supported the conclusion that burnout had more than one dimension.

Several limitations need to be considered when interpreting the study results. First, most of the study participants were male. Sex-related perspectives toward studies may be a confounding factor in academic burnout symptoms and their relationship with depression. Second, the sampling method prevented us from obtaining a complete picture of college students' burnout. As we adopted a dimensional method to conceptualize burnout and depression, the results may lack clinical implications for those who meet the diagnostic criteria. Future studies that focus on categorical methods may yield novel findings. Additionally, this cross-sectional study lacked longitudinal observations. Future studies should include more diverse and comprehensive study participants and a follow-up design to advance our research. Finally, the network structure was limited to the selected scales. Given that the MBI is not the only or most reliable instrument for measuring burnout (Shoman et al., 2021), further validation of the burnout structure and its overlap with depression using other instruments is required.

5. Conclusion

The current study was designed to determine the structure of burnout and the burnout-depression overlap among college students at the network level. This study identified cynicism symptoms as crucial factors for burnout and burnout-depression comorbidity. Additionally, community detection analysis suggested a multidimensional structure for burnout, emphasizing that burnout should be considered distinct from the concept of depression. This study provides insights into the structure of burnout from the perspective of network analysis, and delineates the overlap between burnout and depression.

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Declaration of competing interest

None

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Figures

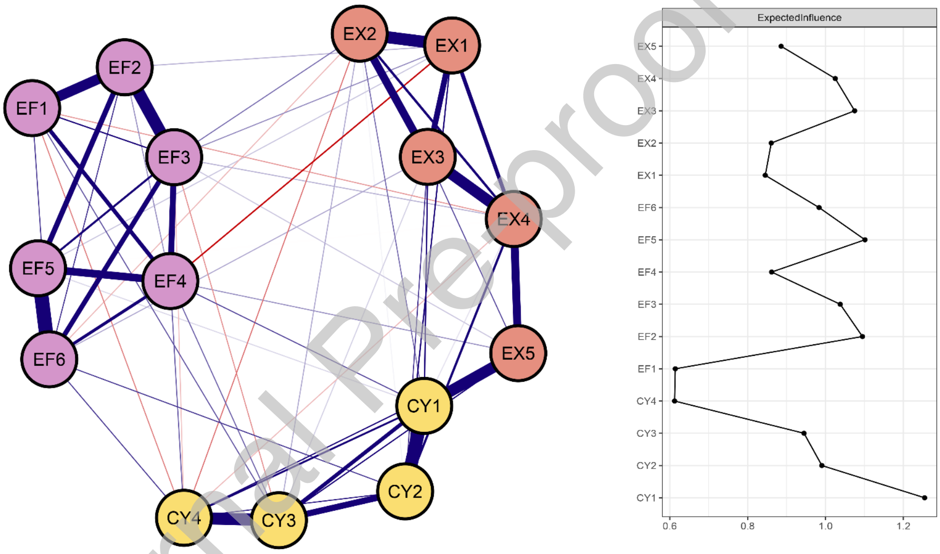

Figure 1. Burnout network and node EI values. The three different node colors represent three dimensions of burnout: exhaustion, cynicism, and lack of professional efficacy. Dark blue and red edges represent positive and negative correlations between nodes, respectively. The node EI raw values are listed on the right. Refer to Table 2 for the symptoms assigned to the respective items.

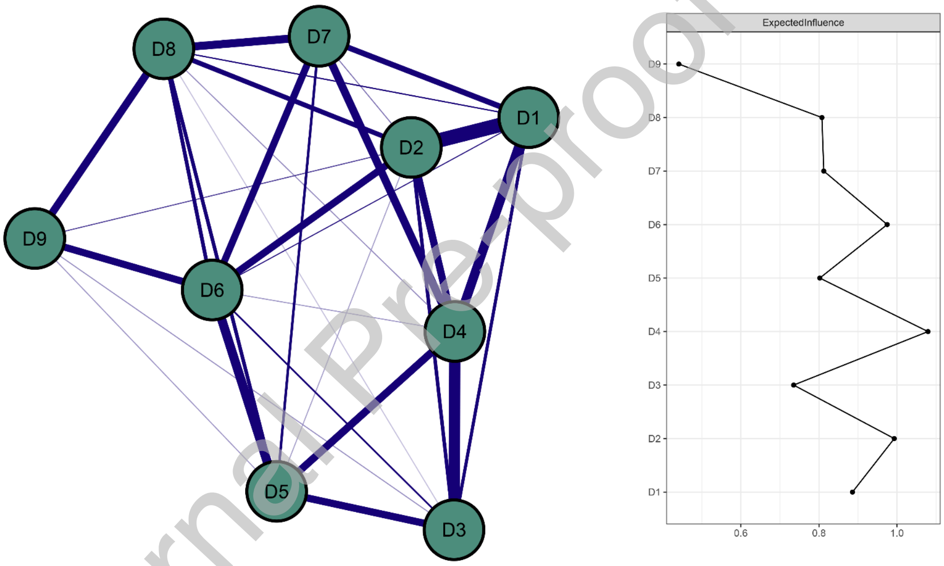

Figure 2. Depression network and node EI values. Dark green nodes and dark blue edges indicate depressive symptoms and positive correlations between nodes, respectively. The node EI raw values are presented on the right. Refer to Table 2 for the symptoms assigned to the respective items.

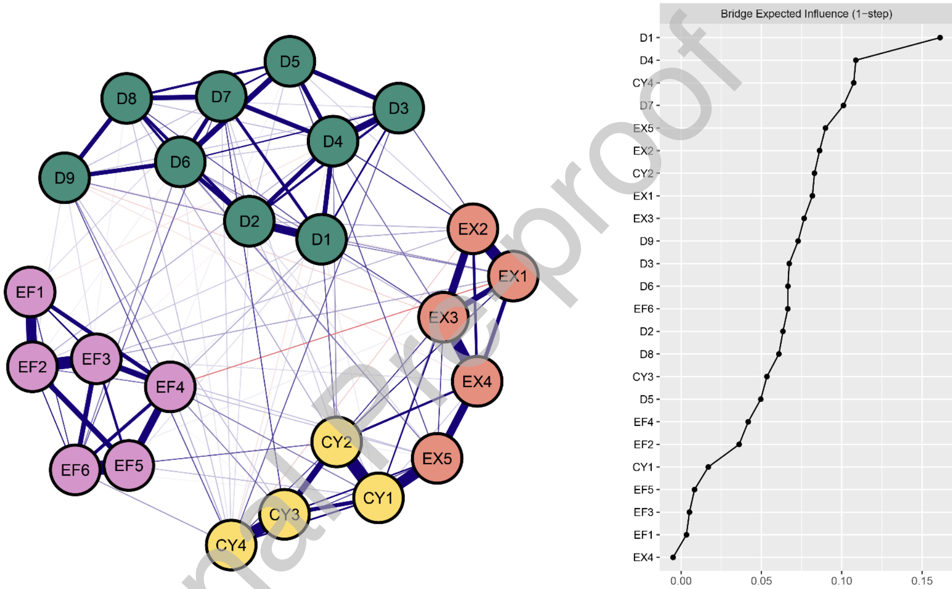

Figure 3. Co-occurrence network of burnout and depression and node BEI values. Dark green color indicates depressive symptoms, and the three dimensions of burnout are distinguished by three different colors, as seen in the burnout network. Dark blue and red color edges point to positive and negative correlations, respectively. Node BEI raw values are listed on the right in descending order. Refer to Table 2 for the symptoms assigned to the respective items.

Tables

Table 1 Descriptive information of demographic variables

	N or M	% or SD
Age	20.83	1.75
Sex		
Male	1036	95.13%
female	53	4.87%
Only child in the family		
Yes	423	38.84%
No	666	61.16%
Single-parent family		
Yes	109	10.01%
No	980	89.99%
Average monthly income per person in family (RMB)		
Below 3000	269	24.70%
3000-5000	440	40.40%
5000-10000	303	27.82%
Above 10000	77	7.07%

Table 2 Descriptive data of node psychometrics

Item	M	SD	Expected influence	Bridge Expected influence
Burnout symptoms				
EX1: I feel emotionally drained by my studies	1.607	1.440	0.845	0.082
EX2: I feel used up at the end of a day at university	1.486	1.384	0.861	0.086
EX3: I feel tired when I wake up in the morning and have to face another day at the university	1.461	1.471	1.075	0.077
EX4: Studying or attending class is a real strain for me	1.370	1.353	1.025	-0.005
EX5: I feel burned out from studying	0.970	1.199	0.886	0.090
CY1: I have become less interested in my studies since enrolling at the university	0.987	1.265	1.255	0.017
CY2: I have become less enthusiastic about my studies	1.049	1.263	0.991	0.083
CY3: I have become more cynical about the potential usefulness of my studies	0.831	1.208	0.945	0.053
CY4: I doubt the significance of my studies	0.929	1.419	0.612	0.107
EF1: I can effectively solve study-related problems	1.806	1.844	0.614	0.003
EF2: I believe I contribute effectively in the classes I attend	1.624	1.757	1.095	0.036
EF3: In my opinion, I am a good student	1.624	1.708	1.038	0.005
EF4: I feel stimulated when I achieve my study goals	1.235	1.566	0.862	0.042
EF5: I have learned many interesting things during the course of my studies	1.466	1.660	1.101	0.008

EF6: In class, I feel confident in my ability to get things done	1.382	1.595	0.983	0.066
Depression symptoms				
D1: Anhedonia	0.443	0.673	0.886	0.161
D2: Depressed mood	0.318	0.562	0.993	0.063
D3: Sleep-related problems	0.388	0.648	0.735	0.067
D4: Fatigue	0.422	0.612	1.079	0.109
D5: Eating problems	0.303	0.629	0.802	0.050
D6: Hopelessness	0.212	0.494	0.975	0.067
D7: Concentration problems	0.319	0.611	0.812	0.101
D8: Psychomotor agitation	0.154	0.431	0.808	0.061
D9: Suicidal ideation	0.047	0.228	0.441	0.073

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Declaration of Interest Statement

None.