

A network analysis of depressive symptoms, loneliness, and social media addiction among Chinese medical students

Xinyue Bian

Nantong University

Jiayu Zhou

Nantong University

Jingjing Yan

Nantong University

Yanlin Wang

Nantong University

Yaqin Zhong

Nantong University

Qingyun Lu

Nantong University

Yuexia Gao

gaoyuexia1103@163.com

Nantong University

Miaomiao Zhao

Nantong University

Research Article

Keywords: Depressive symptoms, Loneliness, Social media addiction, Network analysis, Directed acyclic graph

Posted Date: August 6th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9670713/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Background

Depressive symptoms, loneliness, and social media addiction are commonly reported by medical students, yet their symptom-level interrelationships are not well understood.

Objective

This study employed network analysis to investigate the connections between these conditions among Chinese medical students.

Method

A total of 836 Chinese medical students from a university in Nantong were included in this cross-sectional study. Depressive symptoms, loneliness, and social media addiction were assessed using the Patient Health Questionnaire-9, the short-form UCLA Loneliness Scale, and the Bergen Social Media Addiction Scale, respectively. We estimated two complementary networks: a regularized partial correlation network and a Bayesian directed acyclic graph (DAG).

Results

For the regularized partial correlation network, we found that “Isolation” was not only the most central node but also the primary bridge symptom, with “Sad mood” and “Anhedonia” also emerging as highly central. For the DAG, “Anhedonia” was identified as a key driver of other symptoms within the network, and “Unhappy”, “Fatigue” were terminal symptoms.

Conclusion

As the first network analysis of depressive symptoms, loneliness, and social media addiction among Chinese medical students, the findings inform multi-level interventions by identifying central, bridge, and upstream symptoms as potential therapeutic targets, with downstream symptoms serving as key clinical indicators.

1. Introduction

Depression among university students has increasingly emerged as a critical public health concern, attributed to factors such as academic pressure, financial strain, and challenges in social adjustment and identity development[1]. The burden is particularly heavy on medical students[2]. In China, the

prevalence of depression has reached 38.3% among medical students, significantly higher than non-medical students[3]. This heightened prevalence is often attributable to their prolonged and rigorous training, characterized by heavy academic workloads, highly demanding clinical rotations, and, during postgraduate stages, the dual pressures of research and clinical responsibilities[4]. Moreover, the strained doctor-patient relationship in China[5], which is often manifested as violence against medical professionals, likely constitutes a significant external stressor that exacerbates this psychological distress[6]. Depression is a widespread mental disorder that impacts both the physical and psychological well-being of hundreds of millions of individuals across the globe[7, 8]. Existing studies indicate that depression adversely affects academic performance in medical students[9], ultimately compromising the quality of patient care and posing significant long-term risks to healthcare systems. Consequently, greater attention to depression among medical students is critically needed.

Beyond its standalone impact, depression frequently coexists with other mental health issues, one of which is loneliness[10, 11]. Loneliness is the unpleasant subjective experience of being isolated and disconnected from others[12], which arises from a perceived discrepancy between desired and actual social relationships[13]. University students are in a developmental stage of establishing peer relationships, pursuing autonomy, and achieving individuality, making them susceptible to feelings of loneliness[14]. For medical students, this vulnerability is higher, as their high-load, high-stakes and competitive learning environment inevitably restrict opportunities for nurturing social connections, thereby fostering social isolation[15]. Previous research has revealed a complex association between loneliness and depression. Meta-analytic evidence indicates a symmetrical cross-lagged effect between these two psychological disorders[16, 17]. Furthermore, a network analysis has revealed distinct relationships at the symptomatic level[18]. These interconnections result in a comorbidity that exacerbates impairments in psychological well-being beyond the mere sum of individual effects[19]. For medical students, the comorbidity of the two conditions mediates the relationship between their medical student identity and suicide risk[20], underscoring the necessity of investigating how their specific symptoms interact.

Over the past two decades, social media use has become a fundamental part of daily life. However, its high penetration and interactivity have given rise to over-dependence and even addictive behavior, leading to social media addiction (SMA). SMA is characterized by uncontrollable and harmful use of social media that results in significant impairment to daily functioning, including mental health, interpersonal relationships, emotional consequences, academic performance[21]. This behavioral addiction is more prevalent among university students[22], prompting a considerable amount of research on its relationships with mental health. Extensive evidence indicates that social media addiction is deeply associated with depression and loneliness[23–25]. These relationships appear to be complex and potentially bidirectional. For instance, a longitudinal study shows that fatigue, one of the depressive symptoms, and loneliness can both predict subsequent passive social media use[23]. Conversely, limiting social media use can effectively alleviate loneliness and depression[26]. Furthermore, research on Chinese medical students has identified loneliness as a significant mediator

between social media addiction and depression[24], revealing a potential pathway for the interaction of these conditions.

However, most of these findings are based on traditional approaches that rely on sum-scores to estimate severity. These methods assume the interchangeability of symptoms within a disorder[27, 28], thus potentially ignoring both symptom-symptom interactions and important differences between specific symptoms[29]. In contrast, network analysis conceptualizes psychopathology as a network of interacting symptoms, making it ideal for quantifying symptom interactions of mental disorders[30]. Within a network model, symptoms are represented as nodes, and partial correlation coefficients between them are represented as edges[31]. This approach not only allows for the identification of core symptoms that are most influential in the network[32], but also offers insights into psychiatric comorbidity by pinpointing bridge symptoms that are most strongly associated with other disorders [33, 34].

This study was to examine the network characteristics of social media addiction, loneliness and depressive symptoms among Chinese medical students, thereby improving our understanding of their co-occurrence and providing information for targeted intervention.

2. Methods

2.1. Participants and study procedure

This cross-sectional survey was conducted between Oct. and Nov. at a comprehensive university in Nantong, Jiangsu, China. A convenience sampling approach to data collection was used. We recruited 10 student investigators from the School of Medicine and the School of Public Health. They distributed an online questionnaire via Questionnaire Star platform (<https://www.wjx.cn/>) to their schoolmates, inviting voluntary participation. Detailed information regarding the study's purpose, procedures, voluntary nature, and confidentiality assurances, along with an informed consent form, was provided at the beginning of the questionnaire. To prevent duplicate entries, the survey platform restricted submission to one response per IP address. And completion of all items was mandatory to submit the questionnaire. A total of 954 medical students agreed to participate and completed the survey. After data cleaning, 118 questionnaires with the logical errors, uniform responses, and short completion time were excluded, resulting in the inclusion of 836 participants in the present study (efficiency rate of 87.6%).

2.2. Measures

Depression

The nine-item Patient Health Questionnaire (PHQ-9) was used to evaluate depressive symptoms[35]. Each item of the PHQ-9 is scored on a scale from 0 (not at all) to 3 (almost every day), with higher total scores indicating greater severity of depressive symptoms. A score of 5 was used as the cut-off to

indicate the presence of depression[36]. The PHQ-9 has demonstrated good reliability and validity in Chinese university students[37]. In the present study, the Cronbach's α of this scale was 0.932.

Loneliness

The short-form UCLA Loneliness Scale (ULS-6) consisting of 6 items was employed to assess loneliness symptoms[38]. Each item of the scale was rated using a 4-point Likert scale (1 = never, 2 = rarely, 3 = sometimes, 4 = always), with higher total scores reflecting more intense feelings of loneliness. The ULS-6 has shown good reliability and validity in Chinese population[18, 38]. In the present study, the Cronbach's α of this scale was 0.892.

Social media addiction

Social media addiction was measured using the Bergen Social Media Addiction Scale (BSMAS)[39]. The BSMAS is based on addiction theory and includes six items, with each item designed to assess a key symptom of addiction. Responses are recorded on a 5-point Likert scale, ranging from 1 (very rarely) to 5 (very often). Higher scores indicated more severe symptoms of social media addiction. A cut-off value of 19 was used to identify individuals with probable social media addiction[40]. The BSMAS has established good reliability and validity in Chinese university students[41]. In the present study, the Cronbach's α of this scale was 0.887.

2.3. Data analysis

2.3.1. Regularized partial correlation network

Network estimation was performed using the R-package bootnet[42] and qqgraph[31]. In the network model, each node represents a specific symptom and the association between two nodes is regarded as an edge after accounting for other nodes in the system[31]. Blue edges represent positive associations and red edges represent negative associations. The thickness of edges corresponds to the strength of associations between two nodes. A Gaussian graphical model (GGM) was used to estimate the network. The extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) was employed to identify the optimal regularization parameter, leading to a sparse network with explanatory power[42]. Additionally, R package mgm was used to quantify the predictability of each node. The index quantifies how much of a node's variance can be explained by its connections in the network[43] and was visualized as outer rings around each node in the network, with broader bands indicating stronger predictability.

The centrality and bridge centrality were estimated using Expected Influence (EI) and Bridge Expected Influence (BEI). EI is a centrality measure that performs better in networks with both positive and negative edges than other indices[44]. The EI values were calculated using R package qqgraph[31], and nodes with higher EI values exert greater influence on the whole network. In addition, BEI was derived via R package networktools, which assesses inter-community connectivity[33], and nodes with higher BEI values indicate greater potential for activating symptoms across different communities.

Based on 1000 bootstrap iterations for each node, R package bootnet was employed to evaluate the accuracy and stability of the network model[42]. First, the accuracy of edge-weight estimates in the network was examined via 95% non-parametric bootstrap confidence intervals (CIs). Second, the stability of centrality indices was assessed through case-dropping subset bootstrap method with Correlation Stability (CS)-coefficients. A CS coefficient above 0.25 denotes moderate stability while above 0.50 suggesting strong stability. Finally, bootstrapped difference tests were conducted to determine whether significant differences exist between edge weights or centrality indices.

2.3.2. Directed acyclic graph (DAG)

To estimate the Bayesian network and represent it as a DAG, we employed the hill-climbing algorithm in the R package bnlearn[45, 46]. This algorithm optimizes the Bayesian Information Criterion (BIC) by adding, deleting, and reversing edges. To avoid local maxima, we adopted a strategy of 50 random restarts, with each restart allowing up to 100 structural perturbations during initial model construction [45, 47].

To ensure DAG stability, we performed bootstrap resampling with 10,000 replicates. For each bootstrap sample, an independent network was estimated. These networks were then averaged into a final network. This process involved two steps[48]. First, edges were retained when appeared in more than 85% of the bootstrap networks, thereby enhancing the network's interpretability[49]. Second, for retained edges, the direction from node X to node Y was included in the final network if it was consistent in more than 51% of the bootstrap networks.

We applied two visualization approaches for the final network. In the first, thickness corresponds to the absolute magnitude of an edge's BIC value. Thicker edges signify greater importance to the model structure, and their removal would cause more disruption to model fit. In the second, thickness represents the bootstrap-derived probability of the depicted edge direction, where thicker edges indicate higher confidence in that directional relationship.

3. Results

3.1. Participants characteristics

A total of 836 medical students participated in this study, including 470 females and 366 males, with an average age of 19.91 years (SD = 1.21). The prevalence rates of mild to severe depression and social media addiction were 39.47% (95% CI: 36.15–42.79) and 4.90% (95% CI: 3.44–6.36), respectively.

3.2. Regularized partial correlation network

The network of depressive symptoms, loneliness and social media addiction is shown in Fig. 1, with 101 non-zero edges out of 210 possible edges. This density of 48.1% indicates substantial interconnection between symptoms. Within the loneliness community, the strongest edge between them was L5-L6(Unhappy-With me), followed by L1-L2(Companion-Seek help) and L3-L4(Left out-Isolation). The

strongest association among depressive symptoms was D1-D2(Anhedonia-Sad mood), followed by D1-D4(Anhedonia-Fatigue) and D6-D9(Guilt-Suicide). Moreover, social media addiction network showed strongest edges between A5(Withdrawal) and A6(Conflict), followed by A1-A2(Salience-Tolerance), A2-A3(Tolerance-Mood modification), and A3-A4(Mood modification -Relapse). In the network of the three disorders above, the strongest edges (in descending order) were L4-D2(Isolation-Sad mood), L3-D5(Left out-Appetite), and L4-D7(Isolation -Concentration). Notably, the average value of node predictability was 0.620 (Table 1), indicating that 62.0% of variance in each node can be explained by its neighboring nodes.

Table 1
Descriptive statistics of measurement items.

Item abbreviation	Item content	Mean (SD)	Expected influence	Predictability
L1	Lack companionship	1.86 (0.82)	0.954	0.620
L2	No one can turn to	1.59 (0.83)	0.710	0.601
L3	Feel left out	1.63 (0.76)	1.025	0.684
L4	Feel isolation from others	1.72 (0.81)	1.187	0.713
L5	Am unhappy being so withdrawn	1.57 (0.76)	0.816	0.463
L6	People are around me but not with me	1.49 (0.76)	0.861	0.529
A1	Spend much time thinking about or planning use	1.83 (1.09)	0.786	0.593
A2	Feel an urge to use social media more and more	1.79 (1.02)	0.919	0.564
A3	Use social media to forget personal problems	1.68 (0.99)	0.986	0.625
A4	Try to cut down use without success	1.71 (0.96)	0.876	0.535
A5	Become restless if prohibited from using	1.67 (1.01)	0.803	0.554
A6	Use negatively impacted job/studies	1.61 (0.94)	0.985	0.628
D1	Anhedonia	0.66 (0.83)	1.123	0.743

Item abbreviation	Item content	Mean (SD)	Expected influence	Predictability
D2	Sad Mood	0.53 (0.70)	1.171	0.748
D3	Insomnia or hypersomnia	0.54 (0.83)	0.844	0.682
D4	Fatigue	0.60 (0.72)	0.988	0.625
D5	Disordered eating	0.58 (0.79)	0.727	0.537
D6	Low self-esteem	0.42 (0.72)	1.012	0.637
D7	Concentration difficulties	0.58 (0.80)	0.972	0.685
D8	Retardation	0.32 (0.64)	0.745	0.597
D9	Suicide ideation	0.25 (0.63)	0.775	0.640

The EI and BEI values for each node are presented in Fig. 2. L4 (Isolation) exhibited the highest EI value, followed by D2 (Sad mood) and D1 (Anhedonia) (Fig. 2A), these constituted the most influential symptoms in the network. Notably, L4 (Isolation) also served as the primary bridge, with BEI value substantially higher than other nodes (Fig. 2B).

The CS-coefficient of EI was 0.75, meaning the network structure remained largely unchanged even when up to 75% of the sample was excluded. The CS-coefficient of BEI was 0.594, indicating that the stability of the bridge's anticipated effects within the network is acceptable (Fig. 3). The edge weight estimation showed sufficient accuracy, evidenced by the considerable overlap among the 95% confidence intervals of edge weights in bootstrapped confidence intervals (Figure S1). Furthermore, the bootstrap difference tests of edge weights indicated that stronger associations predominantly occur within the same symptom community (Figure S2), and the bootstrap difference tests of EI (Figure S3) showed statistically significant differences in EI values between most nodes.

3.3 DAG

Figure 4 presents the final DAG derived from the aggregation of 10,000 bootstrap replicates, in which edge thickness corresponds to the confidence level of the depicted directional relationship (suggesting a predictive and potentially causal flow). Several key features are notable. First, D1 (Anhedonia) functioned as the primary upstream node in the DAG cascade. It predicted D2 (Sad mood), D3 (Sleep), D4 (Fatigue), D7 (Concentration), and D9 (Suicide). Second, L5 (Unhappy) was identified as a downstream symptom, receiving a directed edge from L6 (With me). Similarly, D4 (Fatigue) also served as a downstream symptom, with directed edges from D1 (Anhedonia), D2 (Sad mood), D3 (Sleep), A1 (Salience), and A5 (Withdrawal). Figure S4 presents an identical DAG, where edge thickness corresponds to each edge's contribution to the overall model fit.

4. Discussion

This was the first study to examine the network of depressive symptoms, loneliness, and social media addiction symptoms among Chinese medical students. We identified the core symptoms within the integrated network of depressive symptoms, loneliness, and social media addiction, as well as the bridge symptoms that serve as the interlinkages among these three constructs. On this basis, a DAG network was further constructed to infer the most plausible causal relationships underlying their interconnections. By providing a more explicit relationship between the symptom structures, our study offers valuable insights into targeted interventions in order to enhance medical students' mental well-being.

Consistent with existing network analyses, our findings demonstrated that the strongest connections were localized within particular communities rather than spanning across different groups[18, 50, 51]. The strongest edge was between A5(Withdrawal) and A6(Conflict) (weight = 0.39), followed by the edge between A1(Salience) and A2(Tolerance) (weight = 0.36). Notably, this finding is not consistent with previous research investigating the relationships between social media addiction symptoms and psychological characteristics, which identified the association between A1 (Salience) and A2 (Tolerance) as the strongest[51, 52]. This discrepancy reflects the unique psychosocial context of medical students, a population characterized by exceptionally high academic demands and chronic stress[53]. Prior evidence suggests that higher pressure fosters escape behaviors, often leading to uncontrolled social media use[54]. This elevated stress explains both withdrawal distress (A5) when social media is unavailable and the perceived conflict (A6) between social media use and academic responsibilities, thereby strengthening the connection between these two symptoms. Other strong edges(weight > 0.30) in the network were generally between loneliness symptoms, indicating a tight intercorrelation among symptoms of loneliness. This finding underscores the clinical significance of loneliness as a core psychological concern among Chinese medical students and suggests that loneliness should be routinely assessed as part of standard mental health evaluations for this population.

Within our network, a loneliness symptom, L4(Isolation), with the highest expected influence value in our analysis, played the most critical role in sustaining the whole network. Although this is the first study identifying "Isolation" as the most central symptom, the node has been found the third most influential

symptom in a relevant study conducted among nursing students[55]. Medical students are required to undergo rotating internship assignments and extended study hours, which may reduce their time for social activities and thereby intensify their sense of isolation[56]. This perceived isolation can further trigger a neurobiological self-preservation state, including hypervigilance for social threat (elevating vascular resistance), a heightened stress response (elevated cortisol), increased impulsivity, upregulated inflammatory activity, and disrupted sleep[57]. These mechanisms are detrimental to long-term health. Notably, within the context of Chinese culture, which emphasizes collectivism, the sense of loneliness associated with individualism may exert a more profound impact on the individual[58]. The symptom also exhibited the highest bridge expected influence, identifying it as the most critical node connecting the different clusters of depression, loneliness, and social media addiction symptoms. This suggests that interventions targeting isolation may not only alleviate overall symptom severity but also disrupt the activation between communities[30]. For medical students, interventions like Build & Belong, based on peer support to directly normalize struggles and alleviate isolation, are particularly well-suited[56]. At the individual level, Cognitive Behavioral Therapy (CBT) can be effective in targeting isolation. The approach is to guide individuals' cognition of automatic negative thoughts regarding others and social interactions. Instead of treating these thoughts as actionable facts, individuals are instructed to identify them as possibly faulty hypotheses that demand validation[59].

Other central symptoms included D2(Sad mood) and D1(Anhedonia), consistent with previous studies[55, 60]. Importantly, the DAG provided further clarification by positioning "Anhedonia" as a key upstream driver, which directly predicts "Sad mood" as well as other depressive symptoms, thereby exerting a significant impact on the entire network. Consistent with its upstream role in DAG, anhedonia has been identified as a causal antecedent in prior network research[61]. Moreover, neurobiological evidence shows that neural markers of anhedonia can prospectively predict depression onset[62]. Anhedonia is characterized by the diminished ability to experience pleasure and is associated with heightened sensitivity to chronic, uncontrollable stress[62]. Therefore, due to relentless academic pressure and repeated exposure to human suffering and death during clinical rotations[63], medical students are particularly vulnerable to the symptom. However, individuals exhibiting social anhedonia are prone to diminished social connectedness, elevated feelings of loneliness, sleep problems, and negative cognitions[64, 65], which further increase their susceptibility to other symptoms in the network. Consequently, interventions that directly target anhedonia, such as Positive Affect Treatment designed to enhance reward sensitivity and approach motivation[66], could be powerful in reducing the severity of symptoms across the entire network.

The DAG positioned D4 (Fatigue) as downstream symptom, which is common in medical education worldwide, spanning from students to practicing physicians[67]. In China, the symptom is intensified by "involution"—a sociocultural phenomenon characterized by intense competition with diminishing returns, particularly prevalent in education[68]. The present study identified that "Fatigue" was directly predicted by several symptoms, including D1 (Anhedonia), D2 (Sad mood), D3 (Sleep), A1 (Salience), and A5 (Withdrawal). The finding suggested that in clinical practice, fatigue is often not an isolated complaint, but rather a final symptom resulting from multiple upstream factors. Previous research indicates that

vulnerability to fatigue can exist years before its full manifestation, with anxiety and depressive symptoms serving as a key risk factor for its development[69]. In addition, the predictive link between sleep and fatigue has been widely supported [70, 71]. Excessive focus on social media can lead to compulsive engagement [72, 73], which involves intensive cognitive and emotional processing and may deplete mental resources, thereby contributing to fatigue [74, 75]. Therefore, fatigue may be better understood as a multidimensional symptom, which has important implications for its assessment and intervention. When fatigue is present, clinicians should conduct a comprehensive evaluation to identify potential upstream drivers. In addition to established usual interventions such as cognitive behavioral therapy[76] and graded exercise therapy[77], targeted treatment of upstream symptoms may also directly reduce fatigue severity.

There were still several potential limitations. First, because our study was cross-sectional, we could not establish causal relationships between symptoms. Although the DAG provided a valuable framework for conceptualizing potential directional links at a specific time point and offers theoretical guidance for future longitudinal research, it does not confirm causal pathways. Second, the exclusive reliance on self-reported measures introduces potential response biases, including recall and social desirability effects. Third, as the study focused specifically on medical students, results may not extend to non-medical student populations or non-academic stress contexts.

Conclusions

This study provided an insight into understanding the relationship between depressive symptoms, loneliness, and social media addiction among Chinese medical students through network and DAG analysis. Results have identified “Isolation”, “Sad mood” and “Anhedonia” as the most critical symptoms within the network, based on highest node and bridge centrality. In addition, “Anhedonia” functions as a primary upstream driver, while “Fatigue” is primary downstream symptom in the DAG network. These findings provide new insights for clinical assessment and targeted interventions, and hold significant promise for alleviating overall mental health burden in this high-risk population.

Declarations

Ethics approval and consent to participate

This study was approved by the Nantong University Research Ethics Committee (2020-12). All procedures followed were in accordance with the Helsinki Declaration. All subjects signed informed consent before filling in the questionnaire, and the survey results were anonymous.

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Data availability statement

The datasets used during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

Funding for this study was provided by the National Natural Science Foundation of China [grant number 72004104]; the 2024 Program of Teaching Reform in Nantong University [grant number 2024E08]. The funders had no role in the design, data collection, analysis, interpretation of the data, and writing of this work.

Authors' contributions

XYB and MMZ conceptualized this study. JYZ, JJY and MMZ design the questionnaire and organized the survey. XYB and JYZ analyzed and interpreted the data, and drafted the original manuscript. YLW and YQZ assisted with data collection and literature review. YXG and QHW contributed to the manuscript's revision. All authors read and approved of the final manuscript.

References

1. Ibrahim AK, et al. A systematic review of studies of depression prevalence in university students. *J Psychiatr Res.* 2013;47(3):391–400.
2. Li W, et al. Prevalence and associated factors of depression and anxiety symptoms among college students: a systematic review and meta-analysis. *J Child Psychol Psychiatry.* 2022;63(11):1222–30.
3. Lin Z, et al. Prevalence of depression among university students in China: a systematic review and meta-analysis. *BMC Psychol.* 2025;13(1):373.
4. Jin T, et al. Prevalence of depression among Chinese medical students: A systematic review and meta-analysis. *Psychol health Med.* 2022;27(10):2212–28.
5. Wang Y, Du S. Time to rebuild the doctor-patient relationship in China. *Hepatobiliary Surg Nutr.* 2023;12(2):235–8.
6. Zhu H, et al. Apoptosis-induced decline in hippocampal microglia mediates the development of depression-like behaviors in adult mice triggered by unpredictable stress during adolescence. *Eur J Pharmacol.* 2024;978:176763.
7. Guan W, Qi W, Sheng X. Evidence for the contribution of vasopressin V1B receptors in the pathophysiology of depression. *Biochem Pharmacol.* 2025;231:116672.

8. Yang Y, Guan W, Gu H. CaMK4, a key target for treating pathogenesis of depression? *Biochem Pharmacol.* 2025;242:117429.
9. Mihăilescu AI, et al. The impact of anxiety and depression on academic performance in undergraduate medical students. *Eur psychiatry.* 2016;33(S1):S284–284.
10. Mann F, et al. Loneliness and the onset of new mental health problems in the general population. *Soc Psychiatry Psychiatr Epidemiol.* 2022;57(11):2161–78.
11. Wolters NE, et al. Emotional and social loneliness and their unique links with social isolation, depression and anxiety. *J Affect Disord.* 2023;329:207–17.
12. Russell D, Peplau LA, Cutrona CE. The revised UCLA Loneliness Scale: concurrent and discriminant validity evidence. *J Personal Soc Psychol.* 1980;39(3):472.
13. Sermat V. Review of Loneliness: A Sourcebook of Current Theory, Research and Therapy. *Can Psychol / Psychologie canadienne.* 1984;25(4):301–3.
14. Laursen B, Hartl AC. Understanding loneliness during adolescence: Developmental changes that increase the risk of perceived social isolation. *J Adolesc.* 2013;36(6):1261–8.
15. Krishnan B, Kumar M, Kumar G. Prevalence, predictors and perception of loneliness among medical undergraduates. *Clin Epidemiol global health.* 2025;31:101882.
16. Santini ZI, et al. Social disconnectedness, perceived isolation, and symptoms of depression and anxiety among older Americans (NSHAP): a longitudinal mediation analysis. *Lancet Public health.* 2020;5(1):e62–70.
17. Chen Z, et al. The robust reciprocal relationship between loneliness and depressive symptoms among the general population: Evidence from a quantitative analysis of 37 studies. *J Affect Disord.* 2023;343:119–28.
18. Yang M, et al. How loneliness linked to anxiety and depression: a network analysis based on Chinese university students. *BMC Public Health.* 2023;23(1):2499–11.
19. Cacioppo JT, et al. Loneliness as a specific risk factor for depressive symptoms: Cross-sectional and longitudinal analyses. *Psychol Aging.* 2006;21(1):140–51.
20. Klugman M et al. Suicide Risk Among Medical Students Associated With Loneliness, Burnout, and Depressive Symptoms. *Omega: Journal of Death and Dying,* 2024: p. 302228241252531.
21. Griffiths M. Internet Addiction - Time to be Taken Seriously? *Addiction research,* 2000. 8(5): pp. 413–8.
22. Salari N, et al. The global prevalence of social media addiction among university students: a systematic review and meta-analysis. *J Public Health.* 2025;33(1):223–36.
23. Aalbers G, et al. Social media and depression symptoms: A network perspective. *J Exp Psychol Gen.* 2019;148(8):1454–62.
24. Gong R, et al. The Impact of Social Network Site Addiction on Depression in Chinese Medical Students: A Serial Multiple Mediator Model Involving Loneliness and Unmet Interpersonal Needs. *Int J Environ Res Public Health.* 2021;18(16):8614.

25. Williams M, Lewin KM, Meshi D. Problematic use of five different social networking sites is associated with depressive symptoms and loneliness. *Current psychology* (New Brunswick, N.J.), 2024. 43(24): pp. 20891–8.
26. Hunt MG, et al. No more FOMO: Limiting social media decreases loneliness and depression. *J Soc Clin Psychol*. 2018;37(10):751–68.
27. Schmittmann VD, et al. Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas Psychol*. 2013;31(1):43–53.
28. Fried EI, Nesse RM. Depression sum-scores don't add up: why analyzing specific depression symptoms is essential. *BMC Med*. 2015;13(1):72.
29. Beard C, et al. Network analysis of depression and anxiety symptom relationships in a psychiatric sample. *Psychol Med*. 2016;46(16):3359–69.
30. Borsboom D. A network theory of mental disorders. *World psychiatry: official J World Psychiatric Association (WPA)*. 2017;16(1):5–13.
31. Epskamp S, et al. qgraph: Network Visualizations of Relationships in Psychometric Data. *J Stat Softw*. 2012;48(4):1–18.
32. Park S, Kim D. The Centrality of Depression and Anxiety Symptoms in Major Depressive Disorder Determined Using a Network Analysis. *J Affect Disord*. 2020;271:19–26.
33. Jones PJ, Ma R, McNally RJ. Bridge Centrality: A Network Approach to Understanding Comorbidity. *Multivar Behav Res*. 2021;56(2):353–67.
34. Borsboom D, Cramer AOJ. Network Analysis: An Integrative Approach to the Structure of Psychopathology. *Ann Rev Clin Psychol*. 2013;9(1):91–121.
35. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med*. 2001;16(9):606–13.
36. Qin B et al. Anxiety and Depression Among College Students During the COVID-19 Lockdown: A Cross-Sectional Survey in Jiangsu, China. *Risk management and healthcare policy*, 2023. 16: pp. 711–723.
37. Zhang YL, et al. Validity and reliability of Patient Health Questionnaire-9 and Patient Health Questionnaire-2 to screen for depression among college students in China. *Asia-Pacific Psychiatry*. 2013;5(4):268–75.
38. Xiao R. Reliability and validity of the 6-item UCLA Loneliness Scale (ULS-6) for application in adults. *Nan Fang yi ke da xue xue bao*. J South Med Univ. 2023;43(6):900–5.
39. Andreassen CS, et al. The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychol Addict Behav*. 2016;30(2):252–62.
40. Bányaí F, et al. Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLoS ONE*. 2017;12(1):e0169839.

41. Yue H, et al. Measurement Invariance of the Bergen Social Media Addiction Scale Across Genders. *Front Psychol.* 2022;13:879259.
42. Epskamp S, Borsboom D, Fried EI. Estimating psychological networks and their accuracy: A tutorial paper. *Behav Res Methods.* 2018;50(1):195–212.
43. Haslbeck JMB, Waldorp LJ. How well do network models predict observations? On the importance of predictability in network models. *Behav Res Methods.* 2018;50(2):853–61.
44. Robinaugh DJ, Millner AJ, McNally RJ. Identifying Highly Influential Nodes in the Complicated Grief Network. *Journal of abnormal psychology* (1965), 2016. 125(6): pp. 747–757.
45. McNally RJ, Heeren A, Robinaugh DJ. A Bayesian network analysis of posttraumatic stress disorder symptoms in adults reporting childhood sexual abuse. *Eur J psychotraumatology.* 2017;8(sup3):1341276–10.
46. Scutari M. Learning Bayesian networks with the bnlearn R package. *J Stat Softw.* 2010;35:1–22.
47. Blanchard MA, et al. A network approach to parental burnout. *Child Abuse Negl.* 2021;111:104826.
48. Peng X, et al. Network analysis of risk and protective factors for suicidal ideation in adolescents. *Child Youth Serv Rev.* 2024;158:107458.
49. Sachs K, et al. Causal protein-signaling networks derived from multiparameter single-cell data. Volume 308. *Science (New York, N.Y.);* 2005. pp. 523–9. 5721.
50. Tang S, et al. A cross-lagged panel network analysis of loneliness, internet use, and depression among Chinese college students. *J Affect Disord.* 2025;381:372–80.
51. Peng P, Liao Y. Six addiction components of problematic social media use in relation to depression, anxiety, and stress symptoms: a latent profile analysis and network analysis. *BMC Psychiatry.* 2023;23(1):321–10.
52. Tullett-Prado D, et al. Conceptualising social media addiction: a longitudinal network analysis of social media addiction symptoms and their relationships with psychological distress in a community sample of adults. *BMC Psychiatry.* 2023;23(1):509.
53. Park J, et al. A structural model of stress, motivation, and academic performance in medical students. *Psychiatry Invest.* 2012;9(2):143–9.
54. Brailovskaia J, Schillack H, Margraf J. Tell me why are you using social media (SM)! Relationship between reasons for use of SM, SM flow, daily stress, depression, anxiety, and addictive SM use – An exploratory investigation of young adults in Germany. *Comput Hum Behav.* 2020;113:106511.
55. Mi Y, Ahn S, Ren L. Exploring the interconnections of loneliness, anxiety, and depression among nursing students: a network analysis approach. *Front Psychiatry.* 2025;16:1537935.
56. Cheng SM et al. Build & Belong: A Peer-Based Intervention to Reduce Medical Student Social Isolation. *Teaching and learning in medicine,* 2022. 34(5): pp. 504–13.
57. Cacioppo JT, Cacioppo S. Social Relationships and Health: The Toxic Effects of Perceived Social Isolation. *Soc Pers Psychol Compass.* 2014;8(2):58–72.

58. Barreto M, et al. Loneliness around the world: Age, gender, and cultural differences in loneliness. *Pers Individ Differ*. 2021;169:110066–110066.
59. Cacioppo S et al. Loneliness: Clinical Import and Interventions. *Perspectives on psychological science*, 2015. 10(2): pp. 238–249.
60. Zhao Y, et al. Network analysis of internet addiction and depression among Chinese college students during the COVID-19 pandemic: A longitudinal study. *Comput Hum Behav*. 2023;138:107424–107424.
61. Collins AC, et al. From anxiety to depression: A longitudinal investigation into the role of anhedonia. *J Affect Disord*. 2025;380:17–25.
62. Pizzagalli DA. Toward a Better Understanding of the Mechanisms and Pathophysiology of Anhedonia: Are We Ready for Translation? *Am J Psychiatry*. 2022;179(7):458.
63. Dyrbye LN, Thomas MR, Shanafelt TD. Medical student distress: causes, consequences, and proposed solutions. in *Mayo Clinic Proceedings*. 2005: Elsevier.
64. Tan M, Shallis A, Barkus E. Social anhedonia and social functioning: Loneliness as a mediator. *PsyCh J*. 2020;9(2):280–9.
65. Barthel AL, et al. Anhedonia is central for the association between quality of life, metacognition, sleep, and affective symptoms in generalized anxiety disorder: A complex network analysis. *J Affect Disord*. 2020;277:1013–21.
66. Craske MG, et al. Positive Affect Treatment for Depression and Anxiety: A Randomized Clinical Trial for a Core Feature of Anhedonia. *J Consult Clin Psychol*. 2019;87(5):457–71.
67. Grover S, et al. Physician burnout: A review. *J Mental Health Hum Behav*. 2018;23(2):78–85.
68. Li C. From involution to education: A glance to Chinese young generation. Atlantis; 2021.
69. ter Wolbeek M, et al. Fatigue, depressive symptoms, and anxiety from adolescence up to young adulthood: A longitudinal study. *Brain Behav Immun*. 2011;25(6):1249–55.
70. Lavidor M, Weller A, Babkoff H. How sleep is related to fatigue. *Br J Health Psychol*. 2003;8(1):95–105.
71. Åkerstedt T, et al. Mental fatigue, work and sleep. *J Psychosom Res*. 2004;57(5):427–33.
72. Meerkerk GJ et al. Is compulsive internet use related to sensitivity to reward and punishment, and impulsivity? *Computers in human behavior*, 2010. 26(4): pp. 729–35.
73. Hirschman EC. The Consciousness of Addiction: Toward a General Theory of Compulsive Consumption. *J consumer Res*. 1992;19(2):155–79.
74. Boksem MAS, Tops M. Mental fatigue: Costs and benefits. *Brain Res Rev*. 2008;59(1):125–39.
75. van der Linden D, Eling P. Mental fatigue disturbs local processing more than global processing. *Psychol Res*. 2006;70(5):395–402.
76. Sharpe M, et al. Cognitive behaviour therapy for the chronic fatigue syndrome: a randomised controlled trial. *BMJ*. 1996;312(7022):22–6.

77. Hulme K, et al. Fatigue interventions in long term, physical health conditions: A scoping review of systematic reviews. PLoS ONE. 2018;13(10):e0203367.

Figures

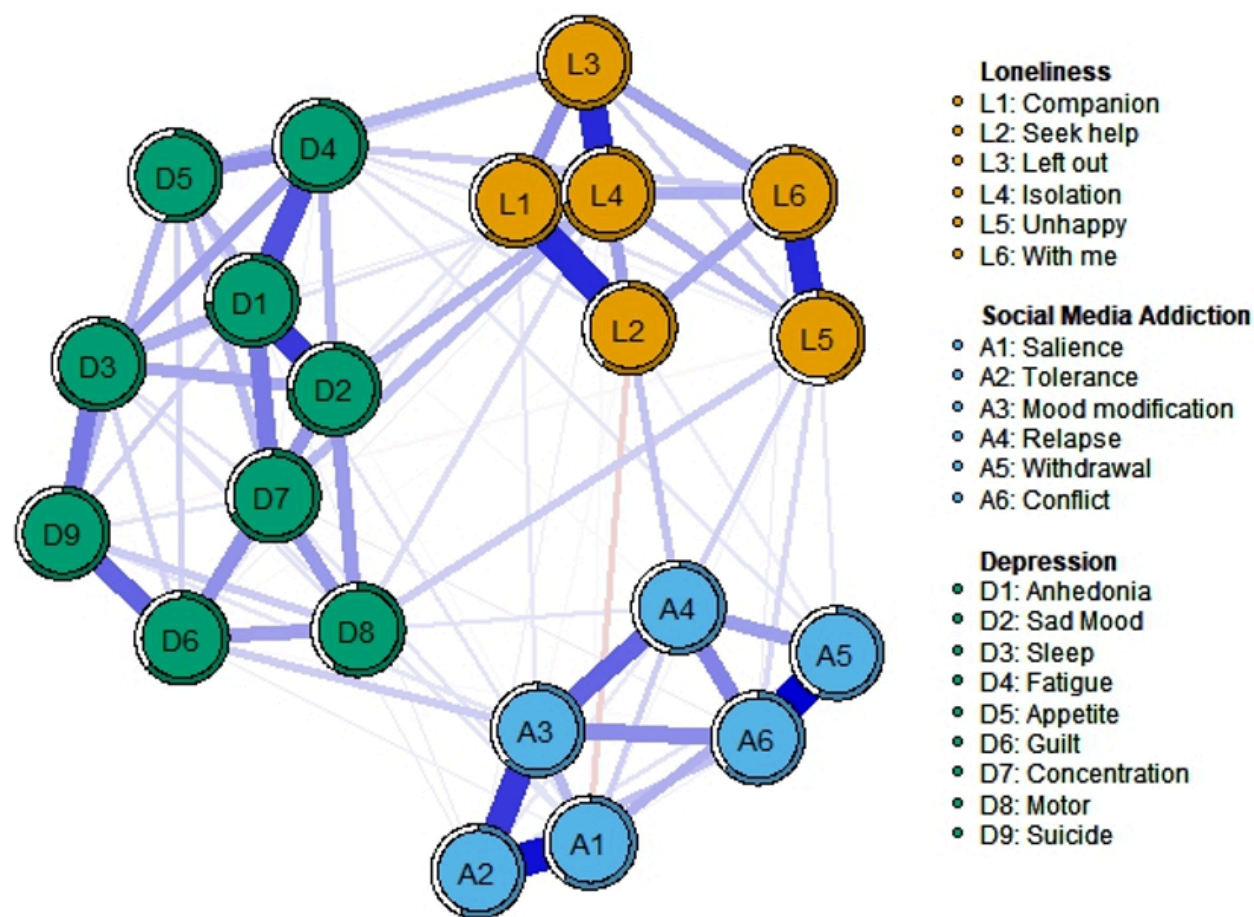
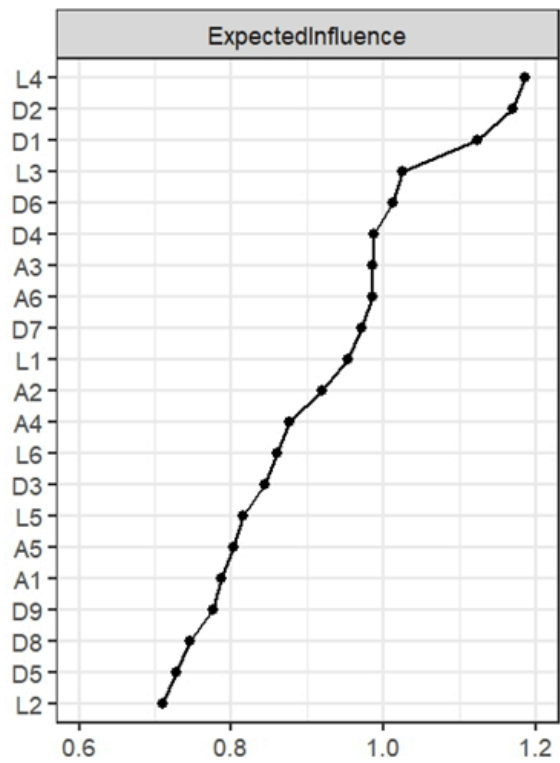


Figure 1

Network structure of depressive symptoms, loneliness and social media addiction in Chinese medical students.

A



B

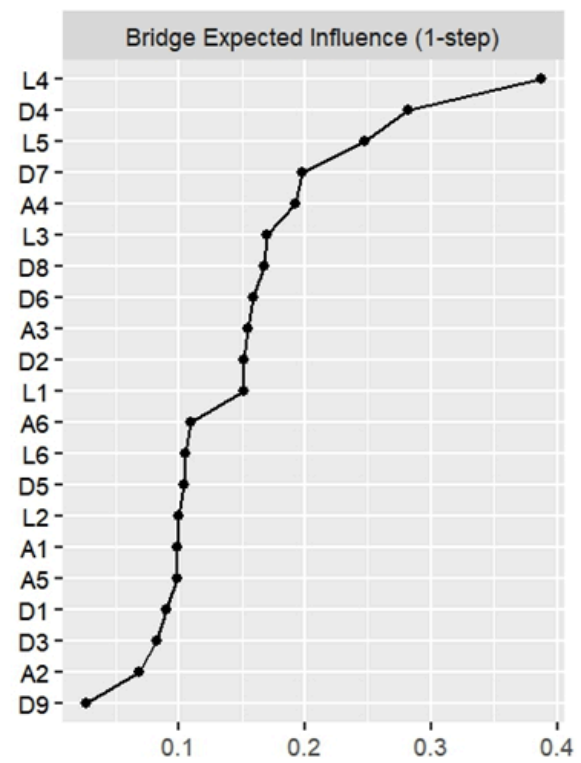


Figure 2

Centrality indices for expected influence (A) and bridge expected influence values(B).

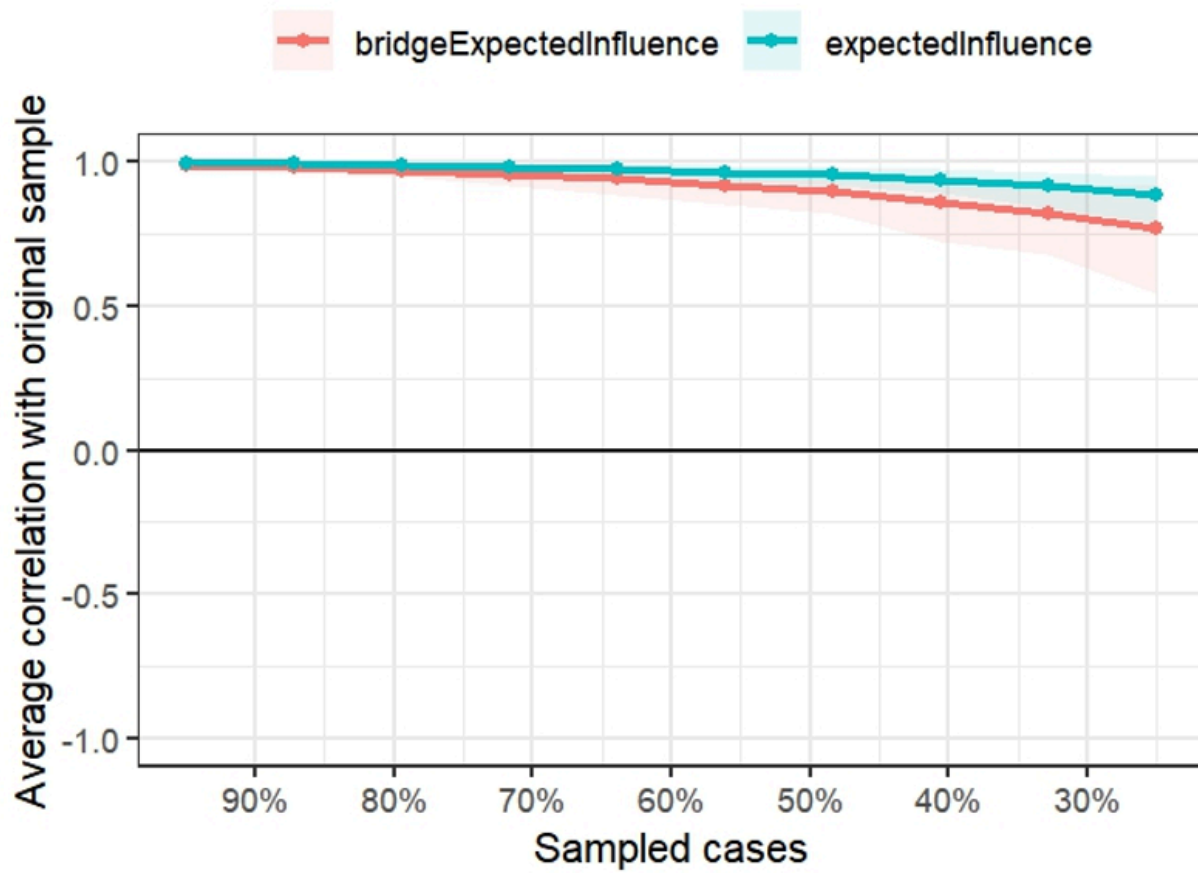


Figure 3

The stability of centrality and bridge centrality indices according to a case-dropping bootstrap method.

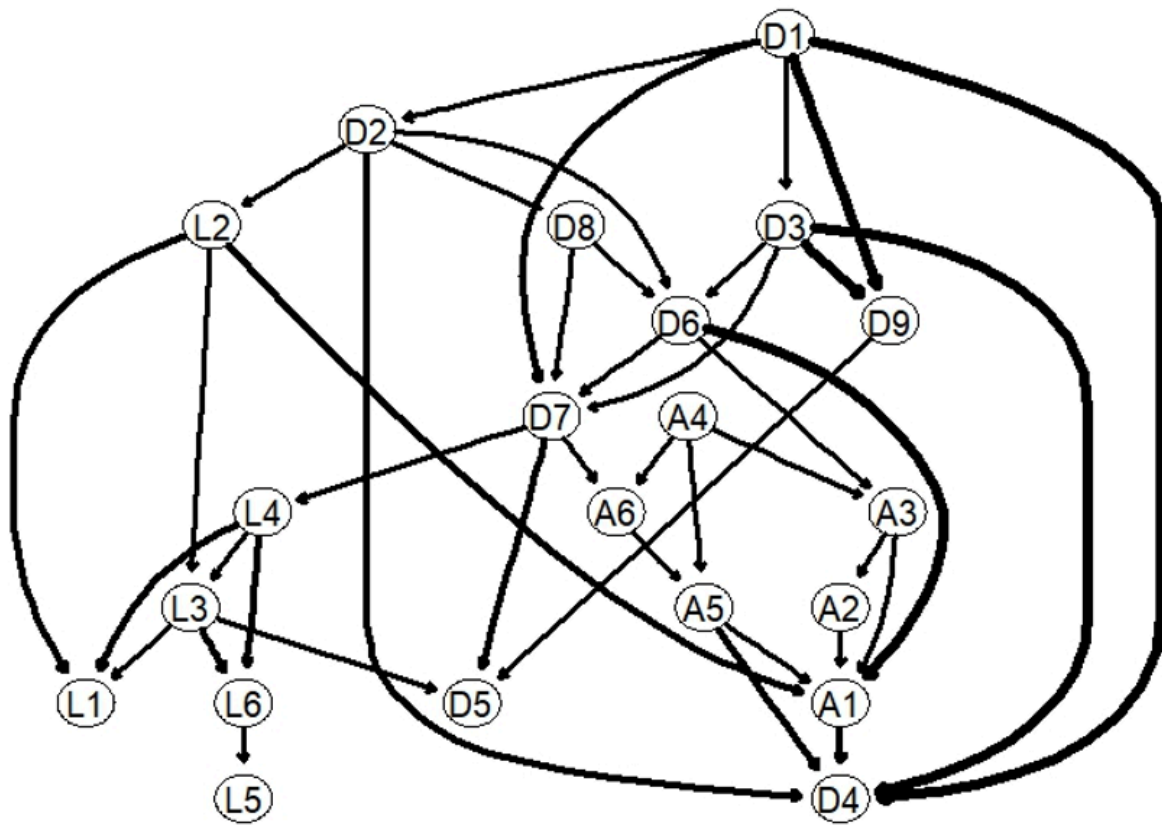


Figure 4

Directed Acyclic Graph of depressive symptoms, loneliness, and social media addiction

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SuppFigures.docx](#)