Zhou *et al. BMC Psychiatry* (2025) 25:482
https://doi.org/10.1186/s12888-025-06920-2

BMC Psychiatry

RESEARCH

Open Access

Symptom network between problematic smartphone use and poor sleep quality in adolescents with depression

Yongjie Zhou[1†], Jian Gong[2†], Jing Shao[3], Nan Yan[4], Linlin Meng[5], Kongliang He[6], Ying Shen[7], Qian Wei[2], Chunyan Zhang[1], Xuan Lei[2], Yuehua Cao[2] and Yanni Wang[2,8*]

Abstract

Background This study established a network structure between problematic smartphone use (PSU) and poor sleep quality (PSQ) to explore their symptomatic relationship in adolescents with depression.

Methods The data were obtained from the baseline data of the Chinese Adolescent Depression Cohort, which included depressed adolescents aged between 12 and 18 years. PSU and PSQ were assessed via the Mobile Phone Addiction Index (MPAI) and Pittsburgh Sleep Quality Index (PSQI). This study utilized network analysis to identify the core and bridge symptoms between PSU and PSQ.

Results The core symptom of the network was 'Anxiety and craving' in the PSU. The symptoms 'Anxiety and craving', 'Daytime dysfunction' and 'Sleep disturbances' could function as bridges between PSU and PSQ. The symptom 'Anxiety and craving' played the most important role in the interaction between PSU and PSQ. It affects 'Sleep disturbances' that contribute to the harm of problematic smartphone use to sleep quality. The symptom 'Daytime dysfunction' of PSQ was the most severely affected by PSU.

Conclusions Interventions that target regulating negative emotion and reducing daytime tiredness would be more effective in managing problematic smartphone use and improving sleep quality.

Clinical trial number Not applicable.

Keywords Network analysis, Directed acyclic graph, Problematic smartphone use, Poor sleep quality, Adolescent, Depression

†Yongjie Zhou and Jian Gong contributed equally to this work and should be considered co-first authors.

*Correspondence:
Yanni Wang
wangyann@lzu.edu.cn
[1]Shenzhen Mental Health Center, Shenzhen Kangning Hospital, Shenzhen, Guangdong Province, China
[2]Department of Maternal, Child and Adolescent Health, School of Public Health, Lanzhou University, 222th South Tianshui Rd, Lanzhou 730000, Gansu Province, China
[3]Department of English Language and Literature, Faculty of Arts, Hong Kong Baptist University, Hong Kong SAR, China
[4]CAS Key Laboratory of Human–Machine Intelligence-Synergy Systems, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong Province, China
[5]Linyi Mental Health Center, Linyi Fourth People's Hospital, Linyi, Shandong Province, China
[6]Hefei Fourth People's Hospital, Hefei, Anhui Province, China
[7]Department of Psychosomatic Medicine, Ganzhou Third People's Hospital, Ganzhou, Jiangxi Province, China
[8]Mental Health Center, Second Provincial People's Hospital of Gansu, Lanzhou, Gansu Province, China

Background

Depression is one of the most prevalent psychological disorders. It is projected to be one of the leading causes of disease burden by 2030 [1]. Adolescents are particularly vulnerable to depression [2], with more than 40% of depression patients experiencing onset during this stage of life [3]. In fact, research suggests that the prevalence of depressive symptoms among Chinese adolescents is approximately 20.3% [4].

Problematic smartphone use (PSU), also known in some studies as smartphone dependence, smartphone overuse, or smartphone addiction. PSU is characterized by the inability to control one's mobile phone usage, resulting in adverse effects on an individual's daily life [5]. It is a behavioral addiction with six characteristics: salience, tolerance, mood modification, relapse, conflict, and withdrawal symptoms [6, 7]. PSU has been consistently linked to depression in adolescents [8]. A study revealed that depression was significantly greater among adolescents with smartphone addiction (77.2%) than among general adolescents (35.4%) [9]. Another study revealed that the prevalence of PSU in patients with major depressive disorder was 58.6%, which was higher than that reported in the general population. PSU has a detrimental effect on the psychological well-being of adolescents, leading to stress, anxiety, depression and sleep disturbance [10, 11].

Poor sleep quality (PSQ) refers to unsatisfactory sleep in either the objective aspect (sleep duration, sleep latency, and number of arousals) or the subjective aspect (depth, restfulness and self-satisfaction with sleep) [12]. PSQ is characterized primarily by insomnia, inadequate sleep time, and daytime dysfunction [13]. It is recognized as a core secondary symptom of depression [14] and is the most prominent symptom in depressed adolescents; it is even more common than low mood [15, 16]. Approximately 92% of adolescent patients with depression suffer from PSQ [15, 17].

PSQ is considered one of the major adverse consequences of PSU. A study revealed that 68.7% of problematic smartphone users had PSQ [18]. Smartphones enable internet access anywhere at any time and provide opportunities to connect with others, making them popular among adolescents for communication or recreation [19]. However, this leads to a delay in the onset of sleep and frequent interruption during sleep due to the use of smartphones [19]. Tavernier et al. [20] observed that once adolescents owned a smartphone, they would sleep less than recommended. Johansson et al. [21] also reported that using smartphones before bedtime was associated with premature awakening, restless sleep, and daytime sleepiness.

These findings have well documented the association between PSQ and PSU. However, most of these studies focused on the relationships between the total scores of the scales for PSQ and PSU. These approaches may overlook nuances in the links between symptoms of these disorders [22]. It is also challenging for these studies to identify which symptom is the core symptom that causes them to be associated.

Network analysis offers a novel approach for conceptualizing psychological constructs to better understand the co-occurrence of PSU and PSQ [22, 23]. In the network analysis model, mental disorders are regarded as complex networks of mutually reinforcing symptoms, providing a new framework to explain why certain disorders may occur more often than others by examining the relationships among multiple symptoms [24–26]. Multi - item psychometric scales, such as the Pittsburgh Sleep Quality Index (PSQI), provide a comprehensive assessment of disease by capturing a wide range of information and include various sub-concepts related to disease. However, the drawback of these scales is that the importance of the sub-concepts is predefined and assumed to be equal to that related to disease [27]. Network analysis can identify core and bridge symptoms, meaning that it can determine which symptoms are more crucial in the pathogenesis and maintenance of diseases [28, 29]. This effectively elucidates the specific interaction between PSU and PSQ.

To the best of our knowledge, few studies have delved into the symptomatic mechanisms involved in the relationship between PSU and PSQ among depressed adolescents. To help us develop prioritized intervention measures to prevent the development of PSU and PSQ. We established a network model of PSU-PSQ and explored the core symptoms and bridge symptoms to better understand the feedback loops among these symptoms.

Methods

Participants and procedure

The study recruited outpatients and inpatients from 14 psychiatric hospitals or psychiatric departments of general hospitals in nine provinces across China. The data was collected following the procedure of Wang et al. and some research has been accomplished based on the dataset [30–34]. Participants were consecutively recruited from Dec. 2020 to Dec. 2022. Inclusion criteria were as follows: (a) age 12 to 18 years, (b) met DSM-V criteria for diagnosis of depressive episode or bipolar depressive episode, and (c) with six schooling years and above, to make sure that participants could accurately understand the questionnaire. Exclusion criteria were as follows: (a) the presence of any severe chronic physical disease, infectious diseases, or immune system diseases, (b) having a history of traumatic brain injury, epilepsy, or other severe neurological or organic brain disease, (c) having a history of severe mental disorders such as schizophrenia, or (d) having a history of mental retardation.

A total of 2343 patients completed the survey, but we excluded 143 questionnaires with missing information. Therefore, the final sample included 2200 depressed adolescents.

To ensure accurate data collection, face-to-face assessments were employed in the survey. A trained investigator was present during the completion of the online questionnaire to address any confusion or questions from the participants.

Questionnaire survey

Demographic profile

A self-administered questionnaire was used to collect participants' sociodemographic data, including age, sex, nationality, if single-child family and left-behind children. We collected professional psychiatrists' diagnoses of the disease characteristics in depressed adolescents, such as unipolar depression, bipolar depression or depressive episode.

Problematic smartphone use (PSU)

The PSU was evaluated via the Chinese version of the Mobile Phone Addiction Index (MPAI) [35]. The MPAI was adapted by Leung [36] to assess the PSU among Chinese adolescents. This scale showed good validity among adolescents and adults [37–40]. The MPAI is a self-reported scale with 17 items rated on a 5-point Likert scale ranging from 1 (not at all) to 5 (always). It includes 4 subscales to describe 4 symptoms of smartphone addiction: Losing control and receiving complaints (M1), Anxiety and craving (M2), Withdrawal/Escape (M3), and Productivity loss (M4). Higher score of subscale indicates more severe symptom. The Cronbach's alpha of the scales was 0.887 in the study.

Poor sleep quality

The Pittsburgh Sleep Quality Index (PSQI) was used to assess sleep quality [12]. The PSQI is an extensively validated psychometric instrument developed by Buysse et al.in 1989 [12], serves as a comprehensive clinical tool for evaluating subjective sleep quality. It is a self-rated questionnaire that consists of 19 items, with higher scores indicating poorer sleep quality [41]. It contains 7subscales: Subjective sleep quality (P1), Sleep latency (P2), Sleep duration (P3), Habitual sleep efficiency (P4), Sleep disturbances (P5), Use of sleeping medication (P6), and Daytime dysfunction (P7). Cronbach's alpha of the scale was 0.724.

Depression symptoms

The Chinese version of the Patient Health Questionnaire (PHQ-9) was used to evaluate depression symptoms [42]. The PHQ-9 is used as a depression screening tool developed by Robert L. et al. in 1999 [43]. The Chinese version of PHQ-9 has been widely used among the Chinese population and has good reliability and validity [42]. The PHQ-9 is a 9-item self-report instrument. Each item is rated on a 4-point Likert scale ranging from 0 (not at all) to 3 (nearly every day). The Cronbach's alpha of the scale was 0.901.

Data analysis

IBM SPSS statistics 25.0 (SPSS Inc., Chicago, Illinois, UPSU) was used for preliminary analysis and description of the data. The mean (M) ± standard deviation (SD) was used to describe continuous variables because the data were approximately normally distributed.

Network analysis

Network analysis was performed via R software. The network model was estimated and validated via the R package *qgraph* [44] and *bootnet* [45]. After controlling for all other symptoms, partial correlation analysis was performed for each pair of symptoms to form a network. In the network model, symptoms are viewed as nodes, and the associations between nodes are viewed as edges (conditional correlations between nodes).

The extended Bayesian information criterion function (EBICglasso) in the R package *qgraph* was used to generate a graphical least absolute shrinkage and selection operator (LASSO) model [46]. This method was employed to shrink trivially small partial correlations to zero, thereby eliminating potential spurious edges from the network. By doing so, the symptom network became sparser and easier to comprehend. The sparsity parameter in the *qgraph* package can be adjusted between 0 and 1. We set the tuning parameter to 0.5 to achieve a balance between sparsity and sensitivity.

Centrality

Centrality refers to the importance of a node in the network. In addition to generating the network, we also calculate different indices to assess the centrality of nodes within the network. The indices included strength (or expected influence), closeness and betweenness. We found that the index of expected influence was the most suitable for our study. Previous studies have demonstrated that closeness and betweenness are less reliable than the expected influence or strength when determining the importance of nodes [47, 48]. The expected influence was deemed more suitable than strength because of the presence of both positive and negative correlations in this network model [49]. As a result, the expected influence was utilized to quantify the significance of each node within the network.

In addition to analyzing the centrality of nodes, our study also examined bridge centrality, which encompasses the expected influence of bridges, bridge closeness, and bridge betweenness. Bridge centrality assesses the importance of a symptom in connecting two disorders. A higher bridge expected influence indicated a greater risk of contagion from one community to another. Symptoms that are linked to two disorders are referred to as bridge symptoms, and their removal could prevent one disorder from activating another. In reference to previous research, the top 30% of symptom nodes with the highest bridge expected influence were selected as bridge symptoms in this study [50]. To identify these bridge symptoms, we utilized the R package *networktools* to compute the expected influence of the bridge.

Stability

To evaluate the stability of our network model, we employed the R package *bootnet.* This method is based on 1000 bootstraps for each node and assesses the stability of centrality indices via correlation stability coefficients (CS-C). CS-C represents the maximum proportion of samples that could be deleted while maintaining a correlation between the original centrality indices and the new network's centrality indices above 0.7 with a 95% probability after deletion. A CS-C greater than 0.25 indicates moderate stability, whereas an index greater than 0.5 indicates strong stability [45].

Directed acyclic graph

The R package *bnlearn* was used to conduct Bayesian network analysis on 11 symptoms and construct a directed acyclic graph (DAG) [51]. The Bayesian Mountain climbing algorithm was used to find the best fitting model via the Bayesian information criterion. Five random restarts and 10 perturbations (add edge, remove edge, reverse edge direction) were set for each random restart. To ensure the stability of the DAG, bootstrapping was used to generate 1000 networks. According to the frequency of an edge in all the DAGs, 85% was taken as the threshold to choose whether to keep the edge. When more than 850 DAGs had edges, the edge was reserved. Then, the direction of the edge is determined. When the direction from node A to node B was present in more than 50% of the DAGs, the direction was reported in the final result.

Table 1 Demographic characteristics of the participants ($N=2200$)

Variables	*N*	%
Sex		
Boy	490	22.3
Girl	1710	77.7
Age (yrs) (M ± SD)	15.0 ± 1.7	
Nationality		
Han	2013	91.5
Minority	187	8.5
Diagnosis		
Unipolar Depression	1835	83.4
Bipolar Depression	331	15.1
Depressive episode	34	1.5
Single-child family	642	29.2
Left-behind children	434	19.7
PHQ-9(M ± SD)	16.8 ± 7.2	
MPAI (M ± SD)	45.3 ± 13.5	
PSQI (M ± SD)	10.8 ± 4.4	

PHQ-9: Patient Health Questionnaire

MPAI: Mobile phone addiction index

PSQI: Pittsburgh Sleep Quality Index

Results

Baseline characteristics

Our study included a total of 2200 depressed adolescents, comprising 490 boys and 1710 girls. The demographic characteristics of these participants are summarized in Table 1. The mean age of the sample was 15.0 years, with the majority nationality being Han. Approximately 29.2% of the depressed adolescents were only children. Approximately 19.7% of the participants were left-behind children. The mean PHQ-9 score was 16.8. The mean MPAI score was 45.3, and the mean PSQI score was 10.8.

Table 2 shows the 11 symptoms associated with PSQ and PSU. The abbreviations P1 to P7 denote the 7 symptoms of PSQ, whereas M1 to M4 refer to the 4 symptoms of PSU. The average predictability of these symptoms was 0.812, indicating that 81.2% of the variance in symptom presentation could be accounted for by neighboring symptoms.

Network structure

Figure 1 illustrates the estimated network between the PSU and PSQ. The network yielded 55 edges (11*(11–1)/2), 40 of which had nonzero weights. Most of the edges with stronger weights were found within the communities. The edge connecting P3 - P4 (Sleep duration-Habitual sleep efficiency, average edge weight = 0.49) had the strongest weight, followed by edges P1 - P2 (Subjective sleep quality-Sleep latency, average edge weight = 0.38), M1 - M2 (Losing control and receiving complaints - Anxiety and craving, average edge weight = 0.35), and M1 - M4 (Losing control and receiving complaints - Productivity loss, average edge weight = 0.35). Interestingly, there was a particular edge between P3 - P6 (Sleep duration - Use of sleeping medication, average edge weight= -0.11) that exhibited a negative correlation, which differed from the other edges in the sleep quality community. Although the weights of the edges connecting the PSU and PSQ were weaker than those of the edges within communities, there were two significant bridges between them: M2 - P5 (Anxiety and craving - Sleep disturbances, average

Table 2 Description of symptoms measured with the PSU and PSQ

Abbreviations	Item	M	SD	Skewness	Kurtosis	Predictability
P1	Subjective sleep quality	1.68	0.82	-0.17	-0.49	0.749
P2	Sleep latency	1.86	1.04	-0.44	-1.00	0.779
P3	Sleep duration	1.35	1.22	0.15	-1.56	0.790
P4	Habitual sleep efficiency	0.82	1.11	1.01	-0.49	0.828
P5	Sleep disturbances	1.57	0.62	0.55	-0.51	0.863
P6	Use of sleeping medication	1.08	1.32	0.57	-1.50	0.954
P7	Daytime dysfunction	2.46	0.82	-1.39	0.98	0.853
M1	Losing control and receiving complaints	2.82	0.92	0.16	-0.54	0.726
M2	Anxiety and craving	2.40	1.05	0.51	-0.63	0.715
M3	Withdrawal/Escape	2.89	1.08	0.37	-0.74	0.916
M4	Productivity loss	2.44	1.06	0.55	-0.40	0.763

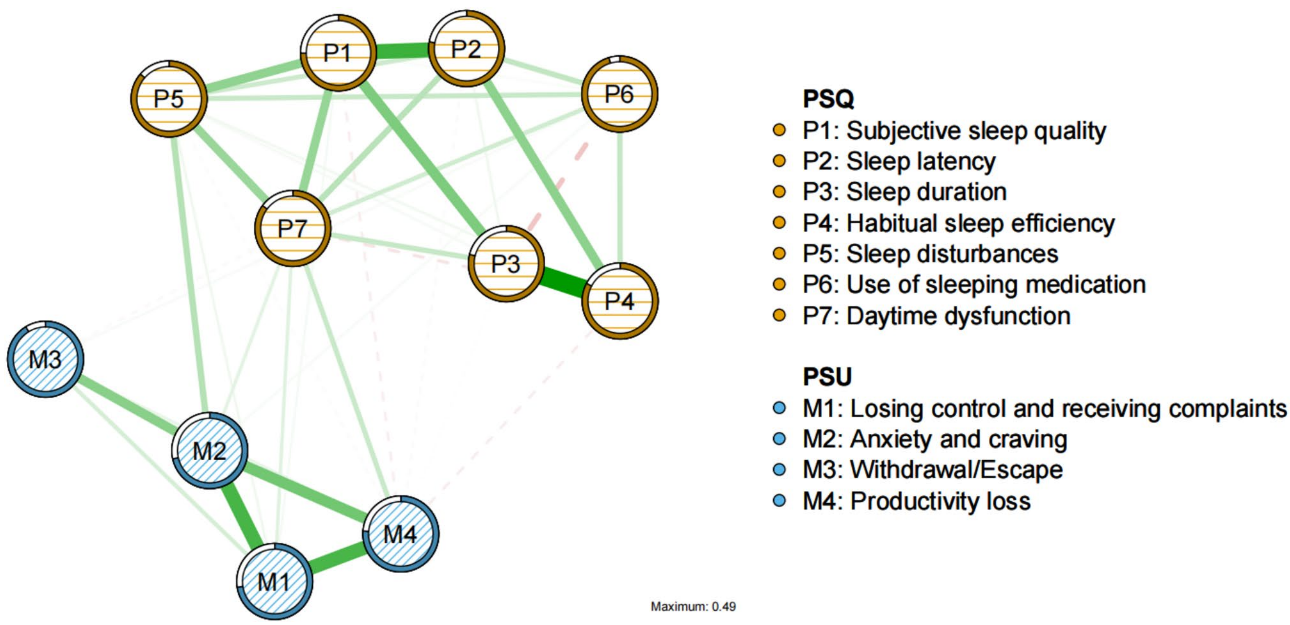

Fig. 1 Network structure of problematic smartphone use (PSU) and poor sleep quality (PSQ) in adolescents with depression. Note: Green edges indicate a positive association between two symptoms, whereas red edges indicate a negative association. A wider edge indicates a stronger association between two symptoms. The predictability of each symptom is illustrated by a circular pie chart

edge weight = 0.14) and M4 - P7 (Productivity loss - Daytime dysfunction, average edge weight = 0.10).

Network centrality and bridge centrality

The centralities of nodes within the entire network are depicted in Fig. 2. The expected influence reflected the total level of involvement of symptoms in the network. M2 (Anxiety and craving) had the highest expected influence value, indicating that it was the core symptom in the 11-symptom network. P1 (Subjective sleep quality), P2 (Sleep latency), and P7 (Daytime dysfunction) also significantly influenced the explanation of the network.

The bridge centralities of the nodes are depicted in Fig. 3. M2 (Anxiety and craving), P7 (Daytime dysfunction) and P5 (Sleep disturbances) had higher bridge expected influence values, indicating that they were bridge symptoms and had the potential to connect PSU and PSQ within the network.

Network stability

As demonstrated in Fig. 4, the values of expected influence, closeness, and betweenness exhibited excellent stability. The CS coefficient for both expected influence and closeness was 0.75, indicating that even if 75% of the participants were removed from the analysis, the order of symptoms in terms of expected influence and closeness would still correlate with the original order by 0.7. The CS coefficient for betweenness was 0.67.

Directed acyclic graph

A directed acyclic graph (DAG) provides another perspective on the relationships between nodes (Fig. 5). Table 3 showed the connection strength and direction

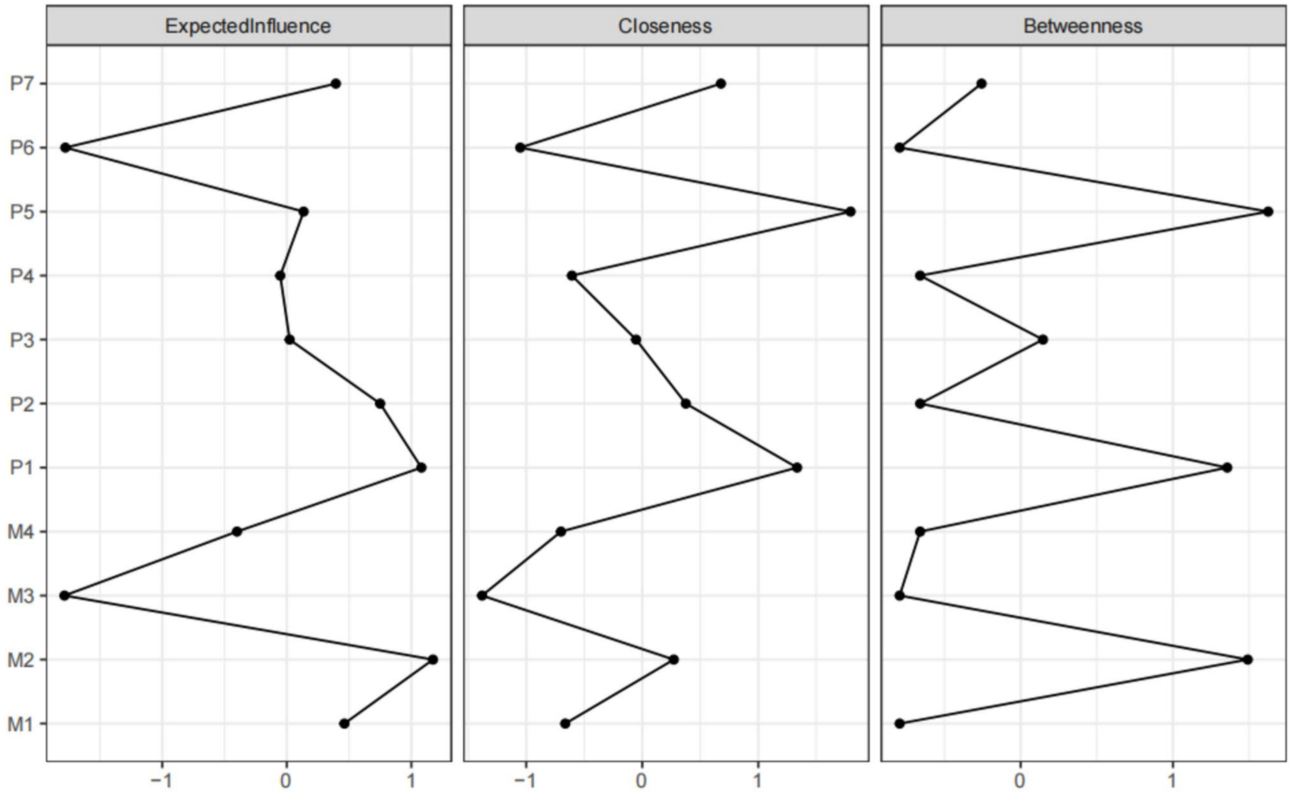

Fig. 2 Network centrality for the network representing each symptom

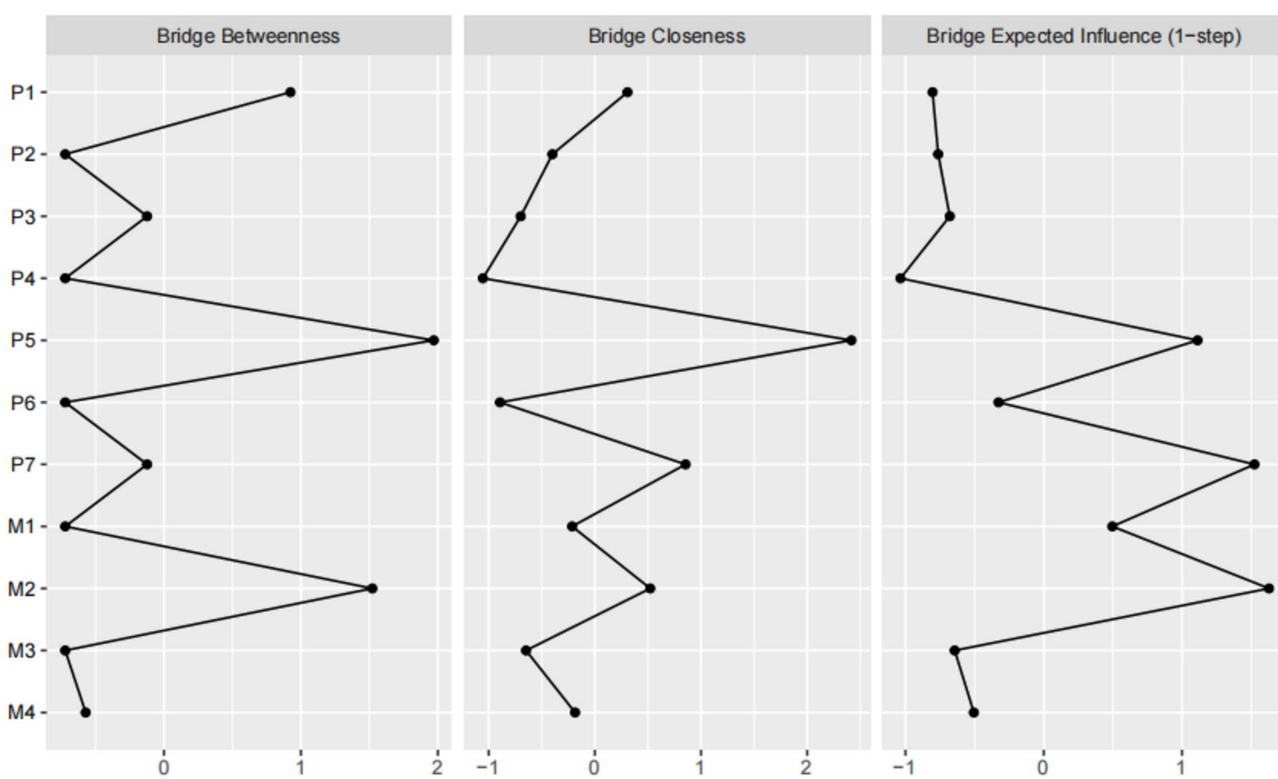

Fig. 3 Bridge centrality for the network representing each symptom

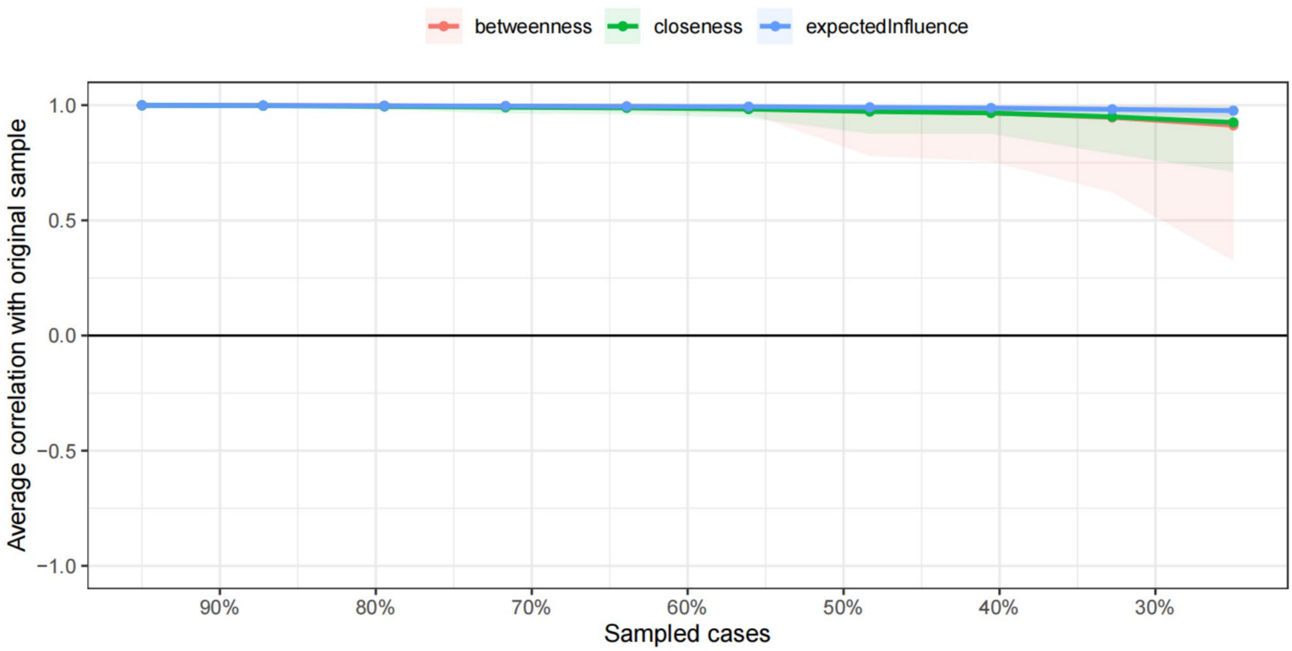

Fig. 4 Stability estimations of centrality

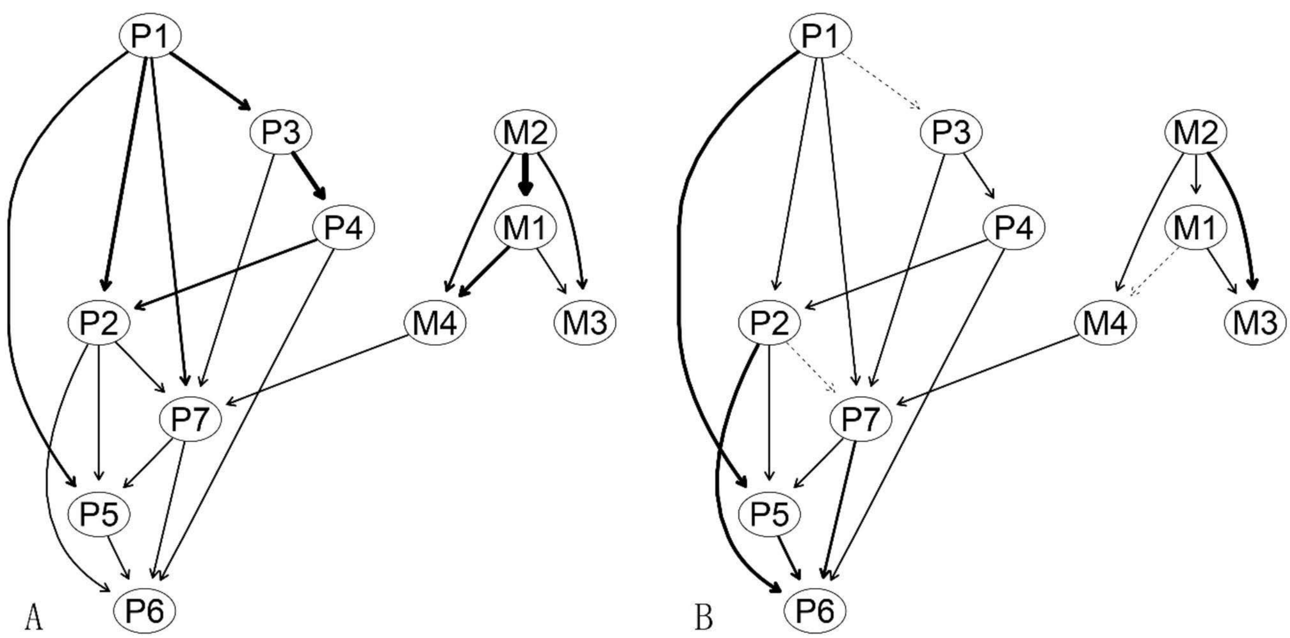

Fig. 5 Directed acyclic graph of problematic smartphone use (PSU) and poor sleep quality (PSQ). Note: (**A**) Connection strength indicates the percentage of networks fitted in the bootstrap procedure in which connections appeared. The arrow is drawn proportionately such that thicker arrows indicate greater connection strength. (**B**) Direction probability indicates in what percentage of the fitted networks the connection went in that direction. The arrow thickness is drawn proportionately such that the thicker arrows indicate a higher direction probability

probability for each arrow. P1 (Subjective sleep quality) and M2 (Anxiety and craving) are at the top of the DAG, whereas P6 (Use of sleeping medication) is at the bottom. As the parent node of P2 (Sleep latency), P3 (Sleep duration), P5 (Sleep disturbances), and P7 (Daytime dysfunction), P1 could directly predict these four sleep symptoms and ultimately affect P6 through related symptom nodes. As the parent nodes of M1 (Losing control and receiving complaints), M3 (Withdrawal/Escape), and M4 (Productivity loss), M2 not only directly affects the symptoms of the PSU but also affects P7 through M4. P6 is at the bottom of the DAG and is affected by other symptoms of PSQ and PSU. All 20 edges of the DAG also

Table 3 Arrow thickness of the directed acyclic graph

Parent→Children	Arrow thickness	
	Connection strength(A)	Direction probability(B)
P1→P2	-318.44	0.54
P1→P3	-241.71	0.50
P1→P5	-51.93	0.77
P1→P7	-60.99	0.62
P2→P5	-16.05	0.68
P2→P6	-8.37	0.80
P2→P7	-27.32	0.52
P3→P4	-332.83	0.58
P3→P7	-3.04	0.57
P4→P2	-65.48	0.53
P4→P6	-3.10	0.65
P5→P6	-6.57	0.74
P7→P5	-26.60	0.55
P7→P6	-2.85	0.74
M1→M3	-7.99	0.61
M1→M4	-163.02	0.52
M2→M1	-505.43	0.58
M2→M3	-74.88	0.78
M2→M4	-105.90	0.62
M4→P7	-44.60	0.54

appeared in the network structure, indicating that there was consistency in the selection of strong edges.

Discussion and conclusions

This study constructed a network structure to investigate the interactions between symptoms of PSU and PSQ. Through this analysis, we identified the core symptoms and bridge symptoms within the PSU-PSQ network. Additionally, we explored the maintenance factors of these two disorders by examining the symptoms with the strongest weights connected to the bridge symptoms in each community. The high average predictability of symptoms suggested that there was a large role for interactions between symptoms rather than external factors in influencing the network and that interventions for symptoms could significantly improve PSU and PSQ through the network. The expected influence, closeness, and betweenness exhibited excellent stability, indicating that the study accurately evaluated the importance of symptoms in the network.

In the constructed network, the symptoms of PSU and PSQ cluster into two separate communities. The strongest edge was identified between 'Sleep duration' and 'Habitual sleep efficiency', which was within a community rather than between two communities. This result was consistent with previous research findings [52, 53]. The results revealed that different disorders were independent of each other, while one symptom of the disorder was closely linked to other symptoms. An improvement in one symptom could lead to greater improvement in the overall disorder.

The core symptom in the network was identified as the symptom 'Anxiety and craving' of PSU, suggesting that this symptom had the greatest level of interaction with other symptoms and played a crucial role in maintaining the overall structure of the network. On the basis of these findings, it is possible to hypothesize that interventions targeting symptom 'Anxiety and craving' may be more effective in preventing other symptoms of PSU and PSQ. 'Anxiety and craving' refers to the feeling of anxiety, loss, or preoccupation experienced by adolescents when they are unable to use their smartphone normally [35]. It is an unpleasant withdrawal experience. A previous study revealed that withdrawal experience was fundamental to the concept of internet gaming addiction being considered an addictive disorder [54]. Therefore, PSU may be primarily maintained by withdrawal symptoms [54, 55].

In addition, the symptom of 'Anxiety and craving' was identified as a bridge symptom in the network and exhibited a strong correlation with PSQ symptoms. Among the PSQ community, the edge between the bridge symptoms of 'Sleep disturbances' and 'Anxiety and craving' had the highest weight. 'Sleep disturbances' encompass various physical discomforts that impact sleep quality, including early awakening, breathing disturbances, coughing or snoring, chills or fever, nightmares, and pains [12]. It is known that emotions play a crucial role in sleep quality [56]. An integrated psychobiological model of normal sleep proposed good sleep as the natural state of the human organism. The core of the model was involuntary harmonious interaction between homeostat and timer, which was associated with the self-perception of good quality sleep. The model illustrated that good sleeper experiences little emotional fluctuation associated with sleep. Dysregulation would occur with intense (negative or positive) emotions, both of which are arousing [57]. The internalization of conflicts model illustrates those internalizing problems of negative emotions, such as depression and anxiety, can heighten emotional arousal, increase autonomic activity, provoke physiological hyperarousal and make it difficult for individuals to fall asleep [58, 59]. A previous study revealed that negative thoughts at bedtime were positively associated with a longer sleep onset period [60]. Similarly, as depression and anxiety lead to PSQ, negative emotions related to withdrawal experience could also contribute to PSQ. Additionally, unpleasant withdrawal experiences may worsen existing depression in adolescents and further deteriorate their sleep quality. Therefore, one of the important pathways in which PSU leads to PSQ involves the induction of negative emotions, which subsequently impair sleep-related physiological functions.

Bridge symptom 'Daytime dysfunction' had the strongest bridge centricity in PSQ. These findings suggest that symptoms of PSU widely affect 'Daytime dysfunction'. 'Daytime dysfunction' refers to the severity of fatigue and low energy in the daytime [12]. In clinical settings, fatigue and sleep disturbances often overlap. Substantial daytime impairment is an essential feature of sleep disorders [61]. Therefore, the effect of PSU on PSQ may primarily manifest as 'Daytime dysfunction'. Previous studies also confirmed that PSU was associated with fatigue and physical dysfunction [62, 63]. Inappropriate postures during PSU can lead to various health issues, such as back pain, wrist pain, a stiff neck, digital eye strain, and loss of focus and attention [64].

'Daytime dysfunction' was strongly connected with the symptom of 'Productivity loss'. 'Productivity loss' indicated that excessive smartphone usage had caused problems in their lives and decreased productivity at work or study [35]. Fatigue is known to reduce productivity at work, and daytime deficits presumably have a more negative impact on quality of life than does the night-time frustration associated with sleep difficulties [65]. A study conducted in Japan revealed that daytime dysfunction had a more pronounced impact on work productivity than other symptoms of PSQ [66]. The effects of 'Daytime dysfunction' and 'Productivity loss' on productivity illustrated the synergistic effect of PSU and PSQ on productivity reduction. When two symptoms were present, there was a greater likelihood of experiencing a decline in productivity.

An intriguing finding emerged from the network structure. In the universal positive correlation network, the symptom of 'Sleep duration' was negatively correlated with the symptom of 'Use of sleeping medication', which contrasted with the results of another study conducted among general university students [52]. Nevertheless, a study in patients with sleep problems also revealed a negative correlation between these two symptoms, albeit with a relatively small coefficient [67]. It is well known that using sleeping medication increases sleep duration and improves sleep quality [68]. Thus, we assumed that this particular correlation might be observed only in patients who require sleeping medication.

Although the assumptions and preconditions of the DAG and network differ, they yield similar results in terms of the choice of strong edges and core symptoms of networks. From the perspective of probability and statistics, 'Subjective sleep quality' and 'Anxiety and craving' might be the active sources and first symptoms of PSQ and PSU. These factors have a potential causal relationship with other symptoms. Compared with other symptoms, 'Anxiety and craving' and 'Subjective sleep quality' had higher expected influence values in the network. The consistency of the DAG and network support that 'Subjective sleep quality' and 'Anxiety and craving' are the core symptoms of PSQ and PSU. Therefore, prioritizing interventions may have the most beneficial effect.

To the best of our knowledge, this is the first study to explore the symptom network between problematic smartphone use and poor sleep quality among adolescents with depression. However, several limitations should be considered. Firstly, although a well-trained investigator was involved in guiding the evaluation and reverse scoring was adopted in some items to avoid bias, there might still be influences caused by self-bias because of self-assessment questionnaires. Therefore, future research should consider alternative measurement methods, such as scales evaluated by others or interviews. Secondly, the ratio of girls to boys in the sample was unbalanced at 3.5:1, which significantly deviates from the gender balance in the general adolescents. This is likely because the rate of depression in females significantly exceeds and doubles that in males once they reach adolescence [69]. Thirdly, this study was conducted among depressed adolescents and might not be generalizable to the general adolescents.

To summarize, the symptom of 'Anxiety and craving' was the most crucial factor in the interaction between PSU and PSQ. Specifically, this symptom affected 'Sleep disturbances', which contributed to the harm of problematic smartphone use to sleep quality. Additionally, 'Daytime dysfunction' was the most severe symptom affected by PSU and served as a conduit for further impacting other sleep symptoms. Consequently, interventions aimed at regulating negative emotion and alleviating daytime tiredness are likely to be more effective in managing problematic smartphone use and improving sleep quality among depressed adolescents.

Abbreviations

PSU	Problematic smartphone use
PSQ	Poor sleep quality
MPAI	Mobile phone addiction index
PSQI	Pittsburgh sleep quality index
PHQ-9	Patient health questionnaire
CS-C	Correlation stability coefficients
DAG	Directed acyclic graph
M1	Losing control and receiving complaints
M2	Anxiety and craving
M3	Withdrawal/escape
M4	Productivity loss
P1	Subjective sleep quality
P2	Sleep latency
P3	Sleep duration
P4	Habitual sleep efficiency
P5	Sleep disturbances
P6	Use of sleeping medication
P7	Daytime dysfunction

Acknowledgements
We would like to thank all the participants. We also acknowledge the collaboration of the staff of Shenzhen Kangning Hospital and other hospitals involved in the study.

Author contributions
Yongjie Zhou: Project administration, supervision, study design, funding acquisition (lead); Jian Gong: Methodology, data analysis, writing - original draft (lead); Jing Shao: Data acquisition, investigation (equal); NanYan: Data acquisition, investigation (equal); Linlin Meng: Data acquisition, investigation (equal); Kongliang He: Data acquisition, investigation (equal); Ying Shen: Data acquisition, investigation (equal); Qian Wei: Investigation (equal); Chunyan Zhang: Data acquisition, investigation (equal); Xuan Lei: Investigation (equal); Yuehua Cao: Investigation (equal); Yanni Wang: Conceptualization, writing - review& editing (lead), study design.

Funding
This work was supported by the Sanming Project of Medicine in Shenzhen (No. SZM202011014), the Shenzhen Fund for Guangdong Provincial High-level Clinical Key Specialties (No. SZGSP013), and the Shenzhen Key Medical Discipline Construction Fund (No. SZK072). The funders had no role in the study design; data collection, analysis and interpretation; writing of the report; or decision to submit the article for publication.

Data availability
The data that support the findings of this study are available from the first author, [Yongjie Zhou], upon reasonable request.

Declarations

Ethics approval and consent to participate
Prior to the investigation, all participants and their legal guardians were informed of the purpose and procedures and provided written informed consent forms. All materials, measures, methods, and procedures were performed in accordance with the Declaration of Helsinki and approved by the ethics committee of Shenzhen Kangning Hospital (IRB:2020-k021-02).

Consent for publication
Written informed consent for publication was obtained from all participants.

Competing interests
The authors declare no competing interests.

Received: 14 December 2024 / Accepted: 29 April 2025
Published online: 13 May 2025

References

1. Mathers CD, Loncar D. Projections of global mortality and burden of disease from 2002 to 2030. PLoS Med 2006;3(11).
2. Young KS, Sandman CF, Craske MG. Positive and negative emotion regulation in adolescence: links to anxiety and depression. Brain Sci 2019;9(4).
3. Korczak DJ, Westwell-Roper C, Sassi R. Diagnosis and management of depression in adolescents. Can Med Assoc J. 2023;195(21):E739–46.
4. Zhou M, Zhang G, Rozelle S, Kenny K, Xue H. Depressive symptoms of Chinese children: prevalence and correlated factors among subgroups. Int J Environ Res Public Health 2018;15(2).
5. Billieux JJCPR. Problematic use of the mobile phone: A literature review and a pathways model. 2012;8(4):299–307.
6. Peng P, Chen Z, Ren S, Liu Y, He R, Liang Y, Tan Y, Tang J, Chen X, Liao Y. Determination of the cutoff point for smartphone Application-Based addiction scale for adolescents: a latent profile analysis. BMC Psychiatry. 2023;23(1):675.
7. Csibi S, Griffiths MD, Cook B, Demetrovics Z, Szabo A. The psychometric properties of the smartphone Application-Based addiction scale (SABAS). Int J Mental Health Addict. 2018;16(2):393–403.
8. Elhai JD, Dvorak RD, Levine JC, Hall BJ. Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. J Affect Disord. 2017;207:251–9.
9. Sharma D, Goel NK, Sidana A, Kaura S, Sehgal M. Prevalence of smartphone addiction and its relation with depression among School-going adolescents. Indian J Community Health. 2023;35(1):27–31.
10. Kim J-H, Seo M, David P. Alleviating depression only to become problematic mobile phone users: can face-to-face communication be the antidote? Comput Hum Behav. 2015;51:440–7.
11. Lemola S, Perkinson-Gloor N, Brand S, Dewald-Kaufmann JF, Grob A. Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. J Youth Adolesc. 2015;44(2):405–18.
12. Buysse DJ, Reynolds CF 3rd, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh sleep quality index: a new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193–213.
13. Zhang J, Zhang X, Zhang K, Lu X, Yuan G, Yang H, Guo H, Zhu Z, Wang T, Hao J, et al. An updated of meta-analysis on the relationship between mobile phone addiction and sleep disorder. J Affect Disord. 2022;305:94–101.
14. Morales-Munoz I, Gregory AM. Sleep and mental health problems in children and adolescents. Sleep Med Clin. 2023;18(2):245–54.
15. Gradisar M, Kahn M, Micic G, Short M, Reynolds C, Orchard F, Bauducco S, Bartel K, Richardson C. Sleep's role in the development and resolution of adolescent depression. Nat Reviews Psychol. 2022;1(9):512–23.
16. Fang H, Tu S, Sheng J, Shao A. Depression in sleep disturbance: A review on a bidirectional relationship, mechanisms and treatment. J Cell Mol Med. 2019;23(4):2324–32.
17. Orchard F, Pass L, Marshall T, Reynolds S. Clinical characteristics of adolescents referred for treatment of depressive disorders. Child Adolesc Mental Health. 2017;22(2):61–8.
18. Sohn SY, Krasnoff L, Rees P, Kalk NJ, Carter B. The association between smartphone addiction and sleep: A UK Cross-Sectional study of young adults. Front Psychiatry 2021;12:629407.
19. de Sa S, Baiao A, Marques H, Marques MC, Reis MJ, Dias S, Catarino M. The influence of smartphones on adolescent sleep: A systematic literature review. Nurs Rep. 2023;13(2):612–21.
20. Tavernier R, Heissel JA, Sladek MR, Grant KE, Adam EK. Adolescents' technology and face-to-face time use predict objective sleep outcomes. Sleep Health. 2017;3(4):276–83.
21. Johansson AEE, Petrisko MA, Chasens ER. Adolescent sleep and the impact of technology use before sleep on daytime function. J Pediatr Nursing-Nursing Care Child Families. 2016;31(5):498–504.
22. Borsboom D, Cramer AOJ. Network Analysis: An Integrative Approach to the Structure of Psychopathology. In: *Annual Review of Clinical Psychology, Vol 9. Volume 9*, edn. Edited by NolenHoeksema S; 2013: 91–121.
23. Huth KBS, de Ron J, Goudriaan AE, Luigjes J, Mohammadi R, van Holst RJ, Wagenmakers E-J, Marsman M. Bayesian analysis of Cross-Sectional networks: A tutorial in R and JASP. Adv Methods Practices Psychol Sci 2023;6(4).
24. Borsboom D. A network theory of mental disorders. World Psychiatry. 2017;16(1):5–13.
25. Schumacher L, Burger J, Echterhoff J, Kriston L. Methodological and statistical practices of using symptom networks to evaluate mental health interventions: A review and reflections. Multivar Behav Res. 2024;59(4):663–76.
26. Fried EI, van Borkulo CD, Cramer AOJ, Boschloo L, Schoevers RA, Borsboom D. Mental disorders as networks of problems: a review of recent insights. Soc Psychiatry Psychiatr Epidemiol. 2017;52(1):1–10.
27. Ramlee F, Sanborn AN, Tang NKY. What Sways People's Judgment of Sleep Quality? A Quantitative Choice-Making Study With Good and Poor Sleepers. Sleep 2017;40(7).
28. Lu J-X, Zhai Y-J, Chen J, Zhang Q-H, Chen T-Z, Lu C-L, Jiang Z-L, Guo L, Zheng H. Network analysis of internet addiction and sleep disturbance symptoms. Prog Neuro-psychopharmacol Biol Psychiatry 2023;125:110737.
29. Wang X, Ren L, Zhao X, Shi Y, Li J, Wu W, Yu H, Lv R, Liu N, Wu X et al. Network structure of sleep quality and its bridging association with anhedonia in adolescent major depression disorder. Physiol Behav 2025;292:114833.
30. Wang Y, Zhou Y, Li G, Qin P, Wang J, Qi L, Li L, Wang Y, Wang J, Li J et al. Executive functions in non-suicidal self-injury comorbid first-episode and drug-naive depression among adolescents. Psychiatry Res 2023;328:115476.
31. Meng L, Qu D, Bu H, Huo L, Qi L, Yang J, Zheng T, Du X, He K, Wang Y et al. The psychosocial correlates of Non-suicidal Self-Injury within a sample of adolescents with mood disorder. Front Public Health 2022;10:768400.
32. Qu D, Wang Y, Zhang Z, Meng L, Zhu F, Zheng T, He K, Zhou Y, Li C, Bu H et al. Psychometric properties of the Chinese version of the functional assessment of Self-Mutilation (FASM) in Chinese clinical adolescents. Front Psychiatry 2022;12:755857.
33. Wang Y, Lin J, Zhu Z, Chen S, Zou X, Wang Y, Huo L, Zhou Y. Quantifying the importance of factors in predicting non-suicidal self-injury among depressive Chinese adolescents: A comparative study between only child and non-only child groups. J Affect Disord. 2025;369:834–44.
34. Wang Y, Zhou X, Cao B, Chen L, Wang R, Qi L, Meng L, Zeng L, Liu X, Wang W, et al. The psychological characteristics and risk factors of suicidal attempt

among mood disorders adolescents accompany with non-suicidal self-injury: A multi-center study. J Affect Disord. 2022;298:301–7.
35. Leung L. Leisure boredom, sensation seeking, self-esteem, and addiction: Symptoms and patterns of cell phone use. In: *2008*; 2008.
36. Leung L. Linking psychological attributes to addiction and improper use of the mobile phone among adolescents in Hong Kong. J Child Media. 2008;2(2):93–113.
37. Li X, Hao C. The relationship between parental attachment and mobile phone dependence among Chinese rural adolescents: the role of alexithymia and mindfulness. Front Psychol. 2019;10:598.
38. Mei S, Xu G, Gao T, Ren H, Li J. The relationship between college students' alexithymia and mobile phone addiction: testing mediation and moderation effects. BMC Psychiatry. 2018;18(1):329.
39. Jiang W, Luo J, Guan H, Jiang F, Tang YL. Problematic mobile phone use and life satisfaction among university students during the COVID-19 pandemic in Shanghai, China. Front Public Health. 2021;9:805529.
40. HUANG H, NIU L, ZHOU C. Reliability and validity of mobile phone addiction index for Chinese college students. Chin J Clin Psychol. 2014;22(05):835–8.
41. Xianchen L, Maoqin T, Lei H. Reliability and validity of the Pittsburgh sleep quality index. Chin J Psychiatry 1996;(02):103–7.
42. Wang W, Bian Q, Zhao Y, Li X, Wang W, Du J, Zhang G, Zhou Q, Zhao M. Reliability and validity of the Chinese version of the patient health questionnaire (PHQ-9) in the general population. Gen Hosp Psychiatry. 2014;36(5):539–44.
43. Spitzer RL, Kroenke K, Williams JB. Validation and utility of a self-report version of PRIME-MD: the PHQ primary care study. Primary care evaluation of mental disorders. Patient Health Questionnaire JAMA. 1999;282(18):1737–44.
44. Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D. Qgraph: network visualizations of relationships in psychometric data. J Stat Softw. 2012;48(4):1–18.
45. Epskamp S, Borsboom D, Fried EI. Estimating psychological networks and their accuracy: A tutorial paper. Behav Res Methods. 2018;50(1):195–212.
46. Costantini G, Epskamp S, Borsboom D, Perugini M, Mottus R, Waldorp LJ, Cramer AOJ. State of the aRt personality research: A tutorial on network analysis of personality data in R. J Res Pers. 2015;54:13–29.
47. Epskamp S, Rhemtulla M, Borsboom D. Generalized network psychometrics: combining network and latent variable models. Psychometrika. 2017;82(4):904–27.
48. Bringmann LF, Elmer T, Epskamp S, Krause RW, Schoch D, Wichers M, Wigman JTW, Snippe E. What do centrality measures measure in psychological networks?? J Abnorm Psychol. 2019;128(8):892–903.
49. Robinaugh DJ, Millner AJ, McNally RJ. Identifying highly influential nodes in the complicated grief network. J Abnorm Psychol. 2016;125(6):747–57.
50. Jones PJ, Ma R, McNally RJ. Bridge centrality: A network approach to Understanding comorbidity. Multivar Behav Res. 2021;56(2):353–67.
51. Scutari M. Learning bayesian networks with the Bnlearn R package. J Stat Softw. 2010;35(3):1–22.
52. Lu J-X, Zhai Y-J, Chen J, Zhang Q-H, Chen T-Z, Lu C-L, Jiang Z-L, Guo L, Zheng H. Network analysis of internet addiction and sleep disturbance symptoms. Prog Neuro-psychopharmacol Biol Psychiatry. 2023;125:110737–110737.
53. Bai W, Zhao Y-J, Cai H, Sha S, Zhang Q, Lei S-M, Lok GKI, Chow IHI, Cheung T, Su Z, et al. Network analysis of depression, anxiety, insomnia and quality of life among Macau residents during the COVID-19 pandemic. J Affect Disord. 2022;311:181–8.
54. Kaptsis D, King DL, Delfabbro PH, Gradisar M. Withdrawal symptoms in internet gaming disorder: A systematic review. Clin Psychol Rev. 2016;43:58–66.
55. Petry NM, Rehbein F, Gentile DA, Lemmens JS, Rumpf H-J, Moessle T, Bischof G, Tao R, Fung DSS, Borges G, et al. An international consensus for assessing internet gaming disorder using the new DSM-5 approach. Addiction. 2014;109(9):1399–406.
56. Riemann D, Benz F, Dressle RJ, Espie CA, Johann AF, Blanken TF, Leerssen J, Wassing R, Henry AL, Kyle SD et al. Insomnia disorder: state of the science and challenges for the future. J Sleep Res 2022;31(4).
57. Espie CA. Insomnia: conceptual issues in the development, persistence, and treatment of sleep disorder in adults. Ann Rev Psychol. 2002;53:215–43.
58. Baglioni C, Spiegelhalder K, Lombardo C, Riemann D. Sleep and emotions: A focus on insomnia. Sleep Med Rev. 2010;14(4):227–38.
59. Kales A, Caldwell AB, Preston TA, Healey S, Kales JD. Personality patterns in insomnia. Theoretical implications. Arch Gen Psychiatry. 1976;33(9):1128–1124.
60. Van Egeren L, Haynes SN, Franzen M, Hamilton J. Presleep cognitions and attributions in sleep-onset insomnia. J Behav Med. 1983;6(2):217–32.
61. Morin CM, Drake CL, Harvey AG, Krystal AD, Manber R, Riemann D, Spiegelhalder K. Insomnia disorder. Nat Reviews Disease Primers 2015;1:215–6.
62. Zhang C, Zeng P, Tan J, Sun S, Zhao M, Cui J, Zhang G, Jia J, Liu D. Relationship of problematic smartphone use, sleep quality, and daytime fatigue among quarantined medical students during the COVID-19 pandemic. Front Psychiatry 2021;12:755059.
63. Park N, Lee H. Social implications of smartphone use: Korean college students' smartphone use and psychological Well-Being. Cyberpsychology Behav Social Netw. 2012;15(9):491–7.
64. Priya DB, Subramaniyam M. Fatigue due to smartphone use? Investigating research trends and methods for analysing fatigue caused by extensive smartphone usage: A review. Work-a J Prev Assess Rehabilitation. 2022;72(2):637–50.
65. Riedel BW, Lichstein KL. Insomnia and daytime functioning. Sleep Med Rev. 2000;4(3):277–98.
66. Ishibashi Y, Shimura A. Association between work productivity and sleep health: A cross-sectional study in Japan. Sleep Health. 2020;6(3):270–6.
67. Jin Y, Li J, Ye J, Luo X, Wilson A, Mu L, Zhou P, Lv Y, Wang Y. Mapping associations between anxiety and sleep problems among outpatients in high-altitude areas: a network analysis. BMC Psychiatry 2023;23(1).
68. Boafo A, Greenham S, Sullivan M, Bazaid K, Suntharalingam S, Silbernagel L, Magner K, Robillard R. Medications for sleep disturbance in children and adolescents with depression: a survey of Canadian child and adolescent psychiatrists. Child Adolesc Psychiatry Mental Health 2020;14(1).
69. Weissman MM, Bland RC, Canino GJ, Faravelli C, Greenwald S, Hwu HG, Joyce PR, Karam EG, Lee CK, Lellouch J, et al. Cross-national epidemiology of major depression and bipolar disorder. Jama-Journal Am Med Association. 1996;276(4):293–9.

Publisher's note