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ORIGINAL RESEARCH

Interaction Among Smartphone Addiction, Behavioral Inhibition/Activation Systems and Mental Health Factors Among Chinese Undergraduate Student: A Study Using Network Analysis

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Background: Smartphone addiction, which represents a behavioral concern, has been found to correlate with a diverse range of mental health problems among the undergraduate students. Meanwhile, the modes of behavioral inhibition/activation showed specific characteristics in smartphone addiction individuals. Therefore, clarifying the interaction of mental health and behavioral modes with smartphone addiction is urgent. Here, we used a cross-sectional design, aiming to explore the network interactions among smartphone addiction, mental health (depression, anxiety, stress, loneliness and life satisfaction), and the behavioral inhibition/activation system (BIS/BAS) in undergraduate students.

Methods: We employed network analysis and community detection in R, to investigate the centrality and edge connections, which are the mainly index of key factors and interaction effects between factors respectively. The study was carried out among 701 participants with an average age of 18.27 ± 1.57 years old, all of whom had completed self-report scales.

Results: The network analysis results suggested that depression and anxiety, the behavioral activation of fun seeking, reward responsiveness and behavioral inhibition had significantly higher centrality than the other mental health and BIS/BAS factors respectively. When combining the connections of network analysis and community detection, the stronger connections mainly present in the inner domain of mental health factors and the BIS/BAS, respectively. The findings regarding the transdomain connections imply that stress is likely to serve as a mediator in the relationships between smartphone addiction and both depression as well as BAS-Drive.

Conclusion: Therefore, the current study suggests that although common psychological and behavioral system problems may play a dominant role in smartphone addiction among undergraduate students, it is still necessary to consider whether other factors such as stress may play a potential moderating role. The new insight will help to enhance mental health and facilitating proper smartphone use management to avoid the aggravation of addiction problems among undergraduate student.

Keywords: smartphone addiction, psychological health, college students, network approaches

Introduction

Due to the rapid iteration of smartphone technology, individuals have come to rely on smartphones to an ever-greater extent for social interactions, entertainment pursuits, as well as work and study. According to the data reported by the China Internet Network Information Center (CNNIC) as of January 2025, the quantity of mobile internet users in China has soared to 11.05 billion. Remarkably, the percentage of internet users accessing the web via mobile phones stands at an astounding 99.7%.[1] However, despite the convenience that smartphones bring to our lives, there are risks associated with the overuse of smartphones. Smartphone addiction (SMA) manifests as out-of-control and withdrawal reactions to smartphone use.[2] SMA has become a public issue in many countries among adolescents aged 14–20 years.[3–5] In China,

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18 is the age at which teenagers enter university after passing the national college entrance examination. Before that, they spent most of their time in intense study and rarely use smartphones. However, after entering college, they are often no longer bound by this constraint and thus have considerable freedom with respect to mobile phone use. A previous study revealed that undergraduate students are more vulnerable to SMA[6] compared to children[7] and adolescents from 10–18 years old.[8] Previous studies have indicated a notable upward trend in SMA among Chinese college students over the past decade. Specifically, the average SMA score rose significantly from 36.55 in 2012 to 46.25 in 2022.[9] Furthermore, recent estimates suggest that approximately 36.6% of Chinese undergraduates exhibit symptoms of smartphone addiction.[10] These findings underscore the substantial prevalence of smartphone addiction within this demographic and their deep immersion in the mobile internet ecosystem.

Moreover, accumulating evidence underscores a strong association between SMA and a range of mental health problems. Recent research has demonstrated that anxiety, depression, loneliness, stress, and overall well-being are significantly correlated with the development of SMA among Chinese college students.[9] Conversely, SMA can exert detrimental effects on students' daily lives and academic performance, manifesting in various aspects such as impaired interpersonal relationships, declining academic achievement, and increased procrastination.[11] Specifically, studies have shown that undergraduate individuals with problematic smartphone use or SMA are at a significantly higher risk of experiencing anxiety and depression.[12] Additionally, SMA has been found to be positively correlated with poor sleep quality among college students.[13] In terms of stress, research indicates that SMA is significantly associated with elevated stress levels.[14] Moreover, loneliness has been identified as a key predictive factor for SMA, suggesting that individuals with higher levels of loneliness are more prone to developing smartphone addiction.[15] On the other hand, a significant negative correlation has been observed between SMA and subjective well-being, indicating that Chinese university students with SMA tend to report lower levels of life satisfaction and happiness.[16] Finally, college students with SMA are also more likely to exhibit higher levels of impulsivity, further highlighting the multifaceted impact of smartphone addiction on mental health.[13] Therefore, it is crucial to understand these dynamics to develop effective interventions and support systems for this population.

Several studies have utilized network analysis to explore the interplay between smartphone addiction (SMA) and mental health symptoms, as well as behavioral systems. For instance, one study examined the pathological pathways connecting problematic smartphone use with anxiety and depression among Chinese college students. The findings highlighted that the factor of "Withdrawal" may serve as a critical target for prevention and intervention strategies aimed at addressing anxiety and depression.[17] Another network analysis study revealed that the relationships between specific dimensions of impulsivity and components of problematic smartphone use play a particularly significant role in the development and persistence of problematic smartphone use among Chinese college students.[18] Furthermore, the recent study using network analysis indicated that the protective and risk mental factors are evolving over time in adolescents.[19] However, a single summative investigation cannot clarify the specific and overall relationships between these diverse symptoms and SMA. Therefore, it is necessary to conduct a more fine-grained analysis to explore the interplay between SMA and mental and behavioral factors, thus enhancing knowledge regarding the pathological pathways involved in these associations. Improving knowledge regarding these associations can also lead to the identification of appropriate targets that effectively inhibit the effects of SMA on diverse mental and behavioral health symptoms.

Network analysis, which represents a novel data-driven methodology, is employed to appraise the correlations that exist between complex variables.[20,21] Psychometric network analysis has two basics: nodes and edges. Usually, variables like mental symptoms (such as depression, anxiety) are shown as nodes, attributes of a node (such as size, color, shape) can be used to represent additional information, such as the influence weight, importance, or category of the node. An edge means a partial link between two nodes, the weight of an edge indicates the strength or importance of the relationship.[21,22] Nodes with high centrality tend to be important for the stability of the network, and in psychological or behavioral networks, nodes with high centrality may be key targets for intervention. Connections between nodes can be determined through an intuitive visual network. If there is a line (edge) between the nodes, it means that they are connected, and the color and thickness of the line can indicate the positive and negative relationship and strength of the connection, respectively. In general, the edges with the greatest connection strength tend to occur between the nodes with the greatest centrality. Therefore, network analysis is likely to assist in pinpointing the key variables as well as the distinct relationships that exist between SMA and mental and behavioral elements.

Apart from network analysis, community detection is another valuable psychometric approach. In a given network, the detected communities are groups of nodes. It's possible to identify one or multiple such communities within a network.[23,24] One node may influence a given community but may also have an overlapping effect on another community at the same time. Community detection identifies groups of items in the network that share statistical or conceptual similarities and cluster together into a community.[25,26] Hence, the community serves as a comprehensive summary akin to that in principal component analysis. Notably, it has an edge by incorporating the connections not only within but also between communities.[27,28] Given the strength of community detection, this approach is ideal for demonstrating the clustered and overlapped items/nodes of mental and behavioral factors and SMA.

The present study is to focus on the population of undergraduate students and to improve our understanding of the relationships between SMA, multiple mental health factors and behavioral symptoms (including depression, anxiety, loneliness, stress, life satisfaction and behavioral activation and inhibition) via two psychometric approaches. According to previous studies, we hypothesized that:[1] depression and anxiety would demonstrate the highest centrality compared with other mental health factors (stress, loneliness and life satisfaction), while BAS factors would play more central role within the behavioral activation and inhibition factors;[2] SMA would exhibit stronger connections with depression and anxiety compared to other mental health factors, and would also show a stronger association with the BAS factors than with the BIS.

Methods

Participants

In the initial sample, 902 undergraduate students took part in the primary research questionnaire for next analysis inclusion. But 201 did not finish all the scales (including lack of information, incorrect filling, etc)., so 701 participants (aged 18.27 ± 1.57, 47.6% male) who reported their smartphone use were analyzed. Prior to data collection, informed consent was obtained, ensuring participants that data was for research only with privacy safeguards.

Measures

Smartphone Addiction (SMA)

The level of smartphone addiction was gauged by employing the Chinese version of the Smartphone Addiction Scale-short version (SAS-SV).[29] The scale consists of ten items, with each one scored on a six-point Likert scale: 1 represents "strongly disagree", 2 is "disagree", 3 means "somewhat disagree", 4 stands for "somewhat agree", 5 denotes "agree", and 6 indicates "strongly agree". For males, a score of 31 or above, and for females, a score of 33 or greater, is indicative of smartphone addiction. For example, "I can't wait to turn on my phone early or use it every chance I get". The Cronbach's α coefficient was 0.84 in present sample.

Behavioral Inhibition/Activation System (BIS/BAS)

The Chinese version of the BIS/BAS scale was utilized to measure the Behavioral Inhibition/Activation System (BIS/BAS).[30] This 20-item scale employs a 4-point Likert scale for scoring, where 1 stands for "strongly agree" and 4 for "strongly disagree". It comprises one subscale for gauging the BIS (with 7 items) and three subscales for evaluating the BIS (13 items in total): reward responsiveness (BAS-RR, 4 items), drive (BAS-D, 4 items), and fun seeking (BAS-FS, 5 items). The BIS reflects avoidance behaviors mediated by anxiety and fear. The BAS-RR indicates individual's positive response to an environment or expected reward, the BAS-D reflects the motivation and enthusiasm of the individual to pursue rewards, the BAS-FS reflects the individual's desire to explore new and exciting activities. For example, "I'm afraid I'll make a mistake" for BIS, "I'm excited about winning the game" for BAS-RR, "I'll do whatever it takes to get what I want" for BAS-D, "I like excitement and novelty' for BAS-FS. The Cronbach's α coeficient was 0.81 for BIS, 0.79 for BAS-RR, 0.80 for BAS-D and 0.75 for BAS-FS in present sample.

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Mental Health Factors

Depression

To assess depressive symptoms, the Chinese version of the Center for Epidemiological Studies Depression Scale (CES-D) was employed.[31] The CES-D features 9 items, each scored on a 0–3 Likert scale, gauging the frequency of relevant depressive symptoms over the preceding week. Evidently, a higher CES-D score indicates more pronounced depression symptoms. For example, "I'm upset about little things". The Cronbach's α coefficient was 0.85 in present sample.

Anxiety

The Generalized Anxiety Disorder 7-Item Questionnaire (GAD-7) is employed to assess anxiety symptoms.[32] It consists of seven items, which are scored on a 4-point Likert scale. The higher the GAD-7 score, the more severe the anxiety symptoms. For example, "Feel uneasy, worried and irritable". The Cronbach's α coefficient was 0.83 in present sample.

Stress

The Chinese Perceived Stress Scale (CPSS) is applied to evaluate individual's personal sense of stress.[33] Comprising 14 items, it adopts a 5-point Likert scale that spans from "never" to "always". Notably, higher scores on this scale signify greater levels of perceived stress. For example, "You don't feel in control of what's important in your life". The Cronbach's α coefficient was 0.81 in present sample.

Loneliness

The UCLA Loneliness Scale's 3-item short version[29] was put to use. Here, a score of 1 signified "rarely", 2 stood for "sometimes", and 3 meant "often". A greater score on this scale pointed to a more severe level of loneliness. For example, "Do you often feel a lack of company?". The Cronbach's α coefficient was 0.86 in present sample.

Life Satisfaction

The Chinese adaptation of the Life Satisfaction Scale (SWLS) is employed to gauge an individual's overall subjective perception of life satisfaction.[34] It's a commonly utilized 5-item self-rating scale with a 7-point Likert scale, where 1 corresponds to "completely inconsistent" and 7 to "completely consistent". Evidently, a higher score on this scale implies a greater level of life satisfaction. For example, "My life situation is perfect'. The Cronbach's α coefficient was 0.86 in present sample.

Statistical Analysis

A normal distribution examination was implemented for the variables involved in the network analysis, while an independent sample *t* test was executed based on the smartphone addiction level. These analyses were performed in SPSS 21.0 software, the significance level was set at 95%.

Network Analysis

We used the R package *q*graph 1.9.8 to do the network analyses. Here, nodes act as the representatives of the specific items that are incorporated into the network analysis framework. These nodes are interconnected by what we refer to as edges. These edges are not just simple connections; they signify partial correlations that have been carefully derived after taking into account all other possible correlations within the system. Thicker lines meant stronger correlations. Blue edges were for positive correlations, red for negative. We calculated node correlations with polychoric correlations and estimated the network with the Gaussian graphical model (GGM).[35] GGM is a probabilistic graph model based on Gaussian distribution, which is used to represent the conditional independent structure in the multivariate normal distribution. It shows the conditional dependencies between variables in the form of a graph, where nodes represent variables and edges represent conditional dependencies between variables. The Fruchterman-Reingold algorithm helped us place the nodes in the graph – the closer to the middle, the stronger the node's connection, by simulating a physical system, the nodes of the graph are regarded as charged particles and the edges as springs, and the position of the nodes is adjusted iteratively to achieve the equilibrium state with the lowest energy.[36] To tackle potential false-positive edges during network analysis, we utilized the least absolute shrinkage and selection operator (LASSO)[37,38] and the extended Bayesian information criterion (EBIC).[39,40] LASSO functions by shrinking all edges and reducing small ones precisely to zero, thereby yielding a more stable and sparse network that lends itself more readily to interpretation,[37] it is a linear regression method, by adding L1 regularization terms to the regression model, variable selection and model simplification. Meanwhile, the EBIC estimates 100 network models with varying degrees of sparsity and ultimately opts for the model sporting the lowest EBIC value,[41] EBIC is an extended form of Bayesian Information Criteria (BIC) for model selection in high-dimensional data, it introduces a penalty term on the basis of BIC to better deal with variable selection in high-dimensional data. The construction of the network was grounded on Spearman correlation coefficients.

In this study, we focused on calculating the Expected Influence (EI) value to measure node centrality. The EI value, which is the sum of all an item's edges in the network, reflects its connection to other items.[18] Simply put, a larger EI value means a more important node with greater activation.[42] We did not report traditional centrality indicators like strength, closeness, and betweenness, as they tend to be unstable.[42,43] We adopted the bootstrapping technique within the R package bootnet to evaluate the stability of the EI values by gauging 95% confidence intervals.[20,41] Additionally, the centrality stability coefficient (CS coefficient) served as a benchmark for appraising the stability of the EI. Values exceeding 0.25 were deemed satisfactory, while those surpassing 0.5 were more desirable.[20,22]

Community Detection

We employed bootstrap exploratory graph analysis (EGA) with 1000 samples. This was done to compute the polychoric correlation and, via the Walktrap algorithm, to identify communities within the partial correlation matrix. The Polychoric correlation is a statistical method used to measure the correlation between two ordered categorical variables. It assumes that these ordered variables are the result of discretization based on latent continuous variables. The Walktrap algorithm is a random walk-based community discovery method, it identifies the community structure in the network by the similarity of random walks. The variables used for these operations were the same as those in the network analysis.[23,26,44] The Walktrap algorithm is based on random walks through the network to measure the similarity between vertices. We used EGAnet to calculate the network loading value of the item in the community.[45] Loading not only affected the local community but also allowed to be loaded on all other communities. A larger loading value implies a stronger impact of the node on the community. Regarding the cutoff values for network loading effect sizes, they were set as follows: a value of 0.15 represents a small effect, 0.25 denotes a moderate effect, and 0.35 signifies a large effect.[26,46] The stability of an item was gauged by determining the proportion of occasions in which the item was grouped together with its community characteristics within the replicated bootstrapped samples.[27,47]

In the present study, we combined visual network graphs and quantitative results for the most comprehensive analysis.[26,48]

Results

Sample Characteristics

The cross-sectional study included 701 students who reported smartphone use scores; 294 youths had smartphone addiction, and 407 youths did not. Table 1 summarizes the participants' demographics and clinical features. All of the network analysis variables were normally distributed. The two groups were comparable in terms of age, but SMA participants had significantly higher smartphone use scores than non-SMA participants (p = 0.000). Regarding the BIS/

Table 1 Demographic Summary and Clinical Information for the Present Sample (M±SD)

	SMA (N=294)	Non-SMA (N=407)	Total (N=*701*)	*t*	*p*	*Skewness*	*Kurtosis*
Age	18.27±1.33	18.26±1.73	18.27±1.57	−0.02	0.98		
Gender (male/female)	203/204	164/130	367/334				
Smartphone Addiction	41.38±7.09	23.69±6.26	31.11±10.96	34.91	0.000	0.31	−0.06

(*Continued*)

Table 1 (Continued).

	SMA (N=294)	Non-SMA (N=407)	Total (N=*701*)	*t*	*p*	*Skewness*	*Kurtosis*
Behavioral Inhibition/Activation System Variables							
BAS-Reward Responsiveness	13.59±1.98	13.30±2.08	13.42±2.04	1.87	0.06	−0.96	1.76
BAS- Fun Seeking	**15.74±2.72**	**14.77±2.78**	15.18±2.79	**4.62**	**0.000**	−0.22	−0.06
BAS-DRIVE	12.10±2.27	12.42±2.46	12.29±2.39	−1.79	0.07	−0.33	0.02
BIS	**20.29±2.98**	**19.10±3.16**	19.60±3.14	**5.05**	**0.000**	−0.34	0.66
Mental Health Factors							
Depression	**7.53±4.94**	**5.35±4.32**	6.27±4.72	**6.18**	**0.000**	0.83	0.49
Anxiety	**5.05±5.13**	**2.98±4.03**	3.85±4.64	**6.00**	**0.000**	1.36	1.21
Loneliness	**4.92±1.53**	**4.56±1.58**	4.71±1.57	**3.07**	**0.002**	0.51	−0.52
Stress	**39.90±7.39**	**35.40±7.77**	37.29±7.93	**7.74**	**0.000**	0.11	0.20
Life Satisfaction	**20.60±6.21**	**22.56±6.35**	21.74±6.36	**−4.07**	**0.000**	−0.15	−0.23

Notes: Kurtosis and skewness provide the normality of the sample data. The bold text represents a significant difference between SMA and Non-SMA on this variable.
Abbreviations: BAS, Behavioral Activation System; BIS, Behavioral Inhibition System.

BAS, SMA participants had significantly higher scores for the BIS and BAS-fun seeking scales (p = 0.000). With respect to the clinical variables, SMA participants exhibited substantially elevated levels of depression, anxiety, loneliness, and stress conditions but significantly lower levels of life satisfaction than the non-SMA participants did (all p<0.01).

Network Analysis

Nodes Centrality

First, we did the centrality estimation to examine the hypothesis 1. Figure 1a presents the centrality estimation of all nodes. Notably, the centrality difference test (Figure S1) revealed that nodes of BAS-FS (0.96), BAS-RR (0.93), depression (0.75), BIS (0.69) and anxiety (0.66) had significantly higher EI values than all other nodes in the network did. This indicates that these nodes exerted a significant influence on the overall network structure and functionality.

Nodes Connection

Secondly, we aimed to explore the network structure in all participants to examine hypothesis 2. The adaptive LASSO network in Figure 1b shows the relationships among SMA, the BIS/BAS and the five psychological health factors. Nodes within the BIS/BAS and psychological health factors were shown to be closely interconnected in general. Specifically, positive connections between depression and anxiety (edge: 0.35), BAS-RR and BAS-FS (edge: 0.32), BAS-D and BAS-FS (edge: 0.30), depression and stress (edge: 0.30), BIS and BAS-RR (edge: 0.28), and BAS-RR and BAS-D (edge: 0.27) showed significant edge differences compared with all other edges (Figure S2). More importantly, positive transconnections were found between SMA and stress (edge: 0.21), between SMA and BAS-FS (edge: 0.14), between SMA and BIS (edge: 0.14), and between the BAS-D and stress (edge: 0.18).

Network Stability

Ultimately, with regard to the stability of node centrality, the correlation stability coefficient of the EI attained a value of 0.75, denoting remarkable stability. The resultant data concerning the stability of centrality EI, as well as the precision of edge weights, are illustrated in Figures S3 and S4.

Community Detection

Figure 2 presents the bootstrapped EGA used to detect communities. Two community structures were shown in 1000 bootstrapped samples (100%), community 1 was composed of all the mental health factors, and the other community 2

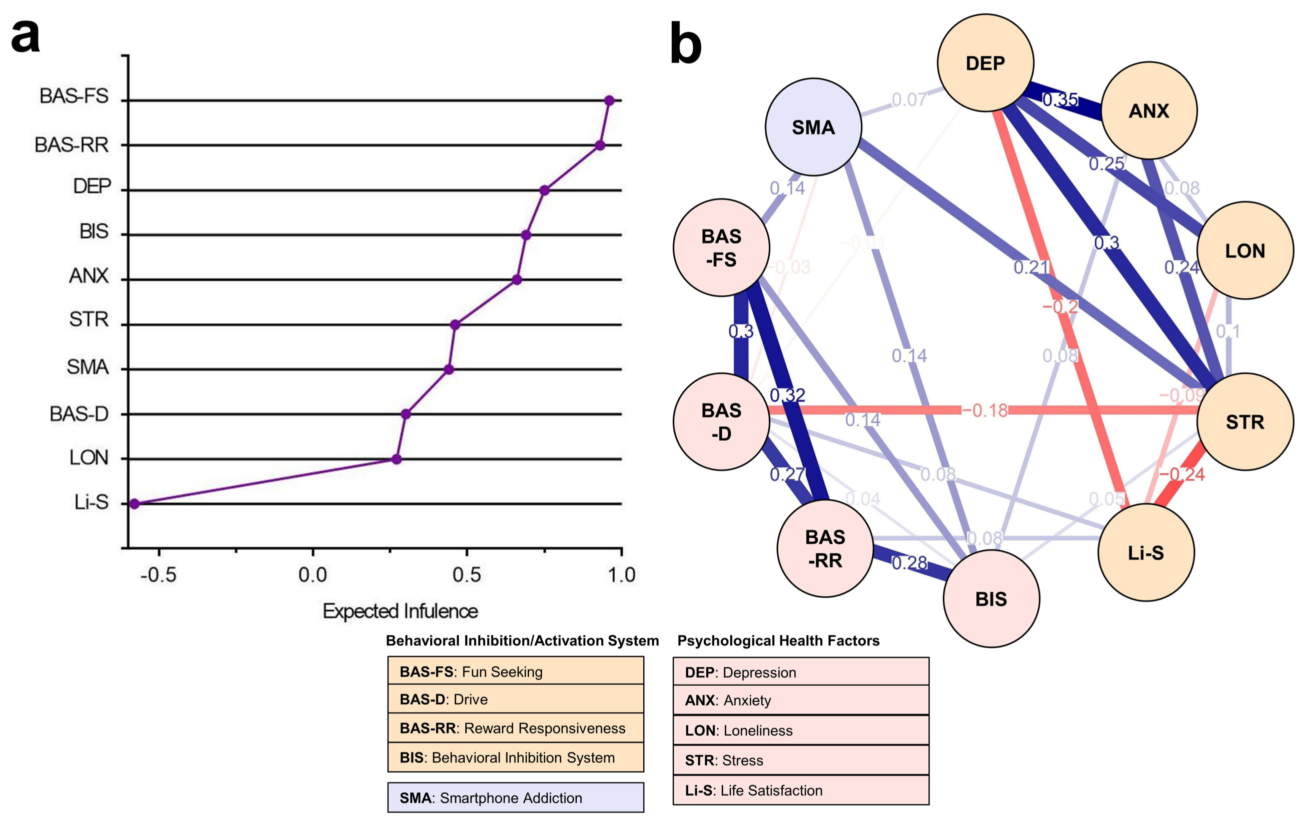

Figure 1 Expected influence estimates (**a**) and transdomain network (**b**) of smartphone addiction, the BIS/BAS system and psychological health factors.

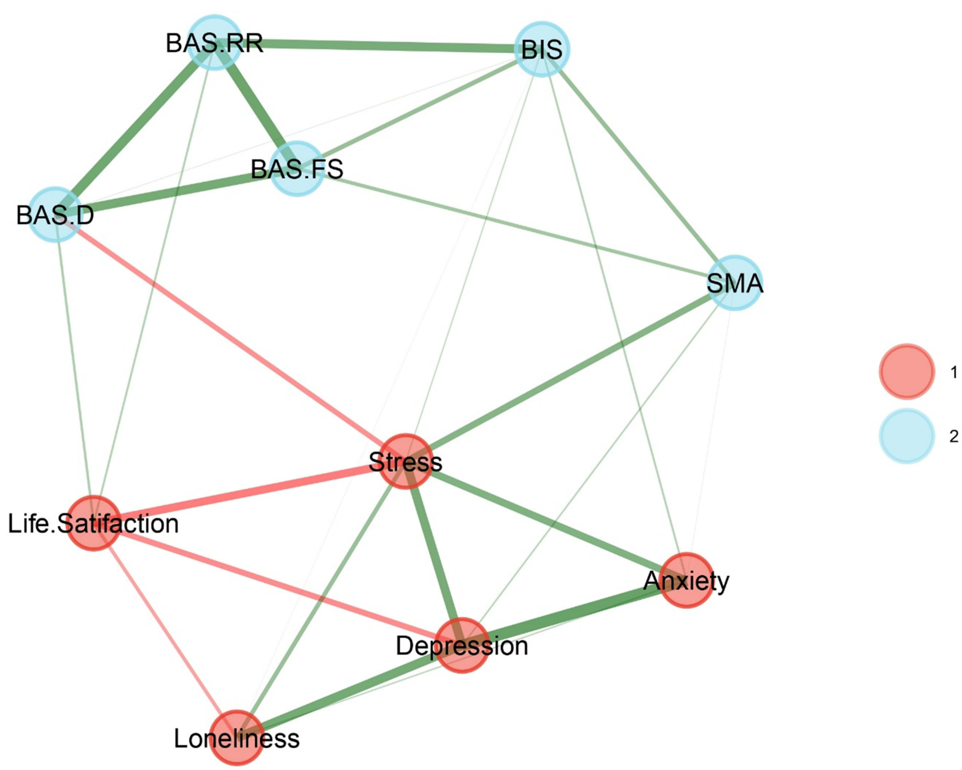

Figure 2 Bootstrap exploratory graph analysis for community detection of smartphone addiction, the BIS/BAS system and psychological health factors.
Notes: Red represents community 1, and blue represents community 2. The nodes represent the following: BAS, Behavioral Activation System; RR, Reward Responsiveness; BAS-D, Drive; BAS-FS, Fun Seeking; BIS, Behavioral Inhibition System.

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Table 2 Item Replicability and Network Loadings of the Two Communities on the Basis of Bootstrap Exploratory Graph Analysis

	Item Replicability		Network Loading	
Community	**1**	**2**	**1**	**2**
Smartphone Addiction	NA	0.68	0.12	0.12
Behavioral Inhibition/Activation System Variables				
BAS-Reward Responsiveness	1	NA	-	0.45
BAS- Fun Seeking	1	NA	-	0.43
BAS-DRIVE	1	NA	0.12	0.30
BIS	1	NA	-	0.27
Mental Health Factors				
Depression	NA	1	0.52	-
Anxiety	NA	1	0.32	-
Loneliness	NA	1	0.25	-
Stress	NA	1	0.42	0.21
Life Satisfaction	NA	1	0.25	-

Abbreviations: BAS, Behavioral Activation System; BIS, Behavioral Inhibition System.

was composed of SMA and BIS/BAS factors. Except for SMA, which was replicated in 680 bootstrapped samples (68%), all other community items were replicated in 1000 samples (100%).

Table 2 presents the item replicability and network loadings for all nodes within the two identified communities. First, we observed that the item replicability of each node was sufficiently high to ensure the stability of the communities. Notably, depression (0.52) and stress (0.42) exhibited the highest loadings in Community 1, while BAS-RR (0.45) and BAS-FS (0.43) demonstrated stronger loadings compared to other items in Community 2. More importantly, the observed overlap between the communities suggests that stress and BAS-D lack adequate differentiation, indicating that they may not require independent treatment modalities.

Discussion

In the present study, we explored the relationships among SMA, behavioral activation and inhibition characteristics and mental health factors among undergraduate students. Based on the results from psychometric approaches of network analysis and community detection, the present study offers new perspectives for understanding the relationships among SMA symptoms and mental health and behavioral characteristics among undergraduate students.

First, the centrality test supported the hypothesis 1. Prior research has demonstrated that excessive or problematic use of smartphones correlates with a heightened likelihood of experiencing depression and anxiety, as well as an amplified perception of stress and feelings of loneliness[49,50] or lower life satisfaction[51] in children, adolescents and young people. Consistent with these results, our network structure further revealed that depression and anxiety had greater centrality among the mental health factors, which suggested that depression and anxiety still play vital roles in SMA. Moreover, it was observed that among all the elements in the network, the behavioral activation factors exhibited the highest centrality, with BAS-FS and BAS-RR being particularly prominent. This finding aligns with the outcomes of previous network analyses concerning problematic smartphone use and the BIS/BAS, wherein it was shown that BAS-RR possessed relatively higher EI values among young individuals.[17,52] The higher centrality of BAS-FF and BAS-RR suggests that these two variables exert the greatest influence within the network, potentially playing a pivotal role in activating other variables and sustaining the current psychopathological network. Consistent with the theoretical framework of the BAS system, BAS-FF reflects an individual's drive to pursue novel and exciting activities, while BAS-RR reflects the sensitivity and intensity of an individual's response to rewards.[53] Therefore, it can be speculated that the pursuit of positive stimuli and rewards may serve as a key behavioral activation mechanism, rather than behavioral inhibition or avoidance, in the context of smartphone use among undergraduate students. From a neuroanatomical perspective, the BAS is primarily associated with brain regions such as the prefrontal cortex, amygdala, basal ganglia, and the dopaminergic system.[54,55] These regions, in conjunction with neurotransmitter systems, collectively regulate an individual's sensitivity to rewards and approach-related behaviors. Consequently, future research could integrate behavioral and neural methodologies to provide converging evidence on the mechanisms underlying SMA among undergraduate students.

Based on the previous studies, we hypothesized that SMA would be closely associated with depression or anxiety compared with other mental health factors. By integrating the results of the network analysis and the Exploratory Graph Analysis (EGA) community detection, a "community" is typically defined as a subset of nodes within a network that exhibit stronger internal connections compared to external connections. This concept helps to further elucidate the relationships and clustering patterns among nodes. However, contrary to expectations, we did not observe that SMA had stronger connections with depression or anxiety within the network. Instead, stress presented a relatively strong connection with SMA. At the same time, stress was connected with depression with the highest edge weights compared with all other edges. From this perspective, we suggest that stress may play a mediating role between SMA and depression and reveal the specific effect path between SMA and stress and depression when we consider multiple factors in one network. This result also indicated the advantages of network analysis in terms of handling possible false-positive edges,[26] which refer to connections (edges) between nodes that are incorrectly identified as present when they do not actually exist in the true underlying network.[56] These edges can distort the structure and properties of the network, leading to inaccurate conclusions about the relationships and interactions among nodes. Therefore, this effect implied that the results in present study do not overestimate the centrality of nodes and the correct representation of connections.

Based on hypothesis 2, in the entire transdomain network, we further observed that stress mediated the relationship between SMA and behavioral activation, especially with the BAS-D. Bootstrapped EGA analysis demonstrated that stress and BAS-D not only loaded in their own community 1 but also loaded in the other's community 2. The network connections also indicated that the connections between the BAS-D score and stress score had higher weights than the other connections between the BIS/BAS score and mental health factors. The BAS-D relates to the effort and determination that an individual demonstrates to achieve a goal.[57] On the basis of these findings, we suggest that a higher level of SMA is positively correlated with higher levels of perceived stress and lower behavioral inner drive. Previous studies have indicated that positive motivation decreases the risk of SMA[58] and that there is a positive relationship between use motivation and SMA.[59] On the basis of these findings, we suggest that stress could be a potential target to improve inner behavioral drive and alleviate SMA in young individuals.

Therefore, the present study provides new insight into how stress should be considered in the relationships between SMA, depression and behavioral activation among college freshmen. Most college students face many sources of stress; in fact, the transition to college-stage learning itself is considered a source of stress because it comes with higher levels of academic independence (such as fewer hours of homework than the high school stage).[60,61] Before college, Chinese adolescents usually experience different types of stress because families and education emphasize academic performance, which leads to greater mental health problems and lower life satisfaction.[62,63] The negative correlation between stress and life satisfaction in our sample suggests that this influence persists during their transition to the university. Smartphones are usually used as tools to alleviate depression and anxiety; however, this relationship does not act directly. The evidence has shown that the associations between SMA and emotional issues are mediated by additional variables that differ from those associated with chemical addiction, such as interpersonal problems or sleep quality, in undergraduate students.[64,65] In our study, we suggested that this relationship could be mediated by stress. In addition, the relatively weak positive connection between SMA and the BIS in the present study also supported the evidence that inadequate impulse control results in uncontrollable urges and excessive mobile phone use.[13] Recent research has shown that in the context of stress in the first year of college, students' negative sense of urgency in response to impulses is most closely associated with stress,[66] and stress exposure is associated with impulsivity and food or alcohol addiction at different life times.[67] However, there is no evidence that the relationship between the SMA and behavioral activation may be mediated by stress, and the transconnections among SMA, stress and BAS-D in the present study indicate that more work is needed to explore the detailed mechanism involved in these relationships.

These findings also suggest that in future studies considering the relationships among variables, a more comprehensive examination may provide a better understanding of the differences between SMA and different psychopathological variables.[68] Furthermore, a more comprehensive and clear understanding of these relationships could offer valuable insights for contributing to the development of more effective intervention strategies in smartphone addiction scenarios.[69]

The current research endeavor was not without its limitations, which warrant our attention. Firstly, given that the study adopted a cross-sectional design, it precluded the establishment of causal relationships. As such, it is advisable that a longitudinal study be carried out in the future to address this shortcoming. Secondly, as digital technology has developed, objective smartphone use records can be obtained from devices,[5] thus providing data that overcome the shortcomings of self-reported smartphone addiction. Lastly, considering all participants were from China, the findings may not be applicable to college students from other districts or countries.

Conclusion

Smartphone addiction has emerged as a growing concern among undergraduate students, with significant implications for their mental health and behavioral patterns. This study employs a network analysis approach to investigate the complex interplay between these factors. Our findings suggest that stress may play a potentially positive regulatory role in the relationship between smartphone addiction, depression, and behavioral activation among undergraduate students. This discovery holds substantial value for enhancing mental health interventions related to smartphone addiction and fostering more effective mobile phone management strategies among the student population.

Data Sharing Statement

The code of above analyses could be obtained from: https://osf.io/mqphe/. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Ethics Approval and Informed Consent

This study was approved by the Ethics Committees of the Shanghai University of Sport. The revised manuscript complies with the Declaration of Helsinki.

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

The authors report no conflicts of interest in this work.

References

1. CNNIC. The 55th statistical report on China's internet development 2025. Available from: https://www3.cnnic.cn/NMediaFile/2025/0220/MAIN1740036167004CKE0DITFO1.pdf. Accessed April 17,2025.
2. Lin YH, Chang LR, Lee YH, Tseng HW, Kuo TB, Chen SH. Development and validation of the smartphone addiction Inventory (SPAI). *PLoS One*. 2014;9(6):e98312. doi:10.1371/journal.pone.0098312
3. Lee K-W, Ching S-M, Ali N, et al. Prevalence and factors associated with smartphone addiction among adolescents–a nationwide study in Malaysia. *Int J Ment Health Promot*. 2023;25(2):237–247.
4. Yilmaz R, Sulak S, Griffiths MD, Yilmaz FGK. An exploratory examination of the relationship between internet gaming disorder, smartphone addiction, social appearance anxiety and aggression among undergraduate students. *J Aff Disor Rep*. 2023;11:100483. doi:10.1016/j.jadr.2023.100483
5. Olson JA, Sandra DA, Colucci ÉS, et al. Smartphone addiction is increasing across the world: a meta-analysis of 24 countries. *Comp Human Behavior*. 2022;129:107138. doi:10.1016/j.chb.2021.107138
6. Long J, Liu TQ, Liao YH, et al. Prevalence and correlates of problematic smartphone use in a large random sample of Chinese undergraduates. *BMC Psychiatry*. 2016;16(1):408. doi:10.1186/s12888-016-1083-3
7. Meng SQ, Cheng JL, Li YY, et al. Global prevalence of digital addiction in general population: a systematic review and meta-analysis. *Clinic Psychol Rev*. 2022;92:102128. doi:10.1016/j.cpr.2022.102128
8. Lai X, Huang S, Nie C, et al. Trajectory of problematic smartphone use among adolescents aged 10-18 years: the roles of childhood family environment and concurrent parent-child relationships. *J Behav Addict*. 2022;11(2):577–587. doi:10.1556/2006.2022.00047
9. Lyu C, Cao Z, Jiao Z. Changes in Chinese college students' mobile phone addiction over recent decade: the perspective of cross-temporal meta-analysis. *Heliyon*. 2024;10(11):e32327. doi:10.1016/j.heliyon.2024.e32327
10. Mei S, Hu Y, Wu X, et al. Health risks of mobile phone addiction among college students in China. *Int J Ment Health Addict*. 2023;21(4):2650–2665.
11. Chen G, Lyu C. The relationship between smartphone addiction and procrastination among students: a systematic review and meta-analysis. *Pers Individ Dif*. 2024;224:112652. doi:10.1016/j.paid.2024.112652
12. Augner C, Vlasak T, Aichhorn W, Barth A. The association between problematic smartphone use and symptoms of anxiety and depression-a meta-analysis. *J Public Health*. 2023;45(1):193–201. doi:10.1093/pubmed/fdab350
13. Li Y, Li G, Liu L, Wu H. Correlations between mobile phone addiction and anxiety, depression, impulsivity, and poor sleep quality among college students: a systematic review and meta-analysis. *J Behav Addict*. 2020;9(3):551–571.
14. Nikolic A, Bukurov B, Kocic I, et al. Smartphone addiction, sleep quality, depression, anxiety, and stress among medical students. *Front Public Health*. 2023;11:1252371.
15. Karaoglan Yilmaz FG, Avci U, Yilmaz R. The role of loneliness and aggression on smartphone addiction among university students. *Current Psychology*. 2022;1–9.
16. Su P, He M. The mediating role of loneliness in the relationship between smartphone addiction and subjective well-being. *Sci Rep*. 2024;14(1):4460. doi:10.1038/s41598-024-54546-3
17. Guo Z, Yang T, Qiu R, et al. Network analysis of the relationships between problematic smartphone use and anxiety, and depression in a sample of Chinese college students. *Front Psych*. 2023;14:1097301. doi:10.3389/fpsyt.2023.1097301
18. Guo Z, He Y, Yang T, et al. The roles of behavioral inhibition/activation systems and impulsivity in problematic smartphone use: a network analysis. *Front Public Health*. 2022;10:1014548.
19. Ji X, Feng N, Zhao T, Cui L. Protective and risk factors in problematic mobile phone use among adolescents: a three-wave longitude study. *Addict Behav*. 2025;165:108299. doi:10.1016/j.addbeh.2025.108299
20. Epskamp S, Fried EI. A tutorial on regularized partial correlation networks. *Psycholog Methods*. 2018;23(4):617–634. doi:10.1037/met0000167
21. Borsboom D, Cramer AO. Network analysis: an integrative approach to the structure of psychopathology. *Ann Rev Clin Psych*. 2013;9:91–121. doi:10.1146/annurev-clinpsy-050212-185608
22. Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D. Qgraph: network visualizations of relationships in psychometric data. *J Statis Software*. 2012;48:1–18. doi:10.18637/jss.v048.i04
23. Golino HF, Epskamp S, Voracek M. Exploratory graph analysis: a new approach for estimating the number of dimensions in psychological research. *PLoS One*. 2017;12(6):e0174035. doi:10.1371/journal.pone.0174035
24. Hoffman M, Steinley D, Gates KM, Prinstein MJ, Brusco MJ. Detecting clusters/communities in social networks. *Multi Behav Res*. 2018;53(1):57–73. doi:10.1080/00273171.2017.1391682
25. Jones PJ, Ma R, McNally RJ. Bridge centrality: a network approach to understanding comorbidity. *Multi Behav Res*. 2021;56(2):353–367. doi:10.1080/00273171.2019.1614898
26. Abplanalp SJ, Braff DL, Light GA, Nuechterlein KH, Green MF. Understanding connections and boundaries between positive symptoms, negative symptoms, and role functioning among individuals with schizophrenia: a network psychometric approach. *JAMA Psych*. 2022;79(10):1014–1022. doi:10.1001/jamapsychiatry.2022.2386
27. Christensen AP, Golino H. Estimating the stability of psychological dimensions via bootstrap exploratory graph analysis: a monte carlo simulation and tutorial. *Psychiatry Res*. 2019.
28. Christensen AP, Golino H, Silvia PJ. A psychometric network perspective on the validity and validation of personality trait questionnaires. *Europ J Personal*. 2019;34(1095):–108.
29. Kwon M, Kim D-J, Cho H, Yang S, Choi D-S. The smartphone addiction scale: development and validation of a short version for adolescents. *PLoS One*. 2013;8(12):e83558. doi:10.1371/journal.pone.0083558
30. Zy LY, Jiang Y, Li H, et al. The Chinese version of the bis/bas scale: reliability and validity. *Chin Mental Health J*. 2008;(08):613–616.
31. He J. *Development of the Chinese Center for Epidemiological Studies Depression Scale*. Beijing: Graduate School of Chinese Academy of Sciences; 2014.
32. Spitzer RL, Kroenke K, Williams JBW, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch Internal Med*. 2006;166(10):1092–1097. doi:10.1001/archinte.166.10.1092

33. Huang Y. An epidemiological study on stress among urban residents in social transition period. *Chin J Epidemiol*. 2003;(09):11–15.
34. Yuanli XCX. Reliability and validity of the satisfaction with life scale for Chinese demos. *China J Health Psychol*. 2009;(8):2.
35. Wainwright MJ, Jordan MI. Graphical Models, Exponential Families, and Variational Inference. *J Found Trends Mach Learn*. 2008;1:1–305.
36. Fruchterman TMJ, Reingold EM. Graph drawing by force-directed placement. *Software Prac Exper*. 1991;21.
37. Friedman J, Hastie T, Tibshirani R. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*. 2008;9(3):432–441. doi:10.1093/biostatistics/kxm045
38. Costantini G, Epskamp S, Borsboom D, et al. State of the aRt personality research: a tutorial on network analysis of personality data in R. *J Res Personality*. 2015;54:13–29. doi:10.1016/j.jrp.2014.07.003
39. Foygel R, Drton M, editors. *Extended Bayesian Information Criteria for Gaussian Graphical Models*. NIPS; 2010.
40. Chen J, Chen Z. Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*. 2008;95(3):759–771. doi:10.1093/biomet/asn034
41. Epskamp S, Borsboom D, Fried EI. Estimating psychological networks and their accuracy: a tutorial paper. *Behavior Res Methods*. 2016;50(195):–212.
42. Robinaugh DJ, Millner AJ, McNally RJ. Identifying highly influential nodes in the complicated grief network. *J Abnormal Psychol*. 2016;125(6):747–757. doi:10.1037/abn0000181
43. Bringmann LF, Elmer T, Epskamp S, et al. What do centrality measures measure in psychological networks? *J Abnormal Psychol*. 2019;128(8):892–903. doi:10.1037/abn0000446
44. Golino H, Christensen AP, editors. *Exploratory Graph Analysis - a Framework for Estimating the Number of Dimensions in Multivariate Data Using Network Psychometrics*. [R package EGAnet version 0.9.6]; 2020.
45. Golino H, Shi D, Christensen AP, et al. Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: a simulation and tutorial. *Psycholog Methods*. 2018;25(3):292.
46. Christensen AP, Golino H. On the equivalency of factor and network loadings. *Behav Res Methods*. 2021;53(4):1563–1580. doi:10.3758/s13428-020-01500-6
47. Ribeiro Santiago PH, Manzini D, Haag D, Roberts R, Smithers LG, Jamieson L. Exploratory graph analysis of the strengths and difficulties questionnaire in the longitudinal study of Australian children. *Assessment*. 2022;29(8):1622–1640. doi:10.1177/10731911211024338
48. Jones PJ, Mair P, McNally RJ. Visualizing Psychological Networks: a Tutorial in R. *Front Psych*. 2018;9:1742. doi:10.3389/fpsyg.2018.01742
49. Sohn SY, Rees P, Wildridge B, Kalk NJ, Carter B. Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: a systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry*. 2019;19(1):356. doi:10.1186/s12888-019-2350-x
50. Reer F, Wehden LO, Janzik R, Quandt T. Examining the interplay of smartphone use disorder, mental health, and physical symptoms. *Front Public Health*. 2022;10:834835. doi:10.3389/fpubh.2022.834835
51. Horwood S, Anglim J. Problematic smartphone usage and subjective and psychological well-being. *Computers in Human Behavior*. 2019;97:44–50. doi:10.1016/j.chb.2019.02.028
52. Gao L, Zhao W, Chu X, Chen H, Li W. A network analysis of the relationships between behavioral inhibition/activation systems and problematic mobile phone use. *Front Psych*. 2022;13:832933. doi:10.3389/fpsyt.2022.832933
53. Davidson TL, Jarrard LE. The hippocampus and inhibitory learning: a 'gray' area? *Neurosci Biobehav Rev*. 2004;28(3):261–271. doi:10.1016/j.neubiorev.2004.02.001
54. Cohen MX, Young J, Baek J-M, Kessler C, Ranganath C. Individual differences in extraversion and dopamine genetics predict neural reward responses. *Brain Res Cognitive Brain Res*. 2005;25(3):851–861. doi:10.1016/j.cogbrainres.2005.09.018
55. Knutson B, Greer SM. Anticipatory affect: neural correlates and consequences for choice. *Philos Trans R Soc London, Ser B*. 2008;363(1511):3771–3786. doi:10.1098/rstb.2008.0155
56. Wang DJ, Shi X, McFarland DA, Leskovec J. Measurement error in network data: a re-classification. *Social Networks*. 2012;34(4):396–409. doi:10.1016/j.socnet.2012.01.003
57. Dong H, Zheng H, Wang M, Ye S, Dong GH. The unbalanced behavioral activation and inhibition system sensitivity in internet gaming disorder: evidence from resting-state Granger causal connectivity analysis. *Prog Neuro Psychopharmacol Biol Psych*. 2022;119:110582. doi:10.1016/j.pnpbp.2022.110582
58. Fischer-Grote L, Kothgassner OD, Felnhofer A. Risk factors for problematic smartphone use in children and adolescents: a review of existing literature. *Neuropsychiatrie Klinik, Diagnostik, Therapie und Rehab*. 2019;33(4):179–190. doi:10.1007/s40211-019-00319-8
59. Jin X, Jiang Q, Xiong W, Zhao W. Effects of use motivations and alexithymia on smartphone addiction: mediating role of insecure attachment. *Front Psych*. 2023;14:1227931. doi:10.3389/fpsyg.2023.1227931
60. Cleary M, Walter G, Jackson D. "Not always smooth sailing": mental health issues associated with the transition from high school to college. *Issues Mental Health Nurs*. 2011;32(4):250–254. doi:10.3109/01612840.2010.548906
61. Hörbo M, Johansson C, Garnow T, Garmy P, Einberg EL. Experiences of stress - a focus group interview study among Swedish adolescents during the COVID-19 pandemic. *J Sch Nurs*. 2023;39(2):189–197. doi:10.1177/10598405211071002
62. Stankov L. Depression and life satisfaction among European and Confucian adolescents. *Psycholog Asse*. 2013;25(4):1220–1234. doi:10.1037/a0033794
63. Zhou X, Bambling M, Bai X, Edirippulige S. Chinese school adolescents' stress experience and coping strategies: a qualitative study. *BMC Psych*. 2023;11(1):91. doi:10.1186/s40359-023-01137-y
64. Chen L, Yan Z, Tang W, Yang F, Xie X, He J. Mobile phone addiction levels and negative emotions among Chinese young adults: the mediating role of interpersonal problems. *Computers in Human Behavior*. 2016;55:856–866. doi:10.1016/j.chb.2015.10.030
65. Gardani M, Bradford DRR, Russell K, et al. A systematic review and meta-analysis of poor sleep, insomnia symptoms and stress in undergraduate students. *Sleep Med Rev*. 2022;61:101565. doi:10.1016/j.smrv.2021.101565
66. Seldin K, Lengua LJ, King KM. The relation between stress and impulsivity during the first year of college. *J Personal*. 2023;91(5):1189–1206. doi:10.1111/jopy.12792
67. McMullin SD, Shields GS, Slavich GM, Buchanan TW. Cumulative lifetime stress exposure predicts greater impulsivity and addictive behaviors. *J Health Psychol*. 2021;26(14):2921–2936. doi:10.1177/1359105320937055

68. Csibi S, Griffiths MD, Demetrovics Z, Szabo A. Analysis of problematic smartphone use across different age groups within the 'components model of addiction'. *Int J Mental Health*. 2019;(3). doi:10.1080/00207411.2019.1578612
69. Gu Y, Shan J, Huang T, et al. Exploring the interplay between addiction and time perception: a systematic review and meta-analysis. *Prog Neuro Psychopharmacol Biol Psych*. 2024;135:111104. doi:10.1016/j.pnpbp.2024.111104