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ORIGINAL ARTICLE

Problematic Social Media Use and Psychological Distress: A Symptom-Focused Network Analysis

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Abstract
The relationship between problematic social media use (PSMU) and psychological distress has been widely investigated and confirmed. However, little is known about the connections between the specific symptoms of these variables within a comorbidity network. The present study aimed to establish a network model of the symptoms of PSMU and psychological distress (anxiety, depression, and stress) and to identify the most central and bridging symptoms using network analysis. A total of 822 participants were recruited to complete surveys assessing PSMU, anxiety, depression, and stress. Results showed that psychological distress symptoms "panic" (anxiety), "agitated" (stress), and "downhearted" (depression) were the most central symptoms in the comorbidity network. PSMU symptoms "mood modification" and "conflict/functional impairment" played a bridging or intermediary role within the network. The present study enhances the understanding of the mechanisms underlying the association between PSMU and psychological distress at the symptom level and provides potential suggestions for interventions to help prevent PSMU.

Keywords Problematic social media use · Social media addiction · Psychological distress · Network analysis · Symptoms

Introduction

As of April 2024, over five billion individuals around the world were using social media (Statista, 2024). The use of social media has become an integral part of individuals' daily lives. However, studies have shown that problematic use of social media is associated with psychological distress such as anxiety and depression (Lopes et al., 2023; Du et al., 2024). Many studies have examined problematic or compulsive use of social media as a behavioral addiction (e.g., Andreassen et al., 2016; Tullett-Prado et al., 2023), which comprise six key components (i.e., salience, mood modification, tolerance, withdrawal, conflict and relapse; Griffiths, 2005).

The term 'internet addiction' (IA) has been largely used to describe problematic use of the internet in general (Young, 1998; Zhao et al., 2023) as opposed to specific online problematic activities (e.g.., problematic internet gaming, problematic internet gambling, problematic internet shopping, etc.). However, scholars have expressed concern about the risk of over-pathologizing daily activities and have recommended using the term 'problematic' to describe behaviors with a wider range of engagement levels (Billieux et al., 2015; Kuss & Lopez-Fernandez, 2016). Therefore, the present study uses the term 'problematic social media use (PSMU), which refers to the uncontrolled and compulsive use of social media that leads to functional impairment in everyday life and compromises education, occupations and/or personal relationships (Billieux et al., 2017; Lopes et al., 2023).

Theoretical frameworks have noted the association between problematic internet use (PIU) and psychological distress (Davis, 2001, Brand et al., 2019; Sonuga-Barke et al., 2024). The cognitive-behavioral model shows that generalized and specific PIU can be predicted by psychopathology (e.g., depression) through maladaptive cognitions (Davis, 2001). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model suggests bidirectional links between addictive behaviors and psychopathological variables (Brand et al., 2019). A recent theoretical model argue that digital activities could lead to depressive mood through cognitive and affective reactions (Sonuga-Barke et al., 2024). The relationship between PIU and psychological distress has also been identified in recent empirical studies using emerging data analysis approaches such as latent profile analysis (LPA) (Stanculescu & Griffiths, 2024) and network analysis

(Zhao et al., 2023).

Empirical studies have demonstrated the association between specific types of PIU, such as PSMU, and psychological distress (Lopes et al., 2023; Stanculescu & Griffiths, 2022; Du et al., 2024). A systematic review of 1747 studies showed a significant and frequently reciprocal link between social media use (mainly PSMU) and depression or anxiety (Lopes et al., 2023). Such an association has also been confirmed in recent studies using a person-centered approach (LPA), which identified social anxiety as a significant predictor of social media addiction profile (e.g., Stanculescu & Griffiths, 2022). Longitudinal studies have also found that PSMU and psychological distress can predict each other bidirectionally over time (Li et al., 2018; Chang et al., 2022). However, multiple studies with large sample sizes did not find a significant negative impact of non-problematic digital activity engagement on the well-being of adolescents (Przybylski & Weinstein, 2017; Orben & Przybylski, 2019). Therefore, it is essential to further examine the relationship between PSMU and psychological distress, placing greater emphasis on the problematic aspects and potential addictive symptoms of social media use.

Network analysis of internet addictions

Increasing numbers of studies have adopted a network analysis approach to examine the association between internet addiction (IA) and psychological distress, such as anxiety and depression (Cai et al., 2021; Bai et al., 2022; Zhao et al., 2023; Jia et al., 2024). Cai et al. (2021) found that negative impacts on academic works and withdrawal symptoms were the most central (influential) symptoms in the IA-anxiety network. Among depressive patients, Bai et al. (2022) found that the central symptoms in the IA network were ‘internet preoccupation’, ‘internet negatively impacts job performance’, and ‘neglect chores for online time’. A longitudinal network analysis study showed that the key bridging symptoms in the IA-depression comorbidity network were ‘interpersonal and physical problems’ and ‘loss of energy’ (Jia et al., 2024). Another longitudinal network analysis study found that the central symptoms in the IA-depression network were ‘escape’ and ‘irritability’ for IA and ‘energy’ and ‘guilty’ for depression (Zhao et al., 2023).

Network analysis has also been used to explore the relationship between specific types of PIU and psychological distress (e.g., Aalbers et al., 2019; Li et al., 2023; Li et al., 2024; Tullett-Prado et al., 2023; Qu et al., 2024; Sánchez-Fernández et al., 2024). Baggio et al. (2022) found support for the spectrum hypothesis of problematic online behaviors by testing a network with six distinct communities of specific online behaviors (e.g., problematic online gaming and problematic online shopping) and concluded that it is important to focus on specific PIU rather than general PIU or smartphone use. Several studies have investigated PSMU and psychological distress (Aalbers et al., 2019; Li et al., 2023; Li et al., 2024; Tullett-Prado et al., 2023; Sánchez-Fernández et al., 2024). Li et al. (2023) found that the PSMU symptoms ‘withdrawal’ and ‘functional impairment’ were the key bridging symptoms in the network including PSMU, internet gaming disorder and problematic smartphone use. The central symptoms in the ‘social media addiction–psychological distress’ network model were ‘tolerance’ and ‘mood-modification’ (Tullett-Prado et al., 2023). However, the aforementioned studies examining PSMU and psychological distress used the total scores of the instruments in their comorbidity networks, specifically the sum of PSMU scores (Li et al., 2023; Li et al., 2024; Sánchez-Fernández et al., 2024) or the sum of psychological distress variables (Tullett-Prado et al., 2023; Li et al., 2024). However, they did not examine the network for the specific symptoms of PSMU, anxiety or depression. Therefore, it is necessary to further explore how the *specific* symptoms of PSMU and psychological distress are connected in a network.

The present study

The associations and links between PSMU and psychological distress (e.g., depression and anxiety) have been supported by theoretical frameworks and empirical studies (Brand et al., 2019; Lopes et al., 2023). Studies have started to use network analysis to further investigate such links (Li et al., 2023; Tullett-Prado et al., 2023; Sánchez-Fernández et al., 2024). However, there is currently a scarcity of network analyses specifically focusing on the symptoms of both PSMU and psychological distress, highlighting a critical need for research that could help elucidate the complex connections at the symptom level. Therefore, the present study examined the associations between the symptoms of PSMU and psychological distress using network analysis. The names of the components of the PSMU items were obtained from Andreassen et al. (2016) based on the addiction components model (Griffiths. 2005). The names of the components of psychological distress were obtained from the item names of the Depression, Anxiety and Stress Scales-21 (DASS-21) outlined in Van den Bergh et al. (2021). The DASS subscales for depression, anxiety and stress were developed based on the Tripartite Model by Clark and Watson (1991; see also: Henry & Crawford, 2005; Lovibond & Lovibond, 1995). The DASS assesses the three components outlined in the tripartite model: low positive affect (DASS-Depression), physiological hyperarousal (DASS-Anxiety), and negative affect (DASS-Stress) (Brown et al., 1997).

There are three specific aims. These were to: (i) establish a network model of the symptoms of PSMU and psychological distress (anxiety, depression and stress); (ii) identify the central symptoms and bridge symptoms in the network; and (iii) estimate the accuracy and stability of the network.

Methods

Participants and procedure

The researchers and several course tutors assisted in promoting the survey among students from universities in South China (i.e., convenience sampling and snowball sampling). Initially, a total of 834 questionnaire responses were collected. The inclusion criteria were being first-year university undergraduate students who volunteered to participate in the study. Among them, 12 responses were excluded as invalid due to patterned responses (e.g., responding with the same response for all questions), leaving 822 valid questionnaires for data analysis (547 females and 275 males). Thus, the questionnaire had a validity rate of 98.56%. The average age was 18.36 years (SD = 0.80). An online survey was distributed in Mandarin through the platform *www.wjx.cn* using a QR code. Participants read the consent form at the beginning of the survey and gave their informed consent to participate voluntarily. The responses were collected over a three-week period from October 1 to October 21 (2021). All answers were anonymous and confidential, and no participant could be recognized after completing the survey. The online surveys could not be submitted unless all survey questions had been answered. Therefore, there were no missing data. Each participant received a reward of 6 Chinese yuan (CNY) after completing the survey.

Measures

Bergen Social Media Addiction Scale (BSMAS)

The BSMAS developed by Andreassen et al. (2016) was used to assess PSMU. The Chinese (simplified) version validated by Chen et al. (2020) was used in the present study. BSMAS items are rated on a five-point Likert scale scoring from 1 (*very rarely*) to 5 (*very often*), including six items developed based on the six components of addiction (Griffiths, 2005). An example item is *"(I) felt an urge to use social media more and more"* (see Table 1). The Cronbach's alpha value in the present study was 0.85. The McDonald's omega Total (ωt) value was 0.90, indicating very good internal consistency.

Depression, Anxiety and Stress Scales-21 (DASS-21)

The DASS-21 validated in Henry & Crawford (2005), developed from the DASS-42 in Lovibond and Lovibond (1995), was used to assess psychological distress variables including depression, anxiety and stress over the past week. The present study used the validated Chinese version (Gong et al., 2010). DASS-21 items are rated on a four-point Likert scale with seven items for each of the three variables respectively, scoring from 0 (*Did not apply to me*) to 3 (*Applied to me very much, or most of the time*). An example item is *"I felt down-hearted and blue"* (depression) (see Table 1). The Cronbach's alpha values in the present study were 0.79 for anxiety, 0.84 for depression, and 0.79 for stress. The McDonald's omega total (ωt) values were 0.85 for anxiety, 0.88 for depression, and 0.85 for stress, indicating very good internal consistency.

Data analysis

Network analysis was conducted using R version 4.2.3. The R packages of 'bootnet' (Epskamp et al., 2018), 'qgraph' (Epskamp et al., 2012) and 'networktools' (Jones, 2024) were used for network estimation, accuracy, and stability check and plotting. The 'NetworkComparisonTest' package (Epskamp & Fried, 2018) was used for Network Comparison Tests (NCT) between females and males. Since the variables examined in the present study can be treated as continuous, an undirected Gaussian Graphical Model (GGM) based on Pairwise Markov Random Fields (PMRFs) was constructed. When estimating the parameters of a model, the estimation is often influenced by the model's complexity. For instance, in the present study, the estimation of parameters in the fitted network model is impacted by the number of edges present in the network. A widely used method for parameter estimation in the context of the PMRF is the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996). In the LASSO approach, the tuning parameter λ is adjusted to shrink the estimated weights of some edges to zero, thereby producing a sparse model (Friedman et al., 2010). Similarly, the Extended Bayesian Information Criterion (EBIC) can be employed to select the simplest model.

This method controls the degree of additional penalty applied to the model through a hyperparameter. In the present study, both LASSO and EBIC methods were combined using the qgraph package. The procedure first generates 100 tuning parameters ranging from 0 to 1 through the LASSO method, followed by the application of EBIC by default (with the hyperparameter set to its default value of 0.5) to select the optimal model (Epskamp et al., 2012).

For the power analysis, the netSimulator function from the 'bootnet' package was employed to determine the study's power (Epskamp & Fried, 2018). For this model, the sensitivity, also known as the true-positive rate, was 0.78 with the current sample size, indicating that edges present in the "true model" had a 78% probability of appearing in this model. The specificity, also termed the true-negative rate, was 0.75 with the current sample size, suggesting that edges absent in the "true model" had a 75% probability of also being absent in this model. The correlation, which represents the relationship between edge weights in the true model and the estimated model, was 0.94. Plots for this analysis can be found in Appendix 3.

Traditional power analysis is used to evaluate the probability of correctly rejecting the null hypothesis (i.e., detecting a true effect) for a given statistical model and dataset. It is also helpful in determining the sample size required to detect an effect with a specified probability. In network models, edges that are present in the "true data" but excluded in the estimated model are referred to as false negatives. The probability of this occurrence is also known as the Type II error rate (β). Sensitivity, in turn, can be interpreted as 1-β (statistical power). Currently, there are numerous algorithms available for selecting which edges should be included in a model, but no gold standard has been established (Isvoranu & Epskamp, 2021). In the present study, the regularization and selection methods applied were considered to provide good sensitivity (Blanken et al., 2022).

The nodes in the network represent the items of the psychometric scales, the edges represent the partial correlations between the items. Centrality indices were obtained to evaluate the most central and influential symptoms in the network. Bridge centrality indices were obtained to evaluate the bridging symptoms. The correlation-stability (CS[cor = 0.7]) coefficients were computed to assess the stability of the network which indicates maximum drop proportions to retain correlations of 0.7 in at least 95% of the samples. A CS coefficient of 0.70 indicates excellent stability (Epskamp et al., 2018). Strength difference and bridge strength differences between the nodes were calculated to test network stability using non-parametric bootstrapping approach (1000 times) (Epskamp et al., 2018).

Ethics

The present study has been approved by the Ethics Committee of the first author's university. The study was were carried out in accordance with the Declaration of Helsinki. All participants were informed about the study and all provided informed consent before participating.

Results

Network structure estimation

Descriptive statistics and abbreviations of the items are shown in Table 1. Figure 1 shows the network structure of PSMU and psychological distress. The comorbidity network included 27 nodes, which represent the items of the BSMAS and the DASS-21. The number of non-zero edges was 179 (out of the total 351 edges), network density was 0.51, and average path length was 0.02. The mean weight was 0.034. The weights matrix (partial correlations) is reported in Appendix 1. The symptoms/items of PSMU, anxiety, depression and stress were grouped in distinct communities in the network plot. Network Comparison Tests (NCT) were conducted for gender difference. Network invariance testing showed that there was no significant difference for network structure between females and males (test statistic M = 0.18, $p = 0.58$). Global strength invariance testing show that there was no significant difference for global strength between females and males (test statistic S = 0.06, $p = 0.90$).

Centrality estimation

The centrality indices including 'strength', 'closeness', 'betweenness', and 'expected influence' are shown in Figure 2. The symptoms A5 (anxiety5: panic), S4 (stress4: agitated), and D4 (depression4: down-hearted) had the highest strength (strength coefficients: 1.72, 1.70, 1.61) and expected influence (expected influence coefficients: 1.76, 1.75, 1.66), which were the most influential and connected symptoms in the comorbidity network. However, the PSMU symptoms P3 (psmu3: mood modification) and P6 (psmu6: conflict/functional impairment) had the highest betweenness values, which indicates that these two symptoms played critical roles in facilitating communication as intermediaries in the network. The psychological distress symptoms S1, S6, A1 had the lowest strength, while the PSMU symptom P1 had the lowest betweenness. The values of the centrality indices are reported in Appendix 2.

Bridge centrality estimation

To evaluate the bridge symptoms between communities in the comorbidity network model, bridge centrality indices including 'bridge strength', 'bridge betweenness', 'bridge closeness', and 'bridge expected influence' were calculated (see Figure 3). Similar to the centrality characteristics, the symptoms D4 (depression4: down-hearted), A5 (anxiety5: panic), and S4 (stress4: agitated) had the highest bridge strength (coefficients: 0.891, 0.887, 0.844) and bridge expected influence (coefficient: 0.891, 0.887, 0.844). More specifically, according to the partial correlation matrix (see Appendix 1), In the depression subscale, D4 (down-hearted) was most strongly connected to P3 (psmu3: mood modification) in the PSMU community (part $r = 0.01$). In the anxiety subscale, A5 (anxiety5: panic) was most strongly connected to P5 (psmu5: withdrawal) in the PSMU community (part $r = 0.02$). In the stress subscale, S4 (stress4: agitated) was most strongly connected to P3 (psmu3: mood modification) in the PSMU community (part $r = 0.01$).

Within the PSMU community, P3 (psmu3: mood modification) and P6 (psmu6: conflict/functional impairment) had the highest bridge centrality indices. They also had the highest bridge betweenness in the whole network. P3 was most strongly connected to S2 (stress2: overreactive) in the psychological distress community (part $r = 0.07$). P6 was most strongly connected to S1 (stress1: no wind down) in the psychological distress community (part $r = 0.08$). These connections are also depicted in the network plot (see

Figure 1).

Therefore, looking at the results as a whole the key bridge pathways between the psychological distress and PSMU communities were: D4-P3, A5-P5, S4-P3, P3-S2, and P6-S1. P3 (psmu3: mood modification) appeared to the core bridging symptom. The values of the bridge centrality indices are reported in Appendix 2.

Accuracy and stability estimations

Figure 4 shows the estimated confidence intervals (CIs) of edge weights by non-parametric bootstrapping. The narrow CIs indicate acceptable accuracy of the network model. The network had excellent stability: edge CS coefficient = 0.75, strength CS coefficient = 0.75, expected influence CS coefficient = 0.75. Bridge stability was also excellent: bridge strength CS coefficient = 0.75, bridge expected influence CS coefficient = 0.75. The stability of centrality indices and bridge centrality were good as shown by case dropping bootstrapping approach (see Figure 5). Figure 6 shows the non-parametric bootstrapping difference tests for node strength and bridge strength, which shows the stability of the network. Overall, the accuracy and stability of the network model were proved to be good for the sample of 822 participants.

Discussion

The present study estimated an accurate and stable network model including PSMU and psychological symptoms (anxiety, depression and stress). A5 (panic), S4 (agitated), and D4 (down-hearted) were the most central symptoms in the whole comorbidity network. P3 (mood modification) and P6 (conflict/functional impairment) were the key intermediate variables. The key connections between communities were ‘mood modification’ (PSMU) and psychological states such as being ‘down-hearted’, ‘agitated’, and ‘overreactive’ (psychological distress). The other important links between communities were ‘withdrawal’ (PSMU) and ‘panic’ (psychological distress), as well as ‘conflict/functional impairment’ (PSMU) and ‘no wind down’ (psychological distress).

Using the same psychometric scales as the present study, Wang et al. (2022) identified ‘enthusiasm’ (D5) as the most central symptom in the whole comorbidity network of PSMU, anxiety, and depression. However, in the present study, D5 was not a central or influential symptom in the network, exhibiting moderate node strength (10^{th} among the 27 nodes) and low bridge strength (bottom third among the 27 nodes) (see Figures 2 and 3). Although the centrality indices were not the same, both the present study and Wang et al. (2022)’s indicated that psychological distress items were central symptoms in the comorbidity network.

The major intermediate symptoms (with higher node betweenness and bridge betweenness values) in the comorbidity network were the PSMU symptoms ‘mood modification’ (*“used social media to forget about personal problems”*) and “conflict/functional impairment” (*“used social media so much that it has had a negative impact on your job/studies*). This is in line with previous network analysis studies which identified ‘mood modification’ (Guo et al., 2022; Tullett-Prado et al., 2023), ‘conflict/functional impairment’ (Wang et al., 2022), ‘escape’ (mood modification) (Zhao et al., 2023), ‘interpersonal and physical problems’ (conflict) (Jia et al., 2024), and ‘negative impacts on academic works’ (conflict) (Cai et al., 2021) as the key bridging or central symptoms in the IA-mental health or PSMU-mental health comorbidity networks. Therefore, for the PSMU symptoms, it is crucial for intervention programs to focus on individuals’ strategies of dealing with the negative impacts of PSMU on occupational and/or educational conflicts.

However, several core symptoms of behavioral addiction, as noted in previous studies (Kuss & Griffiths, 2017; Stanculescu, 2023), such as 'withdrawal' (PSMU5), were not the most central items in the network in the present study. PSMU5 ranked 10th in strength and betweenness values. As aforementioned, the results of the present study were similar to previous symptom-focused network analysis for PSMU (Guo et al., 2022; Wang et al., 2022; Tullett-Prado et al., 2023), which indicated that ‘withdrawal’ was not the most influential node. However, Guo et al. (2022) found that ‘withdrawal’ was the key symptom in the PSU (problematic smartphone use)-impulsivity network but not the PSMU-impulsivity network. Therefore, the importance of behavioral addiction symptoms, such as ‘withdrawal’, may vary across different types of addiction (e.g., PSMU and PSU). However, more symptom-focused network analysis studies are needed to compare the differing roles of the six components across various behavioral addictions.

Moreover, Stanculescu (2023) found that Item 1 (salience) and Item 5 (withdrawal) were the most central symptoms in the Romanian version of the BSMAS, while Item 4 (relapse) had the lowest centrality. Such results were similar to another study among a Chinese sample (Wang et al., 2022). In the present study, P3 (mood modification) and

P6 (conflict/functional impairment) only acted as the intermediate symptoms (with highest betweenness values), while the psychological distress symptoms had the highest and lowest strength indices in the comorbidity network. PSMU1 (salience) had the lowest centrality in the comorbidity network among the six PSMU items. However, it should be noted that the present study explored the comorbidity network of PSMU and DASS symptoms, while Stanculescu (2023) tested the PSMU network without involving the other variables or communities. Therefore, the centrality of the PSMU symptoms might be different depending on whether the network only includes addiction symptoms or combines addiction with other variables (i.e., single-community networks and comorbidity networks may produce different results when interpreting the importance and centrality of PSMU or other addiction symptoms).

The bridging links among the PSMU and psychological distress communities in the network were ‘mood modification’ (PSMU) and symptoms such as being ‘downhearted’, ‘agitated’, and ‘overreactive’. Such findings can deepen the understanding of the widely investigated association between PSMU and psychological distress. Previous studies identified a bidirectional association between the overall scores of PSMU and anxiety or depression (Lopes et al., 2023; Du et al., 2024), but how these concepts were connected at the symptom level remains unknown.

It is important to delineate the relationship between IA and the other variables at the symptom level and domain level (Li et al., 2021; 2022). Tullett-Prado et al. (2023) found that tolerance and mood changes were central symptoms, and they utilized the total subscale scores of anxiety, depression, and stress as nodes in their network analysis.

The present study further clarified that, underlying the association of the total scores, the symptom of ‘mood modification’ in PSMU played a key role in connecting PSMU symptoms and anxiety, depression and stress symptoms. Individuals appear to use social media to have a stable and predictable change in their mood, which could be a coping strategy to ‘self-medicate’ symptoms such as being ‘downhearted’ or ‘agitated’ (Griffiths, 2005, p. 194). The present study highlights the need to concentrate on the effects of specific symptoms of PSMU, advocating for more targeted interventions for PSMU or related psychological distress.

The findings suggest that symptoms of anxiety, depression, and stress play a central role in the comorbidity network of PSMU and psychological distress. In other words, psychological distress variables could be more influential or the primary driving force in this comorbidity. This may further explain the stronger pathway from predisposing factors, including psychopathological variables, to addictive behaviors in the I-PACE model, compared to the weaker returning pathways from addictive behaviors to the risk factors (Brand et al., 2019).

In the bidirectional link between PSMU and psychological distress, according to the node centrality in the network of the present study, resolving psychological distress may lead to solutions for all other issues in the vicious cycle of PSMU and mental health risks. The theoretical model of the reciprocal pathways between digital activity and depression also suggests the central role of depressive mood in the whole cycle (Sonuga-Barke et al., 2024). Therefore, when designing prevention strategies for PSMU, based on the findings of the present study, it appears necessary to prioritize solutions that address individuals' anxiety, depression, and stress. For example, practitioners (e.g., therapists, counselors) need to understand why individuals feel panic-stricken, agitated, and down-hearted, and include strategies to overcome these negative emotional states. More specifically, workshops could offer sessions with a focus on coping skills and emotional regulation, specifically aimed at managing feelings of panic, agitation, and down-heartedness related to social media use. Guidelines could be provided for responsible social media use, such as setting time limits and curating feeds to prioritize uplifting or supportive content. This approach can help mitigate feelings of panic or down-heartedness associated with negative posts or comparisons on social media. Because 'mood modification' and 'conflict/functional impairment' in PSMU were identified as the key bridging symptoms, developing cognitive-behavioral strategies to help reduce mood dependence on social media or functional impairment would be beneficial for clinicians and mental health professionals. For example, clinicians could suggest stress management techniques such as meditation or exercise as healthier options for finding emotional relief rather than relying on social media use. However, all of these suggested clinical applications and interventions require evaluation of their efficacy.

There are several limitations in the present study. The sample was only recruited among young adults from universities in China, which may not reflect the broader student or more global population (inside or outside of China). Therefore, the generalizability of the findings may be limited. Future studies could recruit larger samples from various countries or cultures and across different demographic and educational backgrounds, as well as exploring and comparing the networks of behavioral addictions and the comorbidity network of addiction and mental health among individuals from different cultures. Self-reported scores of PSMU and psychological distress were collected using self-report surveys, and there is always the possibility of individual biases (socially desirable answers, memory recall problems). Future research could broaden data sources to include more than just self-reports by incorporating objective measures, such as the actual frequency of social media use or objectively tracked social media activity on smartphones, alongside survey data. Moreover, the present study only examined one type of specific PIU (i.e., social media) and three psychological distress variables. The comorbidity network model of the selected variables might only reflect the situation of social media use and anxiety, depression and stress. Therefore, future studies should conduct network analysis for the other specific PIU variables such as online gaming disorder or online gambling disorder, and the other psychological distress factors, such as alexithymia and loneliness (Li et al., 2021). Moreover, the present study did not recruit equal numbers of male and female participants, which might limit the generalizability of the findings. Future studies need to recruit more gender balanced samples and test for gender effects in network analysis. The present study also utilized a cross-sectional design, which meant that causal effects between the variables could not be determined. Therefore, caution is advised when interpreting the findings. results should not be overinterpreted. Further studies using longitudinal designs are needed, and longitudinal network analysis approaches, such as cross-lagged panel network analysis, could also be conducted.

Conclusion

The present study estimated an accurate and stable symptom-based network of PSMU and psychological distress. 'Panic', being 'agitated', and being 'down-hearted' were the most central symptoms in the network. The PSMU symptoms of 'mood modification' and 'conflict/functional impairment' were the key bridging symptoms in the comorbidity network between communities. The findings contribute to the understanding of the mechanisms underlying the PSMU-psychological distress connection and benefit the design of potential interventions for PSMU and related mental health risks.

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Table 1. Descriptive statistics and abbreviations for the items

Labels	Items	Component	*Mean*	*SD*
BSMAS				
P1: psmu1	. . . spent a lot of time thinking about social media or planned use of social media?	Salience	3.14	1.12
P2: psmu2	. . . felt an urge to use social media more and more?	Craving/tolerance	3.11	1.13
P3: psmu3	. . . used social media to forget about personal problems?	Mood modification	2.34	1.04
P4: psmu 4	. . . tried to cut down on the use of social media without success?	Relapse/loss of control	2.56	1.14
P5: psmu5	. . . become restless or troubled if you have been prohibited from using social media?	Withdrawal	2.48	1.12
P6: psmu6	. . . used social media so much that it has had a negative impact on your job/studies?	Conflict/functional impairment	2.34	1.00
DASS-21				
S1: stress1	I found it hard to wind down	No wind down	1.92	0.75
A1: anxiety1	I was aware of dryness of my mouth	Dry mouth	1.82	0.79
D1: depression1	I couldn’t seem to experience any positive feeling at all	No positive	1.59	0.74
A2: anxiety 2	I experienced breathing difficulty (e.g., excessively rapid breathing, breathlessness in the absence of physical exertion)	Breathing difficulty	1.41	0.64
D2: depression2	I found it difficult to work up the initiative to do things	No initiative	1.89	0.80
S2: stress2	I tended to over-react to situations	Overreactive	1.67	0.77
A3: anxiety3	I experienced trembling (e.g., in the hands)	Trembling	1.44	0.68
S3: stress3	I felt that I was using a lot of nervous energy	Nervous energy	2.06	0.85
A4: anxiety4	I was worried about situations in which I might panic and make a fool of myself	Worried	2.68	0.95
D3: depression3	I felt that I had nothing to look forward to	Not looking forward	1.66	0.82
S4: stress4	I found myself getting agitated	Agitated	1.87	0.80

S5: stress5	I found it difficult to relax	No relaxing	1.83	0.84
D4: depression4	I felt down-hearted and blue	Down-hearted	1.79	0.81
S6: stress6	I was intolerant of anything that kept me from getting on with what I was doing	Intolerant	2.02	0.86
A5: anxiety5	I felt I was close to panic	Panic	1.45	0.67
D5: depression5	I was unable to become enthusiastic about anything	Not enthusiastic	1.49	0.73
D6: depression6	I felt I wasn't worth much as a person	Worthless person	1.27	0.60
S7: stress7	I felt that I was rather touchy	Touchy	1.75	0.81
A6: anxiety6	I was aware of the action of my heart in the absence of physical exertion (e.g., sense of heart rate increase, heart missing a beat)	Heart aware	1.45	0.72
A7: anxiety7	I felt scared without any good reason	Scared	1.54	0.73
D7: depression7	I felt that life was meaningless	Meaningless of life	1.33	0.65

Note. *N*= 822. The components of the PSMU items were obtained from Andreassen et al. (2016); the components of the DASS-21 items were obtained from Van den Bergh et al. (2021).

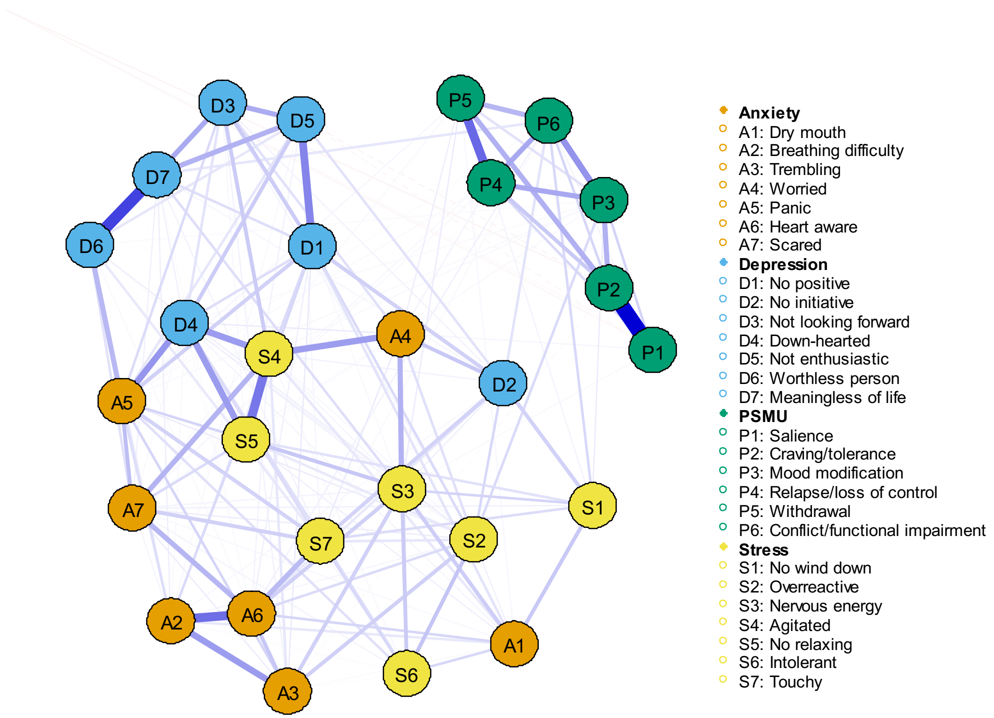


Figure 1. The estimated network structure of problematic social media use and psychological distress

Note. Nodes with the same color in the figure represent members of the same cluster. The color corresponding to each cluster can be identified in the legend on the right. Blue lines (solid) represent positive correlations, while red lines (dashed) represent negative correlations. Thicker lines indicate stronger relationships. The letters and numbers within the nodes represent the specific item from each scale. The corresponding symptoms for each item can be found in the legend on the right.

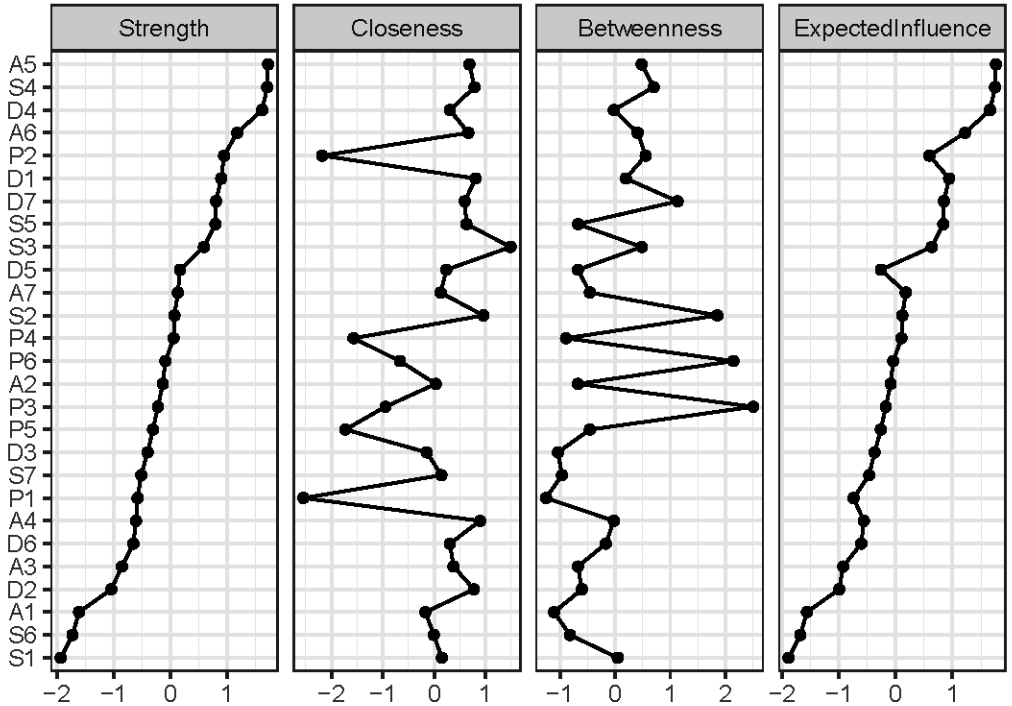


Figure 2 Centrality indices of the PSMU and psychological distress symptoms

Note. The nodes were ordered according to the 'strength' values. Standardized values z scores were presented. The y-axis labels represent the labels of each symptom, which can be found in Figure 1 or Table 1 for the corresponding symptoms. A larger value indicates stronger centrality/importance of the corresponding node in the network model.

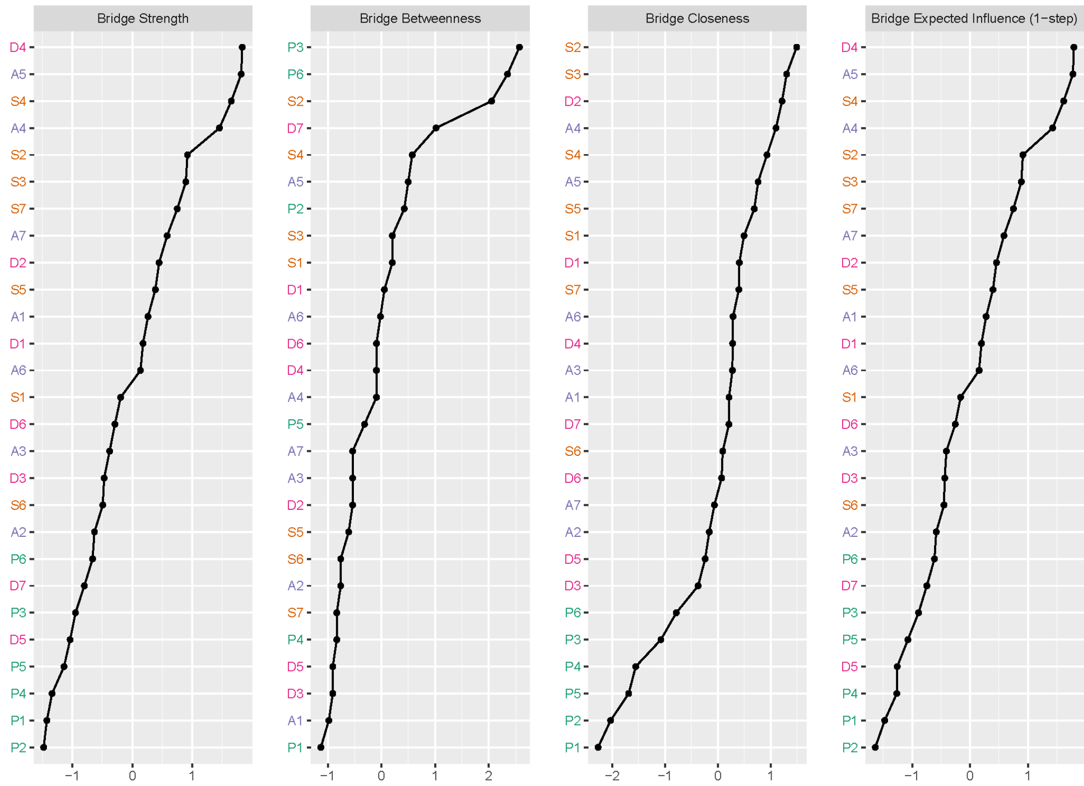


Figure 3 Bridge indices of the PSMU and psychological distress symptoms

Note. The nodes were ordered according to the values of each specific index. Standardized values z scores were presented. The y-axis labels represent the labels of each symptom, which can be found in Figure 1 or Table 1 for the corresponding symptoms. The same color on the y-axis labels indicates that the items belong to the same cluster. A larger value indicates a greater importance/strength of the corresponding node in connecting different clusters within the network model.

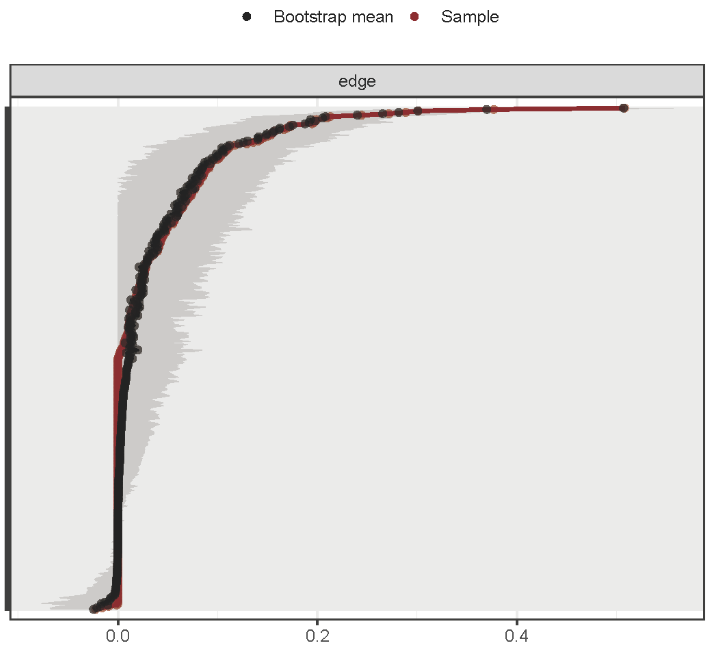


Figure 4 Edge weights and bootstrapped confidence intervals. (N = 822).

Note. The y-axis represents the edges. The red line represents the estimated edge, while the dark area indicates the 95% bootstrap confidence interval.

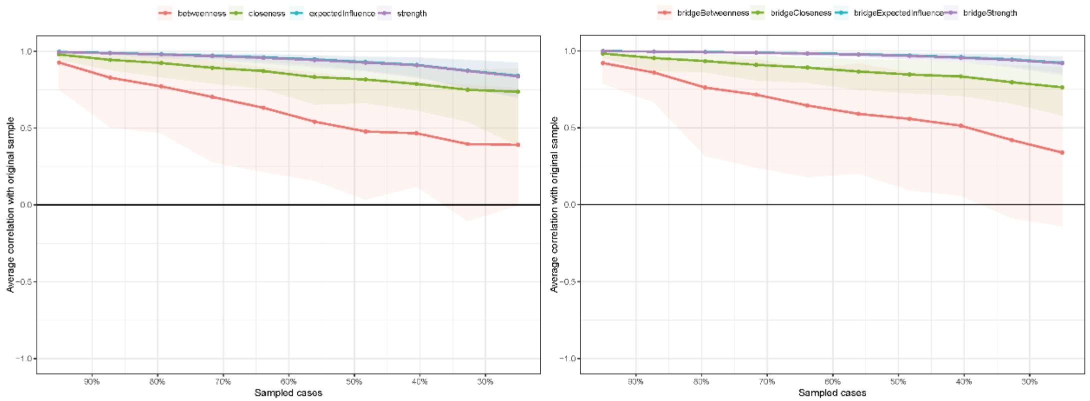


Figure 5 Stability of centrality indices (left) and bridge centrality indices (right) by case dropping bootstrapping approach.

Note: The lines in the figure indicate the variation trend of the centrality correlation between subsamples and the original sample as the subsample sampling rate changes.

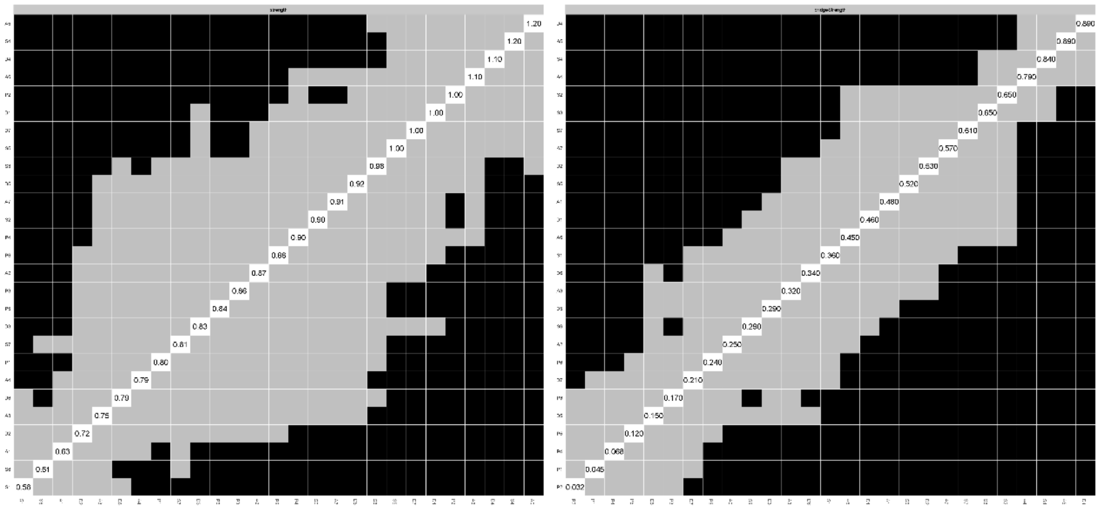


Figure 6 Non-parametric bootstrapped difference tests for node strength (left) and bridge strength (right).

Note. Black boxes represent significant differences ($p < 0.05$) and gray boxes represent non-significant differences. Diagonal values represent the strength or bridge strength score of each node.

Appendices

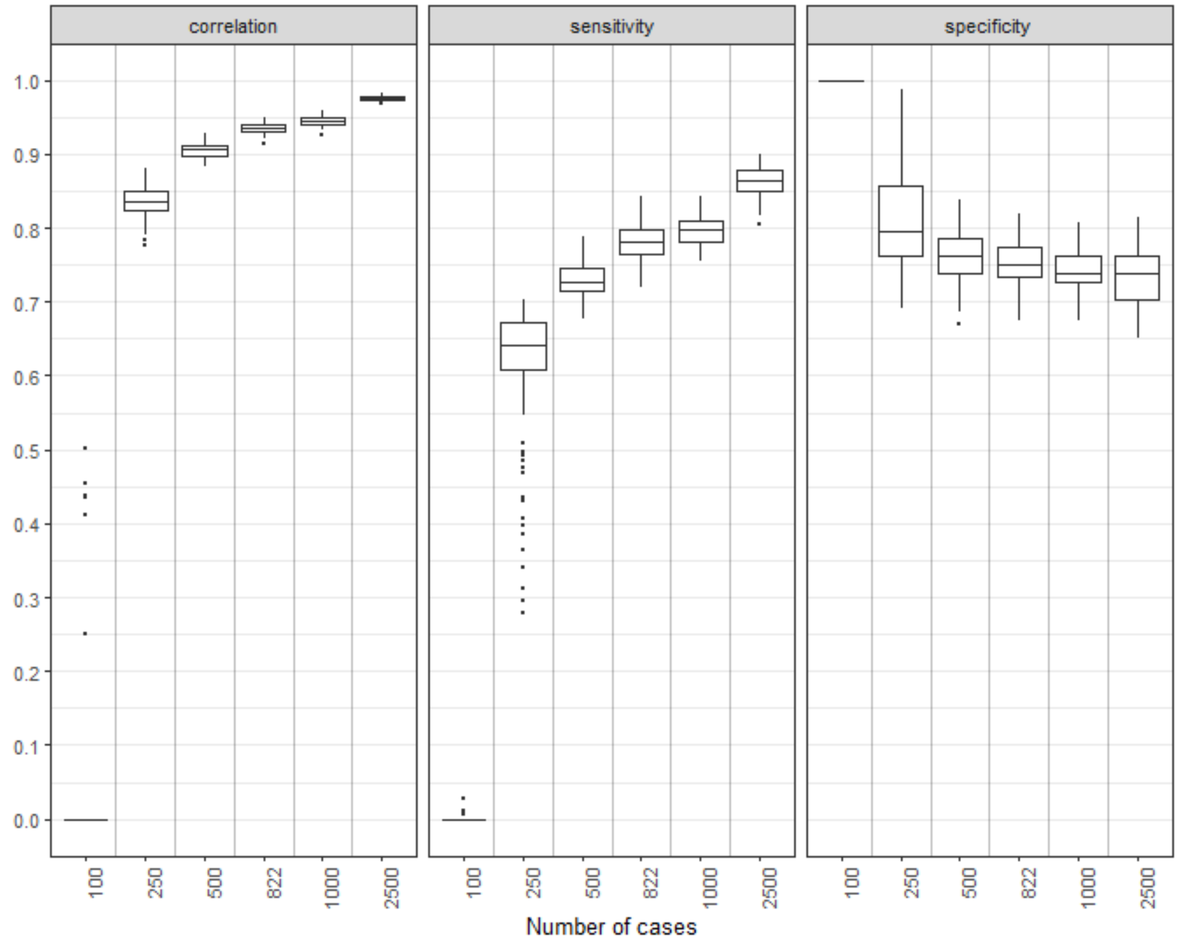
Appendix 1. Partial correlation matrix

	P1	P2	P3	P4	P5	P6	S1	A1	D1	A2	D2	S2	A3	S3	A4	D3	S4	S5	D4	S6	A5	D5	D6	S7	A6	A7	D7
P1	0	0.507963	0.085764	0.076724	0.060812	0.021142	0	0	0	0	0	0	0	0.011465	0.017255	-0.00119	0	0	0	0	0	-0.01556	0	0	0	0	0
P2	0.507963	0	0.15551	0.106768	0.157519	0.082069	0	0	0	0	0	0	-0.00928	0	0	0	0	0	0	0	0	-0.02236	0	0	0	0	0
P3	0.085764	0.15551	0	0.172746	0.058696	0.212886	0.04022	0	0	0	0	0.074225	0	0	0	0	0.011452	0	0.010626	0	0.012817	0	0.007133	0.00201	0	0.01103	0
P4	0.076724	0.106768	0.172746	0	0.301363	0.173431	0.022554	0	0	0	0	0	0	0	0.023685	0	0	0	0	0	0.010838	0	0	0	0	0.011203	0
P5	0.060812	0.157519	0.058696	0.301363	0	0.143116	0	0.016738	0	0	0	0	0	0.039691	0.034704	0	0	0	0	0	0.017541	0	0	0	0	0.011109	0
P6	0.021142	0.082069	0.212886	0.173431	0.143116	0	0.077719	0	0	0	0.055021	0	0	0	0	0	0	0	0	0	0.006178	0	0	0.012244	0.02786	0.014397	0.050015
S1	0	0	0.04022	0.022554	0	0.077719	0	0.108499	0	0	0.088672	0	0	0.086109	0	0	0	0.060025	0	0	0	0	0	0.070591	0	0.027246	0
A1	0	0	0	0	0.016738	0	0.108499	0	0.056505	0.046003	0	0.027075	0.008072	0.099573	0.000752	0	0.044828	0.029962	0.020166	0.0801	0	0	0	0	0.081598	0.013113	0
D1	0	0	0	0	0	0	0	0.056505	0	0.074072	0.092365	0.07366	0.042529	0.011113	0	0.101813	0	0.082181	0.067784	0	0.092439	0.244475	0	0	0.02927	0	0.065332
A2	0	0	0	0	0	0	0	0.046003	0.074072	0	0.013757	0.018158	0.196479	0	0	0	0.041319	0	0.009591	0.00603	0.066051	0.011933	0.045634	0	0.288775	0.020069	0.031061
D2	0	0	0	0	0	0.055021	0.088672	0	0.092365	0.013757	0	0.078033	0	0.030491	0.109336	0.024262	0.026461	0	0	0	0	0.057379	0	0.086825	0.042909	0	0.018293
S2	0	0	0.074225	0	0	0	0	0.027075	0.07366	0.018158	0.078033	0	0.094119	0.019568	0.061587	0.020103	0.016648	0.044249	0.026366	0.117089	0.039782	0.00092	0.032614	0.05009	0.072047	0.035532	0
A3	0	-0.00928	0	0	0	0	0	0.008072	0.042529	0.196479	0	0.094119	0	0.09136	0	0.025252	0.047897	0	0	0.004093	0.083147	0	0.002828	0	0.111485	0.03724	0
S3	0.011465	0	0	0	0.039691	0	0.086109	0.099573	0.011113	0	0.030491	0.019568	0.09136	0	0.1542	0	0.017156	0.111132	0.028085	0.103595	0	0	0	0	0.093955	0.021844	0.065365
A4	0.017255	0	0	0.023685	0.034704	0	0	0.000752	0	0	0.109336	0.061587	0	0.1542	0	0.059572	0.1948	0.00611	0.041211	0.048349	0	0	0	0.041928	0	0	0
D3	-0.00119	0	0	0	0	0	0	0	0.101813	0	0.024262	0.020103	0.025252	0	0.059572	0	0.104503	0.013147	0.055353	0	0.069585	0.166494	0.015579	0	0	0	0.169255
S4	0	0	0.011452	0	0	0	0	0.044828	0	0.041319	0.026461	0.016648	0.047897	0.017156	0.1948	0.104503	0	0.271606	0.198619	0.01376	0	0	0	0	0.024405	0.149639	0
S5	0	0	0	0	0	0	0.060025	0.029962	0.082181	0	0	0.044249	0	0.111132	0.00611	0.013147	0.271606	0	0.198181	0.015027	0.085119	0.025929	0	0	0	0.074527	0
D4	0	0	0.010626	0	0	0	0	0.020166	0.067784	0.009591	0	0.026366	0	0.028085	0.041211	0.055353	0.198619	0.198181	0	0.064355	0.209561	0.101473	0.005066	0.067479	0.007829	0.009243	0.027899
S6	0	0	0	0	0	0	0	0.0801	0	0.00603	0	0.117089	0.004093	0.103595	0.048349	0	0.01376	0.015027	0.064355	0	0.062704	0	0	0.077372	0	0.021984	0
A5	0	0	0.012817	0.010838	0.017541	0.006178	0	0	0.092439	0.066051	0	0.039782	0.083147	0	0	0.069585	0	0.085119	0.209561	0.062704	0	0.04948	0.14103	0.086913	0	0.129261	0.002975
D5	-0.01556	-0.02236	0	0	0	0	0	0	0.244475	0.011933	0.057379	0.00092	0	0	0	0.166494	0	0.025929	0.101473	0	0.04948	0	0.048388	0.01809	0	0.001953	0.153228
D6	0	0	0.007133	0	0	0	0	0	0	0.045634	0	0.032614	0.002828	0	0	0.015579	0	0	0.005066	0	0.14103	0.048388	0	0.043399	0.010487	0.05698	0.377082
S7	0	0	0.00201	0	0	0.012244	0.070591	0	0	0	0.086825	0.05009	0	0	0.041928	0	0	0	0.067479	0.077372	0.086913	0.01809	0.043399	0	0.135634	0.091664	0.024037
A6	0	0	0	0	0	0.02786	0	0.081598	0.02927	0.288775	0.042909	0.072047	0.111485	0.093955	0	0	0.024405	0	0.007829	0	0	0	0.010487	0.135634	0	0.145559	0.006467
A7	0	0	0.01103	0.011203	0.011109	0.014397	0.027246	0.013113	0	0.020069	0	0.035532	0.03724	0.021844	0	0	0.149639	0.074527	0.009243	0.021984	0.129261	0.001953	0.05698	0.091664	0.145559	0	0.02786
D7	0	0	0	0	0	0.050015	0	0	0.065332	0.031061	0.018293	0	0	0.065365	0	0.169255	0	0	0.027899	0	0.002975	0.153228	0.377082	0.024037	0.006467	0.02786	0

Appendix 2. Centrality and bridge centrality indices

	Betweenness	Closeness	Strength	Expected Influence	Bridge Strength	Bridge. Betweenness	Bridge. Closeness	Bridge. Expected.Influence.1.step.	communities
P1	-1.254	-2.546	-0.578	-0.744	0.045	0.000	0.028	0.012	psmu
P2	0.555	-2.182	0.943	0.594	0.032	21.000	0.029	-0.032	psmu
P3	2.507	-0.947	-0.221	-0.176	0.170	50.000	0.036	0.170	psmu
P4	-0.892	-1.570	0.055	0.100	0.068	4.000	0.032	0.068	psmu
P5	-0.458	-1.728	-0.307	-0.263	0.120	11.000	0.032	0.120	psmu
P6	2.146	-0.667	-0.090	-0.045	0.243	47.000	0.038	0.243	psmu
S1	0.048	0.149	-1.929	-1.887	0.365	18.000	0.046	0.365	stress
A1	-1.109	-0.170	-1.608	-1.565	0.483	2.000	0.044	0.483	anxiety
D1	0.193	0.808	0.894	0.940	0.462	16.000	0.046	0.462	depression
A2	-0.675	0.030	-0.134	-0.090	0.252	5.000	0.042	0.252	anxiety
D2	-0.603	0.773	-1.041	-0.997	0.532	8.000	0.051	0.532	depression
S2	1.856	0.958	0.071	0.116	0.654	43.000	0.053	0.654	stress
A3	-0.675	0.378	-0.854	-0.926	0.317	8.000	0.045	0.299	anxiety
S3	0.482	1.490	0.589	0.634	0.647	18.000	0.052	0.647	stress
A4	-0.024	0.895	-0.606	-0.562	0.793	14.000	0.050	0.793	anxiety
D3	-1.037	-0.144	-0.402	-0.372	0.293	3.000	0.040	0.291	depression
S4	0.699	0.786	1.703	1.750	0.844	23.000	0.049	0.844	stress
S5	-0.675	0.629	0.792	0.838	0.515	7.000	0.047	0.515	stress
D4	-0.024	0.306	1.614	1.661	0.891	14.000	0.045	0.891	depression
S6	-0.820	-0.007	-1.724	-1.681	0.288	5.000	0.043	0.288	stress
A5	0.482	0.687	1.718	1.765	0.887	22.000	0.048	0.887	anxiety
D5	-0.675	0.237	0.170	-0.259	0.146	3.000	0.041	0.070	depression
D6	-0.169	0.306	-0.651	-0.607	0.340	14.000	0.043	0.340	depression
S7	-0.964	0.140	-0.513	-0.469	0.610	4.000	0.045	0.610	stress
A6	0.410	0.665	1.173	1.220	0.451	15.000	0.045	0.451	anxiety
A7	-0.458	0.126	0.131	0.176	0.566	8.000	0.042	0.566	anxiety
D7	1.133	0.596	0.802	0.848	0.208	29.000	0.044	0.208	depression

Appendix 3. Plots of power analysis using the netSimulator function in ‘bootnet’ R package.



correlation
sensitivity
specificity
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
100
250
500
822
1000
2500
Number of cases