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# Using Network Analysis to Subgroup Risk Factors for Depressive Symptoms in College Students

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**Purpose:** Network modeling has been suggested as an effective method to explore intricate relationships among antecedents, mediators, and symptoms. In this study, we aimed to investigate whether the severity of depressive symptoms in college students affects the multivariate relationships among anhedonia, smartphone addiction, and mediating factors.

**Methods:** A survey was conducted among 1347 Chinese college students (587 female) to assess depressive symptoms, anhedonia, addictive behaviors, anxiety, and insomnia. The participants were categorized the non-depressive symptom (NDS) and depressive symptom (DS) groups based on a cut-off score of 5 on the 9-item Patient Health Questionnaire-9. Network analysis was performed to investigate the symptom-to-symptom influences of symptoms in these two groups.

**Results:** The network of the DS group was more densely connected than that of the NDS group. Social anticipatory anhedonia was a central factor for DS, while withdraw/escape (one factor of smartphone addiction) was a central factor for NDS. The DS group exhibited greater strength between the PHQ9 score and social anticipatory anhedonia, as well as between the PHQ9 score and alcohol misuse score, compared to the NDS group. On the other hand, the NDS group had higher strength between anxiety and feeling lost, as well as between anxiety and withdraw/escape, compared to the DS group.

**Conclusion:** The findings suggest that there is a close relationship between social anhedonia, smartphone addiction, and alcohol consumption in the DS group. Addressing on ameliorating social anhedonia and smartphone addiction may be effective in preventing and managing depression in college students.

**Keywords:** depressive symptoms, anhedonia, smartphone addiction, network analysis, college students

## Introduction

Depression is a common mental disorder characterized by symptoms such as depressed mood, anhedonia, and sleep disturbance.[1] There is mounting evidence that depressive symptoms are prevalent among college students worldwide.[2–6] Furthermore, the prevalence rates have increased over time, putting many at risk for clinical depression and suicide.[3,4] Depressive symptoms are linked to cognitive impairments,[2] poor academic performance and dropout,[4] interpersonal problems,[6] and substance abuse[5] among college students. Problematic cell phone use,[7] hazardous alcohol drinking,[5] tobacco use,[8] and sleep disturbance[5] are significant risk factors for subsequent depressive symptoms in young adults. Early detection and prevention of depressive symptoms and related factors among college students is paramount.

Anhedonia is a core symptom of depression, characterized by reduced ability to experience pleasure.[1] It can be manifested as physical anhedonia, inability to feel physical pleasure, or social anhedonia, diminished capacity for pleasure in social activities.[9] Additionally, anhedonia becomes more stable throughout adolescence and, in some instances, slightly intensifies.[10–12] Moreover, the desire for social interaction is among the most basic human needs.[13] Social anhedonia may pose a greater risk for the development of mental health issues in youth,[10] including anxiety,[12] internet addiction,[14] alcohol and tobacco use,[15] and related consequences, than general anhedonia.

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Individuals with anhedonia may lack pleasure from routine rewards such as food or social interaction.[12,16] Consequently, they may require greater reward stimulation to trigger hedonic response, although potent and novel rewards can evoke hedonic reactions.[16] Individuals with trait anhedonia may compulsively engage in internet use to counteract hedonic deficits, drawn by its low-cost, plentiful reward sources.[14] Additionally, anhedonic youth may form the cognitive expectations that internet use is rewarding, potentially alleviating anhedonia symptoms.[17] They may ignore the adverse effects of internet overuse due to the rewarding expectations.

Depression and anxiety, frequently co-occurring emotional disturbances, may mediate secondary issues like insomnia.[18,19] Additionally, individuals with insomnia have higher levels of depression and anxiety compared to those without insomnia.[19] Moreover, previous research has indicated a positive correlation between anxiety and smartphone addiction, with the latter potentially acting as an anxiety coping strategy.[19,20] Furthermore, excessive engagement in online social networking can serve as a diversion from emotional distress.[21] Therefore, further investigation on depression is imperative to elucidate its complex relationship with various comorbid factors.

## The Present Study

Previous studies have utilized network modeling to examine the intricate connections between depressive symptoms and related factors.[22,23] Network analysis provides a robust methodological approach to establish a model of relationships between multivariate factors and enables the exploration of complex psychological systems.[24] Network theory is utilized to probe the connections among symptoms, positing psychiatric disorders as networks of interdependent symptoms.[25] Given that depressive symptoms and associated factors may influence each other, exploring the interactions between symptoms yields critical insights for clinical research and practice.[26] Network analysis can reveal conditional independence relationships at the group level, potentially forming a constellation of syndromic symptoms.[27] Moreover, network structure facilitates the identification of core features, elucidating the most pivotal features within the symptom network.[24]

The aim of this study was to examine the relationships between anhedonia, addictive behaviors, anxiety and insomnia symptoms in individuals with depressive symptom (DS) and those with non-depressive symptom (NDS) among college students. We assessed pivotal factors and their interrelations within the network to pinpoint core factors and explore group-level structural variances between the two groups. We hypothesized a dense network of interconnections among depressive symptoms and related factors in college students. We anticipated that analyzing the network structure would provide insights into the complex associations among symptom-by-symptom networks. Furthermore, we expected that network analysis would elucidate potential risk factors for individuals transitioning from NDS to DS.

# Material and Methods

## Study Sample

We employed cluster-stratified sampling by academic year to recruit participants from first-year through senior-level students at Hangzhou City University. Data collection occurred via an online survey between May 2022 and October 2022. A total of 1347 participants (587 female) with no prior psychiatric history completed the survey after providing online informed consent.

## Measurements

### Sociodemographic Data

The study collected sociodemographic information, including age, sex, grade, whether the participant came from a one-child family, and individual income.

### The 9-Item Patient Health Questionnaire-9 (PHQ-9)

The severity of depressive symptoms were assessed using the PHQ-9,[28] which was consisted of 9 items rated on a 4-point scale ranging from "Not at all" (1) to "Nearly every day" (4). The total score ranged from 9 to 36, with higher scores indicating more severe depressive symptoms. The scale has robust internal consistency and reliability.[29] Cronbach's α for the PHQ-9 was 0.95.

### The Snaith Hamilton Pleasure Scale (SHAPS)

The SHAPS was utilized to assess individuals' self-reported experiences of positive emotions in enjoyable situations.[30] The scale included six items for social anhedonia (Soc) and eight items for physical anhedonia (Phy). The total score on the SHAPS ranged from 14 to 56, with higher scores indicating more severe levels of anhedonia. The Chinese version of the SHAPS has good internal consistency and reliability.[31,32] Cronbach's α for the SHAPS was 0.94.

### The Anticipatory and Consummatory Interpersonal Pleasure Scale (ACIPS)

The ACIPS was employed to assess hedonic capacity for social and interpersonal pleasure. It included seven items for social anticipatory pleasure (Sap) and ten items for social consummatory pleasure (Scp).[33] Lower total scores indicated a higher likelihood of social anhedonia. The Chinese ACIPS version has demonstrated good internal consistency and reliability.[12] Cronbach's α for the ACIPS was 0.97.

### The Mobile Phone Addiction Index (MPAI)

The MPAI was used to evaluate smartphone addiction across four domains, including inability to control craving (IACC), anxiety and feeling lost (AFL), withdrawal and escape (WE), and productivity loss (PL).[34] The MPAI is comprised of 17 items, each rated on a 5-point Likert scale ranging from 1 (not at all) to 5 (always). The Chinese MPAI version exhibits good internal consistency and reliability.[35] Cronbach's α for the scale was 0.94.

### The Alcohol Use Disorders Identification Test (AUDIT)

The AUDIT was utilized to assess the frequency and quantity of alcohol consumption.[36] The AUDIT comprised 9 items designed to assess recent alcohol use, symptoms of alcohol dependence, and alcohol-related problems. The Chinese AUDIT version has good internal consistency and reliability.[37] Cronbach's α for the scale was 0.95.

### The Heaviness of Smoking Index (HSI)

The HSI was used to measure nicotine dependence based on two questions: time to first smoking in the morning and number of cigarettes per day.[38] Higher scores indicate higher levels of nicotine dependence. The scale has good internal consistency and reliability.[39] Cronbach's α for the scale was 0.93.

### The 7-Item Generalized Anxiety Disorder Scale (GAD-7)

The GAD-7 was employed to evaluate self-reported anxiety severity.[40] Responses to all items are graded on a 4-point Likert scale: 1 (not at all), 2 (several days), 3 (more than half the days), and 4 (nearly every day), with higher scores indicating greater severity of anxiety disorders. The scale has good internal consistency and reliability.[41] Cronbach's α for the GAD-7 was 0.95.

### The Insomnia Severity Index (ISI)

The ISI is a self-report questionnaire comprising seven items that assess the perceived severity of insomnia.[42] Each item was rated on a 5-point Likert scale from "1 = not at all" to "5 = extremely", with higher scores indicating greater severity of insomnia. The Chinese ISI version has good reliability and validity.[43] Cronbach's α for the scale was 0.83.

## Statistical Analysis

### General Differences

Data analysis took place in November and December 2022. Participants were sorted into DS or NDS groups based on their PHQ-9 scores, with a cut-off score of 5.[44] Categorical variables, including grade, sex, single-child family, individual income, and smoking status, were compared using the chi-square test, and scale scores between the two groups were compared using the Mann–Whitney *U*-test. Statistical significance was set at a two-sided *p value* $< 0.05$. All analyses were conducted using R (Version 4.1.3).[45]

### Network Construction

The data was fitted using a Gaussian graphical model (GGM), an undirected model for modeling conditional dependency relationships in multivariate data.[46] Networks were constructed at the sub-domain level, consisting of 13 nodes [PHQ-9, Soc, Phy, Sap, Scp, IACC, AFL, WE, PL, HSI, AUDIT, GAD-7, and ISI] for both groups. Edge weights of the GGM were determined using partial correlation coefficients. Gaussian Markov random fields were employed to infer the graphical structure. The graphical least absolute shrinkage and selection operator (LASSO) algorithm[47] and the extended Bayesian information criterion (EBIC) model[48] were utilized to select the optimal regularization parameter. The hyperparameter (γ) for the EBIC model was set to 0.5, a default value known for accurate network estimations,[49] using the R packages "bootnet (estimateNetwork)" Version 1.5 and "qgraph (EBICglasso)" Version 1.9.2.[50] Visualization of the networks was done using the Fruchterman–Reingold algorithm.[51]

### Global Network Metrics

Global network metrics, including network density, global strength, average clustering coefficient, and characteristic path length, were computed using the R packages "qgraph"[50] and "igraph" (Version 1.3.2).[52] Network density was calculated as the ratio of the number of edges to the total number of possible edges, while global strength was defined as the weighted absolute sum of all edges in the network. The clustering coefficient indicates the likelihood that neighboring nodes of a node are connected in a graph, with a higher value suggesting a more interconnected neighborhood around a specific node. The characteristic path length represents the average shortest distance between all pairs of nodes in the network. For network comparisons, we utilized the R package "NetworkToolbox" (Version 1.4.2)[53] to analyze discrepancies in network density, average clustering coefficient, and characteristic path length. The R package "Network Comparison Test" (NCT) (Version 2.2.1)[54] was employed to assess the invariance of global strength between networks. The NCT conducted a resampling-based permutation test by randomly regrouping participants from each network and repeating the process 1000 times, calculating differences among networks.

### Local Network Metrics

In this study, node strength served as the centrality index, chosen over betweenness and closeness centrality, which were considered inappropriate for psychological networks in previous research.[55,56] Node strength was computed as the sum of *z*-scores of absolute weights connected to the central node using the R package "qgraph".[50] The analysis revealed a high node strength value, indicating a strong direct influence on neighboring nodes. Additionally, we employed the R package NCT[54] to assess the consistency of network structure and node strength among the networks. The network invariance test examined the differences in the overall network structure.[57] If significant differences in network structure were detected, the specific edges were then calculated and identified.

## Stability Analysis

The study evaluated network accuracy and stability using the "bootnet" package.[58] Edge weight accuracy was determined by calculating 95% confidence intervals (CIs) for each edge through nonparametric bootstrapping method with 1000 iterations. The correlation stability coefficient (CS-coefficient) assessed the stability of node centrality indices using case-dropping bootstrapping. A CS-coefficient exceeding 0.25 is considered ideal, with a preference for it to surpass 0.5.[58] Bootstrapped difference tests were conducted on edge weights and centrality indices to identify any significant disparities.

## Procedure

All students involved in the study provided informed consent before data collection. They completed self-reported measures in a quiet classroom, with the assurance that their participation was voluntary and that they had the right to withdraw at any time. They were instructed to independently complete the questionnaires and were assured of privacy protection. The study received approval from local research ethics committee, adhering to the Declaration of Helsinki.

# Results

## Sample Characteristics

This study included 1347 participants, with 587 (43.58%) being female. They consisted of 351 freshman students (26.06%, average age 19.07 years), 354 sophomore (26.28%, average age 19.53 years), 360 junior (26.73%, average age 20.44 years), and 282 senior (20.94%, average age 21.40 years). The NDS group, comprising younger individuals, had a higher proportion of freshman and sophomore students compared to the DS group. The DS group showed higher smoking frequency and scale scores compared to the NDS group. See Table 1. There were no significant differences observed in sex, single-child family status, or individual income between the two groups. Online Supplementary Figure S1 presents the heat map of the Pearson correlation matrix for all thirteen variables in each group.

## Global Network Metrics

The resulting network exhibited robust connectivity without any isolated nodes (see Figure 1). The DS group had denser network connectivity than the NDS group ($p = 0.001$). See Table 2. However, no significant differences were observed in other global network metrics between the NDS and DS groups.

## Local Network Metrics

In the NDS group, the top three positive edge weights involved connections between Sap and Scp, those between Soc and Phy, and those between AFL and WE. In the DS group, the top three positive edge weights were featured the connections between Sap and Scp, those between Soc and Phy, and those between the PHQ-9 score and GAD-7 score. See Figure 2.

**Table 1** Psychological Manifestations in the NDS and DS Groups

| Characteristics | NDS (n = 668) | DS (n = 679) |
|---|---|---|
| College students [a] | | |
| Freshman | 191 (28.59%) | 160 (23.56%) |
| Sophomore | 190 (28.44%) | 164 (24.15%) |
| Junior | 164 (24.55%) | 196 (28.87%) |
| Senior | 123 (18.42%) | 159 (23.42%) |
| Sex (F/M) | 307 / 361 | 280 / 399 |
| Age (years) [b] | 19.83 (1.49) | 20.25 (1.56) |
| Single-child or not (Y/N) | 310 / 358 | 288 / 391 |
| Individual income | | |
| No | 453 (67.81%) | 429 (63.18%) |
| =< 2000 RMB | 105 (15.72%) | 119 (17.52%) |
| 2000–5000 RMB | 82 (12.28%) | 86 (12.67%) |
| >5000 RMB | 28 (4.19%) | 45 (6.63%) |
| Smoking or not (Y/N) [a] | 79 / 589 | 115 / 564 |
| PHQ-9 [c] | 0 [0, 2] | 9 [7, 13] |
| HSI [c] | 0 [0, 6] | 0 [0, 6] |
| AUDIT [c] | 0 [0, 2] | 1 [0, 7] |
| SHAPS [c] | 23 [16, 28] | 27 [21, 29] |
| Social anhedonia [c] | 10 [7, 12] | 11 [9, 12] |
| Physical anhedonia [c] | 13 [9, 16] | 16 [12, 17] |
| ACIPS [c] | 77 [63, 88] | 69 [57, 83] |
| Anticipatory anhedonia [c] | 31 [26, 37] | 28 [23, 34] |
| Consummatory anhedonia [c] | 46 [37, 52] | 41 [34, 50] |
| MPAI [c] | 41 [30.75, 51] | 51 [43, 60] |
| Inability to control craving [c] | 14 [10, 19] | 19 [15, 22] |
| Anxiety and feeling lost [c] | 12 [8, 16] | 15 [12, 19] |
| Withdrawal and escape [c] | 8 [6, 11] | 9 [8, 12] |
| Productivity loss [c] | 5 [3, 6] | 6 [5, 8] |
| GAD-7 [c] | 0 [0, 3] | 7 [6, 10.5] |
| ISI [c] | 3 [1, 6] | 9 [5.5, 12] |

**Notes**: Age is presented as mean and standard deviation. Scale scores are reported as median with interquartile range [Q1, Q3], and HSI scores as median [minimum, maximum]. [a] Chi-square test, $p < 0.05$. [b] Two-sample $t$ test, $p < 0.05$. [c] Mann–Whitney $U$-test, $p < 0.05$.

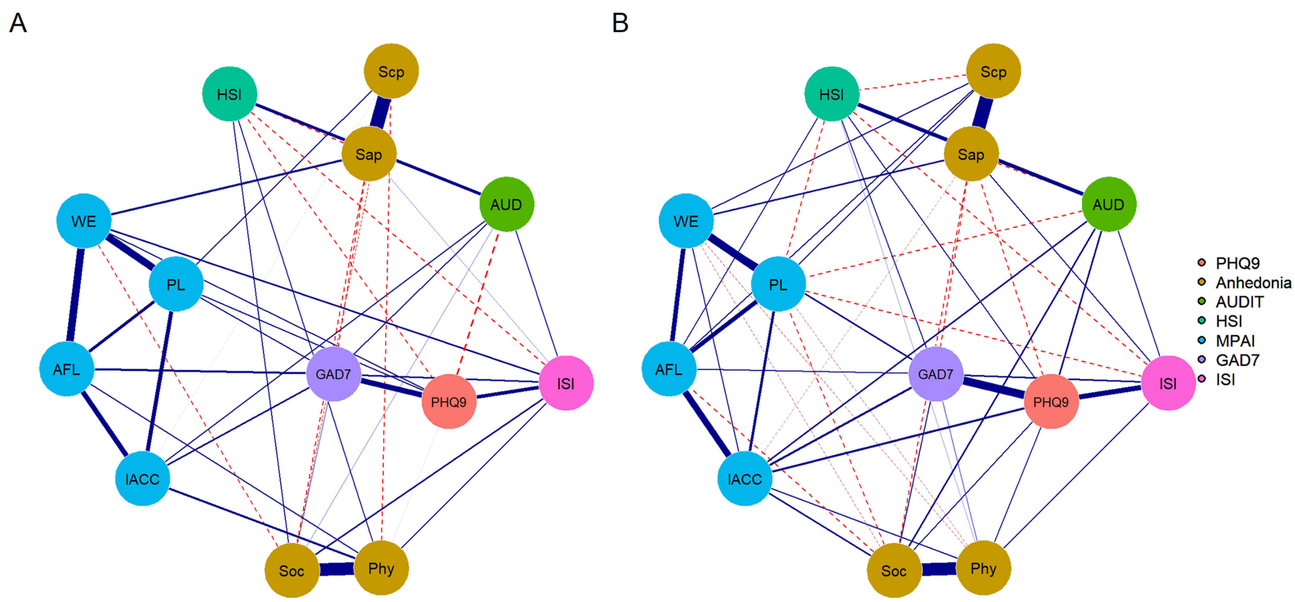


**Figure 1** Estimated network structures within the NDS and DS groups. (**A**) The non-depressive symptom (NDS) group. (**B**) The depressive symptom (DS) group. Red dashed lines indicate negative weights, while blue lines indicate positive weights.

In the NCT analysis, the examination for network structure invariance uncovered a significant contrast in edge weights between the NDS and DS groups. Specific edges with significant variations were identified with Bonferroni-Holm correction. The edge weights between the PHQ-9 score and Sap were statistically significant between the two groups. Specifically, the DS group displayed a negative correlation between the PHQ-9 score and Sap, compared with the NDS group (–0.04 versus 0). Additionally, the DS group exhibited a stronger connection between the PHQ-9 score and AUDIT score compared to the NDS group (0.07 versus –0.07). The NDS group showed a stronger connection between AFL and WE compared to the DS group (0.47 versus 0.28). Tables S1–S2 list the weights of all edges in both groups.

Regarding centrality, the DS group's network highlighted Sap as the item with the highest node strength, while the NDS group's network identified WE as the strongest node (Figure 2A). The most notable difference in node strength between DS and NDS was observed for PHQ-9 scores (Figure 2B). Network comparison tests indicated significant differences in node strength between the NDS and DS groups for the PHQ-9 scores and GAD-7 scores (see Table S3).

## Network Accuracy and Stability

The edge weight bootstrap analysis indicated overlap in the 95% confidence intervals of edge weights, particularly in the strongest edges (see Figure S2). Figure S3 illustrated the robust stability of centrality estimates. Bootstrapped difference tests results for edge weights and node centralities were displayed in Figures S4–S5. In the robustness analysis, CS-coefficients for node strength surpassed 0.50, and exceeded 0.40 in both groups, indicating the network's stability despite

**Table 2** Global Connectivity of the Networks in the NDS and DS Groups

| Characteristics | NDS | DS | $p$ [a] |
|---|---|---|---|
| Density | 0.46 | 0.56 | 0.001 |
| Global strength | 5.11 | 5.63 | 0.06 |
| Average clustering coefficient | 0.49 | 0.64 | 0.13 |
| Average shortest path length | 1.46 | 1.35 | 0.26 |

**Notes**: [a]Is the results of permutation test (global strength from NCT and the others from Network Toolbox).

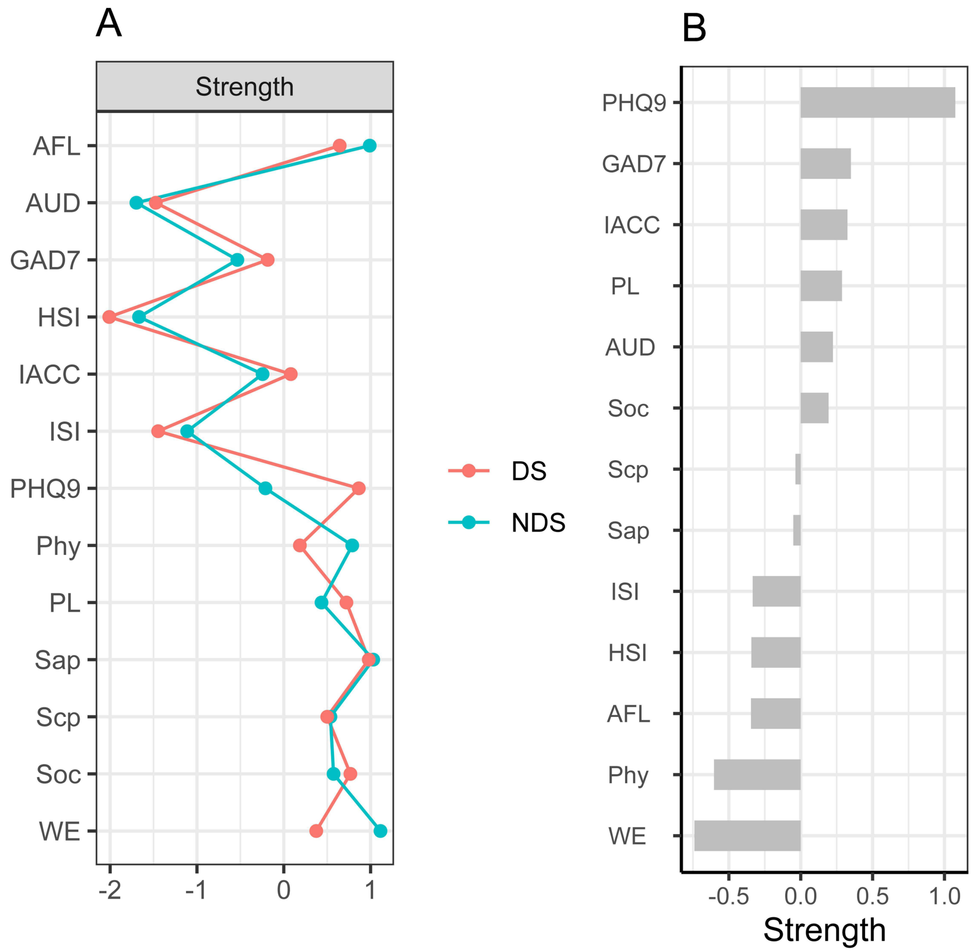


**Figure 2** Nodal strength centrality index. (**A**) Nodal strength comparison between the depressive symptom (DS) and non-depressive symptom (NDS) group. The red line depicts DS, while the green line represents NDS. (**B**) Variation in node strength between DS and NDS. Nodes are arranged from lowest to highest based on their strength values.

removing more cases. See Table 3. However, the CS-coefficient for betweenness was only 0.13 in both groups, suggesting caution in interpreting its stability compared to the other indices.

## Discussion

The study utilized network analysis to investigate the relationships among anhedonia, addictive behaviors, anxiety, insomnia, and depressive factors in both the DS and NDS groups. Results showed variations in global density, node strength, and edge weights of the network between the groups. Notably, the DS group displayed a denser network compared to the NDS group, with social anhedonia as a key node, while withdrawal/escape stood out for the NDS group.

**Table 3** Correlation Stability Coefficient of Centrality Indices in NDS and DS

| Centralities | NDS | DS |
|---|---|---|
| Strength | 0.75 | 0.75 |
| Closeness | 0.67 | 0.44 |
| Betweenness | 0.13 | 0.13 |

**Note**: Values are correlation coefficients.

High levels of withdrawal/escape behavior due to mobile phone addiction in individuals with NDS may elevate the risk of transitioning DS.

Global network metrics revealed notable differences in network density between the DS and NDS groups, with permutation tests confirming statistical significance. The results parallel earlier clinical research, which found that individuals with enduring depression exhibited denser network connections initially compared to those who eventually recovered.[22] Similarly, stronger and more resilient interactions among mental states were observed in a general population sample experiencing psychopathological syndromes.[59]

In the DS group, social anhedonia emerged as the symptom with the highest nodal strength. The DS group exhibited a stronger negative correlation between the PHQ-9 score and social anticipatory pleasure compared to the NDS group. Consistent with prior research, anhedonia was central in the network of depression symptoms,[26] with anticipatory pleasure playing a crucial role.[23] Depression is characterized by deficits in anticipatory pleasure, reward association formation, and past experiences integration.[60] Anticipatory anhedonia predicted reduced reward anticipation and hedonic response in college students with depressive symptoms.[61] Anhedonia was linked to decreased reward sensitivity and ventral striatum responsiveness to positive stimuli.[62] Moreover, this study found that the DS group showed a stronger correlation between the PHQ-9 score and AUDIT score compared to the NDS group. The self-medication model posits that young adults may consume alcohol to manage negative emotions.[63] Depressed individuals appeared to drink alcohol to relieve negative feelings,[64] potentially leading to hazardous drinking patterns.[5] Additionally, binge drinking has been linked to depression,[5] while depressive symptoms have been shown to predict hazardous alcohol use.[65]

In the NDS group, network analysis revealed that the withdrawal/escape, a facet of smartphone addiction, had the highest node strength. The NDS group showed a stronger connection between anxiety, feeling lost, and withdrawal/escape compared to the DS group. Research by Kaczmarek & Drążkowski found that the stronger link between feeling anxious, feeling lost, and withdraw/escape was associated with more severe cell phone addiction among college students.[66] Excessive use technology and social media among college students has been linked to social isolation, strained friendships,[67] poor academic performance,[66] and a decline in overall health-related quality of life. Excessive smartphone use in the transition from adolescence to adulthood is associated with increased depressive symptoms and impulsive internet use.[20] Additionally, social media use has been reported to correlate with a subsequent rise in depressive symptoms in the general population.[7] These findings indicated that withdrawal/escape behavior, which were characteristic of problematic cell phone use in the NDS group, could be contributing factors to the emergence of depressive symptoms.

In summary, this study yields theoretical and practical insights. Theoretically, it examines the intricate relationship between depressive symptoms, anhedonia, smartphone addiction, and other factors among college students via network analysis. Practically, it informs intervention strategies for adolescents to alleviate depression and bolster mental health. For instance, strengthening offline peer interactions, fostering social skills, and enriching social activities effectively regulate mobile phone usage and bolster positive emotions.

## Limitations

The current study had several limitations. First, the cross-sectional design limits our ability to establish causal relationships between variables. Therefore, future longitudinal studies are needed to track how anticipatory anhedonia and withdrawal/escape change over time in nonclinical populations affected by smartphone addiction. Second, the study sample, restricted to a single college, may limit the findings' generalizability. Future research should expand to larger, geographically diverse populations for enhanced representativeness. Third, reliance on self-report measures alone may introduce reporting bias. Future studies could supplement self-reports with clinical interviews to gain deeper insights into depression-related factors. Moreover, future research should explore additional factors such as personality traits[23] and the impact of the COVID-19 pandemic.

## Conclusions

In summary, the DS and NDS groups exhibited differing network structure with the DS group presenting a denser network with social anhedonia as a central node. This research illuminates the prevalent factors associated with depressive symptoms among college students. Our findings underscore the necessity of addressing smartphone addiction to preempt and manage depression in young adults. These findings offer insights for crafting mental health initiatives geared towards primary prevention, early detection, treatment of depression, and the promotion of well-being among young adults.

## Abbreviations

DS, Depressive Symptom; NDS, Non-depressive Symptom; PHQ-9, The 9-item Patient Health Questionnaire Score; SHAPS, The Snaith Hamilton Pleasure Scale Score; Soc, Social Anhedonia; Phy, Physical Anhedonia; ACIPS, The Anticipatory and Consummatory Interpersonal Pleasure Scale Score; Sap, Social Anticipatory Pleasure; Scp, Social Consummatory Pleasure; MPAI, The Mobile Phone Addiction Index; IACC, Inability to Control Craving; AFL, Anxiety and Feeling Lost; WE, Withdrawal and Escape; PL, Productivity Loss; AUDIT, Alcohol Use Disorders Identification Test Score; HIS, Heaviness of Smoking Index; GAD-7, The 7-item Generalized Anxiety Disorder Scale Score; ISI, Insomnia Severity Index Score; GGM, Gaussian Graphical Model; LASSO, Least Absolute Shrinkage and Selection Operator; EBIC, Extended Bayesian Information Criterion; NCT, Network Comparison Test; CIs, Confidence Intervals; CS-coefficient, Correlation Stability Coefficient.

## Data Sharing Statement

The dataset generated and analyzed for this study can be obtained from corresponding author. The code generated and analyzed for this study can be obtained from corresponding author.

## Ethical Approval

This study was approved by the research ethics committee of Affiliated Mental Health Center, Zhejiang University School of Medicine. The research was performed in accordance with the ethical standards as laid down in the Declaration of Helsinki.

## Informed Consent

The parents of all participants gave informed consent and all participants gave informed assent prior to participation. Informed consent included consent for publication of reports using data from this study.

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## Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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## Disclosure

All authors declare no conflicts of interest.

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