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ORIGINAL ARTICLE

A Network Analysis Perspective on the Relationship Between Boredom, Attention Control, and Problematic Short Video Use Among a Sample of Chinese Young Adults

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Abstract
Playing short videos has been an everyday leisure activity in recent years, and problematic use has raised concerns. The present study was based on the boredom feedback model, using network analysis to explain the interactive relationships between boredom, attention control, and problematic short video use (PSVU) (in domain-level analysis) and elaborate visually on the symptom presentation and associations between these variables (in facet-level analysis). A sample comprising 632 Chinese young adults (330 males) aged 18–30 years completed self-report questionnaires to assess state boredom, boredom proneness, attention control, and PSVU. The results showed significant associations between state boredom, boredom proneness, attention control, and PSVU. In domain-level network, boredom proneness was the most central node. In facet-level network, inattention had the highest strength and closeness centrality, and conflict had the highest betweenness centrality. The findings suggested the intervention of inattention and conflict in PSVU users that will contribute to future research and practice.

Keywords Network analysis · State boredom · Boredom proneness · Attention control · Problematic short video use

In China, as of December 2022, the size of short video users exceeded one billion for the first time, of which the user usage rate grew from 78.2 to 94.8% in 2019–2022 (CNNIC, 2024). Short video users spend an average of 168 min daily on it, and young adults are the primary users (https://news.znds.com/article/62906.html). While short videos enrich people's lives, they may also create digital dependency or problematic use. Problematic short video use (PSVU) could be regarded as a specific form of general problematic social media use (PSMU), which manifests addiction-like symptoms (Yao et al., 2023), such as salience (e.g., a dominant preoccupation with short videos), tolerance (e.g., the need to utilize short videos to a greater extent to achieve the same level of pleasure), conflict (e.g., conflicts, both personal and interpersonal, as short-term pleasure leads to the neglect of long-term adverse consequences), and mood modifications (e.g., using short videos to adjust emotional states) (Ndasauka et al., 2019). Previous research has identified factors that directly affect PSMU and the negative effects that it triggers, such as negative emotions (e.g.,

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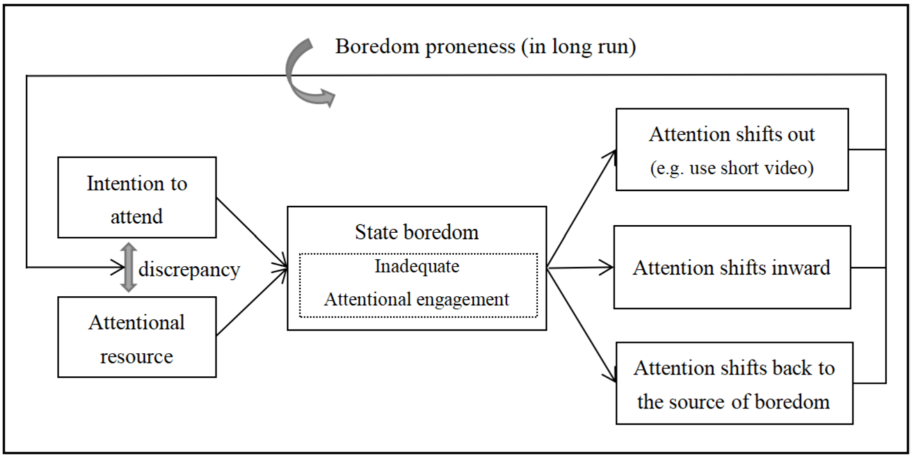

Fig. 1 Boredom feedback model (Tam et al., 2021) *Note* State boredom would arise when there is a discrepancy between individual desired (intention to attend) and actual attention engagement levels (attention resource). When experiencing boredom, people shift their attention outward (e.g., use short videos), inward, or back to the source of boredom to exit the boredom cycle. If the attention focus is insufficiently engaging, the model enters a feedback loop and starts again from the beginning. If the circle goes on and on, dysfunctional regulatory feedback loops may result in boredom proneness

boredom, anxiety, depression) (Hawes et al., 2020; Li et al., 2023; Lopes et al., 2022), impaired inhibitory control (Gao et al., 2019; Reed, 2023), and attention dysfunction (Fu et al., 2018). One of the critical factors is boredom (S. Huang et al., 2021; Yao et al., 2023). However, research on PSVU is just beginning to receive attention (N. Zhang et al., 2023; X. Zhang et al., 2019). Since short video platforms differ from traditional social media platforms (Yao et al., 2023), it is worth examining whether the literature on PSMUs can transfer an understanding of PSVU.

It is a common phenomenon that when people get bored, they take out their smartphones and gain amusement by swiping through short videos. Is there a correlation between boredom and PSVU? The boredom feedback model (BFM; Tam et al., 2021) (Fig. 1) points out that the core of state boredom is inadequate attention engagement, which is closely related to attention control. When experiencing boredom, people engage in trial-and-error learning through three forms of attention shifts (shift outward, inward, or back to the source of boredom) to test which strategies can exit the boredom cycle (Tam et al., 2021). In people's daily lives, short videos have been spreading rapidly in recent years. Short video platforms have powerful personalized algorithm recommendations that can push video content of interest to users (X. Wang et al., 2019). People would be drawn to the vast amount of content with a simple slide on the screen, allowing them to disrupt state boredom quickly. Individuals with poor attention control often experience an attention engagement drop, which can become a conditioned stimulus. Once attention engagement drops, people may alleviate the boredom experience by using short videos. If the circle goes on and on, dysfunctional regulatory feedback loops may result in chronic boredom (boredom proneness) (Tam et al., 2021). In addition, the negative reinforcement of the feedback loop may also develop into PSVU.

The boredom feedback model and some empirical studies have indicated that boredom is related to attention control and PSVU (Barkley & Lepp, 2021; Eastwood et al., 2012; Elhai et al., 2018; Ksinan et al., 2021). However, few studies have used network analysis as a radically new method of understanding the interactive relationships between these variables (Huang et al., 2021). Therefore, the present study used network analysis to better explain these relationships in a sample of Chinese adults (in domain-level analysis) and elaborate more visually on the symptom presentation and associations between boredom, attention control, and PSVU (in facet-level analysis).

The Relationship Between Boredom (Both State Boredom and Boredom Proneness) and PSVU

Boredom has two different constructs: state boredom and boredom proneness (trait boredom) (Mercer-Lynn et al., 2014). *State boredom* is an aversive state in which the individual wants to engage attention in a satisfying activity but fails (Eastwood et al., 2012). *Boredom proneness* has been defined as a tendency toward experiencing boredom (Farmer & Sundberg, 1986). Studies have found boredom proneness to predict risk behaviors (Layland et al., 2021; Oxtoby et al., 2019). Higher levels of boredom proneness contribute to Internet addiction (Chou et al., 2018; Liang et al., 2022), Internet gaming disorder (Ferraro et al., 2020; L. Li et al., 2021), smartphone addiction (Z. Wang et al., 2020; Wu-Ouyang, 2022; Zhao et al., 2021, 2022), and problematic social media use (Stockdale & Coyne, 2020; Yao et al., 2023). Meanwhile, previous studies have proven that state boredom alleviation is a common motivation for smartphone and social media use (Brailovskaia et al., 2020; Fullwood et al., 2017). However, research also suggests high-frequency cell phone usage could increase state boredom (Lepp et al., 2017). Donati et al. (2022) found that adolescents' boredom proneness leads to state boredom through the mediating mechanism of problematic Facebook use (PFU). Specifically, boredom proneness may be an antecedent of PFU. In turn, PFU also exacerbates adolescents' situational experience of state boredom. An experimental study found that 30 min of social media use produced higher state boredom levels than taking a course and walking in 30 min (Barkley & Lepp, 2021). Therefore, there may be an interaction between state boredom, boredom proneness, and PSVU.

H1: Boredom (both state boredom and boredom proneness) will be positively associated with PSVU.

The Relationship Between Attention Control and Boredom (Both State Boredom and Boredom Proneness)

Attention control is the ability to regulate attention allocation with attention shifting and attention focusing (Derryberry & Reed, 2002; Posner & Rothbart, 2000). Attention control can affect attention engagement (Gaertner et al., 2008; Tam et al., 2021). Low attention control levels can result in inadequate attention engagement, which is a significant characteristic of state boredom (Danckert & Merrifield, 2018; Hunter & Eastwood, 2018; Westgate & Wilson, 2018). Therefore, there is a close relationship between attention control and state boredom. And many studies have demonstrated the association between boredom proneness and low attention control (Crawford et al., 2023; Struk et al., 2017; X. Wang et al., 2021). An EEG study of go/no go also demonstrates that state boredom and boredom proneness are both associated with low attention control from an electrophysiologic perspective (Yakobi et al., 2021). Individuals with high boredom tendencies are more likely to experience more state boredom in daily life due to insufficient attentional control (Peng et al., 2020; Weiss et al., 2022). In turn, the BFM hypothesizes that individuals experiencing state boredom over time may gradually develop boredom proneness, ranging from a state deficit of attention engagement to a long-term impact on attentional control ability (Tam et al., 2021). Therefore, there may be an interaction between state boredom, boredom proneness, and attention control.

H2: Low attention control will be positively associated with high boredom (both state and boredom proneness).

The Relationship Between PSVU and Attention Control

Although few studies have attempted to examine the potential relationship between PSVU and attention control directly, some indirect findings suggest that such a relationship may exist. A study (Kay et al., 2017) investigated the frequency and impact of distracting activities using mobile technology devices in secondary school classrooms. Results indicated that more than half of the students occasionally or regularly engaged in social media activities despite their initial purpose of using mobile devices to complete learning tasks. Shifting attention between tasks and distracting activities was influenced by attention control (Posner & Rothbart, 1998). A hierarchical regression analysis study showed that the severity of attention-deficit/hyperactivity symptoms (ADHS), particularly attention deficit, was a predictor for Internet addiction risk (Dalbudak et al., 2015). Similarly, a meta-analysis found that children and adolescents with ADHD had more severe problematic Internet use compared to non-clinical controls without ADHD (Werling et al., 2022). These findings demonstrate the vital role of attention control ability in preventing PSMU. The other way around, one recent study utilizing a short video-watching task and a Stroop task based on eye-tracking technology found that addicted users were less centration and more distracted when dealing with interferences than non-addicted users (Y. Chen et al., 2022).

H3: PSVU will be positively associated with attention control.

Methods

Participants and Procedure

The present study utilized a cross-sectional design, and we used the Wenjuanxing platform (a popular Chinese survey website) to generate the link to the online questionnaire. Then, we sent the link to several of China's most popular social media platforms (Douyin, Kuaishou, Weibo, WeChat, Little Red Book, and QQ) with short video capabilities. Recruitment instructions and informed consent accompanied the link, and users who have had experience with short videos can participate in the survey. A total of 720 adults from 34 provincial administrative regions in China were recruited. We included adults in the 18–30 age range and excluded data from two attention check items (i.e., for this question, select "always") answered incorrectly and the same selecting response (i.e., they selected the same number). The final sample consisted of 632 participants (330 males [52.2%]) aged 18–30 years ($M = 21.94$, SD $= 2.64$). Additional participant information appears in Table 1. This project has been supervised and approved by the Institutional Review Board of the Faculty of Psychology, Southwest University. Participants who completed the questionnaire in good faith were paid 5 RMB.

Measures

The Multidimensional State Boredom Scale (MSBS)

The Multidimensional State Boredom Scale measures a concrete experience that is situated in time (MSBS, Fahlman et al., 2013). The Chinese version of MSBS was validated by Liu et al. (2013). This scale has 24 items with five subscales: inattention, time perception, low arousal, high arousal, and disengagement (e.g., "Time is passing by slower than usual," "My mind is wandering," and "Everything seems to be irritating me right now"). All items are scored on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Higher scores indicate a higher level of state boredom. In this study, Cronbach's alpha and McDonald's ω for the total scale were 0.962 and 0.962, 0.902 and 0.903 for inattention, 0.873 and 0.876 for time perception, 0.900 and 0.901 for low arousal, 0.892 and 0.894 for high arousal, and 0.820 and 0.824 for disengagement, respectively.

Table 1 Descriptive characteristics of the sample ($n = 632$)

Variables		*N* (100%)/mean ± SD
Age		21.94 ± 2.64
Gender	Male	330 (52.2%)
	Female	302 (47.8%)
Short video applications		
	Douyin	538 (85.1%)
	Kuaishou	287 (45.4%)
	Others	234 (37.0%)
Usage time (years)		
	< 1	12 (1.9%)
	1 ~ 2	56 (8.9%)
	2 ~ 3	152 (24.1%)
	3 ~ 4	164 (25.9%)
	> 4	248 (39.2%)
Time spent on short videos in the past week		
	< 10 min	4 (0.6%)
	10 ~ 30 min	46 (7.3%)
	31 ~ 60 min	127 (20.1%)
	1 ~ 2 h	166 (26.3%)
	2 ~ 3 h	151 (23.9%)
	> 3 h	138 (21.8%)

Boredom Proneness Scale–Short Form (BPS-SR)

Boredom Proneness Scale–Short Form (BPS-SR, Struk et al., 2017) assesses boredom proneness, and the Chinese version of BPS-SR has shown excellent internal consistency (X. Wang et al., 2021). The eight items are assessed on a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). Higher scores indicate a higher level of boredom proneness. In the present study, Cronbach's alpha and McDonald's ω for the total scale were 0.937 and 0.938, respectively.

Attention Control Scale

The Chinese version of the Attention Control Scale (ACS-C) (Siyin He, 2020) is adapted from Derryberry and Reed (2002), referring to a general capacity to control attention concerning positive as well as negative reactions. This scale has 16 items with two sub-factors: (a) to focus attention (e.g., "When concentrating, I can focus my attention so that I become unaware of what is going on in the room around me.") and (b) to shift attention (e.g., "When a distracting thought comes to mind, it is easy for me to shift my attention away from it"). All items are scored on a 4-point Likert scale from 1 (all most never) to 4 (always). Higher scores indicate better attention control. In this study, Cronbach's alpha and McDonald's ω for the total scale were 0.864 and 0.870, 0.833 and 0.849 for attention focus, and 0.706 and 0.709 for attention shift, respectively.

Problematic Short Video Use

A few studies have been on PSVU (Q. Huang et al., 2022; Ye et al., 2023). Some studies (Su et al., 2021; H. Wang & Lei, 2022) measured problematic TikTok use by adapting the Internet Addiction Questionnaire (Young, 1998). Similarly, we used the Chinese version of the Internet Addiction Questionnaire, substituting the word "Internet" with "short video." The scale comprises 20 items and four factors, including salience, conflict, tolerance, and mood modification (e.g., "How often do you find that you use short videos longer than you intended?"; "How often do others in your life complain to you about the amount of time you spend on short videos?"; and "How often do you feel depressed, moody or nervous when you are off-short videos, which goes away once you are back on-short videos?") (Ndasauka et al., 2019). All items are rated on a 5-point scale from 5-point Likert scale from 1 ("almost never") to 5 ("always"). A higher total score indicates a more severe PSVU. In this study, Cronbach's alpha and McDonald's ω for the total scale were 0.941 and 0.943, 0.872 and 0.874 for salience, 0.746 and 0.749 for conflict, 0.863 and 0.865 for tolerance, and 0.746 and 0.754 for mood modification, respectively.

Data Analysis

Network Analysis

Network analysis is an efficient method for exploring the interactions between psychological variables, which provides a new perspective on therapeutic interventions, shifting the target from some ephemeral "underlying disorders" or problematic behaviors to symptoms or the relation between associated factors (e.g., mood states, symptoms, or attitudes) (Borsboom & Cramer, 2013; Epskamp & Fried, 2018). In our study, the subdimensions of the variables we analyzed (state boredom, attention control, and PSVU) reflect symptomatic representations of short video users' cognition, emotion, and problematic behaviors. The partial correlation network is the most commonly used model for estimating psychological networks based on continuous data (Epskamp & Fried, 2018). Partial correlation networks are usually estimated using regularization techniques. Regularization involves estimating a statistical model with an extra penalty for model complexity to limit the number of spurious connections (Friedman et al., 2008). In the network model, each node represents a variable, and each edge represents two variables that have interrelationships after conditioning on all the variables in the dataset. The partial correlation coefficient is the weight of the edge (Epskamp & Fried, 2018). When drawing a network model, the color and weight of an edge indicate its direction and magnitude. Red lines indicate a negative partial correlation, green or blue lines indicate a positive partial correlation, and broader and more saturated lines indicate a stronger partial correlation (Epskamp et al., 2012). Centrality indices (strength, closeness, and betweenness) can further investigate how important nodes are in the network using measures (Epskamp & Fried, 2018).

Statistical Analysis

Descriptive statistics, Cronbach's α, McDonald's ω, and Bayesian correlation were conducted using JASP (Jeffrey's Amazing Statistics Program). The R software (version 4.2.2) was used to estimate Spearman's correlation, the correlation matrix, and network. For network estimation, we applied the R package qgraph and glasso for estimating the network structure and visualization. Since the data are continuous, we choose the Gaussian Graphical Model (GGM) as the estimation model and use the Extended Bayesian Information Criterion (EBIC) glasso for estimation (Epskamp et al., 2012). Centrality was calculated by the qgraph package's centrality Plot function, including strength (degree centrality), betweenness (degree of connectivity), and closeness (the distance centrality) (Friedman et al., 2008). Moreover, the correlation stability coefficient (CS-coefficient) was used to describe the node centrality stability, which was suggested to not be below 0.25 and preferably above 0.5 (Epskamp & Fried, 2018).

Results

Descriptive Statistics and Correlation Analyses

The PSVU scores in the range of 40–69 comprised half of all participants (53.8%, males = 162, females = 178). The proportion of participants with PSVU scores of 70 and above was 23.4% (males = 88, females = 63). The remaining one-fifth are non-problematic users (22.3%, males = 80, females = 61). Descriptive statistics for the study variables are shown in Table 2; Spearman's correlations and Bayesian correlations are shown in Table 3. Boredom proneness was significantly positively associated with the total and sub-factor scores of state boredom (all $p < 0.001$). The total and sub-factor scores of state boredom and boredom proneness were significantly negatively associated with attention control (all $p < 0.001$) and were significantly positively associated with PSVU (all $p < 0.001$). The total and sub-factor scores of attention control were significantly negatively associated with PSVU (all $p < 0.001$). The correlations between all variables were moderate to strong. The Bayesian correlation test found that all of log (BF_{10}) were more than 3. The effect sizes of

Table 2 Mean scores and standard deviations of all variables

	M	*SD*	Min	Max
Age	21.94	2.64	18.00	30.00
State boredom	85.43	32.01	24.00	162.00
Inattention	18.49	7.81	5.00	35.00
Time perception	16.71	7.29	5.00	35.00
Low arousal	17.19	7.89	5.00	35.00
High arousal	12.45	6.16	4.00	28.00
Disengagement	20.59	7.07	5.00	35.00
Trait boredom	30.30	12.33	8.00	56.00
Attention control	41.20	8.17	19.00	64.00
Attention focus	20.75	4.82	9.00	32.00
Attention shift	20.44	4.08	8.00	32.00
PSVU	54.89	17.20	20.00	100.00
Salience	13.67	5.27	5.00	25.00
Conflict	12.22	4.54	5.00	25.00
Tolerance	17.16	5.57	6.00	30.00
Mood modification	11.84	3.67	4.00	20.00

the relationship between state boredom, boredom proneness, attention control, and PSVU were verified effectively by Bayesian correlation analysis (Gray et al., 2018).

Network Estimation

The EBICglasso domain-level network, including the total scores of state boredom, boredom proneness, attention control, and PSVU for the 632 Chinese young adults are represented in Fig. 2A. Nodes state boredom and boredom proneness had the most vigorous edge intensity ($r=0.71$). The edge-linked PSVU to attention control ($r=-0.26$) was the strongest, followed by the positive edges to boredom proneness ($r=0.18$) and state boredom ($r=0.10$) (Appendix S1). Collectively, these results supported all of our hypotheses (from H1 to H3). The *CS*-coefficients of state boredom, boredom proneness, attention control, and PSVU were 1.00, 1.10, 0.65, and 0.53, respectively (Appendix S2). The nodes' centralities were stable and interpretable in the network. Boredom proneness was the most central node (strength = 0.98, betweenness = 1.50, closeness = 1.12) (Appendix S3). The mean node predictability was 0.61, suggesting that, on average, 61% of the variance of each node could be explained by its neighbors in this network model (Zhou et al., 2023).

The facet-level network structure composed of the state boredom sub-scales, the boredom proneness total score, the attention control sub-scales, and the PSVU sub-scales for the total sample is presented in Fig. 2B. There were 12 nodes and 39 non-zero edges in the network. Nodes low arousal and high arousal had the strongest edge intensity ($r=0.44$). Among all non-zero edges across communities, node 7 (attention focus) had a direct association with node 6 (boredom proneness) ($r=-0.16$), node1 (inattention) ($r=-0.15$), and node 11 (tolerance) ($r=-0.14$). Node 4 (high arousal) had a direct association with node 10 (conflict) ($r=0.10$) (Appendix S4). The *CS*-coefficients of inattention, time perception, low arousal, high arousal, disengagement, boredom proneness, attention focus, attention shift, salience, conflict, tolerance, and mood modification were 1.30, 0.50, 1.20, 0.92, 0.89, 1.10, 0.94, 0.58, 1.10, 1.10, 1.00, and 0.80, respectively (Appendix S5). The

Table 3 Spearman correlations and Bayesian correlation of all variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 State boredom	—														
Log (BF_{10})	—														
2 Inattention	0.91***	—													
Log (BF_{10})	543.54	—													
3 Time perception	0.77***	0.56***	—												
Log (BF_{10})	292.96	117.08	—												
4 Low arousal	0.94***	0.83***	0.66***	—											
Log (BF_{10})	663.45	362.31	172.66	—											
5 High arousal	0.90***	0.79***	0.63***	0.85***	—										
Log (BF_{10})	494.48	296.69	148.74	395.15	—										
6 Disengagement	0.89***	0.82***	0.60***	0.80***	0.72***	—									
Log (BF_{10})	505.08	343.04	145.37	321.62	221.81	—									
7 Boredom proneness	0.86***	0.80***	0.61***	0.83***	0.73***	0.82***	—								
Log (BF_{10})	426.14	333.49	146.24	365.39	231.55	345.80	—								
8 Attention control	-0.66***	-0.68***	-0.42***	-0.62***	-0.57***	-0.61***	-0.66***	—							
Log (BF_{10})	174.48	192.34	61.66	155.33	114.41	131.22	185.06	—							
9 Attention focus	-0.67***	-0.68***	-0.44***	-0.63***	-0.58***	-0.63***	-0.69***	0.93***	—						
Log (BF_{10})	186.68	197.00	65.11	162.71	125.85	146.42	203.48	628.80	—						
10 Attention shift	-0.48***	-0.52***	-0.31***	-0.48***	-0.43***	-0.43***	-0.48***	0.84***	0.60***	—					
Log (BF_{10})	95.95	110.89	36.03	88.71	62.11	69.36	97.64	524.91	193.40	—					
11 PSVU	0.58***	0.52***	0.43***	0.54***	0.55***	0.51***	0.59***	-0.56***	-0.60***	-0.38***	—				
Log (BF_{10})	123.56	99.36	61.48	104.94	106.10	90.31	133.37	113.83	135.54	54.87	—				
12 Salience	0.57***	0.52***	0.43***	0.54***	0.52***	0.51***	0.59***	-0.55***	-0.59***	-0.36***	0.94***	—			
Log (BF_{10})	116.30	94.20	57.42	103.33	92.82	87.10	126.96	110.27	131.90	52.80	650.57	—			

Table 3 (continued)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
13 Conflict	0.44***	0.36***	0.39***	0.40***	0.47***	0.37***	0.43***	-0.37***	-0.41***	-0.23***	0.88***	0.76***	—		
Log (BF_{10})	64.56	38.14	48.96	51.40	72.38	39.25	57.95	36.90	49.27	13.91	457.32	262.09	—		
14 Tolerance	0.56***	0.56***	0.38***	0.52***	0.52***	0.51***	0.59***	-0.59***	-0.62***	-0.43***	0.91***	0.82***	0.72***	—	
Log (BF_{10})	117.98	120.17	45.92	97.82	93.00	90.51	133.47	139.29	154.85	73.81	560.53	337.03	216.84	—	
15 Mood modification	0.48***	0.42***	0.35***	0.46***	0.44***	0.44***	0.52***	-0.49***	-0.51***	-0.33***	0.87***	0.78***	0.72***	0.71***	—
Log (BF_{10})	82.92	62.12	40.27	75.09	68.79	67.98	98.19	78.64	92.49	38.78	445.89	291.60	218.71	222.56	—

Note *$p < .05$, **$p < .01$, ***$p < .001$

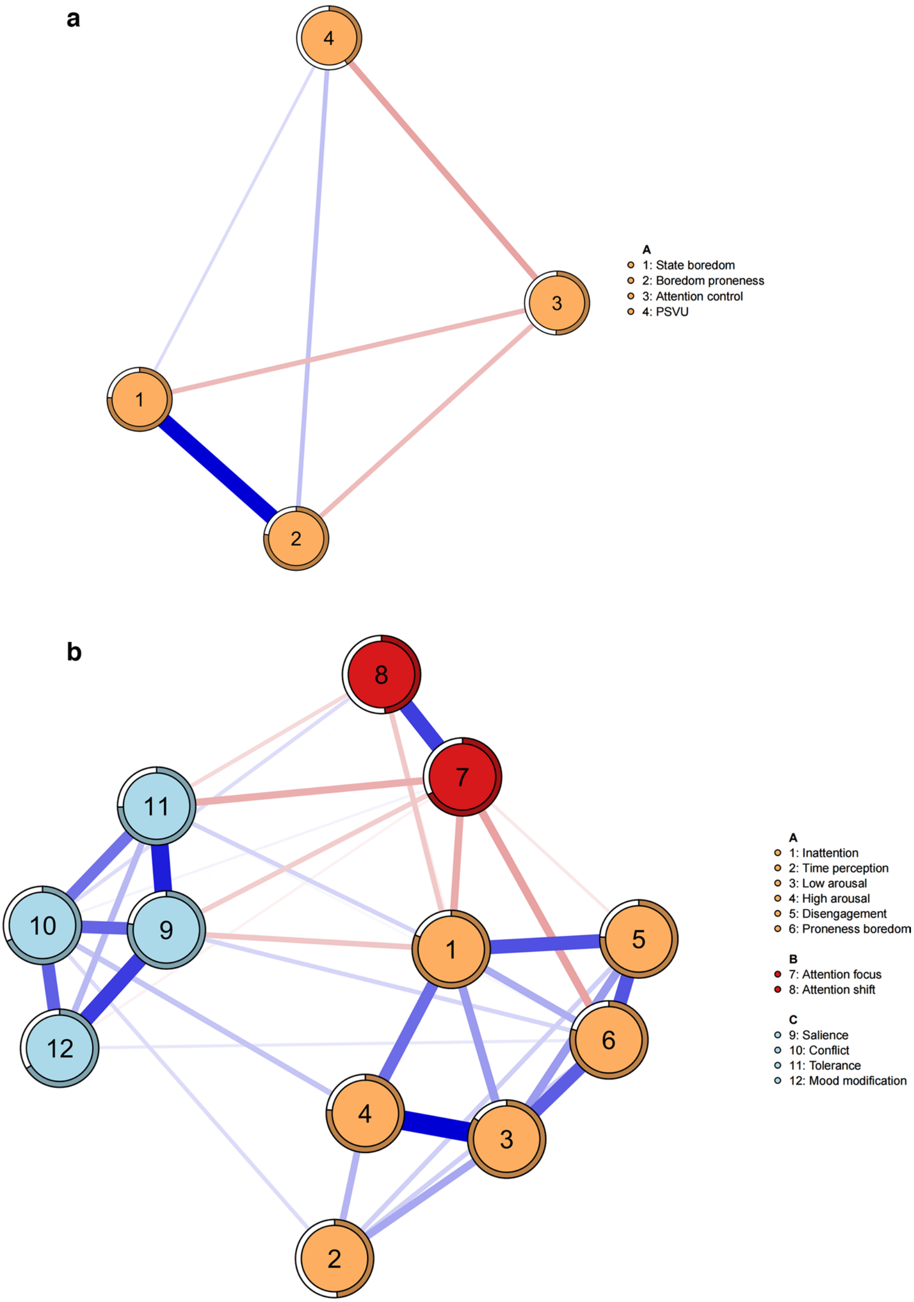

Fig. 2 EBICglasso model based on the domain-level (**A**) and the facet-level (**B**) network analysis according to the relationships between state boredom, boredom proneness, attention control, and PSVU among 632 Chinese young adults

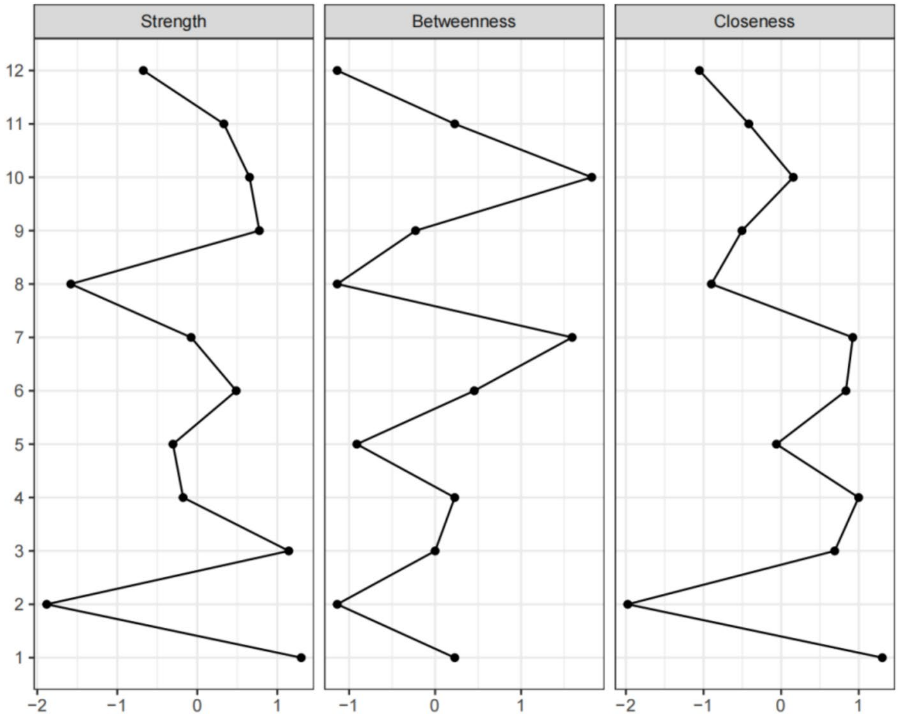

Fig. 3 Centrality Plots for EBICglaaso network depicting the strength, betweenness, and closeness of each node (variable) among 632 Chinese adults. Note: 1 = inattention, 2 = time perception, 3 = low arousal, 4 = high arousal, 5 = disengagement, 6 = boredom proneness, 7 = attention focus, 8 = attention shift, 9 = salience, 10 = conflict, 11 = tolerance, and 12 = mood modification

Table 4 Centrality study variables relationship network

	R^2	Strength	Betweenness	Closeness
1 Inattention	0.44	1.30	0.23	1.30
2 Time perception	0.72	− 1.88	− 1.14	− 1.98
3 Low arousal	0.40	1.14	0.00	0.69
4 High arousal	0.48	− 0.18	0.23	1.00
5 Disengagement	0.50	− 0.30	− 0.91	− 0.06
6 Boredom proneness	0.45	0.49	0.46	0.84
7 Attention focus	0.57	− 0.08	1.59	0.92
8 Attention shift	0.72	− 1.58	− 1.14	− 0.90
9 Salience	0.47	0.78	− 0.23	− 0.50
10 Conflict	0.56	0.65	1.82	0.16
11 Tolerance	0.50	0.33	0.23	− 0.42
12 Mood modification	0.58	− 0.67	− 1.14	− 1.05

centrality stability of nodes was excellent in the network (i.e., all $CS \geq 0.5$). The study variables' betweenness, closeness, and strength (degree) are shown in Fig. 3 and Table 4. Node 1 (inattention) had the highest strength centrality (1.30) and closeness centrality (1.30), indicating the node has a significant influence on the whole network, and the effect of changes in this node can reach other variables faster than other nodes. Node 10 (conflict) had the highest betweenness centrality (1.82), followed by node 7 (attention focus) (1.59), suggesting that "conflict" and "attention focus" control the connectivity of other nodes and play the roles of a bridge. The mean node predictability was 0.71, suggesting that, on average, 71% of the variance of each node could be explained by its neighbors in this network model.

Discussion

The present study utilized a network analysis approach to explore the complex associations among state boredom, boredom proneness, attention control, and PSVU in a sample of 632 Chinese young adults, which produced two main findings. First, there were significant associations between state boredom, boredom proneness, attention control, and PSVU, which proved hypotheses 1 to 3. Second, in domain-level network, boredom proneness was the most central node. Third, in facet-level network, inattention had the highest strength centrality and closeness centrality. The conflict had the highest betweenness centrality, followed by attention focus, thus more strongly connecting the three symptom communities of the network (one referring to attention control ability, one related to boredom features, and one including PSVU symptoms).

In the domain-level network, the boredom proneness and state boredom nodes were found to have the most vigorous edge intensity. It is consistent with previous findings that individuals with boredom proneness are more likely to experience state boredom (Mercer-Lynn et al., 2014). The present study also found that the negative edges linked PSVU to attention control were the strongest, followed by the positive edges to boredom proneness and state boredom. Low levels of attention control could increase the risk of PSVU by shifting to distracting tasks rather than focusing on relevant tasks (e.g., using short videos). One preliminary fMRI study found that people at high risk for smartphone addiction have difficulty shifting their attention from distracting stimuli to goal-directed behaviors (Han & Kim, 2022). In addition, attention control is significantly negatively associated with negative emotions such as boredom, depression, and anxiety (Eysenck et al., 2007; Keller et al., 2020; Shi et al., 2019), which may lead people to use short videos to escape negative emotions (Brailovskaia et al., 2020; Fokker et al., 2021; Pettorruso et al., 2020). The boredom proneness and PSVU had a stronger edge intensity than state boredom, which is reasonable. Although state boredom may prompt people to seek alternative activities (e.g., using short videos) to defuse the current aversive state (Bench & Lench, 2013), boredom proneness is the long-term consequence of the boredom feedback loop (Elpidorou, 2018; Tam et al., 2021). This also explains why boredom proneness was the most central node in the entire network. As for the relationship between boredom proneness and attention control, boredom proneness may be affected by chronic weaknesses in the attention system (Eastwood et al., 2012).

In the facet-level network, nodes with low arousal and high arousal had the strongest edge intensity, which verified the close relationship in the present network. This study further confirms that state boredom is a mixture of both high arousal (e.g., frustration, anger, anxiety) and low arousal (e.g., apathy, sadness) (Chin et al., 2017; Raffaelli et al., 2018; Tam et al., 2021). We should also pay attention to the importance of the emotional dimension in the structure of state boredom. Facet inattention with the highest strength and closeness centrality illustrated the significant impact of inattention on both symptom performance of attention control and PSVU, as well as being influenced by them. Moreover, this effect can quickly reach other variables across the network. The association between inattention and attention focus indicates that individuals cannot focus on target-related stimuli and are susceptible to distractions from target-irrelevant information. It is no coincidence that short videos are rich, short, and varied, and they leverage personalized recommendations to capture users' attention (Z. Chen et al., 2019; Deng et al., 2014; Gong, 2022). A fMRI study exploring the neural activity of watching short videos found that the activation of the default mode network (DMN) and its enhanced coupling to visual and auditory pathways may contribute to the problematic TikTok use through modulations of attention and high-level perception (Su et al., 2021). The features of short videos attract users to settle their attention on short videos, which also brings risks for PSVU. In turn, the fragmented usage pattern of short videos is not conducive to keeping our attention on the task over time. This is consistent with previous research findings (Y. Chen et al., 2022). In addition, the conflict node has the highest betweenness centrality, followed by the attention focus node in the whole network. The conflict factor has five questions such as "using short videos before something else that you need to do"; "feeling depressed, moody or nervous when off-short video, going away once back on-short video"; and "trying to hide how long you have been on-short video" (Ndasauka et al., 2019). It reflects the individual's resistance and contradiction in what he or she wants to do or should do, and it may be both factual and psychological. Conflict interferes with attention control and further affects attention engagement, resulting in state boredom or negative emotions. It is consistent with previous findings (Mahalingham et al., 2022) that social media use affects psychological distress through the moderating effect of attention control.

Theoretical and Practical Implications

The findings of the study have theoretical and practical implications for PSVU interventions. In terms of theoretical contributions, first, it provided empirical support for the boredom feedback model (Tam et al., 2021). Secondly, it is also a complement and development of the Person-Affect-Cognition-Execution model (Brand et al., 2019), which integrates an individual's characteristics, affective, cognitive responses, and execution functions, offering a holistic understanding of how these elements collectively shape human decision-making and action in diverse settings. In this study, boredom proneness is a personality trait that predicts addictive behaviors (Elhai et al., 2018; Kruger et al., 2020; Lelonek-Kuleta & Bartczuk, 2022; Regan et al., 2020; Z. Wang et al., 2020). State boredom can be seen as a specific affective and cognitive response after an individual perceives internal and external triggers in specific situations (Brand et al., 2019). It can reduce individual self-control (Wolff & Martarelli, 2020) and further affect executive functions (e.g., attention control), leading to problematic use. Furthermore, problematic use can negatively impact an individual's executive functions (e.g., attention control) (Reed, 2023). Insufficient attention engagement with the task can also trigger state boredom, creating a circuit of PSVU. Thus, the boredom feedback model is linked to the I-PACE model, expanding the link between boredom and problematic behavior from a theoretical perspective. In terms of practical implications, we need to pay attention to the inattention and conflict symptoms of problematic users. In the future, cognitive reappraisal strategies (McRae et al., 2012; Webster & Hadwin, 2015) and mindfulness meditation (Hadash et al., 2023; Tanaka et al., 2021) can be utilized to reduce conflict and enhance attention engagement with relevant tasks.

Limitations and Future Research

However, there are several limitations should be considered in the present study. First, although we used good reliability and validity scales to measure state boredom and attention control, the self-report may not reflect the complex phenomena. In future studies, we will add measures of behavioral and physiological indicators. Second, the variables we examined were limited and could be examined by integrating factors such as personality, social environment, objective duration, and intensity of use of short videos in the future. Third, short video platforms evolve rapidly, and future research should pay attention to the changing characteristics of short videos to ensure the generalizability of results.

Conclusions

The relationship between these variables was examined using network analysis. The results showed that state boredom, boredom proneness, attention control, and PSVU have bidirectional associations in the domain-level network among a sample of 632 Chinese young adults. And in the facet-level network, inattention and conflict were the core nodes in the relationship network between state boredom, boredom proneness, attention control, and PSVU. These findings provide empirical evidence for the boredom feedback model, explain why boredom is associated with problematic short video use, and suggest a new perspective on the intervention of inattention and conflict that will contribute to future research and clinical practice.

Data and Code

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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3. Yuhong Zhou: Conceptualization, software, and methodology
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Declarations

Conflict of Interest The authors declare no competing interests.

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Ethics Approval All procedures performed in studies involving human participants were in accordance with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

References

Barkley, J. E., & Lepp, A. (2021). The effects of smartphone facilitated social media use, treadmill walking, and schoolwork on boredom in college students: Results of a within subjects, controlled experiment. *Computers in Human Behavior, 114*, 106555. https://doi.org/10.1016/j.chb.2020.106555

Bench, S., & Lench, H. (2013). On the function of boredom. *Behavioral Sciences, 3*(3), 459–472. https://doi.org/10.3390/bs3030459

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Brailovskaia, J., Schillack, H., & Margraf, J. (2020). 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. *Computers in Human Behavior, 113*, 106511. https://doi.org/10.1016/j.chb.2020.106511

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond Internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews, 104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

Chen, Y., Li, M., Guo, F., & Wang, X. (2022). The effect of short-form video addiction on users' attention. *Behaviour & Information Technology*, 1–18. https://doi.org/10.1080/0144929X.2022.2151512

Chen, Z., He, Q., Mao, Z., Chung, H.-M., & Maharjan, S. (2019). A study on the characteristics of Douyin short videos and implications for edge caching. *Proceedings of the ACM Turing Celebration Conference - China*, 1–6. https://doi.org/10.1145/3321408.3323082

Chin, A., Markey, A., Bhargava, S., Kassam, K. S., & Loewenstein, G. (2017). Bored in the USA: Experience sampling and boredom in everyday life. *Emotion, 17*(2), 359–368. https://doi.org/10.1037/emo0000232

Chou, W.-J., Chang, Y.-P., & Yen, C.-F. (2018). Boredom proneness and its correlation with Internet addiction and Internet activities in adolescents with attention-deficit/hyperactivity disorder. *The Kaohsiung Journal of Medical Sciences, 34*(8), 467–474. https://doi.org/10.1016/j.kjms.2018.01.016

CNNIC. (2024). The 53th statistical reports on internet development in China. Retrieved from https://www.cnnic.net.cn/n4/2024/0322/c88-10964.html

Crawford, C., Ramlackhan, K., Singh, G., & Fenske, M. (2023). Subjective impact of age-related hearing loss is worse for those who routinely experience boredom and failures of attention. *EAR AND HEARING, 44*(1), 199–208. https://doi.org/10.1097/AUD.0000000000001271

Dalbudak, E., Evren, C., Aldemir, S., Taymur, I., Evren, B., & Topcu, M. (2015). The impact of sensation seeking on the relationship between attention deficit/hyperactivity symptoms and severity of Internet addiction risk. *Psychiatry Research, 228*(1), 156–161. https://doi.org/10.1016/j.psychres.2015.04.035

Danckert, J., & Merrifield, C. (2018). Boredom, sustained attention and the default mode network. *Experimental Brain Research, 236*(9), 2507–2518. https://doi.org/10.1007/s00221-016-4617-5

Deng, Z., Yan, M., Sang, J., & Xu, C. (2014). Twitter is faster: Personalized time-aware video recommendation from Twitter to YouTube. *ACM TRANSACTIONS ON MULTIMEDIA COMPUTING COMMUNICATIONS AND APPLICATIONS*, 11(2), 1–23. https://doi.org/10.1145/2637285

Derryberry, D., & Reed, M. (2002). Anxiety-related attentional biases and their regulation by attentional control. *JOURNAL OF ABNORMAL PSYCHOLOGY, 111*(2), 225–236. https://doi.org/10.1037//0021-843X.111.2.225

Donati, M. A., Beccari, C., & Primi, C. (2022). Boredom and problematic Facebook use in adolescents: What is the relationship considering trait or state boredom? *Addictive Behaviors, 125*, 107132. https://doi.org/10.1016/j.addbeh.2021.107132

Eastwood, J. D., Frischen, A., Fenske, M. J., & Smilek, D. (2012). The unengaged mind: Defining boredom in terms of attention. *Perspectives on Psychological Science, 7*(5), 482–495. https://doi.org/10.1177/1745691612456044

Elhai, J. D., Vasquez, J. K., Lustgarten, S. D., Levine, J. C., & Hall, B. J. (2018). Proneness to boredom mediates relationships between problematic smartphone use with depression and anxiety severity. *Social Science Computer Review, 36*(6), 707–720. https://doi.org/10.1177/0894439317741087

Elpidorou, A. (2018). The bored mind is a guiding mind: Toward a regulatory theory of boredom. *Phenomenology and the Cognitive Sciences, 17*(3), 455–484. https://doi.org/10.1007/s11097-017-9515-1

Epskamp, S., Cramer, A., Waldorp, L., Schmittmann, V., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *JOURNAL OF STATISTICAL SOFTWARE, 48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods, 23*(4), 617–634. https://doi.org/10.1037/met0000167

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion, 7*(2), 336–353. https://doi.org/10.1037/1528-3542.7.2.336

Fahlman, S., Mercer-Lynn, K., Flora, D., & Eastwood, J. (2013). Development and validation of the Multidimensional State Boredom Scale. *Assessment, 20*(1), 68–85. https://doi.org/10.1177/1073191111421303

Farmer, R., & Sundberg, N. D. (1986). Boredom proneness—The development and correlates of a new scale. *Journal of Personality Assessment, 50*(1), 4–17. https://doi.org/10.1207/s15327752jpa5001_2

Ferraro, L., Avanzato, C., Maniaci, G., Sartorio, C., Daino, M., Seminerio, F., Tripoli, G., Quattrone, D., Lo Baido, R., La Barbera, D., & La Cascia, C. (2020). Prevalence and risk factors for Internet gaming disorder (IGD) in a sample of 5,979 Italian online gamers. *MEDITERRANEAN JOURNAL OF CLINICAL PSYCHOLOGY*, *8*(3). https://doi.org/10.6092/2282-1619/mjcp-2674

Fokker, E., Zong, X., & Treur, J. (2021). A second-order adaptive network model for emotion regulation in addictive social media behaviour. *Cognitive Systems Research, 70*, 52–62. https://doi.org/10.1016/j.cogsys.2021.07.006

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics, 9*(3), 432–441. https://doi.org/10.1093/biostatistics/kxm045

Fu, J., Xu, P., Zhao, L., & Yu, G. (2018). Impaired orienting in youth with Internet addiction: Evidence from the Attention Network Task (ANT). *Psychiatry Research, 264*, 54–57.

Fullwood, C., Quinn, S., Kaye, L. K., & Redding, C. (2017). My virtual friend: A qualitative analysis of the attitudes and experiences of smartphone users: Implications for smartphone attachment. *Computers in Human Behavior, 75*, 347–355. https://doi.org/10.1016/j.chb.2017.05.029

Gaertner, B. M., Spinrad, T. L., & Eisenberg, N. (2008). Focused attention in toddlers: Measurement, stability, and relations to negative emotion and parenting. *Infant and Child Development, 17*(4), 339–363. https://doi.org/10.1002/icd.580

Gao, Q., Jia, G., Zhao, J., & Zhang, D. (2019). Inhibitory control in excessive social networking users: Evidence from an event-related potential-based go-nogo task. *Frontiers in Psychology, 10*, 1810. https://doi.org/10.3389/fpsyg.2019.01810

Gong, X. (2022). A personalized recommendation method for short drama videos based on external index features. *Advances in Meteorology, 2022*, 1–10. https://doi.org/10.1155/2022/3601956

Gray, K. L. H., Haffey, A., Mihaylova, H. L., & Chakrabarti, B. (2018). Lack of privileged access to awareness for rewarding social scenes in autism spectrum disorder. *Journal of Autism and Developmental Disorders, 48*(10), 3311–3318. https://doi.org/10.1007/s10803-018-3595-9

Hadash, Y., Ruimi, L., & Bernstein, A. (2023). Looking inside the black box of mindfulness meditation: Investigating attention and awareness during meditation using the Mindful Awareness Task (MAT). *PSYCHOLOGICAL ASSESSMENT, 35*(3), 242–256. https://doi.org/10.1037/pas0001194

Han, S., & Kim, C. (2022). Neurocognitive mechanisms underlying Internet/smartphone addiction: A preliminary fMRI study. *Tomography, 8*, 1781–1790. https://doi.org/10.3390/tomography8040150

Hawes, T., Zimmer-Gembeck, M., & Campbell, S. (2020). Unique associations of social media use and online appearance preoccupation with depression, anxiety, and appearance rejection sensitivity. *Body Image, 33*, 66–76. https://doi.org/10.1016/j.bodyim.2020.02.010

Huang, Q., Hu, M., & Chen, H. (2022). Exploring stress and problematic use of short-form video applications among middle-aged Chinese adults: The mediating roles of duration of use and flow experience. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*,19(1), 132.

Huang, S., Lai, X., Xue, Y., Zhang, C., & Wang, Y. (2021). A network analysis of problematic smartphone use symptoms in a student sample. *Journal of Behavioral Addictions,* 9(4), 1032–1043. https://doi.org/10.1556/2006.2020.00098

Hunter, A., & Eastwood, J. D. (2018). Does state boredom cause failures of attention? Examining the relations between trait boredom, state boredom, and sustained attention. *Experimental Brain Research, 236*(9), 2483–2492. https://doi.org/10.1007/s00221-016-4749-7

Kay, R., Benzimra, D., & Li, J. (2017). Exploring factors that influence technology-based distractions in bring your own device classrooms. *Journal of Educational Computing Research, 55*(7), 974–995. https://doi.org/10.1177/0735633117690004

Keller, A. S., Leikauf, J. E., Holt-Gosselin, B., Staveland, B. R., & Williams, L. M. (2020). Correction: Paying attention to attention in depression. *Translational Psychiatry, 10*(1), 64. https://doi.org/10.1038/s41398-020-0748-3

Kruger, T., Dixon, M., Graydon, C., Stange, M., Larche, C., Smith, S., & Smilek, D. (2020). Using deliberate mind-wandering to escape negative mood states: Implications for gambling to escape. *JOURNAL OF BEHAVIORAL ADDICTIONS, 9*(3), 723–733. https://doi.org/10.1556/2006.2020.00067

Ksinan, A. J., Mališ, J., & Vazsonyi, A. T. (2021). Swiping away the moments that make up a dull day: Narcissism, boredom, and compulsive smartphone use. *Current Psychology, 40*(6), 2917–2926. https://doi.org/10.1007/s12144-019-00228-7

Layland, E., Ram, N., Caldwell, L., Smith, E., & Wegner, L. (2021). Leisure boredom, timing of sexual debut, and co-occurring behaviors among South African adolescents. *ARCHIVES OF SEXUAL BEHAVIOR, 50*(6), 2383–2394. https://doi.org/10.1007/s10508-021-02014-8

Lelonek-Kuleta, B., & Bartczuk, R. (2022). Motivation to gamble, boredom proneness and the severity of gambling problems as predictors of online gambling beginning during the COVID-19 pandemics among gamblers: Results of a longitudinal study in Poland. *JOURNAL OF BEHAVIORAL ADDICTIONS, 11*, 150–150.

Lepp, A., Barkley, J. E., & Li, J. (2017). Motivations and experiential outcomes associated with leisure time cell phone use: Results from two independent studies. *Leisure Sciences, 39*(2), 144–162. https://doi.org/10.1080/01490400.2016.1160807

Li, J., Zhou, Y., Lv, X., Leng, X., Jiang, X., & Gao, X. (2023). A network analysis approach to core symptoms and symptom relationships of problematic social media use among young adults. *Information, Communication & Society*,27(6), 1229–1246. https://doi.org/10.1080/1369118X.2023.2245870

Li, L., Niu, Z., Griffiths, M. D., Wang, W., Chang, C., & Mei, S. (2021). A network perspective on the relationship between gaming disorder, depression, alexithymia, boredom, and loneliness among a sample of Chinese university students. *Technology in Society, 67*, 101740. https://doi.org/10.1016/j.techsoc.2021.101740

Liang, L., Li, C., Meng, C., Guo, X., Lv, J., Fei, J., & Mei, S. (2022). Psychological distress and Internet addiction following the COVID-19 outbreak: Fear of missing out and boredom proneness as mediators. *Archives of Psychiatric Nursing, 40*, 8–14. https://doi.org/10.1016/j.apnu.2022.03.007

Liu, Y., Chen, J., Jiang, M., Xu, H., Liu, J., Eastwood, J. D., & Mehranvar, S. (2013). The Chinese version of the Multidimensional State Boredom Scale(MSBS): It's applicability in Chinese college students. *Chinese Journal of Clinical Psychology*,21(04), 558–561. https://doi.org/10.16128/j.cnki.1005-3611.2013.04.012

Lopes, L. S., Valentini, J. P., Monteiro, T. H., Costacurta, M. C. D. F., Soares, L. O. N., Telfar-Barnard, L., & Nunes, P. V. (2022). Problematic social media use and its relationship with depression or anxiety: A systematic review. *Cyberpsychology, Behavior, and Social Networking, 25*(11), 691–702. https://doi.org/10.1089/cyber.2021.0300

Mahalingham, T., Howell, J., & Clarke, P. J. F. (2022). Attention control moderates the relationship between social media use and psychological distress. *Journal of Affective Disorders, 297*, 536–541. https://doi.org/10.1016/j.jad.2021.10.071

McRae, K., Ciesielski, B., & Gross, J. J. (2012). Unpacking cognitive reappraisal: Goals, tactics, and outcomes. *Emotion, 12*(2), 250–255. https://doi.org/10.1037/a0026351

Mercer-Lynn, K. B., Bar, R. J., & Eastwood, J. D. (2014). Causes of boredom: The person, the situation, or both? *Personality and Individual Differences, 56*, 122–126. https://doi.org/10.1016/j.paid.2013.08.034

Ndasauka, Y., Pitafi, A., & Kayange, G. M. (2019). Psychometric properties of Young's Internet Addiction Test (IAT) in Urdu language. *Asian Journal of Psychiatry, 40*, 39–44. https://doi.org/10.1016/j.ajp.2019.01.011

Oxtoby, J., Schroeter, R., Johnson, D., & Kaye, S. (2019). Using boredom proneness to predict young adults' mobile phone use in the car and risky driving. *TRANSPORTATION RESEARCH PART F-TRAFFIC PSYCHOLOGY AND BEHAVIOUR, 65*, 457–468. https://doi.org/10.1016/j.trf.2019.08.008

Peng, J., Guo, W., Zhao, L., Han, X., & Wu, S. (2020). Short Boredom Proneness Scale: Adaptation and validation of a Chinese version with college students. *SOCIAL BEHAVIOR AND PERSONALITY*,48(2), 1–8. https://doi.org/10.2224/sbp.8968

Pettorruso, M., Valle, S., Cavic, E., Martinotti, G., Di Giannantonio, M., & Grant, J. E. (2020). Problematic Internet use (PIU), personality profiles and emotion dysregulation in a cohort of young adults: Trajectories from risky behaviors to addiction. *Psychiatry Research, 289*, 113036. https://doi.org/10.1016/j.psychres.2020.113036

Posner, M. I., & Rothbart, M. K. (1998). Attention, self–regulation and consciousness. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*,353(1377), 1915–1927. https://doi.org/10.1098/rstb.1998.0344

Posner, M. I., & Rothbart, M. K. (2000). *Developing Mechanisms of Self-Regulation.,* 12(3), 427–441. https://doi.org/10.1017/s0954579400003096

Raffaelli, Q., Mills, C., & Christoff, K. (2018). The knowns and unknowns of boredom: A review of the literature. *Experimental Brain Research, 236*(9), 2451–2462. https://doi.org/10.1007/s00221-017-4922-7

Reed, P. (2023). Impact of social media use on executive function. *Computers in Human Behavior, 141*, 107598. https://doi.org/10.1016/j.chb.2022.107598

Regan, T., Harris, B., Van Loon, M., Nanavaty, N., Schueler, J., Engler, S., & Fields, S. A. (2020). Does mindfulness reduce the effects of risk factors for problematic smartphone use? Comparing frequency of use versus self-reported addiction. *Addictive Behaviors, 108*, 106435. https://doi.org/10.1016/j.addbeh.2020.106435

Shi, R., Sharpe, L., & Abbott, M. (2019). A meta-analysis of the relationship between anxiety and attentional control. *Clinical Psychology Review, 72*, 101754. https://doi.org/10.1016/j.cpr.2019.101754

Siyin He. (2020). *Attentional Control Scale factor structure and empirical validity* [Master dissertation, Hunan Normal University].https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CMFD&dbname=CMFD202101&filename=1020320541.nh&v=

Stockdale, L. A., & Coyne, S. M. (2020). Bored and online: Reasons for using social media, problematic social networking site use, and behavioral outcomes across the transition from adolescence to emerging adulthood. *Journal of Adolescence, 79*(1), 173–183. https://doi.org/10.1016/j.adolescence.2020.01.010

Struk, A., Carriere, J., Cheyne, J., & Danckert, J. (2017). A Short Boredom Proneness Scale: Development and psychometric properties. *Assessment, 24*(3), 346–359. https://doi.org/10.1177/1073191115609996

Su, C., Zhou, H., Gong, L., Teng, B., Geng, F., & Hu, Y. (2021). Viewing personalized video clips recommended by TikTok activates default mode network and ventral tegmental area. *NeuroImage, 237*, 118136. https://doi.org/10.1016/j.neuroimage.2021.118136

Tam, K. Y. Y., van Tilburg, W. A. P., Chan, C. S., Igou, E. R., & Lau, H. (2021). Attention drifting in and out: The boredom feedback model. *Personality and Social Psychology Review, 25*(3), 251–272. https://doi.org/10.1177/10888683211010297

Tanaka, M., Nakashima, R., Hiromitsu, K., & Imamizu, H. (2021). Individual differences in the change of attentional functions with brief one-time focused attention and open monitoring meditations. *Frontiers in Psychology, 12*, 716138. https://doi.org/10.3389/fpsyg.2021.716138

Wang, H., & Lei, L. (2022). The relationship between parental phubbing and short-form videos addiction among Chinese adolescents. *Journal of Research on Adolescence, 32*(4), 1580–1591. https://doi.org/10.1111/jora.12744

Wang, X., Gao, C., Ding, J., Li, Y., & Jin, D. (2019). CMBPR: Category-aided Multi-channel Bayesian Personalized Ranking for short video recommendation. *IEEE Access, 7*, 48209–48223. https://doi.org/10.1109/ACCESS.2019.2907494

Wang, X., Zhang, R., Chen, Z., Zhou, F., & Feng, T. (2021). Neural basis underlying the relation between boredom proneness and procrastination: The role of functional coupling between precuneus/cuneus and posterior cingulate cortex. *Neuropsychologia, 161*, 107994. https://doi.org/10.1016/j.neuropsychologia.2021.107994

Wang, Z., Yang, X., & Zhang, X. (2020). Relationships among boredom proneness, sensation seeking and smartphone addiction among Chinese college students: Mediating roles of pastime, flow experience and self-regulation. *Technology in Society, 62*, 101319. https://doi.org/10.1016/j.techsoc.2020.101319

Webster, E. A., & Hadwin, A. F. (2015). Emotions and emotion regulation in undergraduate studying: Examining students' reports from a self-regulated learning perspective. *Educational Psychology, 35*(7), 794–818. https://doi.org/10.1080/01443410.2014.895292

Weiss, E., Todman, M., Maple, E., & Bunn, R. (2022). Boredom in a time of uncertainty: State and trait boredom's associations with psychological health during COVID-19. *BEHAVIORAL SCIENCES*, 12(8), 298. https://doi.org/10.3390/bs12080298

Werling, A. M., Kuzhippallil, S., Emery, S., Walitza, S., & Drechsler, R. (2022). Problematic use of digital media in children and adolescents with a diagnosis of attention-deficit/hyperactivity disorder compared to controls. *A Meta-Analysis. Journal of Behavioral Addictions, 11*(2), 305–325. https://doi.org/10.1556/2006.2022.00007

Westgate, E., & Wilson, T. (2018). Boring thoughts and bored minds: The MAC model of boredom and cognitive engagement. *PSYCHOLOGICAL REVIEW, 125*(5), 689–713. https://doi.org/10.1037/rev0000097

Wolff, W., & Martarelli, C. S. (2020). Bored into depletion? Toward a tentative integration of perceived self-control exertion and boredom as guiding signals for goal-directed behavior. *Perspectives on Psychological Science, 15*(5), 1272–1283. https://doi.org/10.1177/1745691620921394

Wu-Ouyang, B. (2022). Are smartphones addictive? Examining the cognitive-behavior model of motivation, leisure boredom, extended self, and fear of missing out on possible smartphone addiction. *Telematics and Informatics, 71*, 101834. https://doi.org/10.1016/j.tele.2022.101834

Yakobi, O., Boylan, J., & Danckert, J. (2021). Behavioral and electroencephalographic evidence for reduced attentional control and performance monitoring in boredom. *Psychophysiology, 58*(6), e13816. https://doi.org/10.1111/psyp.13816

Yao, N., Chen, J., Huang, S., Montag, C., & Elhai, J. D. (2023). Depression and social anxiety in relation to problematic TikTok use severity: The mediating role of boredom proneness and distress intolerance. *Computers in Human Behavior, 145*, 107751. https://doi.org/10.1016/j.chb.2023.107751

Ye, J., Wu, Y., Nong, W., Wu, Y., Ye, J., & Sun, Y. (2023). The association of short-video problematic use, learning engagement, and perceived learning ineffectiveness among Chinese vocational students. *HEALTHCARE*,11(2), 161. https://doi.org/10.3390/healthcare11020161

Young, K. (1998). *Caught in the net: How to recognize the signs of Internet addiction—and a winning strategy for recovery*. Wiley.

Zhang, N., Hazarika, B., Chen, K., & Shi, Y. (2023). A cross-national study on the excessive use of short-video applications among college students. *Computers in Human Behavior, 145*, 107752. https://doi.org/10.1016/j.chb.2023.107752

Zhang, X., Wu, Y., & Liu, S. (2019). Exploring short-form video application addiction: Socio-technical and attachment perspectives. *Telematics and Informatics,*42, 101243. https://doi.org/10.1016/j.tele.2019.101243

Zhao, J., Ye, B., Luo, L., & Yu, L. (2022). The effect of parent phubbing on Chinese adolescents' smartphone addiction during COVID-19 pandemic: Testing a moderated mediation model. *Psychology Research and Behavior Management, 15*, 569–579. https://doi.org/10.2147/PRBM.S349105

Zhao, J., Ye, B., & Yu, L. (2021). Peer phubbing and Chinese college students' smartphone addiction during COVID-19 pandemic: The mediating role of boredom proneness and the moderating role of refusal self-efficacy. *Psychology Research and Behavior Management, 14*, 1725–1736. https://doi.org/10.2147/PRBM.S335407

Zhou, Y., Lv, X., Wang, L., Li, J., & Gao, X. (2023). What increases the risk of gamers being addicted? An integrated network model of personality–emotion–motivation of gaming disorder. *Computers in Human Behavior, 141*, 107647. https://doi.org/10.1016/j.chb.2022.107647

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