EXCESSIVE AND PROBLEMATIC SMARTPHONE USAGE

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Editorial: Excessive and problematic smartphone usage

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KEYWORDS

problematic smartphone use, excessive smartphone use, social media addiction, problematic smartphone and internet usage, social media

Editorial on the Research Topic
Excessive and Problematic Smartphone Usage

The excessive use of computer screens and smartphones is raising serious concerns among health and educational authorities due to the adverse effects of such use on children and adolescents. During COVID-19, internet usage is increasing. This is supported by the mobility of the gadgets used, one of which is a smartphone. Smartphones have been designed to be more sophisticated over the years, thus increasing a person's motivation and ease in using the internet. Smartphones can be used for various purposes, such as playing games, socializing using social media, shopping for daily necessities, and others. As a result of the convenience provided by the smartphone, someone could use this gadget continuously. Excessive smartphone use requires special attention because excessive use can lead to addiction and affect all aspects of a person's life. Twelve papers have examined various psychological, behavioral, and health issues associated with problematic smartphone use in this Research Topic.

An overall review of the literature by Wacks and Weinstein has shown that excessive smartphone use is associated with psychiatric, cognitive, emotional, medical, and brain changes that should be considered by health and education professionals. Studies showed comorbidity of excessive smartphone use with depression, anxiety, OCD, ADHD, and alcohol use disorder. Excessive smartphone use was also associated with difficulties in cognitive-emotion regulation, impulsivity, impaired cognitive function, addiction to social networking, shyness, and low self-esteem. Medical problems included sleep problems, reduced physical fitness, unhealthy eating habits, pain and migraines, reduced cognitive control, and changes in the brain's gray matter volume. Pera has found that depression and social anxiety constitute risk determinants for greater problematic smartphone use and that particular categories of smartphone applications are positively related to wellbeing.

Furthermore, state anxiety and motivations are significant predictors of problematic smartphone use and affect participation in social engagement. Eichenberg et al. have found that respondents with problematic smartphone use showed higher scores of extraversion and neuroticism and higher rates of depression and anxiety. Contrary to expectations, they showed higher values for perceived social support than individuals without problematic smartphone use. They have argued that personality traits should be considered during therapy for problematic smartphone use.The neurobiology of excessive smartphone use has been examined in two brain imaging studies. Paik et al. have investigated resting-state functional connectivity (rsFC) of the insula, which is implicated in salience processing, interoceptive processing, and cognitive control in adults who used smartphones by functional magnetic resonance imaging (fMRI). They hypothesized that prolonged bedtime smartphone use might serve as one of the relevant behavioral measures of problematic smartphone use, and prolonged bedtime smartphone use might also be associated with insula-centered functional connectivity. Insula has been known to control the human brain's cognitive function, homeostatic, and affective processes. It can influence decision-making processes and integrate internal and external physiological signs in uncertain situations. They have found that prolonged bedtime smartphone use was associated with higher smartphone addiction proneness scale but not with sleep quality. The findings imply that prolonged bedtime smartphone use can be an essential behavioral measure of problematic smartphone use, and altered insula-centered functional connectivity may be associated with it. This study shows that there is currently more effort in describing the PSU phenomenon because there is no standardized consensus on PSU.

Ahn et al. have performed a resting state seed-based functional connectivity (rsFC) analysis in problematic smartphone users and found enhanced FC within the salience network and between the salience and default mode network. The salience network, consisting of nodes in the right frontoinsular cortex and anterior cingulate cortex, works in the process of orientation to stimuli and allocation of attention. Meanwhile, the central executive network consisting of the dorsolateral prefrontal cortex and the posterior parietal cortex has a function in the decision-making process. The default mode network which consists of the medial prefrontal cortex, the rostral part of the anterior cingulate cortex, the precuneus, and the posterior cingulate cortex works in thought processes. Finally, the affective network is responsible for regulating and perceiving emotions and is associated with structures in the amygdala and anterior cingulate subgenual cortex. Moreover, there was decreased FC between the salience and central executive network in problematic smartphone users. They argued that problematic smartphone use is associated with changes in FC of key salience networks. Overall, this study shows neural changes due to smartphone addiction in terms of salience, central executive, default mode, and affective networks.

Olson et al. have found a positive correlation between hypnotisability and smartphone addiction. They have suggested that targeting the absorbed, time-distorted, and automatic use of smartphones may promote healthier phone habits. Gao et al. have found associations between behavioral inhibition/activation systems (BIS/BAS) and problematic mobile use. They have found a positive association between BIS and "mood modification" or "tolerance" and between BAS-fun seeking and "mood modification" or "conflict." These findings explain how individuals with a high behavioral inhibition or activation system may develop problematic mobile use. The results of this study have implications for prevention programs to overcome problematic mobile phone use.

The relationships between excessive smartphone and social media use and the COVID-19 pandemic were examined in two studies. The impact of excessive smartphone and social media use during the COVID-19 pandemic was examined among Bangladeshi college and university students by Islam et al. Excessive smartphone and social media use were associated with lower age, poor sleep, social media use, watching television, anxiety, and depression. Additionally, problematic social media use was associated with being female, living with nuclear family, having urban residence, irregular physical exercise, poor engagement with academic studies, and avoiding earning activities, whilst being male, being married, living with lower-income family, and alcohol consumption were associated with problematic social media use. Zhang et al. examined the relationship between problematic smartphone use, sleep quality, and daytime fatigue among medical students during COVID-19 in six polyclinic hospitals in Beijing. The COVID-19 pandemic has caused medical students to learn primarily online, thereby increasing the risk of problematic smartphone use (PSU) and various other negative impacts such as psychological symptoms. The study used a Short Version Smartphone Addiction Scale (SAS-SV) questionnaire and found that 49.7% of medical students had PSU. Participants with problematic smartphone use reported sleep disturbance, physical fatigue, and mental fatigue. Sleep quality mediated the relationship between problematic smartphone use and daytime fatigue.

Two studies used questionnaires to assess the intention to use smartphones and the risk of smartphone distraction. Choi et al. have investigated the users' behavioral intention to use smartphone management applications in South Korea. They have found that in both non-problematic smartphone use groups and problematic smartphone use groups, facilitating factors and perceived security positively affected users' intentions to use the application. Zhao et al. evaluated the Chinese version of the Smartphone Distraction Scale (C-SDS) to screen the risk of smartphone distraction in Chinese college students. They have shown a 3-factor structure, which consisted of attention impulsiveness, multitasking, and emotion regulation. Females, the purpose of using a smartphone, smartphone usage, fear of missing out, smartphone addiction, and positive and negative metacognitions about smartphone use were related to the C-SDS. C-SDS was found to be valid and reliable among Chinese college students. Zhou and Wang have used a self–reported questionnaire to examine the effects of aerobic exercise and reading on inhibitory control in college students with excessive mobile use. They have used the anti-saccade task to examine the differences in the effects of aerobic exercise and reading on inhibitory control of college students with mobile phone addiction. They have shown that although exercise and reading affect inhibitory control of college students with excessive smartphone use, the effect of reading may be somehow superior to exercise. The questionnaire regarding smartphone addiction needs to be investigated further to produce a standard in terms of diagnosis. Further research is needed in order to produce a sensitive and specific measuring tool for establishing the diagnosis of smartphone addiction. Smartphone users have clinical characteristics similar to other behavioral addiction disorders such as internet gaming disorder and gambling disorder. Excessive use of smartphones has symptoms of the behavior of loss of control and the continuation of smartphone use despite negative consequences. In addition, excessive smartphone use is also reported to have a negative impact on daily activities at work and socially. Based on the Interaction of Person-Affect-Cognition-Execution model, there is a relationship between the imbalance in craving/cues—reactivity with inhibitory control that causes a person to experience behavioral addiction. Smartphone use is also associated with the same neurobiological and cognitive problems as other behavioral addictions, thus creating a conceptual framework where smartphone addiction might be included in the diagnostic criteria in the DSM or ICD. Until now, there is no consensus regarding the pathway and criteria for diagnosing smartphone addiction.

In conclusion, we have collected studies showing that problematic smartphone use was closely related to disturbances in cognitive-emotional regulation, impulsivity, impaired cognitive function, addiction to social networks, shyness, low self-esteem, depression, anxiety, and higher scores of extraversion and neuroticism. PSU is also linked to medical problems, including sleep problems, decreased physical fitness, unhealthy eating habits, pain, migraines, decreased cognitive control, brain gray matter volume changes, and decreased FC between the salience and central executive network. These have become important during the COVID-19 pandemic. Several questionnaires have been developed to assess the risks of having problematic smartphone use. Treatment studies are urgently needed.

Author contributions

AW and KS have contributed to the writing of this editorial. Both authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Prolonged Bedtime Smartphone Use is Associated With Altered Resting-State Functional Connectivity of the Insula in Adult Smartphone Users

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Prolonged bedtime smartphone use is often associated with poor sleep quality and daytime dysfunction. In addition, the unstructured nature of smartphones may lead to excessive and uncontrolled use, which can be a cardinal feature of problematic smartphone use. This study was designed to investigate functional connectivity of insula, which is implicated in salience processing, interoceptive processing, and cognitive control, in association with prolonged bedtime smartphone use. We examined resting-state functional connectivity (rsFC) of insula in 90 adults who used smartphones by functional magnetic resonance imaging (fMRI). Smartphone time in bed was measured by self-report. Prolonged bedtime smartphone use was associated with higher smartphone addiction proneness scale (SAPS) scores, but not with sleep quality. The strength of the rsFC between the left insula and right putamen, and between the right insula and left superior frontal, middle temporal, fusiform, inferior orbitofrontal gyrus and right superior temporal gyrus was positively correlated with smartphone time in bed. The findings imply that prolonged bedtime smartphone use can be an important behavioral measure of problematic smartphone use and altered insula-centered functional connectivity may be associated with it.

Keywords: problematic smartphone use, bedtime smartphone use, insula, resting state functional connectivity, fMRI

INTRODUCTION

For the last decade, smartphones have become indispensable to our life. According to the South Korean national survey conducted in 2016, 85.0% of those aged over 6 years old possessed their own smartphones, and smartphones have largely replaced personal computer-based online behaviors such as gaming, shopping, banking and searching (1). At the same time, however, the dark sides of smartphone use, including musculoskeletal symptoms and sleep disturbances (2, 3), have been highlighted as well. This phenomenon is often referred as "problematic smartphone use," which is characterized as excessive and uncontrolled smartphone use that leads to functional impairment (4, 5). Though there is no consensus for defining this phenomenon and much dispute is ongoing to determine whether this is a disease entity or not, it seems necessary to investigate what behavioral manifestations are relevant to represent problematic smartphone use and whether there are any neural correlates that are associated with this behavior.

Bedtime smartphone use has been known to worsen sleep quality and consequent daytime function in adults, and was associated with depressed mood in adolescents (6, 7). Overuse of smartphones in bed was proven to be associated with poor sleep quality, mental health, and delayed chronotype in Japanese college students (8). There underlie several mechanisms for this phenomenon; firstly, the screen light emitted from smartphones significantly suppresses the secretion of melatonin, and consequently disrupts sleep (9). Secondly, the exciting contents obtained from smartphones may induce arousal, fright and stress reactions, which may make it difficult to fall asleep. In addition, bedtime smartphone use is an unstructured leisure activity, which has no predefined starting or ending points, and thus may bring about time displacement (6). Consequently, individuals may be engaged in smartphone use more than they first intended, especially in bed. However, little is known about the meaning of prolonged smartphone use in bed. Thus we focused this behavior and hypothesized that this can be one of the cardinal features of problematic smartphone use. And if so, this behavior may be associated with altered neural correlates.

Resting-state functional connectivity (rsFC) is a potential approach for the assessment of the interaction among brain regions at network levels and is widely used to map the morbid brain (10). Smartphone use necessitates touching the screen, seeing and paying attention to the material, and bedtime smartphone use entails decision-making and cognitive control on whether to continue or stop smartphone use. The insula is known to be an interface of the cognitive, homeostatic and affective systems of the human brain (11), and to integrate external sensory and internal physiological signs in an uncerta*in situ*ation, affecting the decision-making process (12). In addition, the insula has been implicated in salience processing, drug craving, and cognitive control, all of which are fundamental to addictive disorders (13–15). As well, problematic smartphone use seems to have similarities with Internet gaming disorder (IGD) in that both involve online activity and are mediated *via* devices. Zhang and colleagues demonstrated that individuals with IGD exhibited altered insula-centered rsFC compared to healthy controls (16). Thus we considered that insula would be relevant regions of interest. This study was designed to investigate the following two hypotheses: 1) prolonged bedtime smartphone use may serve as one of the relevant behavioral measures of problematic smartphone use, and 2) prolonged bedtime smartphone use may be associated with insula-centered functional connectivity.

MATERIAL AND METHODS

Participants

Participants were recruited through an online survey regarding smartphone use. We included all responders who agreed to enroll in this study. We excluded those who failed to fill all the self-report measures and whose head motion artifact was too excessive to be included in the final analysis. From a total of 728 adults who participated in the survey on smartphone usage, 91 smartphone users (33 male and 58 female) were recruited for this functional magnetic resonance imaging (fMRI) study. One female participant was excluded due to excessive head motion during scanning and finally 90 participants were included [the mean age: 26.99, standard deviation (SD): 5.582]. From a total of 90 participants, only one male participant was left-handed.

All study procedures were performed in accordance with the guidelines of the Declaration of Helsinki. The Institutional Review Boards of Seoul St. Mary's Hospital approved the study protocol (KC15EISI0103). All subjects were informed about the study and all provided informed and written consent and were financially compensated for their time.

Measures

Bedtime Smartphone Use, Sleep Duration and Sleep Latency

Bedtime smartphone use was measured by asking participants how long they used their smartphone in bed before falling asleep, and the answer was manifested as minutes (min).

Sleep duration was measured by asking participants sleep onset and wake up time and calculating the gap between them, weekdays and weekends respectively. Data on sleep latency, a component of the PSQI, were separately collected as well as used to calculate the global sleep quality.

Pittsburgh Sleep Quality Index (PSQI)

PSQI, a 19-item scale with seven components (subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction), was used to assess the global sleep quality (17). The sum of each component yields the total score, ranging from 0 to 21, with higher scores indicating poorer global sleep quality. The Korean version of PSQI had good internal consistency (Cronbach's alpha = 0.84) and reliability and suggested a best cutoff point of 8.5 to distinguish good and poor sleepers (18). Cronbach's alpha for this study was .599.

Smartphone Addiction Proneness Scale (SAPS)

SAPS is a 15-item scale with a four-point Likert scale (1: "not at all" and 4: "always) and widely used for the assessment of smartphone addiction proneness (19). SAPS consists of four subscales, S1 [daytime dysfunction, items 1, 5, 9, 12, and 15 (reverse)], S2 (virtual life orientation, items 2 and 6), S3 [withdrawal, items 4 (reverse), 8, 11, and 14] and S4 [tolerance, items 3, 7, 10 (reverse), and 13] and a higher score indicated higher smartphone addiction proneness. The reliability of the scale revealed a Cronbach's alpha of .880. Cronbach's alpha for this study was .943, and Spearman's correlation coefficients between total and subscale scores were .899, .762, .863, and .880, respectively.

Brief Self-Control Scale (BSCS)

BSCS, a 13-item questionnaire with a five-point Likert scale (1: "strongly disagree" and 5: "strongly agree"), was used to measure self-control ability (20). BSCS measures the ability to override or change one's inner response as well as to interrupt undesired behavioral tendencies and refrain from acting on them, with higher scores indicating lower self-control ability. BSCS had good internal consistency (Cronbach's alpha = 0.85) in the original study. Cronbach's alpha was .880 in this study.

Imaging Data Acquisition

Resting-state fMRI (rsfMRI) data were acquired using a 3T Siemens MRI system (Siemens, MAGNETOM Verio, Erlangen, Germany) equipped with a 16-channel head coil. Participants' heads were cushioned with attached earmuffs. Participants were instructed to keep their head still and eyes open during scanning. The functional images were obtained using a T2*-weighted gradient echo-planar imaging sequences [37 slices, slice thickness = 4.0mm, no gaps, repetition time (TR) = 2,000 ms, echo time (TE) = 30 ms, flip angle = 90°, field of view (FOV) = 240 mm, acquisition matrix = 64 × 64, voxel size = 3.8 × 3.8 × 4.0 mm^3, time point = 200]. A high-resolution T1-weighted image was obtained to permit functional localization (192 slices, slice thickness = 1.0 mm, TR = 2,300 ms, TE = 2.52 ms, flip angle = 9°, FOV = 256 mm, voxel size = 1.0 × 1.0 × 1.0 mm^3).

Imaging Data Preprocessing and Analysis

Imaging data were preprocessed and analyzed using Statistical Parametric Mapping software (SPM12; http://www.fil.ion.ucl.ac.uk/spm/; Wellcome Trust Centre for Neuroimaging, University College London, London, UK) and DPABI version 3.0 (http://rfmri.org/dpabi). After discarding the first five time points, differences in image acquisition time between slices were corrected. Realignment was performed to minimize head motion artifact and the corrected images were coregistered onto the T1-weighted image of each participant. The T1-weighted images were normalized to the Montreal Neurological Institute (MNI) space and the resulting transformation matrices were applied to the coregistered functional images. rsFMRI data were smoothed with a Gaussian kernel of 6 mm full-width at half maximum, bandpass filtered (0.009–0.08 Hz), and linearly detrended. Signals from rigid body 6 motions, white matter, cerebrospinal fluid and global motion were removed *via* nuisance regression.

To compute the rsFC of the insula, regions of interest (ROIs) were defined by anatomically-defined insula using the Automated Anatomical Labeling (AAL) atlas. The average time series within each seed was correlated with time-series of every voxel in the whole brain to generate cross correlation maps. Voxel-wise correlation coefficients were converted to Z-score *via* Fisher's r-to-Z transformation.

Whole brain voxel-wise regression analyses were performed to examine whether there was a correlation between rsFC and bedtime smartphone use with age and gender as nuisance covariates with a family-wise error (FWE) corrected cluster-level threshold of $p < 0.05$ determined at a height threshold of uncorrected $p < 0.001$. Pearson correlation analyses between SAPS, smartphone time (weekday and weekend), smartphone time in bed, PSQI, sleep latency, sleep duration (weekday and weekend), and BSCS were performed. Correlation analyses were performed between parameters extracted from multiple regression analyses (FC z-scores) and SAPS, total smartphone time, PSQI and BSCS. FDR multiple comparison corrections were conducted to the value of correlation using the Benjamini–Hochberg procedure.

Demographic and clinical data of the sample were analyzed quantitatively and qualitatively using R Statistical Software (Foundation for Statistical Computing, Vienna, Austria).

RESULTS

Sample Characteristics

Demographic characteristics of 90 adult smartphone users and the correlation between variables were shown in **Table 1**. The mean SAPS score was 36.92 (SD = 11.354) and scores for subscales were 11.61 ± 4.016 for S1 (daytime dysfunction), 3.99 ± 1.673 for S2 (virtual life orientation), 10.18 ± 3.74 for S3 (withdrawal) and 11.14 ± 3.59 for S4 (tolerance). Weekday and weekend smartphone time were 4.14 ± 2.48 hours (h) and 4.52 ± 2.67 h respectively. Participants spent 62.3 ± 53.43 minutes (min) using their smartphone in bed. The median value for smartphone use in bed was 60.00 min. The mean sleep latency was 30.01 ± 24.39 min. PSQI and BSCS total scores were 6.70 ± 3.14 and 37.87 ± 8.219 respectively. Among all participants, 32 (35.6%) participants never delayed sleep due to smartphone use while 58 (64.4%) delayed at least once or more in a week. Specifically, 37 (41.1%) participants delayed 1–2 times per week, 17 (18.9%) delayed 3-4 times per week, and 4 (4.4%) delayed 5–7 times per week. When we analyzed SAPS and smartphone time

TABLE 1 | Sample characteristics.

Variables	Overall
Age	26.99 ± 5.582
Male (%)	33 (36.7%)
SAPS	36.92 ± 11.354
S1 (daytime dysfunction)	11.61 ± 4.016
S2 (virtual life orientation)	3.99 ± 1.673
S3 (withdrawal)	10.18 ± 3.74
S4 (tolerance)	11.14 ± 3.59
Weekday smartphone time (hours)	4.14 ± 2.48
Weekend smartphone time (hours)	4.52 ± 2.67
Weekday sleep duration (hours)	7.112 ± 1.248
Weekend sleep duration (hours)	8.142 ± 1.109
Smartphone time in bed (minutes)	62.3 ± 53.43
PSQI total score	6.70 ± 3.14
C1 (subjective sleep quality)	1.33 ± 0.62
C2 (sleep latency)	1.41 ± 0.95
C3 (sleep duration)	1.19 ± 1.19
C4 (habitual sleep efficiency)	0.67 ± 1.11
C5 (step disturbance)	1.18 ± 0.44
C6 (use of sleeping medication)	0.05 ± 0.27
C7 (daytime dysfunction)	0.87 ± 0.77
Sleep latency (minutes)	30.01 ± 24.39
BSCS	37.87 ± 8.219
Delayed sleep due to smartphone use	
Never	32 (35.6%)
1–2 times/week	37 (41.1%)
3–4 times/week	17 (18.9%)
5–7 times/week	4 (4.4%)

SAPS, Smartphone Addiction Proneness Scale; PSQI, Pittsburgh Sleep Quality Index; BSCS, Brief Self-Control Scale.

according to this classification, those who delayed sleep due to smartphone use 5–7 times per week had the highest SAPS score (Never: 31.50 ± 11.254, 1–2 times/week: 37.35 ± 10.541, 3–4 times/week: 41.76 ± 6.915, and 5–7 times/week: 55.75 ± 2.363, $F = 9.100$, $p < .005$, *post hoc* Bonferroni: Never < 3–4 times/week, 1–2 times/week < 5–7 times/week) and smartphone time in bed (Never: 44.75 ± 42.78 min, 1–2 times/week: 60.41 ± 57.71 min, 3–4 times/week: 84.12 ± 43.88 min, and 5–7 times/week: 127.50 ± 61.85 min, $F = 4.594$, $p < .05$, *post hoc* Bonferroni: Never < 5–7 times/week), but total smartphone time did not differ across groups.

Table 2 showed the correlation between variables. Smartphone time in bed was positively correlated with SAPS and total smartphone time, but not with PSQI total score, sleep duration and latency, and BSCS.

rsFC Results

As shown in **Table 3**, prolonged smartphone time in bed was positively correlated with insula-centered rsFC. Prolonged bedtime smartphone use was associated with increased functional connectivity of the left insula with the right putamen, and of the right insula with the left superior frontal gyrus, left middle temporal gyrus, left fusiform gyrus, right superior temporal gyrus, and left inferior orbitofrontal gyrus. (**Figure 1**).

Relationship Between rsFC Strength and Clinical Characteristics

Table 4 shows the relationship between seed-ROI rsFC and SAPS, weekday and weekend smartphone time, PSQI and BSCS. Smartphone addiction proneness was positively correlated with rsFC between the left insula and right putamen (**Figure 2**). Total smartphone time, PSQI and BSCS were not correlated with the strength of insula-ROI rsFC.

DISCUSSION

In this study, we found that smartphone use in bed was positively correlated with smartphone addiction proneness and was associated with enhanced functional connectivity of the insula with a network of brain regions. Specifically, the rsFC between the left insula and the right putamen, and the right insula and the left superior frontal, middle temporal, fusiform and orbital frontal gyrus and right superior temporal gyrus was enhanced. In addition, the strength of rsFC between the left insula and the right putamen, and the right insula and the left superior frontal gyrus was positively correlated with smartphone addiction proneness.

Smartphone time in bed was positively correlated with smartphone addiction proneness scale and its subscales, and total smartphone time. In contrast to previous studies, bedtime

TABLE 2 | Correlation between variables.

	1	2	3	4	5	6	7	8	9
1. SAPS	1								
2. Weekday smartphone time	.383*	1							
3. Weekend smartphone time	.389**	.876**	1						
4. Smartphone time in bed	.395**	.305*	.354**	1					
5. PSQI	.350**	.154	.068	.118	1				
6. sleep latency	.199	.229	.255	−.099	.289*	1			
7. Weekday sleep duration	−.204	−.158	−.191	−.103	−.193	−.058	1		
8. Weekend sleep duration	-.005	.016	.000	.000	−.172	.102	.387**	1	
9. BSCS	.554**	.143	.136	.139	.454**	.210	.037	.043	1

SAPS, Smartphone Addiction Proneness Scale; PSQI, Pittsburgh Sleep Quality Index; BSCS, Brief Self-Control Scale.
***p < .005, *p < .05.*

TABLE 3 | Seed locations and regions showing significantly positive correlation with smartphone time in bed.

Seed	Region	Brodmann area	Cluster size	Peak MNI (mm)			Peak *T*- score
				x	***y***	***z***	
L insula	R putamen	49	195	36	4	−2	4.00
R insula	L superior frontal	4	773	−44	−14	50	4.44
	L middle temporal	39	237	−44	−54	18	4.43
	L fusiform	18	1632	−24	−76	−12	4.38
	R superior temporal	21	1064	44	−32	−2	4.35
	L inferior orbitofrontal	47	194	−20	24	-8	4.18

L, left; R, right.

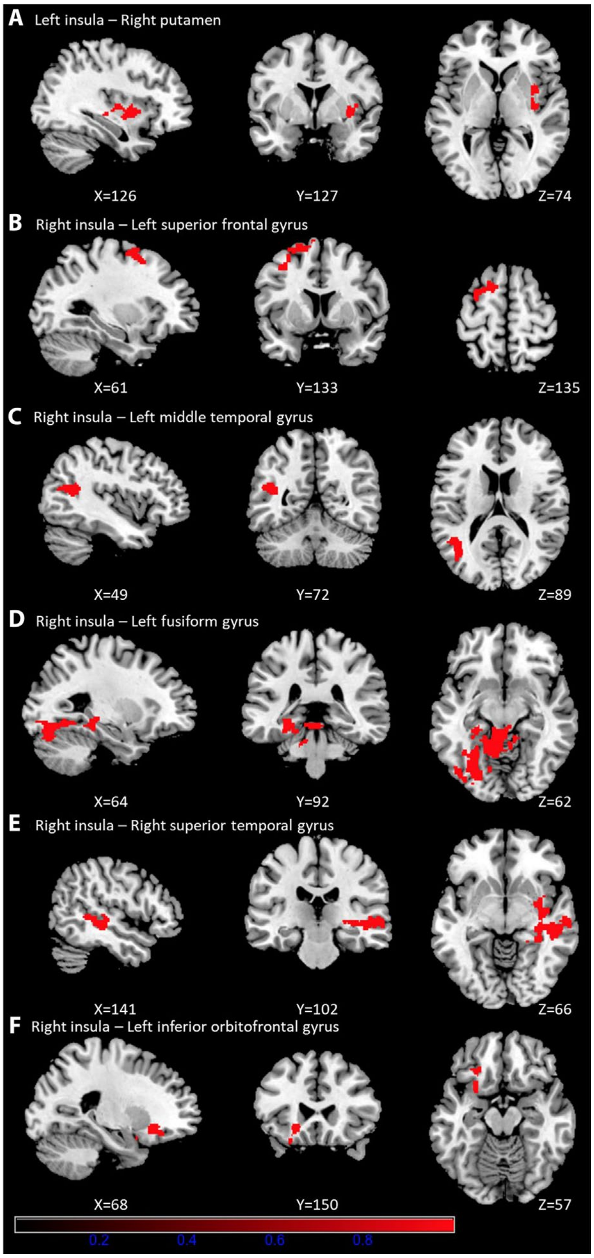

FIGURE 1 | Brain regions showing significantly positive correlation with smartphone time in bed. Prolonged bedtime smartphone use was associated with increased functional connectivity of the left insula with the right putamen **(A)**, and of the right insula with the left superior frontal gyrus **(B)**, left middle temporal gyrus **(C)**, left fusiform gyrus **(D)**, right superior temporal gyrus **(E)**, and left inferior orbitofrontal gyrus **(F)**.

smartphone use was not correlated with general sleep quality, duration, and latency (6, 7). This discrepancy may be due to the difference in sample characteristics. While previous studies focused on adolescents or adults with a broad age range of 18 to 94 years, our study included those aged from 20 to 39 years old. While boy adolescents are well known for the dramatic shift to eveningness and older people are prone to morningness (21, 22), adults in our sample age mostly have an intermediate chronotype. We also found that individuals who postponed their sleep due to smartphone use most frequently showed the highest smartphone addiction proneness score and smartphone time in bed, but total smartphone time did not differ. Though these results need further validation because of the small numbers allocated in each group, this poses an insight that individuals with longer duration of bedtime smartphone use may feel more difficulty to cut down their smartphone use in bed. Taken together, the results suggested that prolonged bedtime smartphone use may be associated with problematic smartphone use, without influencing sleep quality, and may serve as one of the relevant behavioral measures of problematic smartphone use.

Longer bedtime smartphone use was associated with greater strength in five insula-centered rsFC. First, the rsFC between the left insula and right putamen was enhanced in relation to prolonged smartphone use in bed. The striatum is a brain region that dominates the reward processing and both the insula and putamen are involved in time perception (23, 24). Decreased insula-striatum connectivity has been observed in IGD (25, 26), a direction opposite to this study. While stressful situations are associated with the experience of time passing more slowly, relaxed feeling states are associated with experience of passing time more rapidly (27). These findings pose a possibility that feeling relaxed in bed may be associated with longer smartphone time due to greater perceived quickness, and time spent more than they first intended may be associated with increased rsFC between the left insula and right putamen. Second, rsFC of the right insula with left superior frontal gyrus (SFG) and inferior orbitofrontal gyrus (OFG) was increased. The insula is implicated in higher order cognitive functions with a network of brain regions; in association with insula, and IFG is in decision-making and evaluation of risk (13, 28), particularly subjective risk prediction which is influenced by pessimism/optimism or risk aversion/tolerance (28). SFG is involved in planning, motivation, and emotional information processing and the left SFG is particularly involved in spatially orienting processes (29, 30). These findings imply that prolonged bedtime smartphone use would be associated with altered higher order cognitive function. Third, rsFC between the right insula and right superior temporal gyrus (STG) and left middle temporal and fusiform gyrus and right superior temporal gyrus (STG) was increased. A resting brain study on human insula showed that the salience network is lateralized to the right and displays strong connectivity with the left frontal cortex, while the visuomotor integration network has stronger connection with superior temporal cortex and occipital cortex on the right (31). The insula is the brain region in which visceral sensation from temporal cortex and emotional components from the amygdala, nucleus accumbens, orbitofrontal cortex is conveyed to and integrated. While STG serves to process audiovisual information (32), the middle temporal and fusiform gyrus are involved in visual processing, including color information processing, face and body recognition, and word recognition (33, 34). In addition, both STG and insula are involved in the decision-making process, particularly in switching responses relative to staying with the same choice (35). Taken together, these findings support

TABLE 4 | Relationship between seed-ROI functional connectivity and other variables.

Seed	ROI	SAPS	Weekday smartphone time	Weekend smartphone time	PSQI	BSCS
L insula	**R putamen**	.292*	−.010	.019	.106	.152
R insula	**L fusiform**	.145	−.025	−.001	.027	.048
	L inferior orbitofrontal	.153	.006	.019	.037	.069
	L middle temporal	.161	−.051	−.063	.113	.090
	L superior frontal	.229	−.005	.054	−.025	.058
	R superior temporal	.172	−.016	.006	.027	.028

ROI, region of interest; SAPS, Smartphone Addiction Proneness Scale; PSQI, Pittsburgh Sleep Quality Index; BSCS, Brief Self-Control Scale; L, left; R, right.
***p < .005, *p < .05.*

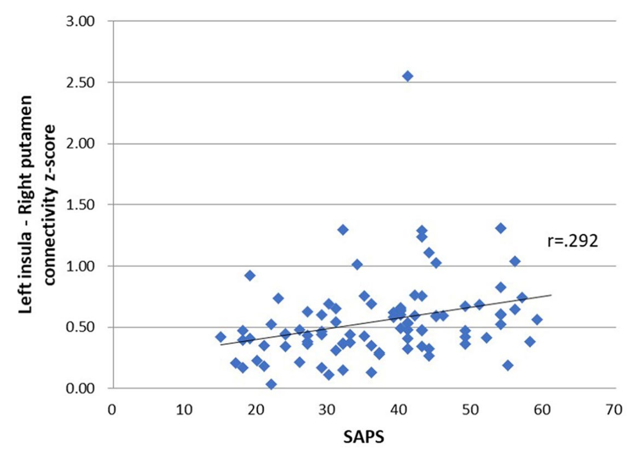

FIGURE 2 | Relationship between seed-region of interest (ROI) functional connectivity and smartphone addiction proneness scale (SAPS) scores. SAPS scores were positively correlated with connectivity *z*-score of left insula and right putamen, $r = .292$, $p = .03$.

that prolonged bedtime smartphone use would be associated with enhanced visceral sensation processing and cognitive overloading, particularly in complex decision making. These findings were also consistent with results observed in IGD (16).

Interestingly, the rsFC between the left insula and right putamen were positively correlated with smartphone addiction proneness. Morbid brains sometimes have enhanced functional connectivity between specific brain regions, which may seem counterintuitive. Since morbid brains may need more cognitive efforts due to inefficiency, enhanced connectivity may support this cognitive overloading, as is the case of IGD and obsessive compulsive disorder (16, 36). Thus, the alteration of insular connectivity in association with prolonged bedtime smartphone use may serve as an indicator of the severity of problematic smartphone use.

As we hypothesized, the functional connectivity of the insula was associated with prolonged smartphone use in bed. The insula has been implicated in the cognitive, affective, and regulatory functions and provides a link between stimulus-driven processing and brain regions involved in monitoring the internal milieu (11). Insula-mediated interoceptive representations have the capacity to "hijack" the cognitive resources necessary for exerting inhibitory control to resist the temptation to smoke, use drugs, or use social media impulsively by disabling the activity of the prefrontal system (37). In IGD, the insula seems to play a crucial role *via* the interoceptive system in modulating equilibrium between impulsive and reflective systems (38). Smartphone use in bed requires integrating external stimuli obtained from smartphones with internal milieu such as balancing between emotional or physical excitement and the need for sleep in appropriate timing. Individuals with problematic smartphone use may necessitate more cognitive effort to manage integrative and interoceptive function than those without.

Several limitations should be noted. First, the cross-sectional nature of this study could not confirm the causal relationship between altered insula-centered rsFC and prolonged smartphone use in bed. Second, we did not screen psychiatric comorbidity including substance use disorder. Third, the amount of smartphone use relied upon self-reporting, and there was no information on smartphone contents that were consumed in bed. Fourth, the amount of smartphone use in bed may also be a part of total daytime smartphone use. However, when classified by the frequency of delaying sleep due to smartphone use, smartphone time in bed was higher in those who delayed sleep most frequently while total smartphone time did not differ. This implies that total smartphone time and smartphone time in bed may have different function on problematic smartphone use. Fifth, we did not have comparative healthy control subjects since the sample was not recruited through clinics, and there is much dispute on defining problematic smartphone use. Thus, our findings are confined to the correlational interpretation. Lastly, functional connectivity is correlational and does not determine the direction between nodes. Further research using effective connectivity would validate the altered direction of the functional connectivity between nodes manifested in individuals with prolonged bedtime smartphone use.

Despite the shortcomings, this study had intriguing strengths. First, to the best of our knowledge, this is the first study investigating the neural correlates of prolonged bedtime smartphone use among adult smartphone users. Second, we explored the alteration in resting-state functional connectivity in association with one particular behavior. Despite increased attention on problematic smartphone use and devoted efforts to define this phenomenon, there is still no standardized consensus for problematic smartphone use. By investigating the neural substrates relevant to prolonged bedtime smartphone use, we deliberately suggested altered insular functional connectivity may be associated with problematic smartphone use.

ETHICS STATEMENT

All study procedures were performed in accordance with the guidelines of the Declaration of Helsinki. The Institutional Review Boards of Seoul St. Mary's Hospital approved the study protocol (KC15EISI0103). All subjects were informed about the study and all provided informed consent and were financially compensated for their time.

AUTHOR CONTRIBUTIONS

S-HP, C-HP, J-SC and D-JK contributed to the conception and design of this study. J-YK and J-WC contributed to the acquisition of behavioral and imaging data. S-HP performed clinical and imaging data analysis. S-HP wrote the first version of this manuscript and prepared the figures and tables. C-HP, J-YK and J-WC assisted with the interpretation of the data. All authors contributed to the revision of the manuscript critically and approved the final manuscript.

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BRIEF RESEARCH REPORT
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Hypnotised by Your Phone? Smartphone Addiction Correlates With Hypnotisability

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Hypnosis and heavy smartphone use are both characterised by absorbed states in which one loses track of time and responds automatically to stimuli. In this pre-registered study, we tested whether there was a relationship between smartphone addiction and hypnotisability: one's tendency to follow suggestions under hypnosis. Over 11 public lectures, we hypnotised 641 student-aged participants; after the hypnosis session, participants completed the Smartphone Addiction Scale (Short Version). There was a positive correlation between hypnotisability and smartphone addiction (r = .17, 95% CI [.09, .24], p < .001) with a magnitude similar to standard predictors of hypnotisability. This correlation was small but unlikely spurious: it was positive in 10 of the 11 samples (including two from psychology courses) and persisted in a follow-up several months later. The addiction scores in this Canadian sample were unexpectedly high (M = 31.41) compared to other countries. We hypothesise that targeting the absorbed, time-distorted, and automatic use of smartphones may promote healthier phone habits.

Keywords: problematic smartphone use, smartphone addiction, technology addiction, hypnosis, hypnotisability

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INTRODUCTION

Smartphone use has risen dramatically in the past decade. In the United States, 96% of young adults own a smartphone (1) and half of teenagers report feeling addicted to their phones (2); other developed countries show similar rates (3). Researchers and reporters have compared this heavy phone use to a trance or hypnosis (4, 5). Madrigal (6) even likens the "hypnotic" state of endless social media scrolling to the trance-like absorption of slot machines (7), due to their intermittent rewards (8). If heavy smartphone use can resemble hypnosis, people who are more hypnotisable may also be more prone to *problematic smartphone use*, in which phone use interferes with daily life (9). No studies have yet attempted to link these phenomena, so we present the first test of this hypothesis.

The American Psychological Association defines hypnosis as a "state of consciousness involving focused attention and reduced peripheral awareness characterised by an enhanced capacity for response to suggestion" (10), though researchers debate aspects of this definition (11). We propose that hypnosis and heavy smartphone use may share phenomenological features such as absorption, time distortion, and automaticity. Absorption refers to the tendency to become immersed in one's thoughts or experiences (12), such as forgetting about the movie theatre while watching a film. Absorption predicts addictive behaviours in the context of gambling (7, 13), video games (14), internet use (15), and problematic smartphone use (16). Heavy smartphone users often find themselves in these absorbed states, leading to the term "smartphone zombie" to describe the head-down phone-absorbed user, who occasionally walks into other pedestrians—or into traffic (17). Several cities have already established special walking lanes for smartphone users, and researchers have developed phone functions to warn users about incoming objects in the environment, highlighting the extent of absorbed attention when using a phone. Similarly, many people report being heavily absorbed in their experience when under hypnosis (18, 19), and trait absorption tends to correlate with hypnotisability (12, 20, 21).

Hypnosis and smartphone use can also both distort time perception. People underestimate the amount of time spent on their phone (22), with heavier smartphone users showing greater distortions (23). Accordingly, several measures of problematic smartphone use probe whether people use their phone longer than they intend (24, 25). Similar time distortions are well known in hypnosis; people consistently underestimate how long they were hypnotised for, and the higher their hypnotisability, the larger this distortion (26, 27).

Finally, hypnosis and smartphone use can both elicit automatic behaviours with a reduced feeling of control. People can become side-tracked while simply trying to check the time on their phone (28) and report being "sucked down a rabbit hole of un-productivity" (29) or "into some mindless … black hole" (30). People commonly report a loss of self-control when using their phones (30), especially if they feel addicted to them (31). Relatedly, people feel less control over their behaviours under hypnosis (32), such as feeling their arm lifting without their apparent control. People can even engage in complex behaviours, such as writing sentences with a pen, without feeling like they are controlling their actions (33).

Given these phenomenological similarities, we hypothesised that people who are more hypnotisable—those more likely to follow suggestions under hypnosis (10)—would be more prone to problematic smartphone use. We anticipated a correlation around r = .19, similar to other predictors of hypnotisability (34, 35).

MATERIALS AND METHODS

Procedure

We held 11 public lectures on hypnosis at McGill University in Montreal, Canada. Two of these lectures were for introductory psychology courses. After a 45-min lecture, we invited the audience to participate in a study, during which we administered standard measures of hypnotisability and problematic smartphone use. Each lecture, almost everyone stayed to participate without compensation, so there was no further selection bias. The protocol was approved by the McGill University Research Ethics Board (#338-0117).

Participants

In total, 718 participants completed the study. We excluded those without smartphones (n = 40) or with missing values on the hypnosis (n = 22) or smartphone questionnaires (n = 15). (Imputing these missing values using mean substitution would have changed no decisions about our hypotheses.) After the exclusions, 641 participants remained; the majority were women (71%) and the average age was 21.2 (SD = 3.6, range: 18 to 47).

Measures

Hypnotisability

After consenting to the study, participants completed the Harvard Group Scale of Hypnotic Susceptibility Form A (36), the most common scale of hypnotisability. This procedure has two parts. First, the experimenter plays a standard 45-min audio recording of a hypnotic induction (e.g., "Your eyelids are getting heavy…") followed by a series of 12 verbal suggestions. For example, the recording suggests that the participant's head will fall forward or that they will be momentarily unable to open their eyes. Second, after the suggestions, the recording leads participants out of hypnosis; they then complete a questionnaire reporting how many of the 12 suggestions they successfully followed. Higher scores indicate greater hypnotisability. The scale has good internal consistency in previous samples from the same city (KR-20 = .84) (37), but it was lower in our sample (.64). We considered the reliability sufficient for this preliminary research (38).

Problematic Smartphone Use

Participants then completed the Smartphone Addiction Scale (Short Version) (25), the most common measure of problematic smartphone use. This scale quantifies how much smartphones interfere with daily life; we are agnostic about whether this constitutes an addiction in the general population (39). An example item is: "I feel impatient and fretful when I am not holding my smartphone". We made minor changes to the wording of some of the questions to fix grammatical issues and improve clarity for our sample (see **Appendix A**). The 10 items use Likert scales ranging from "Strongly disagree" (1) to "Strongly agree" (6), for a total score between 10 and 60. Higher scores indicate a greater risk of addiction as judged by clinicians (25, 40). The scale usually has high internal consistency (Cronbach's α = .91) (25) which was similar in our sample (.83). To assess test-retest reliability, an exploratory subsample of the participants (n = 54) retook the Smartphone Addiction Scale approximately 6 months later (M = 185.5 days, SD = 178.3, range: 3 to 535) in an unrelated study. Beyond demographics, no other measures were collected.

Analysis

All aspects of the study and analysis were pre-registered online (see https://osf.io/juk4n). Using linear regression, we tested whether hypnotisability predicted smartphone use (partial model) before adding sex as an additional predictor (full model). We anticipated a small correlation which would require 300 valid data points for 90% statistical power. We continued to hold public lectures until we reached this number.

We then replicated these results using an identical procedure. We describe both samples together and focus on correlations and robust standardised mean differences signified as d_R (41). The regression results (**Appendix B**) are confirmatory and all other tests are exploratory. All assumptions for the tests were reasonable; hypnotisability (42) and problematic smartphone use are often normally distributed (43). Square brackets denote bootstrapped 95% confidence intervals (44).

RESULTS AND DISCUSSION

Hypnotisability Predicted Problematic Smartphone Use

Scores on the Smartphone Addiction Scale positively correlated with the number of hypnotic suggestions that participants followed ($r(639)$ = .17 [.09, .24], p < .001; **Figure 1A**). The correlation was small, as expected in our pre-registration (r = .186), but it was fairly stable (**Figure 1B**) given the large sample size (45). Indeed, the sample correlations were in the positive direction for 10 of the 11 public lectures. The correlation was unlikely due to selection bias; we also saw a positive correlation in the two samples taken from psychology courses (r = .29 [.11, .44]). Hypnotisability has few strong predictors, so small correlations are common; traits such as the Big Five show correlations with hypnotisability between .01 and .19 (34, 35). There were roughly linear relationships for men ($r(186)$ = .21 [.08, .33], p = .004) and women ($r(449)$ = .15 [.06, .24], p = .001). **Table B1** shows the regression results for each sample.

The average hypnotisability score was 6.12 [5.93, 6.32], with little difference between men (6.10 [5.73, 6.45]) and women (6.13 [5.93, 6.34]; d_R = 0.02 [−0.02, 0.20]). These averages resembled previous samples from the same city (37, 46).

In some studies, predictors of hypnotisability are inflated when completing other measures in the same context as the hypnosis (20, 21). This was unlikely here, since our test-retest sample showed a similar correlation six months later in a different context (r = .21 [−.08, .46], excluding one participant with a difference score of z = 4.16). The test-retest reliability of the smartphone measure was high (r = .78 [.62, .87]) across participants with the full range of hypnotisability scores (i.e., 0 to 12).

Problematic Smartphone Use Was High

The average Smartphone Addiction Scale (Short Version) score was 31.41 [30.68, 32.10]. Women scored 32.62 [31.82, 33.42] and men scored 28.48 [27.13, 29.69] (d_R = 0.43 [0.15, 0.75]). Using the scale authors' criteria (40), 51% of the women and 39% of the men would have a high risk of phone addiction.

These scores from Montreal, Canada were unexpectedly high. Our average was higher than in samples from Spain (21.10) (47), Germany (23.09) (48), Switzerland (23.45) (49), Belgium (24.00) (47), Romania (24.2) (50), and the midwestern United States (27.01) (51), but it was similar to adolescent samples in Turkey (31.37) (52), and China (34.0) (53). The reason for our high scores is unclear. It is unlikely that our minor rewording of the questionnaire items had a large effect, given that the scale has been translated into several languages without apparent inflation of the scores. Further, selection bias cannot entirely explain these findings; our scores resemble those obtained in unrelated studies we are conducting in the same city. The field may benefit from a comprehensive review of problematic smartphone use scores across countries to help explain these regional differences (3).

Limitations and Future Studies

Our study had several limitations. First, all measures were self-reported, as is common when measuring hypnosis and problematic smartphone use. Future studies adding objective measures such as screen time tracking could reveal whether hypnotisable participants use their phones more, especially for absorbing activities such as gaming or social media. Second, our sample was young (primary 18 to 22 years old), so we can only generalise to the student population but not to older adults. Since problematic smartphone use primarily affects youth (40), though, the age of our sample was appropriate. Third, given our correlational design we could not assess causality or the direction of the relationship. It seems unlikely that phone use affected hypnotisability, since hypnotisability is generally stable

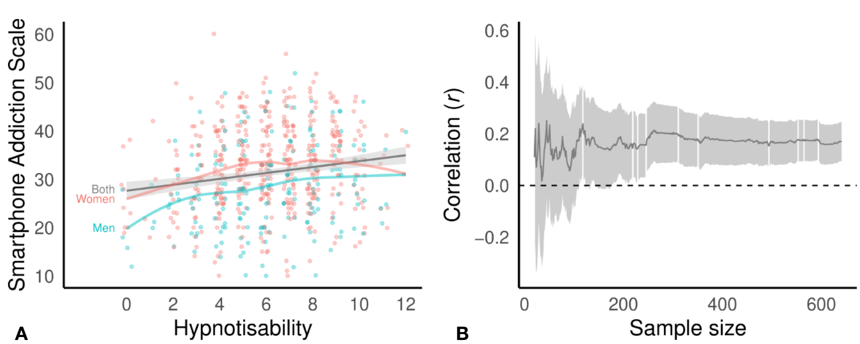

FIGURE 1 | (A) Correlation between problematic smartphone use and hypnotisability **(B)** across the sessions. In **(A)**, curved lines show smoothed averages for each sex, straight line shows linear prediction, band shows 95% confidence interval, and (jittered) dots represent participants. In **(B)**, line shows correlation coefficient across participants, band shows 95% confidence interval, and white lines demarcate sessions.

across adulthood (54). We thus expect that either hypnotisability affects smartphone use, or an underlying construct is acting as a third variable. One candidate may be dissociation, in which one disengages from the sense of self or the environment (55, 56). Similar to absorption, dissociative experiences predict problematic technology use (16, 57). Dissociation is related to hypnotisability in some highly hypnotisable participants (58), but it generally shows inconsistent correlations (59) so cannot account for all of our results. Another possible candidate could be sociality. Some theories posit that hypnosis is primarily a social context involving a set of expectations about what will occur (60), such as the belief that one will automatically follow the hypnotist's suggestions. Hypnotisability may also relate to responsiveness to social cues more generally (61, 62). Relatedly, using phones for social purposes predicts habitual use and addictive behaviour (63, 64). Future studies could test whether dissociation, absorption, or sociality could be the third variable underlying the relationship.

Our findings may also point towards potential interventions. If the positive correlation here reflects the phenomenological similarities between hypnosis and problematic smartphone use (i.e., absorption, time distortion, and automaticity), interventions could target these components. To reduce automatic interactions, behavioural interventions could reduce the salience of the phone or make it more effortful to use (65), for example by keeping the phone further out of reach (66) or limiting sporadic notifications (67). Indeed, combining similar strategies can effectively reduce problematic smartphone use (Olson et al., in preparation).

CONCLUSION

In the current "attention economy", smartphone use translates into data collection and advertising revenue, giving developers economic incentive to keep users absorbed (68). As digital interfaces continue to become more immersive, so too may users' absorption, time distortion, and automatic behaviour. The relationship between hypnotisability and problematic smartphone use may thus continue to strengthen, further necessitating interventions to tackle these components.

DATA AVAILABILITY STATEMENT

The full data set is available on the Open Science Framework (https://osf.io/etyj6/).

ETHICS STATEMENT

This study was reviewed and approved by the McGill University Research Ethics Board (#338-0117). The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

JO led all aspects of the study. MS assisted with data collection. SV provided funding and supervised the study. All authors contributed to the article and approved the submitted version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX A SMARTPHONE ADDICTION SCALE—SHORT VERSION (SAS-SV)

We made minor changes to the wording of the SAS-SV items to fix grammatical issues, improve clarity, and update the examples of social networking sites. We confirmed with the scale's authors that these changes did not impact the intended meaning of the items (Kwon, personal communication, 2019). As in the original measure, each item used a Likert scale from 1 to 6 (strongly disagree, disagree, weakly disagree, weakly agree, and so on). The differences are highlighted in bold below.

1. **I miss work that I planned,** due to smartphone use.
2. **I have** a hard time concentrating in class, while doing assignments, or while working, due to smartphone use.
3. **I feel** pain in my wrists or at the back of my neck while using a smartphone.
4. **I wouldn't** be able to stand not having a smartphone.
5. **I feel** impatient and fretful when I am not holding my smartphone.
6. **I have** my smartphone on my mind even when I am not using it.
7. **I would** never give up using my smartphone even if my daily life **were** greatly affected by it.
8. **I constantly check** my smartphone so as not to miss conversations between other people on Twitter, Facebook, **Snapchat, Instagram, or other social media**.
9. **I use** my smartphone longer than I intend.
10. **People** around me tell me that I use my smartphone too much.

Original items (40):

1. Missing planned work due to smartphone use.
2. Having a hard time concentrating in class, while doing assignments, or while working due to smartphone use.
3. Feeling pain in the wrists or at the back of the neck while using a smartphone.
4. Won't be able to stand not having a smartphone.
5. Feeling impatient and fretful when I am not holding my smartphone.
6. Having my smartphone in my mind even when I am not using it.
7. I will never give up using my smartphone even when my daily life is already greatly affected by it.
8. Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook.
9. Using my smartphone longer than I had intended.
10. The people around me tell me that I use my smartphone too much.

APPENDIX B CONFIRMATORY TESTS

TABLE B1 | Confirmatory regression results for the pre-registered sample (n = 310) and replication (n = 331).

Sample	Model	Sex	Predictor	*B*	SE	*t*	*p*
1	Partial	Both	(Intercept)	26.45	1.36		
			Hypnotisability	0.75	0.21	3.57	<.001
		Men	(Intercept)	22.17	2.54		
			Hypnotisability	1.08	0.41	2.64	.010
		Women	(Intercept)	28.79	1.56		
			Hypnotisability	0.55	0.24	2.33	.021
	Full	Both	(Intercept)	24.29	1.49		
			Hypnotisability	0.71	0.21	3.43	<.001
			Sex (F)	3.55	1.09	3.25	.001
2	Partial	Both	(Intercept)	28.91	1.30		
			Hypnotisability	0.47	0.19	2.44	.015
		Men	(Intercept)	25.67	2.07		
			Hypnotisability	0.45	0.29	1.53	.130
		Women	(Intercept)	29.74	1.57		
			Hypnotisability	0.53	0.24	2.24	.026
	Full	Both	(Intercept)	25.31	1.51		
			Hypnotisability	0.51	0.19	2.69	.007
			Sex (F)	4.60	1.04	4.43	<.001

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The Psychology of Addictive Smartphone Behavior in Young Adults: Problematic Use, Social Anxiety, and Depressive Stress

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This review enhances the existing literature on relationships between problematic smartphone use (PSU), psychopathology, addictive personality, and online social engagement as regards young adults, giving attention to predictive determinants of addictive behavior in smartphone usage. My article cumulates previous research findings on the psychology of addictive smartphone behavior in terms of problematic use, social anxiety, and depressive stress by focusing on the relationship among mobile social media usage, smartphone addiction risk, mental health issues, and individual well-being. The inspected collected findings prove that depression and social anxiety constitute risk determinants for greater PSU and that particular categories of smartphone applications are positively related to well-being. State anxiety and motivations represent significant predictors of PSU. High PSU affects participation in social engagement. As limitations in the current review, my results point towards relevant avenues of research on social consequences of teenagers' smartphone problematic use. Future directions should clarify whether compulsive smartphone use adversely affects both mental and physical health in the long run.

Keywords: smartphone, behavior, anxiety, depression, stress

INTRODUCTION

Problematic smartphone use (PSU) is a complex phenomenon comprising diverse dysfunctional manifestations (*e.g.* social isolation, diminished self-confidence, depression, and anxiety) without being a potential behavioral addiction (1). Smartphones may have negative consequences on the human brain and associated psychological processes. Based on psychiatric symptoms, various kinds of smartphone use disorder have been identified, some of them associated with Internet communication, particularly as PSU is related to depression and self-esteem (2). I will extend the argument by positing that as PSU is negatively related to young adults' psychosocial well-being, time spent using smartphones influences mental health. I initially undertook a review of Web of Science in November 2019, supplemented with updates from this database and from Scopus and ProQuest in May 2020. Search terms included "smartphone addiction", "smartphone addiction risk", "smartphone addiction predisposition", "addictive smartphone behavior", "problematic smartphone use", and "compulsive smartphone use". As I focused on journal articles published between 2017 and 2020, excluding editorial material, only 267 original research and review articles met the eligibility criteria. By removing those whose results were inconclusive, unconfirmed by replication or too general, and because of space constraints, I selected only 67 articles (**Table 1**). My review provides evidence that PSU is adversely associated with diverse notions of well-being and that symptoms of psychopathology are related to severity of PSU, with flimsy evidence though that smartphone use can be addictive as drug and alcohol use disorders are.

PSU has public health relevance (14) because of irrefutable links with alcohol use, particular mental health diagnoses (*e.g.* depression, anxiety, ADHD, PTSD, *etc.*), and inferior academic performance (15). Depressive disorders mediate the link between academic stress and PSU. Individuals having lower or moderate degrees of problem-focused coping are likely to display more depressive symptoms, generating a higher score on PSU (16). The adverse association between smartphone use and academic performance may result in an addictive behavior that may affect students' careers (17).

PSU is associated with anxiety symptom severity and depression psychopathology, shaping personality factors, self-esteem, and perceived social support. Psychological distress, addictive personality, and emotion dysregulation are instrumental in configuring PSU severity.

PSU AND DEPRESSION PSYCHOPATHOLOGY

PSU is sometimes positively associated with adolescent depression. As an illustration, perceived social support moderates the relationship between procrastination and adolescent depression, being relevant only for teenagers having a low degree of perceived social support (3). For such teenagers, the connection between sensation seeking and smartphone use is positively relevant, while for teenagers having a significant degree of perceived social support, the link between sensation seeking and PSU is strong (4). PSU, stress degrees, and perceived social support are more significant among women students (5). Self-command, apprehension, depression, and dysfunctional impulsivities are the most significant predictors of PSU (6), and certain groups of patients having schizophrenia may necessitate special care to hinder PSU (7). Unsociable persons may depend on smartphone wishing to be connected with and obtain support from other users, while possibly leading up to confronting PSU (8).

Difficulties appear when users are addicted to their smartphone, spending an excessive quantity of time using it. Dysfunctional symptoms of PSU mirror substance use disorder criteria (9–11). An immoderate utilization of smartphones leads to symptomatology reminiscent of psychological disorders generated by substance addiction (12). Smartphones are memory extenders, functioning as convenient data depository from the ordinary to the intricate (13).

TABLE 1 | Topics and types of papers identified and selected.

Topic	Identified	Selected
smartphone addiction	102	52
smartphone addiction risk	44	17
smartphone addiction predisposition	42	14
addictive smartphone behavior	60	26
problematic smartphone use	121	54
compulsive smartphone use	69	22
Type of paper		
original research	241	63
review	26	4

Source: Processed by the author. Some topics overlap.

COGNITIVE BEHAVIORAL PROCESSES AND PSU

The effect of cognitive absorption on PSU is mediated by addiction to social media. PSU is higher than social media excessive use (18) and differs by educational expertise, while social media practice is not dissimilar by gender, age, or instruction. Investigating users' degrees of cognitive absorption (their state of participation in software and technology) with PSU may be instrumental in grasping the influence of user experiences in computer-mediated settings. Individuals dependent on smartphones and social media undergo significant degrees of cognitive absorption (19), especially by women when using social media and higher for social media than smartphones. Therefore, users reporting PSU communicate more significant degrees of cognitive absorption than those disclosing inferior degrees of addiction (20), while users having low degrees of PSU display more significant levels of cognitive absorption than those having no degree of PSU. Grasping user experiences or opinions impact user behavior (21), and clarifies how users become immersed in technology. The impact of user experiences and the association with PSU involves how individuals participate in technology (22) and may become thoroughly absorbed in it, in some cases to a troublesome extent (23).

Smartphone application personalities such as collaborative and ambitious, captivating and appealing, communicative and rigorous, and conscientious and righteous all indicate the robust interactive attribute of such devices. Smartphone users' behaviors, smartphone social applications that link individuals, and perceived social capital resulted *via* smartphone social application practice drive smartphone application personality. Besides having hedonic value, leisure applications can be instrumental in social capital in addition to the smartphone application personality aspects (24). Context-awareness is assimilable into the system to adequately detect a smartphone user taking into account the corresponding information. Smartphones are increasingly cognitive and context-aware (25) with developing perceiving, interconnection, and computing capabilities. As soon as a user is located, his/her activities can be monitored for health supervision (26), social networking scrutiny, and prediction and modeling of way of living. Ceaseless authentication of smartphone users can be inspected in conformity with their behavioral features employing activity pattern identification (27). Because of this, functional dependence of PSU draws attention to instrumental practicality of the smartphone (functionally dependent users tend to be more inclined to change PSU), while existential dependence of PSU addresses compulsive, frequently unconscious, attachment (existential dependent users tend to be more disinclined in acknowledging adverse consequences) (28).

Behavioral addiction and pathological personality traits clarify depression and anxiety's associations with PSU-related dysfunctional mechanisms and motivational processes, impacting subjective and psychological well-being.

ADDICTIVE SMARTPHONE BEHAVIOR AND PHYSICAL HEALTH

Physical negative effects are rooted in excessive smartphone use (29). However, addictive smartphone behavior may resemble addiction as regards immoderate use (30), impulse control issues, and adverse effects, without being a disorder with serious consequences on physical and psychological health (31). For example, smartphone texting is associated with a more immobile and more tense spinal position in contrast to desktop computer typing (32). Persistent neck flexion throughout smartphone represents a determinant of neck discomfort and modification of neck muscle performance. Shoulder taping diminishes neck pain without impacting neck muscle performance and tiredness during smartphone texting (33).

Excessive smartphone use also generates poor mental health outcomes, *e.g.* depressive symptoms and sleep issues (34). Concerning smartphone and social platform adoption, positive results are associated with social capital and involvement (35), while detrimental consequences develop out of excessive use, negative correlations, and the anxiety of being perpetually active. As an illustration, not employing smartphones in the bedroom boosts the standard of living, and risk of smartphone overuse diminishes when such devices are kept outside the bedroom. Sleeping without smartphones enhances sleep quality, relationships, motivation, and good physical condition (36). PSU can bring about mobility issues in the wrists, fingers and neck, in addition to intrusion into sleep habits. For teenagers, the quality of sleep impacts growth, emotional constancy, and learning abilities, and thus the handling of PSU is decisive for adequate sleeping habits (37).

Higher sensation seeking persons may be particularly at risk of PSU. Smartphones may enable individuals to be involved in a range of undertakings (38) and assist them in alleviating leisure boredom. More significant levels of leisure boredom and sensation seeking (39) have a positive link with a higher degree of smartphone overuse. Smartphones may be addictive, and their users aiming to attain various purposes can become extremely dependent on them. Individuals having stronger and more straightforward grounds to attempt to accomplish objectives on their smartphones (40) are more predisposed to have a more significant level of smartphone overuse (41).

Excessive smartphone use may lead to addictive smartphone behavior that may result in physical and psychological negative effects, impacting, among others, neck muscle performance and sleep quality.

SMARTPHONE USE AND SOCIAL ANXIETY

There is a moderate link between smartphone use and stress and anxiety (42), but depression severity and anxiety severity are significantly associated with excessive smartphone use (43). State anxiety and motivations represent significant predictors of PSU. State anxiety moderates the link between leisure and social interaction motivations and PSU for the high smartphone-use group, while not moderating such relationship for the low smartphone-use group (44). Bringing together various functions, smartphones supply teenagers with multiple entertainment prospects to alleviate leisure boredom. Smartphone adoption for both interpersonal networking and relaxation (45) has important and direct consequences on smartphone overuse (46), while individuals who use smartphones for news pursuit are not affected by PSU. Incapacity to regulate addiction, escape, anxiety, and productivity loss all constitute a variety of smartphone users' behavioral effects from PSU (41). Significant alienation can escalate PSU (47).

Despite the fact that the compulsive nature of smartphone users is less relevant than extraversion in giving rise to smartphone social application practice, smartphone application personality, and social capital constitution, such devices are beneficial for persons high in anxiety to obtain social capital. The self-observing and selectiveness characteristics of bonding social capital drive it to be negatively instrumental in the collaborative and appealing smartphone application personality (24). Thus, depression and social anxiety constitute risk determinants for greater PSU. Specifically, body image dissatisfaction is a positive predictor of PSU. Social anxiety is a relevant mediator between body image dissatisfaction and PSU. Along with it, for socially anxious persons, smartphone-based online networking is less nerve-racking than offline social one. Emotionally traumatic experiences are related to PSU in teenagers and this link may be somewhat clarified by body image dissatisfaction and psychosocial risk determinants (48).

Depression and social anxiety are correlates of PSU. Psychopathological symptoms, interpersonal sensitivity, and smartphone use articulate the behavioral dynamics of social anxiety symptom severity.

STRESS, SUBJECTIVE AND PSYCHOLOGICAL WELL-BEING, AND PSU

PSU is adversely associated with diverse notions of well-being, *e.g.* subjective contentment, mental health, and depression or stress disorders. Adverse affect, self-determination, and environmental proficiency have negative associations with PSU. Well-being and accompanying dispositional determinants may bring about perceived and actual PSU. Considering the steady and dispositional character of well-being (49), such links are regulated by a shared intrinsic predisposition to experience anxiety, deleterious emotions, and an absence of control, integrated into a propensity to get involved in dysfunctional coping and compulsive behavior (50). Depression, anxiety, and self-control are thus risk determinants or results of PSU that is also compulsive, typified by immoderate time spent on smartphones, invasion of social networking and responsibilities, and stress in detaching from such devices (51). Perceived stress is positively associated with adolescent smartphone overuse. Self-regulation mediates the association between perceived stress and smartphone addiction. The direct and indirect consequences are moderated by mindfulness, being more relevant for persons with inferior degrees of mindfulness (52).

Total application screen time is related to relationship conflict, in addition to anxiety and depression. The adoption of smartphones to interact with friends causes emotional states of deception, remorse, and feeling stressed out to respond promptly to their smartphone communications. Increased smartphone adoption results in problematic use (19) as the outward world effortlessly permeates users' private lives. Smartphones enable the adjustability and non-confinement to collect information, have fun, and interact, with few impediments, while users are also under compulsion to their mobile devices. Particular categories of smartphone applications are positively related to well-being, but the predisposition for incessant connection has generated a range of problems associated with PSU (53). Smartphones may be instrumental in sharing any instinctive reflection or experience with users' social networks. Egocentric teenagers' validation-seeking on social media, especially as a manner to surmount social exclusion (54), may have unwelcome repercussions (38) and eventually results in a developing model of counterproductive behavior. Earlier teenage egocentrism predicts later social media disclosure, PSU, and interactional stress, through increased validation-seeking. Smartphones are equipped to boost teenagers' persistent utilization of social media (49) for intentions of assertiveness, interpersonal relationship, and social attention (55), thus generating higher degrees of stress and dependency associated with such devices (56).

Both process- and social-led smartphone characteristic uses are associated with greater PSU (that is excessive utilization of smartphones increases risk of PSU) (57). PSU has certain patterns depending on age, with preponderance of authority, mood alteration, and discord in prepubescence, and patience, withdrawal symptoms, and indisposition in pubescence (58). For example, grandiose narcissism is positively related to PSU, while the consequence of vulnerable narcissism is entirely mediated by disinterest (59). PSU also can deteriorate teenage self-esteem, procrastination mediating the association between them (60), and more, teenagers are prone to addiction by lacking the strength to regulate impulsive behavior (61). Students having a relationship make more significant use of smartphones than those who are partnerless (62).

PSU shapes subjective and psychological well-being, and may configure associated anxiety and depression psychopathology. Mental health and somatic symptoms are adversely impacted by PSU leading to impaired socio-emotional functioning and possibly causing psychological distress.

PARENTAL NEGLECT AND PSU

Users' psychological features may not clarify every characteristic of PSU. High PSU affects participation in social engagement. Users' absence of social networks may hinder agreeable social communications (49) and emotional states of encouragement in the offline setting, which may intensify their intention to escape to smartphones. As persons having PSU pursue more straightforward interactions than those undergone in the concrete realm (63), smartphones may have distinct consequences on their social ways of life than other users'. Formal organizational involvement, level of interaction with parents, dimension of the peer group, and fellow support diminish PSU (64). Depression moderates the association between sensation seeking and adolescent PSU. Sensation seeking is positively related to adolescent smartphone problematic use. For teenagers having an inferior degree of depression, the link between sensation seeking and PSU is positively relevant, while for teenagers having a significant degree of depression, the connection between sensation seeking and PSU is not relevant (4).

Parental neglect is considerably related to teenagers' smartphone addiction. In the link between parental neglect and PSU, the former is not relevantly connected with the relational instability with peers, negatively shaping PSU. The relational instability with teachers has a fragmentary mediation impact between parental neglect and PSU (65). Parents who have significant degrees of risk perception and mediation performance are more predisposed to carry out restrictive mediation of the Internet and mobile devices use by their children. Children who have unsatisfactory academic performance, depression, possess smartphones, frequently play tablet gaming, and routinely use social media and instant messaging have inferior degrees of parental restrictive mediation and of acknowledged online safety knowledge, while being more inclined to experience PSU (66). Interpersonal adaptation mediates the link between parental attachment and PSU, and is moderated by self-control, being more intense for persons having lower self-control (67).

Parenting style and attachment may mediate young adults' smartphone use, improving interpersonal adaptation and self-control, while articulating family well-being. Young adults' addictive personality may be shaped by parental mediation practices and self-regulation.

CONCLUSIONS

Significant research has considered lately the psychology of addictive smartphone behavior in terms of problematic use, social anxiety, and depressive stress. My article extends previous work by focusing on the relationship among mobile social media usage, smartphone addiction risk, mental health issues, and individual well-being. Progressively relevant degrees of smartphone ownership and utilization give rise to the implicit risk for addictive behaviors and adverse health results, shaping subjective and psychological well-being. The conclusions drawn from the above analyses are that depression and anxiety symptoms are associated with PSU severity, generating, among others, emotion dysregulation, psychological distress, poor sleep quality, and diminished academic performance. Personality traits, social-emotional distress, and duration of daily smartphone use constitute antecedents of PSU, impacting subjective and psychological well-being. As limitations in the current review, my results point towards relevant avenues of research on social consequences of young adults' smartphone addiction. Future directions should clarify whether compulsive smartphone use adversely affects both mental and physical health in the long run.

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The author confirms being the sole contributor of this work and approved it for publication.

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Problematic Smartphone Use—Comparison of Students With and Without Problematic Smartphone Use in Light of Personality

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Background: As a device with multiple functions, a smartphone become more and more relevant in everyday life. However, this goes along with an increase in reports about smartphone addiction and its unwanted consequences. One of the most important variables in the etiopathogenesis of addictive smartphone use is personality.

Objective: This study aimed to investigate predictors of problematic smartphone use. Clinically relevant differences in personality, psychopathology, and social support between students with and without problematic smartphone use were investigated.

Method: All currently enrolled students at the Sigmund Freud University in Vienna (N = 1,836) were surveyed. Response rate was 27.07% (N = 497, age: M = 19.6, SD = 8.04). The Smartphone Addiction Scale (SPAS), the 10-Item Big Five Inventory (BFI-10), the Brief Symptom Inventory (BSI-18), and a questionnaire on social support (F-SozU-K-14) were used.

Results: A total of 75 students (15.1% of the total sample) showed problematic smartphone use. In terms of personality, respondents with problematic smartphone use showed significantly higher values for extraversion and neuroticism compared than non-addicted users. Students with problematic smartphone use showed significantly higher levels in terms of depression and anxiety. Contrary to expectations, individuals with problematic smartphone use showed significantly higher values for perceived social support than with individuals without problematic smartphone use.

Discussion: Therapy for problematic smartphone use should be carried out taking into account discussed, important etiological factors, such as personality.

Keywords: smartphone, internet, addiction, personality, online

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INTRODUCTION

Smartphones have become an essential part of everyday life. In western societies, almost all adolescents (98%) own a smartphone (1). Research suggests that on average adolescents interact with digital media (i.e., watching videos, reading news, or using social media) for more than 6.5 h every day; mobile devices account for nearly half this time (2). Teens aged 18–24 years look at their smartphone an average of 214 times each day (3). Therefore, it is not surprising that literature increasingly finds people to use their phones in ways that may cause problems with their health (4). There are not only problematic physical effects, such as neck pain (5) or accidents affecting pedestrians (6), but also mental health problems, including sleep disturbances, depression, problems with interpersonal relationships (7), and even smartphone addiction (8).

Currently, smartphone addiction has not been mentioned in either the *Diagnostic and Statistical Manual of Mental Disorders* [DSM-5; (9)] or in the *International Classification of Diseases*, 11th Revision [ICD-11; (10)]. "Gambling disorder" and its specific variant the "Internet gaming disorder" are the only non-substance-related disorders included in the DSM-5 (9). Nonetheless, other potential online addictions and Internet use-related disorders have been reviewed. The introduction of the new diagnoses "gaming disorder" and other Internet-related disorders in the upcoming ICD-11 under the category associated with addictive disorders ("Disorders due to addictive behaviors") reflects the importance of media-related disorders for current research and clinic. In addition, a disorder category "hazardous gaming" will be introduced under the cluster "factors associated with health behaviors" in order to address media-related problem behavior diagnostically and avoid future addiction. This indicates that limiting diagnosis to online gaming exclusively may disregard many other Internet-related behaviors that can be engaged in addictively (11). In the literature, it is argued that to not overlook individuals who suffer from considerable impairments as a consequence of their problematic Internet use, until the concept is grasped more comprehensively, research on Internet addiction should not be limited by only focusing on one aspect of media addiction. Consequently, the diagnosis "Internet addiction" is frequently understood more broadly (12). The core diagnostic characteristics of the Internet addiction consist of mental preoccupation with the Internet, development of tolerance, social withdrawal, frustrations with relapse, withdrawal symptoms (irritability, anxiety, and sadness), loss of interest in previous hobbies or activities, continuation of problematic consumption despite the knowledge of the resulting psychosocial problems, dysfunctional affect regulation, and lying to friends, family members, or therapists to conceal actual consumption as well as the loss of a meaningful relationship, job or apprenticeship, or career opportunities (9, 13–15).

As smartphones offer a wide array of possibilities and functions to access the Internet, Elhai et al. (16) highlight that Internet and smartphone addiction are closely related constructs and share much communality. In line with Biang and Leung (17), characteristics of problematic smartphone use are comparable with the diagnostic criteria of an Internet addiction. Similarly, Lin et al. (18) demonstrated that smartphone addiction shares the main diagnostic factors with other DSM-5 substance and non-substance disorders, proposing the following diagnostic criteria for smartphone addiction: compulsive behavior, functional impairment, withdrawal, and tolerance (19). To date, few studies have investigated problematic smartphone use. Existing studies have focused on prevalence rates (20), diagnostic criteria (19), development, and validation of instruments designed to assess smartphone addiction (18, 21, 22). Little is known about indicators and etiopathogenetic factors of problematic smartphone use. A recent study by Eichenberg et al. (23) investigated attachment-specific differences between smartphone-addicted and non-addicted individuals. Overall, the assumption that insecure people more often showed problematic smartphone use was confirmed; especially "ambivalent-closed" attachment styles were related with problematic smartphone use. However, the authors underline the necessity to identify additional predictors that might promote the development of problematic smartphone use (23).

Another particularly important risk factor seems to be psychopathology (24). Available research indicates that depression or anxiety might lead to media addiction. For instance, stressed and depressed individuals use online video gaming as a coping mechanism to relieve depressive and negative emotions (25). This association was confirmed in a systematic review by Elhai et al. (16), showing that both depression and anxiety severity were consistently linked with problematic smartphone use. An important theoretical consideration is whether smartphone addiction is related to the smartphone itself or if the smartphone is just a medium through which individuals access other addictions. Smartphones provide many possibilities and functions that even further increase the likelihood to develop obsessive behaviors (26). Particularly, social aspects, i.e., social networks, such as Facebook, Instagram, and Snapchat, play a considerable role in facilitating the smartphones' addictive potential. This idea is supported by research showing that social network use and gaming play a major role in addictive smartphone use (27). Taking into account these social functionalities that smartphones offer, users' perceived social support can be regarded as a major predictor of smartphone use. It can be argued that the need to obtain social support in users with low social support can increase the potential risk of smartphone addiction (28). On the other side, it seems reasonable that problematic smartphone use can socially isolate individuals and lower their social support.

A widely agreed on etiopathogenetic factor associated with problematic media consumption is personality. One of the most notable personality theories is the five-factor model of personality, which sets apart five main dimensions: "neuroticism" (e.g., being nervous and anxiety prone), "extroversion" (e.g., being talkative and outgoing), "openness to experience" (e.g., being imaginative and intellectually oriented), "agreeableness" (e.g., being sympathetic and warm), and "conscientiousness" (e.g., being organized and prompt) (29). These traits have been validated across most cultures (30). Andreassen et al. (31) carried out one of the first surveys identifying the inter-relationship between the "Big Five" personality traits and behavioral addictions. Whereas, neuroticism was positively related to Internet addiction, agreeableness and conscientiousness were negatively related to Internet addiction. Kayis et al. (32) showed in a meta-analysis that all Big Five personality traits had a significant correlation with Internet addiction, whereas openness to new experiences, conscientiousness, agreeableness, and extraversion were negatively associated with Internet addiction neuroticism and showed a positive association with it. Similarly, Kuss et al. (33) confirmed neuroticism and low agreeableness to be related with Internet addiction. Overall, neuroticism has been associated with Internet addiction or problematic Internet use in several studies (34, 35).

Given the discussed similarities across Internet and smartphone addiction, it is likely that personality traits might also be related to smartphone addiction (36, 37). In this sense, Van Deursen et al. (38) revealed that poor self-control may be a cause of smartphone addiction. Also, shy, lonely, and depressed respondents were prone to a Smartphone addiction (39). In a research project by Hussain et al. (40), a significant association between smartphone addiction and emotional instability was established. In a mixed-method study, narcissistic personality disorder was found to be a risk factor for developing a smartphone addiction (41). Similarly to findings regarding Internet addiction, a very recent publication by Lei et al. (42) has found a poor positive correlation between smartphone addiction and neuroticism. Unfortunately, most studies on personality and problematic smartphone use focus on only some Big Five personality traits, especially neuroticism [e.g., (43)]. In their meta-analysis, Marengo et al. (44) also report an association between conscientiousness, agreeableness, and neuroticism and problematic smartphone use. Time of publication was related with increased strength of the correlation. In this sense, the current studies reported stronger effects than older publications. However, authors strongly highlight existing limitations in the current literature. For example, available data are dated, and the very limited number of studies at hand lowers the meta-analysis' ability to detect small-sized moderation effects, leading to low statistical power (44). A majority of included studies were carried out in English-speaking countries, underlying the need for increased diversity in this research area, especially considering cultural differences in personality traits.

With the growing amount of time that individuals spend with online media, this mentioned scarcity of research investigating smartphone addiction is rather surprising. Therefore, considering the discussed research, the aim of this study was to examine whether certain personality traits are related to problematic smartphone use. Additionally, interrelationships between psychopathology and social support were investigated.

It was hypothesized that there is a positive relationship between extraversion, neuroticism, psychopathology (i.e., depressive symptoms and anxiety), and problematic smartphone use. It was further hypothesized that there is a negative relationship between social support and problematic smartphone use.

METHOD

Study Design

All currently enrolled students at the Sigmund Freud University in Vienna ($N = 1,836$) were surveyed. Participation was voluntary, and no extra university credits were offered. Data were collected with the online survey tool Unipark. A pre-test was carried out with nine participants. Returns were evaluated, and the survey was modified regarding its practicability, comprehensibility, and completeness of item formulation. Data collection took place starting from 17 March 2017 and ending on 13 May 2017. General information about purposes of the study, study design, and confidentiality was given to participants. Altogether, the online study was accessed 843 times. Most dropouts happened on the first page (23%); after the second page, only roughly 8% of respondents discontinued the survey. Consequently, the overall dropout rate of 59.96% is tolerable. Overall, 497 complete records were submitted. It took about 15 min to complete the survey. The Sigmund Freud University Vienna ethics committee granted ethical approval. For data input, processing, and statistical analyses, the Statistical Package for Social Sciences Program (SPSS Version 24) was used. Significance was checked using Whitney U-tests since prerequisites for performing a T-test (no normal distribution of variables in the two groups) were not met.

Material

Sociodemographic data on age, gender, nationality of participants, and field of study were collected. Subsequently, participants reported on their time spent using the smartphone and preferred smartphone services. Four categories were available: research, entertainment (gaming, music, and reading), social media (SMS and calls), and utilities (photos, videos). Categories were rated on a 5-point-Likert scale ("never" to "daily"). In addition, participants were asked to fill out the following questionnaires.

Smartphone Addiction Scale

To assess symptoms of smartphone addiction, the Smartphone Addiction Scale (SPAS) by Biang and Leung (17) was used. This instrument is based on three separate inventories: the Mobile Phone Problem Use Scale [MPPUS-10; (45)], the Internet Addiction Test (46), and the Television Addiction Scale (47). The questionnaire consists of 19 items. A reliability coefficient of 0.70 is reported. The Cronbach α is high at 0.92.

Within this instrument, Young's (46) eight classic criteria of Internet addiction similar to those embedded in DSM-IV for diagnosing gambling-related problems were used to create the composite smartphone addiction index (SPAI). Sample items are "You have tried to hide from others how much time you spend on your smartphone" and "You find yourself engaged on the smartphone for longer periods of time than intended." These eight items were later also used by Leung (48) to develop a scale for assessing addictive mobile phone use. As in this study it was needed to only differentiate between participants with and without problematic smartphone, only these eight items were applied.

Five primary factors are assessed: ignoring harmful consequences, excessive thinking about using the smartphone, inability to control desire, loss of productivity, and anxiety (17).

Equivalent to the method of Young (46), the 5-point Likert scale was dichotomized. Finally, answers were summed up, resulting in total scores ranging from 0 to 8. Consistent with data by Young (46) on Internet addiction participants scoring, more than five were diagnosed with problematic smartphone use.

10-Item Big Five Inventory

The 10-Item Big Five Inventory [BFI-10; (49)] is a short-scale version of the well-established BFI. Only two items per dimension are assessed. This instrument is made up of 10 items rated on a 5-point Likert scale (1 = "completely disagree" and 5 = "completely agree"). Research underlines that the BFI-10 has psychometric properties comparable in size and structure to those of the full-scale BFI. Mean retest stability coefficients were.75. All five subscales show a satisfactory to good retest reliability, ranging from 0.58 for agreeability to 0.84 for extraversion. Factorial validity was confirmed using a confirmatory factor analysis. On the basis of the factor loadings, acceptable validity could be determined. Convergent validity correlations with the NEO-PI-R domain scales averaged 0.67, showing substantial convergent and discriminant validity (49).

Short Version the Brief Symptom Inventory (BSI-18)

The BSI-18, the short version of the Brief Symptom Inventory, comprises 3 six-item scales (somatization, depression, and anxiety) and a global parameter. All scales show good reliability coefficients [Cronbach's $\alpha = 0.79$ for somatization, 0.84 for depression, 0.84 for anxiety, and 0.91 for Global Severity Index (GSI)]. The postulated three-factor structure could be confirmed with both exploratory and confirmatory factor analyses. The questionnaire separates sufficiently between different patient groups. External assessment by therapists correlated well with the self-assessment. In summary, psychometric values of the BSI-18 are satisfactory. Compared with the full Symptom Checklist (SCL-90-R), loss of information due to the reduction to 18 items is acceptable in the analysis of large samples (50).

Short version of the Social Support Questionnaire

The Short version of the Social Support Questionnaire (F-SozU-K-14) is a 14-item questionnaire to assess perceived and anticipated social support. Items are rated on a 5-point Likert scale (1 = "does not apply at all" to 5 = "totally applies"). The inventory is characterized by very good item statistics as well as good internal consistency (Cronbach's $\alpha = 0.94$). Correlations with sociodemographic variables and correlations with external criteria were checked for validity of the Social Support Questionnaire. Taken together, both internal consistency and other psychometric properties can be rated as very satisfactory (51). The final value is determined by summing the item responses and then dividing by the number of items answered, whereby higher values indicate higher social support.

Sample

The final sample consisted of $N = 497$ participants ($n = 120$ men (24.2%) and $n = 377$ women (75.8%). Subjects were mainly from Germany (72.8%) and Austria (13.6%), and just 3% had another nationality. No data on nationality were available for 10.6% of participants. The age range was from 17 to 70 years (M = 19.38 years, SD = 16.50). A majority of participants were students of psychotherapy ($n = 286$, 57.5%) or psychology ($n = 125$, 25.2%); 16.5% were enrolled in medicine ($n = 82$) and 0.6% in law ($n = 4$). In light of the composition of currently enrolled students at the Sigmund Freud University, this distribution was expected.

TABLE 1 | Mean scores and standard deviations for study variables.

	Mean (M)	Standard deviation (SD)
Personality		
Extraversion	3.45	0.98
Agreeableness	3.23	0.83
Conscientiousness	3.47	0.89
Neuroticism	2.99	0.99
Openness	3.76	0.94
Psychopathology	26.58	8.1
Depression	9.31	3.96
Anxiety	9.34	3.16
Social support	4.45	0.63

RESULTS

Personality, Psychopathology, and Social Support

Regarding personality, participants scored the highest on openness (M = 3.76, SD = 0.94) and conscientiousness (M = 3.47, SD = 89) and the lowest on neuroticism (M = 2.99, SD = 0.99). In terms of psychopathology study, participants scored relatively high (depression M = 9.31, SD = 3.96; anxiety M = 9.34, SD = 3.16) than a clinical sample [depression scores for a sample of patients with depression (M = 11.64, SD = 6.09) and anxiety (M = 7.90, SD = 5.61)] (50). Overall, participants report high values on social support (M = 4.45, SD = 0.63).

Table 1 presents mean scores and standard deviations for the following study variables: psychopathology (depression, anxiety), personality (extraversion, agreeableness, conscientiousness, neuroticism, and openness), and social support.

Problematic Smartphone Use

For a comprehensive analysis, essential data were missing for $n = 19$ subjects (1.4%). Problematic smartphone use was diagnosed in $n = 75$ (15.1%) of participants, 86.7% were female, and a minority (13.3%) were male. Yet this distribution is comparable with the gender ratio of the study sample.

Presented services were used roughly for the same amount of time. The most important smartphone service was "communication" (M = 4.9, SD = 0.5). The service "entertainment" (M = 4.4, SD = 1.02) was used least frequently. For information research and other utilities, smartphones were used comparably often (M = 4.6, SD = 0.77).

Problematic Smartphone Use and Personality, Psychopathology, and Social Support

For a comprehensive overview of differences between users with and without problematic smartphone use for the variables personality, psychopathology, and social support, see **Table 2**.

Problematic Smartphone Use and Personality

A significant difference between users with and without problematic smartphone use in light of extraversion ($U = 13{,}021$,

TABLE 2 | Results of Mann–Whitney *U*-tests for personality, psychopathology, social support, and problematic smartphone use (significant differences are highlighted).

Problematic smartphone use and	*U*	*Z*	*p*
Personality			
Extraversion	13,021.00	2.28	**0.023**
Agreeableness	14,564.5	−0.902	0.364
Conscientiousness	13,604.5	−1.731	0.084
Neuroticism	11,763.00	3.35	**0.001**
Openness	14,890.5	−0.538	0.590
Psychopathology			
Depression	10,322.50	−4.70	**<0.001**
Anxiety	11,118.50	−3.98	**<0.001**
Social support	12,604.00	−2.63	**0.009**

00, $Z = -2.28$, $p = 0.023$) was found. Participants with problematic smartphone use (M = 3.71, SD = 0.92) were found to have higher scores on extraversion than users without problematic use (M = 3.39, SD = 0.99). Similarly, groups differed significantly considering neuroticism ($U = 11{,}763.00$, $Z = -3.35$ $p = 0.001$). Users with problematic smartphone use showed higher levels of neuroticism (M = 3.35, SD = 0.88) than non-dependent users (M = 2.93, SD = 1.00).

As expected, considering the personality factors agreeableness ($U = 14{,}564.5$, $Z = -0.902$, $p = 0.364$), openness ($U = 14{,}890.5$, $Z = -0.538$, $p = 0.590$), and conscientiousness ($U = 13{,}604.5$, $Z = -1.731$, $p = 0.084$), no significant differences between groups were found.

Problematic Smartphone Use and Social Support

A significant difference between study respondents with and without problematic smartphone use behavior and perceived social support was found ($U = 12{,}604.00$, $Z = -2.63$, $p = 0.009$).

Surprisingly, users with problematic smartphone use (M = 4.59, SD = 0.66) indicated higher perceived social support than users without problematic smartphone use (M = 4.44, SD = 0.59).

Problematic Smartphone Use and Psychopathology

Further analyses revealed a significant difference between groups for depressive symptoms ($U = 10{,}322.5$, $Z = -4.70$, $p \geq 0.001$). Participants with problematic smartphone use (M = 11.27, SD = 4.71) had higher depression scores than users without problematic smartphone use (M = 8.99, SD = 3.72).

Finally, a significant difference between users with and without problematic smartphone regarding anxiety ($U = 11{,}118.5$, $Z = -3.98$, $p \geq 0.001$) was found. Users with problematic smartphone use (M = 10.71, SD = 3.59) showed higher anxiety levels than users without problematic smartphone use (M = 9.13, SD = 3.03).

Bonferroni–Holm Corrections

The Bonferroni–Holm method was used to counteract the problem of multiple comparisons in this study and control the family-wise error rate. All significant findings could be confirmed using the Bonferroni–Holm method (**Table 3**).

TABLE 3 | Bonferroni–Holm corrections for study hypotheses.

Comparison (problematic smartphone use)	*p*	Adjusted Bonferroni–Holm p	Significance
Extraversion	$p = 0.023$	$\alpha = 0.050$	Significant
Neuroticism	$p = 0.001$	$\alpha = 0.010$	Significant
Depression	$p < 0.001$	$\alpha = 0.007$	Significant
Anxiety	$p < 0.001$	$\alpha = 0.008$	Significant
Social Support	$p = 0.009$	$\alpha = 0.016$	Significant

DISCUSSION

Despite an abundance of evidence showing the relationship between personality traits and addictive behavior (32), the scientific literature is scarce in studies emphasizing the interconnections between Big Five personality traits and problematic smartphone use (44). There are some findings showing that psychopathology is associated with problematic use of technology (52, 53). The purpose of this study was to replicate and add to previous studies and fill in knowledge gaps particular in regard to problematic smartphone use.

In the present study, 15.1% of respondents were diagnosed with problematic smartphone use. This prevalence rate is in line with other current research (41, 54).

Neuroticism and extraversion were found to be positively related to problematic smartphone use. Neuroticism most probably reflects underlying traits of social interaction-based anxiety, fear of failure, or a firm superego [Kets (55)]. It has been proposed that due to social insecurity, communicating online is favored to offline communication by individuals with high scores on neuroticism (37). Therefore, one explanation for this finding might be that problematic smartphone use might be a way of escaping from social anxiety (31). Similarly, virtual communication might allow for easier interpersonal exchange as a punitive superego might be attenuated. Extroverted individuals are assumed to frequently seek out stimulation and consequently being more prone to addictive behaviors (56). This is consistent with the theory proposed by Bianchi and Philips (45) that the facet excitement-seeking of the dimension extraversion can be regarded as a risk factor for problematic smartphone use.

No relationship was found for agreeableness, openness, and conscientiousness and problematic smartphone use. These results are similar to those of Trub and Barbot (57) and Volungis et al. (58), who found no associations between these personality traits and Smartphone addiction. However, older research by Hwang and Jeong (59) even showed a positive association. This might be due to smartphones no longer representing novel products. Therefore, the interest of open-minded individuals might decrease and consequently the association between openness and problematic smartphone use. In line with the notion that people high on agreeableness scores are likable and pleasant and emphasize harmony in relationships, this personality trait might even be a protective factor against problematic smartphone use (60). Similarly, conscientious people are described as organized and hardworking and therefore might be less susceptible to problematic smartphone use.

Study findings indicate that problematic smartphone use commonly co-occurred with psychopathology, i.e., depression and anxiety. There is literature suggesting that chronically stressed individuals use smartphones as a coping mechanism to relieve depressive symptoms (16). In this sense, smartphone use might serve as an avoidance strategy to avoid negative emotions—even though being ineffective and even having adverse emotional consequences (61). On the other hand, there is research showing that higher levels of technology use go along with psychopathology (7). This might be due to problematic smartphone use keeping users awake at night (8) or increasing work demands, for instance, working from home or being available even after work hours (62). In conclusion, there might be a bidirectional association whereby problematic smartphone use drives psychopathology and vice versa (16). This mutual influence of symptom severity (media use and depression score) became clear in a longitudinal study by Gentile (63). Interestingly, as addictive digital media use increased or decreased, so did depressive symptoms.

In the present study, participants with problematic smartphone use reported higher perceived levels of social support than users without problematic smartphone use. This can be interpreted as individuals with problematic smartphone use dysfunctionally attribute smartphone use as effective and maybe their only means to establish and receive social support, while in fact their non-face-to-face communication might make them feel even more lonely and isolated (64). Alternatively, it can be argued that smartphone use actually goes along with more perceived social support and a feeling of being connected with others. In the digital era, the concept of social support needs to be critically reviewed. What is regarded as social support needs to be reevaluated. "Likes" on Facebook or Instagram might be experienced as actual social reciprocity.

LIMITATIONS

This study needs to be interpreted with caution due to methodological limitations. First of all, the sample was drawn from a specific population, and an even smaller subset completed the study. Subjects were mainly enrolled in psychology/psychotherapy courses at Sigmund Freud University. Little is known about individuals who did not complete the study. This selection bias is inherent to web-based surveys, and the self-selection process limits the validity of findings. For instance, smartphone users who are interested in relativizing the negative image of technology addiction might be more encouraged to participate. Additionally, age distribution was very narrow, and female participants contributed disproportionately to study data. This gender bias in web-based studies has commonly been reported (65). Future studies need wider recruitment methods to produce more generalizable data. As a retrospective study, the possibility of memory biases needs to be discussed (66). Memory gaps might have been replaced with previously anchored schemata. Therefore, the validity of the study might be affected. Nonetheless, the risk of memory distortions can be regarded as insignificant considering that at the time of the study respondents were actively using smartphones on a daily basis. Therefore, study participants' responses can be viewed as a reliable source of data. Further, it can be argued that data on smartphone usage and preferred services are somewhat unreliable, as they were gathered from participants' self-reports. However, these self-reports were only used for descriptive measures; no further statistical analyses were conducted with these data. Therefore, this form of collecting data can be regarded as sufficient.

CONCLUSION

Overall, current findings add to previous reports in several ways. First of all, up-to-date findings fill the surprising lack of current data in this research area (44). This is especially important, considering that the association between personality traits and smartphone use might change over time (i.e., discussed relationship between openness and problematic smartphone use). Second, German study results help fill knowledge gaps due to proposed cross-cultural differences in personality (67). Third, in contrast to other literature that did not investigate other traits beyond neuroticism, the current paper explored all Big Five personality traits.

Results show that assessment of personality traits is of high importance for therapy. Patients with problematic smartphone use should be evaluated on neuroticism and extraversion. Therapeutic measures to lessen levels on these personality traits might also help in reducing smartphone-related problems. Also, the findings from this study suggest that clinicians should consider problematic smartphone use as a potential maladjustment related to psychopathology (depression and anxiety). Problematic smartphone use can be regarded as a dysfunctional strategy to regulate depressive emotions and feelings of loneliness. Psychotherapeutic interventions can support patients effectively in solving existing difficulties and problems.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Sigmund Freud University Vienna ethics committee. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CE was involved in planning and supervising the work. AS processed the experimental data, performed the analysis, and drafted the manuscript. MS took the lead in writing the manuscript. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

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Problematic Smartphone and Social Media Use Among Bangladeshi College and University Students Amid COVID-19: The Role of Psychological Well-Being and Pandemic Related Factors

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Background: Smartphone and social media use are an integral part of our daily life. Currently, the impact of excessive smartphone and social media use during the COVID-19 pandemic is poorly understood. The present study aimed to investigate problematic smartphone use (PSPU) and problematic social media use (PSMU) among Bangladeshi college and university students during the COVID-19 pandemic.

Methods: A cross-sectional study was carried out involving 5,511 Bangladeshi college and university students (male: 58.9%; mean age: 21.2 years [*SD* = 1.7]; age range: 18–25) during the social-distancing in the COVID-19 pandemic (July 2020). A self-reported survey containing questions regarding socio-demographic, lifestyle, and home quarantine activities along with four psychometric scales was completed by participants.

Results: The mean scores of PSPU and PSMU were 20.8 ± 6.8 (out of 36) and 14.7 ± 4.8 (out of 30). Based on a hierarchical regression analysis, PSPU and PSMU were positively associated with lower age, poor sleep, social media use, watching television, anxiety, and depression. Additionally, PSMU was linked to being female, living with nuclear family, having urban residence, irregular physical exercise, poor engagement with academic studies, and avoiding earning activities, whilst being male, being married, living with lower-income family, and alcohol consumption were linked to PSMU.

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Conclusions: The findings indicate that PSPU and PSMU were linked to poor psychological well-being (i.e., anxiety and depression) and other factors (especially lower age, poor sleep) during the pandemic, further suggesting the need for interventions including virtual awareness programs among college and university students.

Keywords: problematic use, smartphone, social media, college, university, students, Bangladesh

INTRODUCTION

Currently, the world is facing a public health emergency declared by the World Health Organization due to international concerns regarding the highly contagious nature of COVID-19 (1). In Bangladesh (where the present study was carried out), the first three cases of COVID-19 were identified on March 8th 2020 (2, 3). Since then, the virus has continued to spread swiftly, and resulted in 430,496 positive cases with 6,173 fatalities by November 14th, 2020 (4, 5). As an immediate response to control the rapid spread of COVID-19, the Bangladesh government declared a "lock-down" or "stay at home order" on March 26, 2020 (6, 7). Everything including transports, shopping malls, offices, industries, and educational institutions got closed (8) and therefore, the government encouraged individuals to carry study, shopping, and work online at home. The initial restrictions (i.e., lock-down and social-distancing) aimed at controlling the spread of COVID-19 may have led to negative psychological impacts (e.g., anxiety, depression, frustration, fear, stress) to many individuals (9, 10). To help to cope with these negative mood states, individuals may engage in psychoactive substance use or engage problematically in specific technology use behaviors such as smartphone use, social media use, and video gaming as these potentially addictive behaviors may help alleviate the burden of stress and difficult thoughts experienced by individuals (11). However, the use of social media grew exponentially in the context of the COVID-19 pandemic (12). Higher amounts of time spent using social media may be problematic as these online platforms can be addictive (13). Social media platforms promote constant scrolling and do not have a definite "stop point," which is why they can lead to individuals spending several hours using these online platforms (14). The use of social media is widespread amongst adolescents attending college and university (15–17). Recently, adolescents' smartphone use has been reported to constitute a potentially problematic issue (18, 19) due to the rise in smartphone use and its increased popularity through applications such as social media, gaming, streaming, and education to individuals with low levels of health literacy.

As shown by previous research, dysregulated use of smartphone is associated with sleep disturbance, and depressive symptoms among adolescents (20). The use of social media in classroom for educational purposes is becoming increasingly popular, with educators massively adopting it during the social-isolation period because of its enhanced communication potential, content distribution, collaborations, and engagement with the students (12). Furthermore, a recent study found that internet-based smartphone use can increase perceived quality of life by providing positive connections on social media, online shopping, online conferencing, and constant interaction with friends and family living in different countries (21).

Psychological health issues such as depression and anxiety have been positively linked with problematic smartphone use (PSPU) (22). Moreover, the COVID-19 pandemic and subsequent home quarantine and social-distancing requirements, have increased anxiety levels, and the extent of negative emotions experienced across society (23, 24), and through easily available means, many individuals seek emotional comfort by using smartphones and the internet as potential coping mechanisms. However, the adoption of such coping mechanisms may lead to many potential negative consequences because of functional impairments due to excessive usage (25, 26). PSPU has been characterized as severe levels of dysregulated smartphone use leading to problems in areas such as social, professional, and/or academic, with symptoms arguably similar to substance use disorders [e.g., withdrawal use, tolerance, careless use; (27)].

Bangladesh (where the present study was carried out) is a developing nation that is trying to become increasingly digitalized by enhancing internet use within the population, thus potentially increasing the extent of excessive usage of digital devices and the internet. At the end of January 2020, the total number of internet users in the country was over 99 million (28), and with this figure gradually increasing. Moreover, most of the country's internet users have smartphones. It is likely that, the required social-distancing measures may exacerbate excessive usage of smartphones and social media websites, especially among youth (29, 30).

To date, there are no previous studies focusing on PSPU and problematic social media use (PSMU) among college and university students in Bangladeshi in the context of the COVID-19 pandemic. Therefore, the present study aims to investigate the correlates of PSPU and PSMU with psychological well-being, socio-demographics, lifestyle, and home quarantine regular/frequent activities among college and university students in Bangladeshi during the COVID-19 pandemic. The study will inform future similar research and the development of new policies aiming to ascertain how Bangladeshi college and university students might be affected smartphone and social media use during the COVID-19 pandemic.

MATERIALS AND METHODS

Participants and Procedure

The present cross-sectional study was conducted among Bangladeshi college and university students during the social-distancing period in the context of the COVID-19 pandemic.

Data collection took place during in July 2020 using an online self-reported survey. All questions related to the survey were administered using Google Forms and a shareable link was generated to help disseminate the survey across different online platforms used by college and university students. The online survey detailed the study's informed consent, purpose, inclusion, and exclusion criteria on the first page. The inclusion criteria included (i) being 18 years old and above, (ii) being a Bangladeshi college or university student, (iii) owning a smartphone and having access to the internet, and (iv) being surveyed voluntarily. The exclusion criteria were (i) being under 18 years and (ii) not being completing the online survey entirely.

Measures

A self-reported and structured online survey containing questions regarding participants' socio-demographic, lifestyle, and home quarantine activities along with four psychometric tests to measure the variables of the study were employed to collect data.

Socio-Demographic and Lifestyle Measures

Socio-demographic information concerning gender, age, marital status, education level, family type, and residence (urban/rural) was collected from all participants. Socio-economic status (SES) was categorized into three classes according to previous literature: lower, middle, and upper based on monthly family income of <15,000 Bangladeshi Taka (BDT) ≈ 177 US$, 15,000–30,000 BDT ≈ 177–354 US$, and more than 30,000 BDT ≈354 US$, respectively (31, 32). Moreover, numbers of average sleep hours classed as normal [7–9 h], less than normal [<7 h], or more than normal [>9 h] based on previous literature (33–35), physical exercising (yes/no), smoking cigarettes, and alcohol consumption (yes/no) were collected with regard to lifestyle measures.

Home Quarantine Activities Measures During COVID-19

Additional dichotomous questions (yes/no) were asked regarding the engagement in frequent activities during the pandemic, including home quarantine regular/frequent activities (i.e., academic/other studies, social-media use, watching television, household chores, and professional activities).

Patient Health Questionnaire (PHQ-9)

The PHQ−9 is a nine-item scale that measures depressive symptoms in the last 2 weeks (36). The items are rated from 0 (*Not at all*) to 3 (*Nearly every day*). Total scores can be obtained by summing up all responses on each item, and they range from 0 to 27. The present study used the Bangla version PHQ-9 (37) to assess participants' depressive symptoms as in previous research (38–40). The cutoff score ≥10 was used as a potential indication of depression in the sample recruited as previously in Bangladesh (32, 38, 41). In the present study, the PHQ-9 scale presented excellent internal consistency (Cronbach's alpha = 0.89).

Generalized Anxiety Disorder (GAD-7)

The GAD-7 is commonly used to screen symptoms and severity of generalized anxiety in epidemiological research (42). This scale consists of seven items that can be responded to on a four-point Likert scale ranging from 0 (*Not at all*) to 3 (*Nearly every day*). The present study adopted the Bangla version of the GAD-7 to assess participants' levels of anxiety as in previous research (39, 43, 44). The cutoff score ≥10 was used as indicative of anxiety as previously done in Bangladesh (39, 43). In the present study, the GAD-7 scale was observed as excellent reliability (Cronbach's alpha = 0.91).

Bergen Social Media Addiction Scale (BSMAS)

The BSMAS assesses PSMU with six questions based on the components model of addiction (i.e., salience, mood, modification, tolerance, withdrawal conflict, and relapse) proposed by Griffiths (49). The BSMAS was developed by Andreassen et al. (45), and was used to assess social media addiction by symptoms and related negative outcomes due to problematic use over the past year (e.g., "*How often during the last week have spent a lot of time thinking about social media or planned use of social media?*"). All items of the BSMAS can be responded using a five-point Likert scale ranging from 1 (*very rarely*) to 5 (*very often*). The total score is yielded by summating each items' raw score, with higher scores suggesting greater levels of PSMU symptoms. In the present study, the translated Bangla version of BSMAS was used to investigate PSMU. The BSMAS used in the study was adapted using a "back translation" procedure [i.e., (46)], similar to previous research conducted in Bangladesh (7, 47). In the present study, the Cronbach's alpha of BSMAS was 0.80.

Smartphone Application Based Addiction Scale (SABAS)

The SABAS was developed by Csibi et al. (48) and it consists of six items that measure PSPU. The scale was used to determine the extent of PSPU. The SABAS was developed based on the components model of addiction (i.e., salience, alteration of the mood, tolerance, withdrawal conflict, and relapse) which was proposed by Griffiths (49). Sample items include: "*During the past week, my smartphone is the most important thing in my life.*" All items are rated on a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Total scores are summed up to reflect participants' overall levels of PSPU, with elevated scores suggesting a higher degree of PSPU. In the present study, the Bangla version of the SABAS was translated using a "back translation" procedure [i.e., (46)], similar to previous studies in Bangladesh (7, 47). In the present study, the Cronbach's alpha of the SABAS was 0.85.

Statistical Analysis

Data were analyzed using Microsoft Excel 2019 and SPSS version 25. Firstly, the data set was cleaned, sorted, and coded using Microsoft Excel and exported onto SPSS. Using SPSS, descriptive statistics (i.e., frequencies, percentages, means, standard deviation estimates) were computed. Inferential statistics included conducting *t*-tests or one-way Analysis of Variance (ANOVA) to determine mean differences in the scores of the SABAS and BSMAS in relation to all variables examined applying Bonferroni correction (via dividing *p*-value significance threshold [0.05] into the number of independent variables:

TABLE 1 | Descriptive analyses of all examined variables ($N = 5,511$).

Variables	n	(%)
SOCIO-DEMOGRAPHICS		
Gender		
Male	3245	(58.9)
Female	2266	(41.1)
Educational level		
College	1260	(22.9)
University	4251	(77.1)
Marital status		
Unmarried	5281	(95.8)
Married	230	(4.2)
Family type		
Nuclear	4313	(78.3)
Joint	1198	(21.7)
Socioeconomic status (SES)		
Lower	1224	(22.2)
Middle	2358	(42.8)
Upper	1929	(35.0)
Residence		
Rural	2729	(49.5)
Urban	2782	(50.5)
LIFESTYLE FACTORS		
Physical exercise		
Yes	3224	(58.5)
No	2287	(41.5)
Sleeping hours		
Less than normal	1224	(22.2)
Normal (7–9 h)	3723	(67.6)
More than normal	564	(10.2)
Smoking cigarettes		
Yes	614	(11.1)
No	4897	(88.9)
Alcohol consumption		
Yes	179	(3.2)
No	5332	(96.8)
HOME QUARANTINE REGULAR/FREQUENT ACTIVITIES		
Academic/other studies		
Yes	4044	(73.4)
No	1467	(26.6)
Social media use		
Yes	5069	(92.0)
No	442	(8.0)
Watching television		
Yes	4723	(85.7)
No	788	(14.3)
Household chores		
Yes	4295	(77.9)
No	1216	(22.1)
Earning activities		
Yes	1523	(27.6)
No	3988	(72.4)
PSYCHOLOGICAL WELL-BEING		
Anxiety		
No	4027	(73.1)
Yes[a]	1484	(26.9)
Depression		
No	3416	(62.0)
Yes[b]	2095	(38.0)
Continuous variables	**Mean**	**(SD)**
Age	21.2	(1.8)
GAD-7	6.2	(5.74)
PHQ-9	6.2	(5.7)
SABAS	20.8	(6.8)
BSMAS	14.7	(4.8)

GAD-7, Total score of Generalized Anxiety Disorder scale; PHQ-9, Total score of Patient Health Questionnaire scale; SABAS, Smartphone Application Based Addiction Scale; BSMAS, Bergen Social Media Addiction Scale.
[a]*PHQ-9 ≥10.*
[b]*GAD-7 ≥10.*

0.05/18 = 0.003). Finally, multiple linear regression analyses predicting PSPU and PSMU across two independent models were conducted using a hierarchical approach including four blocks of predictors pertaining to: socio-demographic, lifestyle, home quarantine regular/frequent activities, and psychological well-being factors.

Ethics

All procedures of the present study were performed in compliance with the Declaration of Helsinki, and adopting with guidelines of institutional research ethics. The present study has obtained ethical approval, which was given by the Ethical Review Committee (Ref. no: UAMC/ERC/17/2020). After being informed about the study's aims and procedures, all participants consented to participate in the study. Participants' information was strictly kept anonymous and confidential.

RESULTS

Participants' Socio-Demographic Features

A total of 5,511 participants were included in the final analysis (see **Table 1**). Of these, 58.9% were male participants. The sample's average age was 21.2 years ($SD = 1.7$ years) and ages ranged from 18 to 25 years. The sample comprised college (22.9%) and university (77.1%) students. In terms of marital status, most participants were unmarried (95.8%). The majority of participants lived with their nuclear families (78.3%), held middle-class socioeconomic status (42.8%), and were from urban areas (50.5%). A sizeable minority did not engage in regular exercising (41.5%), and the majority were classed as normal sleepers (7–9 h/day) (67.6%). Last but not least, about 11.1% of all participants reported smoking cigarettes while a minority reported consuming alcohol (3.2%).

TABLE 2 | Associations between Problematic Smartphone Use (PSPU) and Problematic Social Media Use (PSMU) with all variables examined (N = 5,511).

Variables	*PSPU*				*PSMU*			
	Mean	**(SD)**	***t/F***	***p*-value**	**Mean**	**(SD)**	***t/F***	***p*-value**
SOCIO-DEMOGRAPHICS								
Age			1.92	0.002			3.09	<0.001
Gender								
Male	20.2	(7.0)	7.38	<0.001	14.6	(4.9)	4.00	<0.001
Female	21.8	(6.4)			14.8	(4.8)		
Educational level								
College	20.8	(6.9)	2.14	<0.001	15.2	(5.1)	3.61	<0.001
University	20.9	(6.8)			14.5	(4.8)		
Relationship status								
Unmarried	20.8	(6.8)	1.04	0.413	14.6	(4.8)	1.76	0.012
Married	20.8	(6.8)			15.3	(5.1)		
Family type								
Nuclear	21.2	(6.6)	14.25	<0.001	14.7	(4.8)	7.20	<0.001
Joint	19.5	(7.3)			14.4	(4.9)		
Socioeconomic status (SES)								
Lower	21.1	(6.2)	3.87	<0.001	15.2	(4.9)	4.42	<0.001
Middle	19.8	(7.2)			14.3	(4.8)		
Upper	21.9	(6.5)			14.8	(4.8)		
Residence								
Rural	19.9	(7.1)	9.40	<0.001	14.4	(4.9)	6.98	<0.001
Urban	21.8	(6.3)			15.0	(4.8)		
LIFESTYLE FACTORS								
Physical exercise								
Yes	19.5	(7.0)	14.31	<0.001	14.3	(4.9)	6.21	<0.001
No	22.7	(6.0)			15.2	(4.7)		
Sleeping hours								
Less than normal	21.5	(6.7)	2.41	<0.001	15.3	(4.9)	2.23	0.001
Normal (7–9 h)	20.4	(6.8)			14.4	(4.8)		
More than normal	22.0	(7.0)			15.3	(5.1)		
Smoking habits								
Yes	21.5	(6.7)	2.13	<0.001	15.2	(4.8)	2.10	0.001
No	20.8	(6.8)			14.6	(4.9)		
Alcohol consumption								
Yes	20.0	(7.3)	3.51	<0.001	15.6	(4.8)	3.33	<0.001
No	20.9	(6.8)			14.6	(4.8)		
HOME QUARANTINE REGULAR/FREQUENT ACTIVITIES								
Academic/other studies								
Yes	20.0	(6.9)	10.72	<0.001	14.4	(4.8)	5.08	<0.001
No	23.2	(6.1)			15.5	(4.8)		
Social media use								
Yes	21.3	(6.6)	33.13	<0.001	14.9	(4.8)	15.81	<0.001
No	15.8	(6.6)			12.5	(4.4)		
Watching television								
Yes	21.1	(6.8)	2.78	<0.001	14.7	(4.8)	2.57	<0.001
No	19.5	(7.0)			14.2	(4.9)		
Household chores								
Yes	20.5	(6.9)	6.65	<0.001	14.6	(4.8)	5.35	<0.001
No	22.0	(6.4)			15.0	(4.9)		
Earning activities								
Yes	18.0	(7.5)	27.01	<0.001	14.0	(5.1)	9.79	<0.001

(Continued)

TABLE 2 | Continued

Variables	PSPU				PSMU			
	Mean	(SD)	*t*/*F*	*p*-value	Mean	(SD)	*t*/*F*	*p*-value
No	21.9	(6.2)			14.9	(4.7)		
PSYCHOLOGICAL WELL-BEING								
Anxiety								
No	19.4	(6.6)	27.96	<0.001	13.5	(4.4)	47.82	<0.001
Yes	24.7	(5.7)			17.8	(4.5)		
Depression								
No	18.5	(6.5)	48.73	<0.001	12.9	(4.2)	69.69	<0.001
Yes	24.6	(5.5)			17.5	(4.4)		

Associations Between PSPU and PSMU With Other Variables

The mean score of PSPU was 20.8 ($SD = 6.8$) out of 36. Moreover, high PSPU scores were positively associated with lower age, being female, being a university student, living in a nuclear family, being from an upper-class family, having urban residence, exhibiting poor physical exercising habits, greater sleep, smoking cigarettes, not consuming alcohol, not engaging with study, using social media, watching television shows, avoiding household chores, not in engaging earning activities, high levels of anxiety, and depression (**Table 2**).

The mean score of PSMU was 14.7 ($SD = 4.8$) out of 30. Similarly, high PSMU scores were positively associated with lower age, being female, being a college student, living in a nuclear family, being from a lower-class family, having urban residence, exhibiting poor physical exercising habits, less/more sleep, smoking cigarettes, alcohol consumption, not engaging with study, using social media, watching television, avoiding household chores, not engaging earning activities, high levels of anxiety, and depression (**Table 2**). Finally, a statistically significant positive correlation emerged between PSPU and PSMU ($r = 0.61$, $p < 0.001$).

Factors Affecting PSPU and PSMU

The results of the hierarchical regression analysis predicting PSPU are presented in **Table 3**. Factors that were statistically significant in the group difference analyses (*t*-tests and ANOVA) were included in a hierarchical regression analysis. Socio-demographic factors (i.e., age, gender, educational level, family type, monthly family income, and residence) were included in Block 1. Lifestyle factors (i.e., physical exercise, sleeping hours, smoking cigarettes, and alcohol consumption) comprised Block 2. In Block 3, home quarantine activities (i.e., study, social media use, watching television, household chores, and earning activities) were included, while Block 4 comprised psychological well-being factors (i.e., anxiety and depression).

Overall, the regression model (Model 4) estimated predicted about 30% of the total variance in PSPU [$F_{(17,5,493)} = 139.12$, $p < 0.001$]. In terms of specific predictors (applying Bonferroni correction), PSPU was predicted by irregular physical exercise, poor engagement with academic studies, social media use, watching television, avoiding earning activities, high levels of anxiety and depression. Consequently, age, gender, educational level, family type, monthly family income, residence, sleeping hours, smoking cigarettes, alcohol consumption, and household chores were not statistically significant predictors in the hierarchical regression analysis.

In relation to PSMU, the results of the hierarchical regression analysis indicated that the regression model (Model 4) predicted about 25% of the total variance in PSMU [$F_{(17,5,493)} = 110.44$, $p < 0.001$; see **Table 4**]. Factors that were statistically significant in the group difference analyses (*t*-tests and ANOVA) were included in a hierarchical regression analysis. Socio-demographic factors (i.e., age, gender, educational level, family type, monthly family income, and residence) were included in Block 1. Lifestyle factors (i.e., physical exercise, sleeping hours, smoking cigarettes, and alcohol consumption) comprised Block 2. In Block 3, home quarantine activities (i.e., study, social media use, watching television, household chores, and earning activities) were included, and Block 4 comprised psychological well-being factors (i.e., anxiety and depression). Accordingly, PSMU was predicted (applying Bonferroni correction) by younger age, poor sleep (<7 h/day), alcohol consumption, social media use, high levels of anxiety, and depression. Consequently, gender, educational level, family type, monthly family income, residence, physical exercise, smoking cigarettes, study, watching television, household chores, and earning activities were not statistically significant predictors in the hierarchical regression analysis.

DISCUSSION

Since the beginning of the COVID-19 pandemic, the use of smartphone and social media has rapidly increased globally, with digital technology use being associated with poorer mental health (50). Throughout modern societies, smartphone use became pervasive and can be seen across the entire lifespan. Moreover, social media and smartphone use has become essential in daily life as it provides access to a wide range of mobile applications, information, communication, education, and entertainment tools. The use of smartphones and the internet are a cause for concern for various communities due to the deleterious effects stemming from problematic use (51, 52).

TABLE 3 | Hierarchical regression analysis predicting Problematic Smartphone Use (PSPU).

Model	Model 1				Model 2				Model 3				Model 4					
	B	**SE**	**β**	***t***	**B**	**SE**	**β**	***t***	**B**	**SE**	**β**	***t***	**B**	**SE**	**β**	***t***	**ΔR^2**	**R^2_{Adj}**
Block 1—Socio-demographics [$F_{(6,5,504)}$ = 33.74; p < 0.001]																	0.04	0.04
Age	−0.21	0.06	−0.05	−3.70*	−0.20	0.06	−0.05	−3.60*	−0.10	0.05	−0.03	−1.80	−0.10	0.05	−0.03	−2.03		
Gender[a]	1.12	0.19	0.08	5.87*	1.03	0.19	0.08	5.36*	0.83	0.19	0.06	4.42*	0.49	0.17	0.04	2.83		
Educational level[b]	0.43	0.23	0.03	1.83	0.33	0.23	0.02	1.45	−0.02	0.22	0.00	−0.11	0.34	0.20	0.02	1.70		
Family type[c]	−1.33	0.22	−0.08	−5.98*	−1.16	0.22	−0.07	−5.34*	−0.51	0.21	−0.03	−2.45	−0.51	0.19	−0.03	−2.68		
Socioeconomic status (SES)[d]	0.11	0.13	0.01	0.84	0.16	0.13	0.02	1.29	0.07	0.12	0.01	0.57	0.19	0.11	0.02	1.69		
Residence[e]	1.39	0.20	0.10	7.00*	1.11	0.19	0.08	5.73*	0.69	0.19	0.05	3.68*	0.34	0.17	0.03	2.00		
Block 2—Lifestyle factors [$F_{(10,5,500)}$ = 50.21; p < 0.001]																	0.06	0.08
Physical exercise[f]					2.91	0.18	0.21	16.10*	1.84	0.18	0.13	9.99*	1.49	0.17	0.11	8.80*		
Sleeping hours[g]					−0.21	0.16	−0.02	−1.32	−0.33	0.15	−0.03	−2.20	−0.38	0.14	−0.03	−2.69		
Smoking habits[f]					−1.44	0.31	−0.07	−4.64*	−0.74	0.30	−0.03	−2.49	−0.13	0.27	−0.01	−0.48		
Alcohol consumption[f]					0.91	0.53	0.02	1.71	0.58	0.51	0.02	1.14	0.37	0.47	0.01	0.79		
Block 3—Home quarantine regular/frequent activities [$F_{(15,5,495)}$ = 72.62; p < 0.001]																	0.14	0.16
Study[f]									2.08	0.20	0.14	10.40*	1.21	0.19	0.08	6.51*		
Social media use[f]									−4.13	0.32	−0.17	−12.91*	−3.55	0.29	−0.14	−12.10*		
Watching television[f]									−1.32	0.25	−0.07	−5.37*	−1.43	0.23	−0.07	−6.37*		
Household chores[f]									0.45	0.21	0.03	2.12	0.21	0.20	0.01	1.06		
Earning activities[f]									2.42	0.21	0.16	11.83*	2.16	0.19	0.14	11.53*		
Block 4—Psychological well-being [$F_{(17,5,493)}$ = 139.12; p < 0.001]																	0.12	0.30
Anxiety[h]													1.65	0.22	0.11	7.49*		
Depression[h]													4.30	0.20	0.31	21.03*		

B, unstandardized regression coefficient; SE, standard error; β, standardized regression coefficient.
[a] 1 = Male, 2 = Female.
[b] 1 = College, 2 = University.
[c] 1 = Nuclear, 2 = Joint.
[d] 1 = Lower, 2 = Middle, 3 = Upper.
[e] 1 = Rural, 2 = Urban.
[f] 1 = Yes, 2 = No.
[g] 1 = <7 h, 2 = 7–9 h, 3 = >9 h.
[h] 1 = Negative, 2 = Positive.
$^*p$ < 0.001.

TABLE 4 | Hierarchical regression analysis predicting Problematic Social Media Use (PSMU).

Model	Model 1				Model 2				Model 3				Model 4					
	B	SE	β	*t*	B	SE	β	*t*	B	SE	β	*t*	B	SE	β	*t*	ΔR^2	R^2_{Adj}
Block 1—Socio-demographics [$F_{(6,5,504)} = 10.38$; $p < 0.001$]																	0.01	0.01
Age	−0.14	0.04	−0.05	−3.55**	−0.15	0.04	−0.06	−3.75**	−0.13	0.04	−0.05	−3.18*	−0.13	0.04	−0.05	−3.61**		
Gender[a]	0.05	0.14	0.01	0.35	0.11	0.14	0.01	0.80	0.07	0.14	0.01	0.50	−0.24	0.13	−0.03	−1.91		
Educational level[b]	−0.42	0.17	−0.04	−2.51	−0.43	0.17	−0.04	−2.60	−0.56	0.17	−0.05	−3.37*	−0.25	0.15	−0.02	−1.74		
Family type[c]	−0.13	0.16	−0.01	−0.82	−0.07	0.16	−0.01	−0.45	0.20	0.16	0.02	1.25	0.20	0.14	0.02	1.38		
Socioeconomic status (SES)[d]	0.11	0.09	−0.04	−2.76	−0.24	0.09	−0.04	−2.53	−0.27	0.09	−0.04	−2.89	−0.16	0.08	−0.03	−1.99		
Residence[d]	0.71	0.14	0.07	4.96**	0.62	0.14	0.06	4.33**	0.50	0.14	0.05	3.53**	0.20	0.13	0.02	1.56		
Block 2—Lifestyle factors [$F_{(10,5,500)} = 12.30$; $p < 0.001$]																	0.01	0.02
Physical exercise[f]					0.83	0.13	0.08	6.20**	0.50	0.14	0.05	3.60**	0.20	0.12	0.02	1.59		
Sleeping hours[g]					−0.25	0.12	−0.03	−2.14	−0.29	0.12	−0.03	−2.54	−0.32	0.10	−0.04	−3.12*		
Smoking habits[f]					−0.66	0.23	−0.04	−2.87	−0.40	0.23	−0.03	−1.76	0.15	0.20	0.01	0.75		
Alcohol consumption[f]					−0.74	0.39	−0.03	−1.89	−0.87	0.39	−0.03	−2.24	−1.06	0.34	−0.04	−3.09*		
Block 3—Home quarantine regular/frequent activities [$F_{(15,5,495)} = 17.81$; $p < 0.001$]																	0.02	0.04
Study[f]									0.89	0.15	0.08	5.81**	0.12	0.14	0.01	0.90		
Social media use[f]									−2.22	0.24	−0.12	−9.11**	−1.70	0.22	−0.10	−7.89**		
Watching television[f]									−0.33	0.19	−0.02	−1.79	−0.46	0.17	−0.03	−2.77		
Household chores[f]									0.09	0.16	0.01	0.55	−0.12	0.14	−0.01	−0.80		
Earning activities[f]									0.36	0.16	0.03	2.29	0.14	0.14	0.01	0.99		
Block 4—Psychological well-being [$F_{(17,5,493)} = 110.44$; $p < 0.001$]																	0.21	0.25
Anxiety[h]													1.92	0.16	0.18	11.90**		
Depression[h]													3.44	0.15	0.34	22.88**		

B, unstandardized regression coefficient; SE, standard error; β, standardized regression coefficient.
[a] *1 = Male, 2 = Female.*
[b] *1 = College, 2 = University.*
[c] *1 = Nuclear, 2 = Joint.*
[d] *1 = Lower, 2 = Middle, 3 = Upper.*
[e] *1 = Rural, 2 = Urban.*
[f] *1 = Yes, 2 = No.*
[g] *1 = <7 h, 2 = 7–9 h, 3= >9 h.*
[h] *1 = Negative, 2 = Positive.*
*$p < 0.003$ and **$p < 0.001$.

To the best of the authors' knowledge, this is the first study investigating the intricacies between PSPU and PSMU in relation to key associated factors during the COVID-19 pandemic in Bangladesh. According to the findings obtained in this study, PSMU was positively associated with irregular physical exercise, poor engagement with academic studies, social media use, watching television, ignoring earning activities, anxiety, and depression. Similarly, PSMU was positively associated with lower age, poor sleep, alcohol consumption, social media use, anxiety, and depression. Moreover, according to the hierarchical regression analyses conducted, individuals with irregular physical activity were found to exhibit higher levels of PSPU than physically active individuals, a finding that corroborates the results of previous research conducted in Korea (53) and Switzerland (54) reporting that problematic users were less willing to exercise regularly.

The present study found that PSPU was significantly associated with poor study engagement. Previous studies reported that PSPU has an adverse effect on academic performance (55, 56). This finding is aligned with existing evidence indicating that prolonged smartphone use in adolescents is linked with poorer academic performance (52). Additionally, students at high risk of PSPU are less likely to have high grade point averages (GPAs) (57). Furthermore, PSPU was higher among social media users, which is consistent with previous research indicating that PSMU can occur among smartphone users (58).

Using smartphone as a source of entertainment (e.g., social media), has been found to be linked with PSPU according to an earlier study (59). Furthermore, participants using social media through their smartphones have been found to spend 0.5–3 h daily using social media (60), with greater time spent using social media posing greater addictive risk, and potentially contributing to greater PSPU risk (58). Moreover, the results of this study found that depression, and anxiety were positively associated with PSPU, which is consistent with several preceding studies showing a significant association between PSPU and both depression and anxiety symptoms (59, 61, 62). According to the findings obtained in this study, lower age was found to be positively associated with PSMU, which is similar to an earlier study (63). During home quarantine and self-isolation period, the main way to meet new people and socialize was through social media platforms, which potentially contributing to greater time spent on social media sites in order to alleviate the venerable psychological sates brought about by the pandemic (64, 65). Social media in today's society is widespread and, with excessive usage potentially leading to PSMU, particularly young people. Although social media may be used to communicate and establish connections with friends and significant others, excessive use can occur, leading to the development of PSMU (66).

In the hierarchical regression analysis conducted, reporting with less sleep (<7 h/day) were more prone to PSMU. An earlier study in the same country also supports this finding (67). Research has shown that both inadequate and prolonged sleep (68) are associated with PSMU. Another important finding was that alcohol consumption and PSMU were positively associated in the present study. Participants consuming alcohol may become more engaged in alcohol-related social media usage (69), spending more time using social media, which may lead to excessive use. Depression and anxiety were also positively associated with PSMU according to the findings of obtained. Several preceding studies have found an association between both depression and anxiety with PSMU (61, 67, 70–72), with longitudinal research showing a strong association between depression and trend of internet use (73).

The present study investigated potential factors associated with PSPU and PSMU during the COVID-19 pandemic. We have examined several factors (i.e., psychological well-being, socio-demographics, lifestyle, and home quarantine activities) predicting PSPU and PSMU during home quarantine in the context of the COVID-19 pandemic. Further evaluation is needed after the pandemic in order to estimate the potential psychiatric toll in terms of post-traumatic stress disorder symptoms among both excessive and problematic digital technology users.

Limitations

The present study is not without potential limitations. Firstly, causality cannot be established based on the findings reported due to the cross-sectional design adopted. As we did not have pre-COVID-19 data, the findings obtained cannot be causally inferred in that the COVID-19 pandemic leads to PSPU and PSMU. In this context, longitudinal and experimental studies will assist in exploring causal factors leading to PSPU and PSMU. Secondly, this study employed a self-report approach, which is likely to introduce specific biases (e.g., social desirability and memory recall biases). Furthermore, this study was conducted on a convenience sample of college and university students from Bangladesh, which cannot be representative of other populations and users around the globe. So, a longitudinal study focusing on different groups is needed.

CONCLUSIONS

The present study focused on the factors associated with PSPU and PSMU during the COVID-19 pandemic. It can therefore be concluded that the COVID-19 pandemic led to an innovative utilization of smartphone and social media that helped keeping the population informed and socially connected during the COVID-19 pandemic, but excessive use may become an issue, leading to problematic usage. Psychosocial education and counseling programs should be implemented to prevent and mitigate the development of PSPU and PSMU and related psychological problems especially among vulnerable populations.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethical Review Committee, Uttara Adhunik Medical College, Uttara, Dhaka-1260, Bangladesh (Ref. no: UAMC/ERC/17/2020). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MSI, MSuj, RT, and MF: conceptualization. MSI, MSuj, and MF: methodology. MSI: formal analysis and investigation. MSI, MSuj, RT, and RM: writing—original draft preparation. MSI, MF, MSik, and HP: writing—review and editing. SK, TT, MSak, KP, MRI, MSid, FA, AH, and IH: resources. MF and MSik: supervision. All authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.647386/full#supplementary-material

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MINI REVIEW
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Excessive Smartphone Use Is Associated With Health Problems in Adolescents and Young Adults

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Background and Aims: This present paper will review the existing evidence on the effects of excessive smartphone use on physical and mental health.

Results: Comorbidity with depression, anxiety, OCD, ADHD and alcohol use disorder. Excessive smartphone use is associated with difficulties in cognitive-emotion regulation, impulsivity, impaired cognitive function, addiction to social networking, shyness and low self-esteem. Medical problems include sleep problems, reduced physical fitness, unhealthy eating habits, pain and migraines, reduced cognitive control and changes in the brain's gray matter volume.

In Conclusion: Excessive smartphone use is associated with psychiatric, cognitive, emotional, medical and brain changes that should be considered by health and education professionals.

Keywords: internet addiction, smartphone addiction, problematic smartphone use, internet use disorder, excessive smartphone use

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INTRODUCTION

Excessive Smartphone Use in Young Adults

The effects of excessive use of computer screens and smartphones are raising serious concerns among health and educational authorities due to negative effects of such use in children and adolescents. Recent reviews have argued that the evidence supporting excessive smartphone use as an addictive behavior is scarce. In particular, Billieux (1) have argued that there is insufficient evidence for behavioral and neurobiological similarities between excessive smartphone use other types of addictive behaviors. Panova and Carbonell (2) also argued that there is insufficient evidence to support for the diagnosis of smartphone addiction and finally Montag et al. (3) have argued that excessive smartphone use is a form of Internet Use Disorder. The smartphones are being used for various purposes such as gaming, Social Network Services (SNS), watching video clips (YouTube). Therefore, excessive use of smartphones may have difference characteristics according to the type of smartphone use. This present paper will review the existing evidence on excessive smartphone use, and it will discuss its similarities with and differences from Internet addiction.

METHODS

A PubMed Central® and Web of Science search engines have been used with the terms: "excessive smartphone use" and "smartphone addiction" until February 2021 that resulted in 84 research studies in English language.

Predictors of Excessive Smartphone-Use

The main factors predicting excessive smartphone use were being female, preoccupation, conflict, and use for ubiquitous trait whereas the protective factor was use for learning (4). Excessive use of smartphones was correlated with impairment in the function of the family and relationship with friends, impulsiveness, and low self-esteem in South Korean adolescents (5). Finally, smartphone gaming was associated with excessive smartphone use among adolescents (6).

Sensation Seeking and Boredom

Turgeman et al. (7) have reported an interaction between high sensation seeking and abstinence whereby abstinence for 1.5 h increased excessive smartphone use ratings in high sensation seeking students. This may be explained by boredom, avoidance of uncomfortable situations and the need for entertainment (8–12). Lepp et al. (13) have found an association between excessive smartphone use and living sedentary life or being an "active couch potato. "Ben-Yehuda et al. (14) have investigated the effects of involvement and of interest in three conditions: state of boredom, passive activity and active activity in counter-balanced order in University students. Excessive smartphone use was not influenced by any interest or involvement in the lecture, indicating a compulsive behavior. Finally, Li et al. (15) have demonstrated that individuals with an external locus of control had less control over their smartphone use and therefore could have more negative effects such as poor sleep quality, lower academic achievements, and lower ratings of well-being.

Insecure Attachment, Poor Cognitive-Emotional Regulation and Communication Problems

Insecure attachment positively correlated with problematic smartphone use in students with unhealthy family function but not with mother-infant bonding or maternal mental health (16). Eichenberg et al. (17) showed an association between excessive smartphone use and an insecure attachment style in Problematic adolescent users. A following study reported high scores in maladaptive Cognitive-emotion regulation (CER) strategies such as self-blame, blaming of others ruminating and catastrophizing thoughts (18). Experiential avoidance (i.e., attempts to avoid thoughts, feelings, memories and physical sensations) has been associated with excessive smartphone use and social networks (19). Childhood emotional maltreatment correlated with problematic smartphone use in adolescents, and it was mediated by body image difficulties, depression, and social anxiety (20). Emotion regulation difficulties, unregulated eating, restrained eating, food addiction, and higher percent body fat were associated with excessive smartphone use among adolescents (21). Mahapatra (22) showed a strong association between both lack of self-regulation and loneliness on problematic smartphone use among adolescents that ultimately resulted in family, interpersonal conflicts, and poor academic performance. Among students, problematic smartphone users have shown high measures of worry and anger (23) whereas excessive reassurance seeking behavior mediated the association between rumination and problematic smartphone use (24). Poor communication skills were shown in Medical students who preferred to communicate emotions through texting rather than verbal communication (25) and they correlated with excessive smartphone use (26). Excessive use of the smartphone has negative impacts on people's lives by reducing face-to-face interactions, and increasing loneliness (27).

Impaired Cognitive Function

Problems in inhibitory control mechanisms in excessive smartphone users were reported (28). They have reported that while performing on the Go/NoGo task excessive smartphone users showed a negative N2 event-related potentials (ERPs) component showing reduced inhibitory control. There is further evidence for impaired attention, reduced numerical processing capacity, increased impulsivity, hyperactivity and negative social concern in heavy smartphone users (29). Heavy smartphone users showed. Inattention problems correlated with Transcranial Magnetic Stimulation (TMS) evoked potentials in the right prefrontal cortex. Wegmann et al. (30) have found no correlations between problematic social networks use and executive function and inhibitory control measured by the Go/NoGo task. However, regression analyses showed that increased problematic social networks use is associated with higher impulsivity, especially if executive functions or specific inhibitory control were impaired.

Social Media Use and Personality

Problematic social media use has been shown to be associated with "fear of missing out" (FOMO) (31, 32). FOMO mediated relations between both fear of negative and positive evaluation with both problematic and social smartphone use. Withdrawal and FOMO ratings were higher among participants with 72 h restricted access to smartphones compared with those without (33). There was a correlation between Social communication use and excessive use of smartphones. FOMO mediated the relationships between anxiety and depression with problematic smartphone use (24, 34). Excessive smartphone use has been associated with social comparisons on social networking sites and perceived stress (35). Personality factors such as conscientiousness, openness, emotional stability and neuroticism have been associated with problematic smartphone use (36, 37) whereas impulsivity, excessive reassurance seeking, but not extraversion related to problematic smartphone use in other studies (38, 39).

Comorbidity With Anxiety, Depression OCD, ADHD and Alcohol Use Disorder

There are several studies on the comorbidity of excessive smartphone use and mental disorders and its association with sleep problems, reduced fitness and pain. Excessive smartphone use has been associated with depression, anxiety (40, 41) and social anxiety (7, 42–44) shyness and low self-esteem (5–12, 12–47) low psychological well-being (48) and low mental well-being (49). Excessive reassurance seeking correlated with problematic smartphone use severity, and its combination with rumination mediated the relationship between depression and anxiety severity with problematic smartphone use (50). Anxiety during the COVID-19 epidemic correlated with severity of problematic smartphone use, depression and generalized anxiety (51).

Early problematic smartphone use was found as a significant predictor of depression in a three-year longitudinal study from adolescence to emerging adulthood (52). Excessive mobile use was associated with high levels of depressive moods, with loneliness serving as a moderator of this mediation particularly in men (53). Depression and anxiety were significantly associated with both excessive smartphone use (54). Depressive mood and suicidal ideation were associated with social network smartphone use (55). Interestingly, the time spent in excessive smartphone use has predicted the level of stress in users who hardly used the smartphone for self-disclosure whereas those who engaged in disclosure of their emotions and problems online, this reduced their emotional problems (56). Problematic smartphone use has been associated with psychological distress and emotion dysregulation and emotion dysregulation was shown as a mediator in the relation between psychological distress and problematic smartphone use (57). Excessive smartphone use has been also associated with Obsessive Compulsive Disorder symptoms (58) and ADHD (59, 60).

History of alcoholism and father's education level explained 26% of the variance of problematic smartphone use (60). In addition, alcohol use disorder, impulsivity (Barratt scale and ADHD) and elevated occurrence of PTSD, anxiety, and depression were associated with excessive smartphone use (61). Finally, the relationship between PTSD severity and problematic smartphone use was mediated by negative urgency (a component of impulsivity) (62).

Medical Complications- Sleep, Physical Fitness, Eyesight, Migraine and Pain

Excessive smartphone use was associated with reduced sleep time and sleep quality in adolescents (63). The association between media use in bed before sleep and depression was mediated by sleep disturbance (64, 65). Furthermore, there was an association between excessive screen time and problems in sleep onset (66), insufficient sleep (67), and insomnia (68). Long-term problematic mobile use predicted new incidences of sleep disturbances and mental distress, which was ameliorated by its discontinuation (69). Excessive mobile phone use correlated with disturbed sleep pattern and quality (70) Excessive smartphone use was associated with poorer sleep quality and higher perceived stress (71, 72), lowered physical activity, lower muscle mass and higher fat mass (73). Other medical conditions include acquired comitant esotropia (AACE) (74) increased ocular symptoms (75), headache complaints (76, 77) and headache duration and frequency in migraine patients (78). Young chronic neck pain patients with overuse of smartphones had higher Cervical Disc Degeneration (79). Finally, excessive smartphone users had higher median nerve Cross sectional areas (CSA's) in their dominant hands (80).

Brain Imaging

A recent study has used diffusion MRI for assessment of white matter structural connectivity, and it has shown a positive association between activity in the right amygdala and excessive smartphone use in adolescents (81). Excessive smartphone users have shown impairment in cognitive control during emotional processing of angry faces and social interaction in fMRI (82). They also showed reduced functional connectivity in regions related to cognitive control of emotional stimuli including reward (83). Reduced Gray Matter Volume (GMV) was shown in problematic smartphone users and negative correlations between GMV in the right lateral Orbito Frontal Cortex (OFC) and measures of smartphone addiction (84). Lower activity in the right anterior cingulate cortex (ACC) and a negative correlation between individuals with excessive smartphone use and both ACC GMV and activity was reported (85). Furthermore, the strength of the resting state functional connectivity (rsFC) between several brain regions in fMRI positively correlated with smartphone time in bed (86). Finally, exposure to smartphone pictures in fMRI was associated with activation of brain regions associated with drug addiction and correlations of these regions with smartphone addiction scores were reported (87).

Supplementary Table 1 shows details of the studies reviewed in this paper.

DISCUSSION

There have been several reviews in recent years that have discussed the issue whether excessive smartphone use is considered a behavioral addiction (1, 2). In addition, studies have examined whether there are differences between excessive smartphone use and Internet use disorder (IUD). Montag et al. (3) have proposed that excessive smartphone use is essentially a type of IUD. In this sense, IUD should be divided into two types of use: a mobile use and a non-mobile use. They have suggested that there is a specific use of IUD of a particular content and a generalized IUD where several channels are overused. The rationale for this division is that motivation, cognitive and affective factors predispose individuals to prefer a specific application and type of device.

However, there is little empirical evidence in support of these assumptions (88, 89). Although there may be small differences between some mechanisms and risk factors underlying online behavioral addictions, such as pornography use, gaming disorder and social network use, the resemblance between them is very strong (90). In addition, there are few studies that have examined whether specific cognitive and motivational mechanisms could lead to a preference of a specific type of device. Nevertheless, recent studies show that excessive use of the screens including, computer screens and smartphones is associated with serious mental problems and cognitive impairments (91, 92). Therefore, we argue that research should focus on the negative consequences of excessive smartphone use rather than on whether it should be considered as a behavioral addiction.

Recent studies show that excessive smartphone use is associated with problems of mental health and impaired psychological well-being. There is consistent evidence for comorbidity between excessive smartphone use and other psychiatric disorders, such as depression, anxiety, OCD, and

ADHD similar to Internet addiction (93). In addition, excessive smartphone use is related to loneliness, stress, and other negative emotions (56, 94).

In addition to these psychological consequences, the excessive use of smartphones can potentially lead to impairments of cognitive functions. Such excessive use is related to impairments of specific attention domains (such as focused attention and divided attention), low inhibitory control, impaired working memory, reduced numerical processing capacity, and changes in social cognition. Since cognition and emotion are often intertwined it is not surprising that a common cognitive-emotional mechanism related to loss of control would be associated with impulsiveness, impairment in communication and relationship with friends and family.

Recent studies have also shown an association between an excessive use of smartphones and abnormal activity of regions in the prefrontal cortex and in the networks that connect to these regions (29, 82). Novel findings show reduced lateral orbitofrontal gray matter, especially in social networking platforms overuse and that prolonged bedtime smartphone use has been associated with altered insula-centered functional connectivity. Gray matter volume reduction was observed also in the anterior cingulate similar to Internet and gaming disorder (95). Excessive smartphone use has also been associated with reduced cognitive control during the emotional processing in the brain.

The effects of excessive use of the media including TV, computer screens and smartphones is raising serious concerns among health and educational authorities due to deleterious effects of such use in children and adolescents. A recent study has shown an association between increased screen-based media use and lower microstructural integrity of brain white matter tracts that are associated with language and literacy skills in 5-year-old pre- school children, (96). Furthermore, a large study of 4,277 adolescents has shown a negative correlation between screen media activity and cortical thickness in fMRI implying premature aging of the brain (97). Finally, young adults and heavy media "multi-taskers" are more susceptible to interference from irrelevant environmental stimuli and from irrelevant representations in memory, and they performed worse on a task-switching ability (98). The findings so far that span from early childhood to adolescents, rapidly growing societal phenomena, emphasize the need to assess the effects of media screens on cognitive function and the brain in children, adolescents and young adults.

Excessive smartphone use shares underlying mechanisms with other addictive behaviors such as gambling disorder, in particular, reduced cognitive control and impaired activity in the prefrontal cortex which affects decision-making and emotional processing (99). Addictions in adolescents share the tendency to experience poor emotional regulation, impulsivity and impaired cognitive control and reduced ability to experience pleasure in everyday life (100).

The major limitations in studies of excessive smartphone use and Internet addiction are that they are mainly cross-sectional studies without baseline measures and rely on associations between structural and functional changes in the brain and subjective measures and no proof of a causal role in the development of the adolescent or adult brain. Finally, the review is non-systematic and it has excluded non-English language articles.

Summary

The excessive use of the smartphone has been associated with impaired cognitive functions and mental health problems. There are unique findings on the association between using smartphones, need of constant stimulation, deficits in everyday cognitive functioning and brain changes which should send alarm signals to clinicians and educators in the modern world.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.669042/full#supplementary-material

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Behavioral Intention to Use a Smartphone Usage Management Application Between a Non-Problematic Smartphone Use Group and a Problematic Use Group

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Despite the many advantages of smartphone in daily life, there are significant concerns regarding their problematic use. Therefore, several smartphone usage management applications have been developed to prevent problematic smartphone use. The purpose of this study is to investigate the factors of users' behavioral intention to use smartphone usage management applications. Participants were divided into a smartphone use control group and a problematic use group to find significant intergroup path differences. The research model of this study is fundamentally based on the Technology Acceptance Model and Expectation-Confirmation Theory. Based on this theorem, models were modified to best suit the case of problematic smartphone use intervention by smartphone application. We conducted online surveys on 511 randomly selected smartphone users aged 20–60 in South Korea, in 2018. The Smartphone Addiction Proneness Scale was used to measure participants' smartphone dependency. Descriptive statistics were used for the demographic analysis and collected data were analyzed using IBM SPSS Statistics 24.0 and Amos 24.0. We found that in both non-problematic smartphone use group and problematic smartphone use group, facilitating factors and perceived security positively affect the intentions of users to use the application. One distinct difference between the groups was that the latter attributed a lower importance to perceived security than the former. Some of our highlighted unique points are envisioned to provide intensive insights for broadening knowledge about technology acceptance in the field of e-Addictology.

Keywords: problematic smartphone use, smartphone usage management application, behavioral intention, TAM, ECT, MGCFA

INTRODUCTION

Smartphones have become crucial in everyday life worldwide, affecting all business, research, and social sectors (1, 2). Smartphone use is ever increasing, with usage in some countries reaching 90% and usage in most Western countries reaching more than half the population (3). Also, adults' smartphone usage reaches over 93% in South Korea (4). Despite the many advantages that smartphones provide to our daily lives, concerns related to problematic smartphone use have been increasing (3). Considering the advancement of Fourth Generation Mobile Communication Systems (4G) and Fifth Generation Mobile Communication Systems (5G) communication methods, smartphone usage is expected to increase even further.

The problem is that excessive smartphone use may lead to problematic smartphone use behavior. Problematic smartphone use is referred to as excessive smartphone use, which related with substance use disorder (5, 6). Meanwhile, according to ICD-11 or DSM-5, problematic smartphone use is yet defined as an addiction (7). Therefore, in this study, we use "Problematic Smartphone Use" instead of "Smartphone Addiction." The term "problematic smartphone use" was used in a recent study of smartphone use types of psychiatric symptoms. According to a recent study by Chen et al., problematic smartphone use can be divided into two categories in the field of Internet addiction: general problematic smartphone use and specific problematic smartphone use (8–10). General problematic smartphone use indicates general behavioral patterns of excessive smartphone use, which may have negative consequences to the individuals (11). Specific problematic smartphone use indicates the use of smartphones that are problematic for certain types of smartphone activities (e.g., games, social networking service, etc.) (8–11). Prior research suggests that problematic smartphone use is associated with depression, anxiety, obsessive-compulsive behavior, and impulsiveness (12–14).

Internet of Things (IoT) is widely applied in many fields, most notably in healthcare (15, 16). Applied IoT in the medical field is called the Internet of Medical Things (IoMT) (17). The smartphone application (App) used in our research performs the function of IoMT, which makes it easier to collect and manage health data. In this regard, by adopting the IoMT, we were able to able to monitor the status of app users' continuous smartphone usage, and through collected data analysis and monitoring functions, it can be expected to be an effective solution for behavior change caused by the problematic smartphone use (18, 19).

In our previous research, we proposed the use of the Smartphone Overdependence Management System (SOMS), the smartphone background software app for collecting the usage data. This system was implemented to analyze the problematic smartphone use (20). Earlier researches using SOMS data were able to predict usage patterns that directly correlate with problematic smartphone use and classified problematic smartphone use with a data-driven prediction algorithm (21). According to this perspective, since SOMS functions well as an IoMT system, we have adopted SOMS as a smartphone usage management app. The app used in this study was enhanced by adding various factors that aim to prevent problematic smartphone use by providing personalized health care services based on the SOMS functions. The system was unique compared to other management systems which lacked a proper automated measurement algorithm (22). The idea of this study was to support behavior change in such a way that problematic smartphone use is controlled using smartphone technology, which has been widely and successfully applied to other healthcare systems (19).

The research model of this paper was fundamentally based on the Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT). The TAM is developed by Davis (23), which is a widely accepted and influential model that predicts users' perceptions or acceptance of information system use (24–26). The ECT was originally used for studying consumer satisfaction, post-purchase behavior, and service marketing in general (27), but its predictive ability has been demonstrated over a wide range of fields (27–29).

Based on the aforementioned background, the purpose of this study was to examine the factors that positively or negatively affect behavioral intention to use a system, in order to successfully develop an application and implement programs for users. We also aimed to find out the differences in the factors influencing the intention to use such a smartphone usage control system between those who have a general usage behavior and those with problematic usage behavior. For that, we divide them into non-problematic smartphone use group and problematic smartphone use group. The results will be compared with other related research regarding the behavioral intention to use smartphone devices and envisioned to be used as baseline data to increase the success rate when developing intervention programs using smartphone apps.

MATERIALS AND METHODS

Study Design

Based on the fundamentals of TAM and ECT, we modified these models by converging, excluding, or including important variables that were identified as appropriate in the case of problematic smartphone use intervention by smartphone app, as shown in **Figure 1**. Because the main dynamics of TAM and ECT was similar, they were converged into the dynamic relation between facilitating conditions, effort expectancy, performance expectancy, and behavioral intention to use. In this model, perceived security was added, since personal security issues in network services have been a threat to many services, including in the field of healthcare, which obtains sensitive private information. Another factor, self-regulation, was added,

Abbreviations: IoT, Internet of Things; IoMT, Internet of Medical Things; App, Application; SOMS, Smartphone Overdependence Management System; TAM, Technology Acceptance Model; ECT, Expectation-Confirmation Theory; FC, Facilitating Conditions; EE, Effort Expectancy; PE, Performance Expectancy; BIU, Behavioral Intention To Use; PS, Perceived Security; SR, Self Regulation; PU, Perceived Usefulness; NPSU, Non-Problematic Smartphone Use; PSU, Problematic Smartphone Use; GFI, Goodness-of-Fit Index; TLI, Tucker–Lewis Index; CFI, Comparative Fit Index; RMSEA, Root Mean Square Error of Approximation; CR, Critical Ratio.

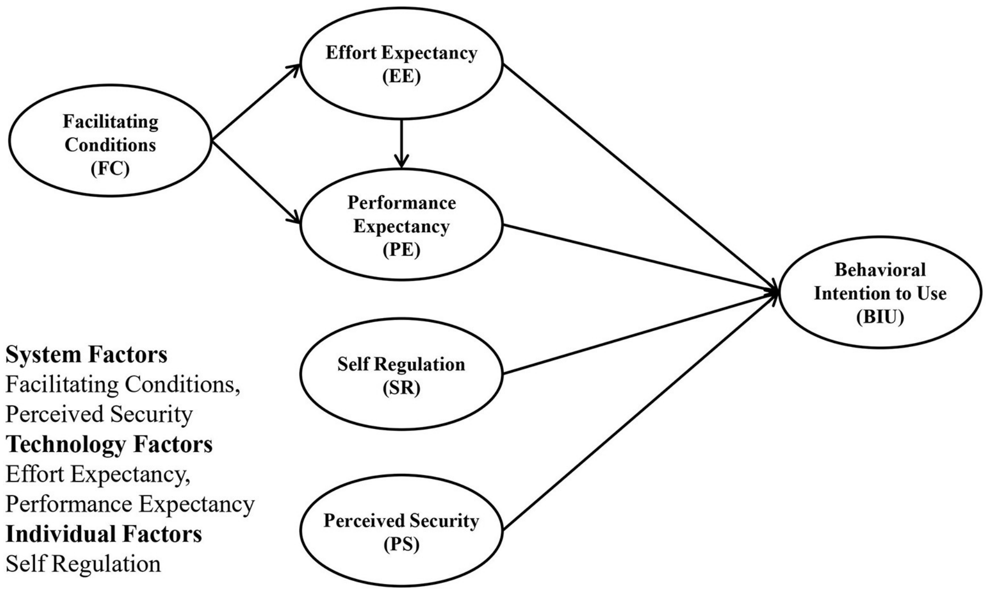

FIGURE 1 | Modified study model.

because this was considered an important construct regarding problematic smartphone use behavior.

In this model, FC and PS comprise system factors, which are the factors that help facilitate information system use. Additionally, EE and PE represent technology factors that affect intention to use. Lastly, SR represents individual factors related to intention to use.

Research hypotheses have been tested in relation to the model proposed above in two groups and are shown as follows.

H1: FC has a significant influence on EE regarding intention to use smartphone usage management application in two groups.

H2: FC has a significant influence on PE regarding intention to use smartphone usage management application in two groups.

H3: EE has a significant influence on PE regarding intention to use smartphone usage management application in two groups.

H4: EE has a significant influence on BIU regarding intention to use smartphone usage management application in two groups.

H5: PE has a significant influence on BIU regarding intention to use smartphone usage management application in two groups.

H6: SR has a significant influence on BIU regarding intention to use smartphone usage management application in two groups.

H7: PS has a significant influence on BIU regarding intention to use smartphone usage management application in two groups.

As a pilot study to validate the questionnaire, confirmatory factor analysis was performed to observe how well the prior conceptualized, theoretically grounded model are constructed (related results are provided in **Supplementary Materials**).

Study Subjects and Data Collection

The online surveys were conducted anonymously from a social survey institution panel. Five hundred eleven smartphone users were randomly selected, who were of age 20 years or older. Participants were evenly pooled from metropolitan areas of South Korea in September 18–28, 2018. In this study, non-probability sampling methods were used. The survey were provided in Korean version (translated version available in **Supplementary Materials**). Only participants who used smartphones for at least 1 h per day were included in the study. Informed consent was obtained prior to the survey. Non-adult participants were excluded as parental consent is a legal requirement for underage research, and the approval process in the Korean Institutional Review Board is strict and difficult. Before the survey, participants were informed about the developed smartphone usage management app, as shown in **Figure 2**.

The size of the sample population was selected based on the following criteria. According to the March 2018 statistics, eight out of 10 people use smartphones (population n = 51,779,892) (4). For reliability within the 95% confidence interval, the appropriate recommended sample size was 480, but we successfully collected over 500 (30).

The study procedures were performed in accordance with the Declaration of Helsinki. The Institutional Review Board of the Catholic University of South Korea, St. Mary's Hospital (MC18QESI0065), approved the study.

Measures

The Korean Smartphone Addiction Proneness Scale for Adults (S-Scale) was used for the two groups: non-problematic smartphone use (NPSU) group and problematic smartphone use (PSU) group. The S-Scale is a 15-item scale, rated on a four-point Likert scale ranging from "Strongly disagree" to "Strongly agree" from Kim et al., which measures smartphone addiction proneness scale for youth and adults (31, 32). The S-Scale is classified into three groups: high-risk (cutoff: $\geq$45), at-risk (44 $\geq$ x $\geq$ 42), and normal (41 $\geq$ x $\geq$0). In this study, we regrouped

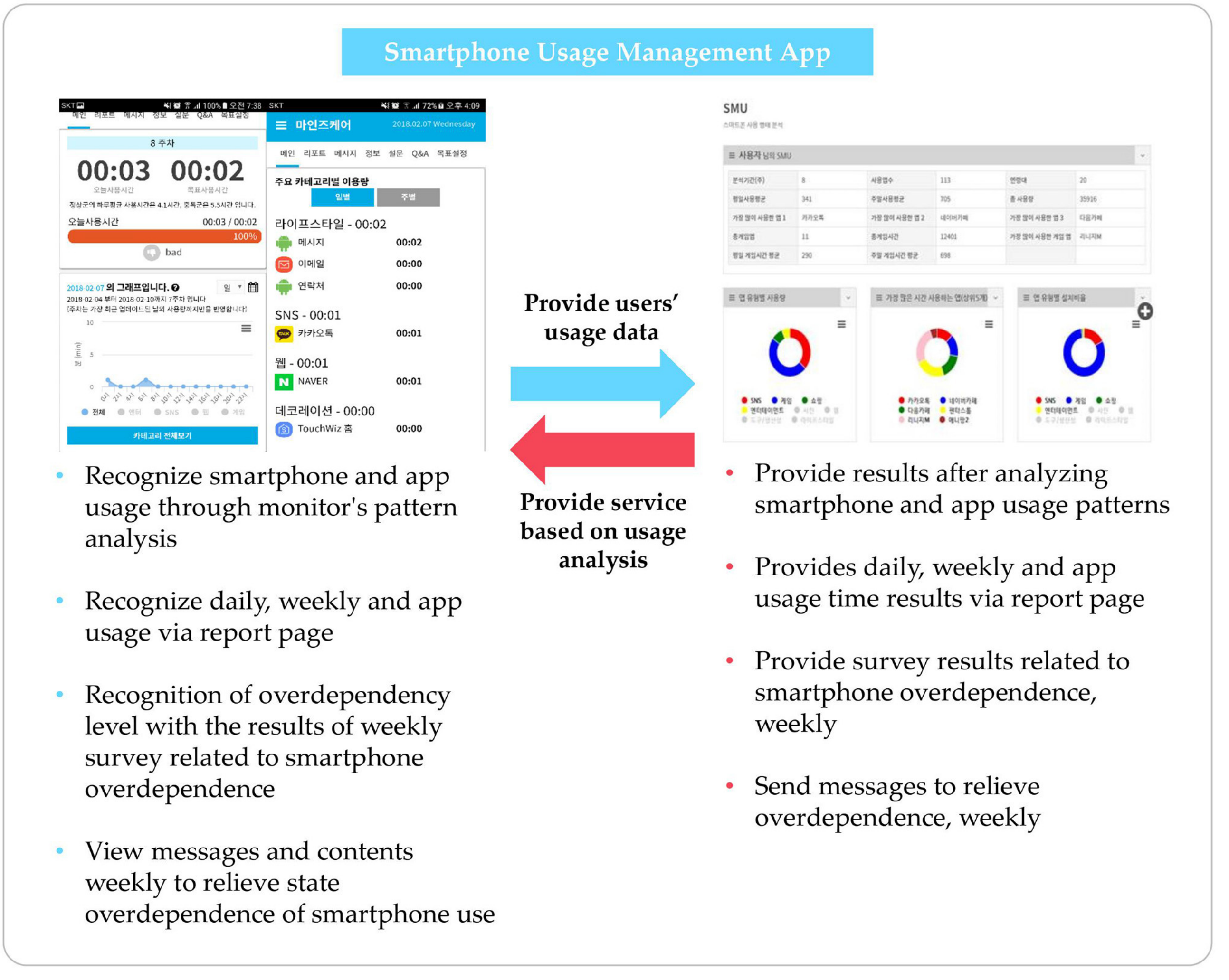

FIGURE 2 | Description of developed application.

the high-risk and at-risk groups as the PSU group and the normal group as the NPSU group for convenience of analysis.

Facilitating conditions (FC) were defined by Venkatesh (33) as a factor that helps facilitate system use (34). A total of five questions was asked, rated on a five-point Likert scale ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use. In this study, the reliability of this measure is Cronbach's alpha 0.85.

Effort expectancy (EE) refers to how easy and comfortable a system is to use. This measure was defined by Davis (23) and Venkatesh and Davis (34), which comprises a total of five questions rated on a five-point Likert scale ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use (23, 33). In this study, the reliability of this measure is Cronbach's alpha 0.86. We deleted two items to improve internal reliability.

Performance expectancy (PE) represents how useful a system is for the PSU group. This measure was also defined by Davis (23) and Venkatesh and Davis (34), which includes a total of five questions measured on a five-point Likert scale, ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use (23, 33). In this study, the reliability of this measure is Cronbach's alpha 0.90.

Self-regulation (SR) is the scale of people's ability to control themselves. It was defined by Diehl, Semegon, and Schwarzer (35), which comprises a total of nine questions rated on a four-point Likert scale, ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use. In this study, the reliability of this measure is Cronbach's alpha 0.83. We deleted two items to improve internal reliability.

Perceived security (PS) measure was defined by David et al. (36) which comprises a total of five questions rated on a five-point Likert scale, ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use. In this study, the reliability of this measure is Cronbach's alpha 0.92.

Behavioral intention-to-use (BIU) measure was defined by Davis and Gefen et al. (23, 37) which comprises a total of three questions rated on a five-point Likert scale ranging from "Strongly disagree" to "Strongly agree" with a higher score indicating a higher intention to use. In this study, the reliability of this measure is Cronbach's alpha 0.88.

Data Analysis

The collected data were analyzed using IBM SPSS Statistics 24.0 and Amos 24.0. Socio-demographic characteristics and the frequency and percentage of measurement variables were analyzed with descriptive statistics, and t-test was used to analyze differences between variables among the groups. Pearson's correlation coefficient was used to determine the correlation between variables. This study comprised a multigroup path analysis study to identify factors affecting the intention to use smartphone usage management app through FC, EE, PE, SR, PS, and BIU. Amos 24.0 was used to analyze the path difference between groups. The following procedure was conducted for analysis. First, we found the correlation between FC, EE, PE, SR, PS, and BIU, which are the main variables. Second, we constructed the hypothesized path model and measurement equivalence to determine whether both groups are recognized as the main variables identically, through multigroup confirmatory factor analysis. Third, through verification of the conducted path model, we found differences between groups on the direct effects of variables affecting intention to use smartphone usage management apps. To evaluate the goodness-of-fit index (GFI) of the research model, we used χ^2 statistic, chi-square ratio χ^2/df, Tucker–Lewis index (TLI), the comparative fit index (CFI), and the root mean square error of approximation (RMSEA) (38–40). The most basic measure of overall goodness of fit for evaluating the research model is the χ^2 statistic, which is calculated based on the normal distribution of data and is sensitive to the size of the data. A good fit was obtained when the χ^2/df value was $\leq$3 and the CFI value was >0.90. The smaller the RMSEA value is, the better the overall goodness of fit is. In general, <0.05 indicates very good fit, <0.08 indicates good fit, <0.10 indicates a normal fit, and above 0.10 indicates a poor fit. Furthermore, TLI and GFI values more than 0.90 indicate a good fit. However, acceptable RMSEA, CFI, or χ^2/df values were enough to indicate goodness of fit, despite TLI and GFI values below 0.9 (41, 42). Multigroup confirmatory factor analysis is an analysis conducted before multigroup path analysis in order to find whether each group equally identifies the measurement survey items. The measurement invariance test was approached in five steps: (1) unconstrained, (2) measurement weights, (3) structural covariances, (4) structural covariances, and (5) measurement residuals (43). If the difference between the χ^2 value of the unconstrained model and the χ^2 of each constrained model is significant, this implies a significant difference between the groups. To confirm if PSU and NPSU perceived the variables identically, measurement equivalence was conducted through multigroup confirmatory factor analysis. The maximum likelihood estimation was used to estimate the model and analyze the p-value using a bootstrapping procedure to verify the significance of each path coefficient and indirect effect.

RESULTS

Socio-Demographic Data and Correlations of Measured Variables

The socio-demographic results are shown in **Table 1**. A percentage of 64.1% ($N = 328$) of participants were NPSU and 35.8% ($N = 183$) were PSU. Our subjects ranged from age 20–50, with a relatively equal proportion for each age group. Most of our subjects were married (45.8%), were graduate school students (70.3%), and had white-collar occupations (41.9%). A vast proportion of our respondents (75.1%) did not experience using any smartphone usage management app. The most used apps were SNS (30.3%), followed by web surfing (26%), life style (11.4%), and game (10.6%).

Correlations of Measured Variables

The measurement models' fit indices, including the acceptable thresholds, are shown in **Table 2**.

The chi-square/degrees of freedom (χ^2/df) was 2.370, the GFI was 0.890, the TLI was 0.892, the CFI was 0.945, and the RMSEA was 0.052. Although the values of the GFI and TLI were slightly lesser than recommended, it was concluded that all fit indices were acceptable and supported a reasonable fit assumption (44, 45). This was also supported by prior studies, which accepted models that had GFI or TLI values marginally lower, but with good fit RMSEA, CFI, or χ^2/df value supplementing the lack of GFI or TLI (41, 42).

The results of analyzing the mean, standard deviation, and correlation of the variables are shown in **Table 3**. There was a positive correlation between FC and EE as well as in EE and PE. Additionally, there was a quantitative correlation between PE and SR, SR and PS, and PS and BIU.

Multigroup Confirmatory Factor Analysis

The focus of this study was to determine the differences of intention to use smartphone usage management apps between groups. The results of this study confirmed that configure invariance was normal (unconstrained models fit $\chi^2 = 1346.676$, $p < 0.001$, TLI $= 0.922$, CFI $= 0.931$, RMSEA $= 0.041$). As a result of the χ^2 test of the unconstrained model and constrained model 1, it was insignificant at the $p < 0.05$ level. Therefore, we were able to conduct the multigroup path analysis, since both of the groups' model form and measurement equivalence of factor coefficients were confirmed between latent and measured variables. As prior studies suggest that the chi-squared test was not suitable for the model-fit index, we were able to conduct multi-path analysis as other model-fit indexes (TLI, CFI, RMSEA) between the two groups were shown to be a good fit (**Table 4**) (46, 47).

Multigroup Path Analysis

The critical ratio (CR) value was also used to check whether the difference between groups was significant (intergroup path difference). As a result of this study, FC in the NPSU group had a significant positive effect on EE ($\beta = 0.545$, $p < 0.001$). In addition, the FC of the PSU group had a significant positive effect on EE ($\beta = 0.734$, $p < 0.001$). The difference in the FC$\rightarrow$ EE pathway between groups was not statistically significant. FC in

TABLE 1 | Characteristic of socio-demographics.

Characteristics		NPSU (*N* = 328) (%)	PSU (*N* = 183) (%)	Overall (*N* = 511) (%)	χ^2	*p*
Gender	Male	164 (50.0)	85 (46.4)	249 (48.7)	0.593	0.441
	Female	164 (50.0)	98 (53.6)	262 (51.3)		
Age group	20–29	82 (25.0)	50 (27.3)	132 (25.8)	7.103	0.069
	30–39	76 (23.2)	54 (29.5)	130 (25.4)		
	40–49	82 (25.0)	48 (26.2)	130 (25.4)		
	Over 50	88 (26.8)	31 (16.9)	119 (23.3)		
Marital status	Married	145 (44.2)	89 (48.6)	234 (45.8)	1.804	0.406
	Unmarried	183 (55.8)	94 (51.4)	277 (54.3)		
Education	High school or lower	44 (13.4)	20 (10.9)	64 (12.5)	2.147	0.342
	College student	51 (15.5)	37 (20.2)	88 (17.2)		
	Graduate or above	233 (71.0)	126 (68.9)	359 (70.3)		
Occupation	White-collar	142 (43.3)	72 (39.3)	214 (41.9)	8.589	0.476
	Student	31 (9.5)	22 (12.0)	53 (10.4)		
	Professional	24 (7.3)	18 (9.8)	42 (8.2)		
	Unemployed	25 (8.2)	15 (8.2)	40 (7.8)		
	Others	106 (31.7)	56 (30.7)	162 (31.7)		
Experience to use smartphone usage management app	Yes	57 (17.4)	70 (38.3)	127 (24.9)	27.403	0.000
	No	271 (82.6)	113 (61.7)	384 (75.1)		
Playing smartphone game	Yes	158 (48.2)	124 (67.8)	282 (55.2)	18.225	0.000
	No	170 (51.8)	59 (32.2)	229 (44.8)		
Most used App for the past 1 year	SNS	94 (28.7)	61 (33.3)	155 (30.3)	15.171	0.297
	Web surfing	85 (25.9)	48 (26.2)	133 (26.0)		
	Game	32 (9.8)	22 (12.0)	54 (10.6)		
	Entertainment	30 (9.1)	12 (6.6)	42 (8.2)		
	Shopping	14 (4.3)	12 (6.6)	26 (5.1)		
	Lifestyle	47 (14.3)	11 (6.0)	58 (11.4)		
	Others	26 (7.9)	17 (9.3)	43 (8.5)		
Total		328	183	511		

NPSU, Non-problematic smartphone use; PSU, problematic smartphone use.

TABLE 2 | Goodness-of-fit statistics.

Model-fit index	Recommended value	Scores
Chi-square/degree of freedom (χ^2/df)	≤3.00	2.370
Goodness-of-fit index (GFI)	≥0.90	0.890
Tucker–Lewis index (TLI)	≥0.90	0.892
Comparative fit index (CFI)	≥0.90	0.945
Root mean square error of approximation (RMSEA)	<0.1	0.052

the NPSU group had a significant positive effect on PE (β = 0.364, $p < 0.001$). In addition, FC in the PSU group was found to have a significant effect on PE (β = 0.376, p <0.001). The differences in the FC→ PE pathways between groups were not statistically significant. EE in the NPSU group was found to have a significant positive effect on PE (β = 0.444, $p < 0.001$). The EE of the PSU group was found to have a positive effect on PE (β = 0.519, $p < 0.001$). Differences in the EE→ PE pathway between groups were not statistically significant. In both NPSU and PSU, SR did not significantly affect BIU. PS in the NPSU group was found to have a significant effect on BIU (β = 0.412, $p < 0.001$). PS in the PSU group was found to have a significant effect on BIU (β = 0.314, $p < 0.001$). Differences in the PS→ BIU pathway among the groups were statistically significant (CR = 2.411 > 1.96). Both NPSU and PSU showed that EE had no significant effect on BIU. PE in the NPSU group had a significant positive effect on BIU ($\beta = 0.319$, $p < 0.001$). In addition, the PE of the PSU group was found to have a significant effect on BIU ($\beta = 0.672$, p <0.001). The differences in the PE→

TABLE 3 | Correlations, means, and standard deviations for measured variables.

	FC	EE	PE	SR	PS	BIU
FC	1					
EE	0.531**	1				
PE	0.572**	0.623**	1			
SR	0.248**	0.252**	0.205**	1		
PS	0.263**	0.373**	0.496**	0.281**	1	
BIU	0.341**	0.430**	0.584**	0.184**	0.590**	1
Mean	3.649	3.531	3.373	2.578	2.874	2.836
SD	0.645	0.714	0.753	0.537	0.864	0.919

$^{**}p < 0.01$.
SD, Standard deviations; FC, facilitating conditions; EE, effort expectancy; PE, performance expectancy; SR, self-regulation; PS, perceived security; BIU, behavioral intention to use.

TABLE 4 | Multigroup confirmatory factor analysis.

Model	χ^2	Df	TLI	CFI	RMSEA	χ^2 difference	df difference	*p*
Unconstrained	1346.676	724	0.922	0.931	0.041			
Constrained 1[a]	1363.216	747	0.925	0.931	0.040	48.514	23	0.831
Constrained 2[b]	1389.133	745	0.922	0.928	0.041	67.272	21	0.004
Constrained 3[c]	1493.291	797	0.921	0.922	0.041	434.003	73	0.000
Constrained 4[d]	1601.674	826	0.915	0.914	0.043	317.004	102	0.000

[a]Constrained 1: measurement weights.
[b]Constrained 2: structural covariances.
[c]Constrained 3: structural covariances.
[d]Constrained 4: measurement residuals.
TLI, Tucker–Lewis Index; CFI, comparative fit index; RMSEA, root mean square error of approximation.

TABLE 5 | Multigroup path analysis.

Path	NPSU			PSU			Intergroup path difference (C.R.)
	B	β	S.E.	B	β	S.E.	
FC → EE	0.509***	0.545***	0.059	0.705***	0.734***	0.082	1.950
FC → PE	0.367***	0.364***	0.063	0.333***	0.376***	0.085	−0.319
EE → PE	0.479***	0.444***	0.070	0.479***	0.519***	0.093	0.002
SR → BIU	−0.041	−0.018	0.122	−0.119	−0.061	0.134	−0.793
PS → BIU	0.447***	0.412***	0.058	0.297***	0.314***	0.067	2.411*
EE → BIU	0.118	0.085	0.100	−0.012	−0.010	0.129	−0.430
PE → BIU	0.411***	0.319***	0.092	0.837***	0.672***	0.151	−1.695

$^{*}p < 0.05$; $^{***}p < 0.001$.
S.E., standard errors; C.R., Cretial ratio; NPSU, non-problematic smartphone use; PSU, problematic smartphone use; FC, facilitating conditions; EE, effort expectancy; PE, performance expectancy; SR, self-regulation; PS, perceived security; BIU, behavioral intention to use.

BIU pathways between groups were not statistically significant (**Table 5**, **Figure 3**).

A higher value of the coefficient means stronger intention to the relative variable. In this study, there was a statistically significant difference in the path of intergroup differences between PS→ BIU. This means that the PSU group considered the security factor less important than the NPSU group, and the difference between the two groups was significant.

DISCUSSION

Common results for both NPSU and PSU

This section explains the common results found in both NPSU and PSU. FC→ EE was analyzed to prove that if certain facilitating conditions were met, it would significantly affect users by making them feel that less effort was needed to use the proposed monitoring system. Once users' expected effort was reduced, we predicted that it would have a positive effect on their intention to use EE→ BIU.

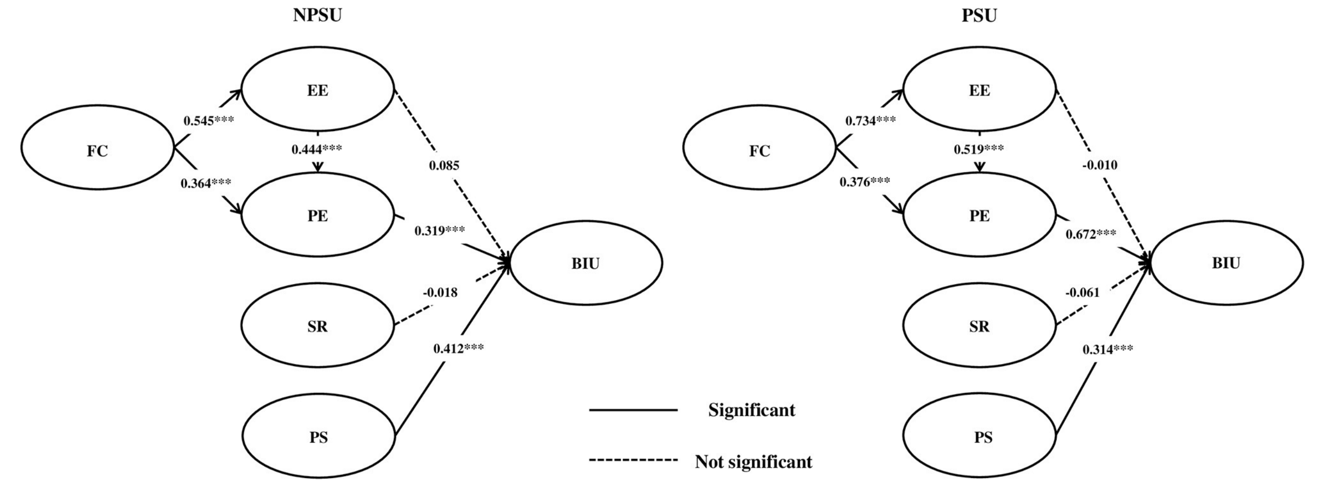

FIGURE 3 | Result of multigroup path analysis.

Although FC→ EE was significant, EE→ BIU all turned out to be statistically insignificant, contrary to many prior studies. For instance, a similar research by Bhattacherjee (48) suggested that users' continuance intention is determined by their satisfaction with information system use, which is positively affected by the expectation confirmation. Our results were inconsistent with another prior study (49), which reported that perceived ease of use as a similar variable to EE was a statistically significant determinant of BIU. Even psychologically, Melas et al. stated that users are naturally attracted to easy tools (25) rather than complex ones. Considering that even up-to-date research on subjects in Malaysia shows that easy usage leads to enhanced usability (50), our results may have been due to South Koreans' unique characteristics, with over 90% of the population already accustomed to smartphones. That is, EE may not be a significant factor for Koreans, who naturally take it for granted that use of a smartphone app is easy. This is a unique point of our research, considering that no studies have determined this relationship in South Korea to date.

Another unique and important point that should be noted here is that although the findings of EE→ BIU did not have a direct effect, nonetheless EE did have an indirect effect on BIU. That is, EE positively affected PE, and PE eventually positively affected BIU (this pathway will be discussed separately below). This link from FC→ EE→ PE and eventually to BIU was found to be statistically significant for both groups in our analysis. The core link from EE to PE enabled this phenomenon. Similarly, research conducted by Dhiman et al. (51) supported our link by investigating consumer adoption of smartphone fitness apps and revealing a significant relationship between EE and performance expectation.

An important point to note is that the finding of EE→ PE directly contradicts the findings of our 2018 research (49), in which we found that perceived ease of use had a statistically significant negative effect on BIU. It can be assumed that the more recent results may have been different, due, first, to changes in recent users' attitudes/perceptions toward smartphone usage monitoring apps, and second, because we upgraded our survey contents when modifying perceived ease of use into EE. In conclusion, the findings of this study comprise an up-to-date empirical study in analyzing factors affecting users' BIU of a smartphone over dependence management monitoring system according to NPSU and PSU.

Similarly, FC→ PE was analyzed to prove that if certain facilitating conditions are met, it would also affect users by making them expect some good performance from the system. Once their expectations of the system's effective performance were high, we predicted that it would naturally link to a positive effect on their intention to use PE→ BIU, and these effects did turn out to be statistically significant. This was congruent with research in many other fields historically (25, 52, 53), which used perceived usefulness (PU) as a similar variable to PE in this research. In 2013, Deng et al. (54) found that perceived value had significant effects on both attitudes toward smartphone health services and BIU. Similarly, Hung et al. (55) found that PU influences BIU because it positively influences users' attitudes toward certain suggested systems. Compared to these studies, the uniqueness of our research lies in the fact that we conducted deeper investigations into some factors like FC, which proved to be the core fundamental before the "PE to BIU" influence relations when adopting e-Health-related systems.

As for EE→ PE, we analyzed whether users' enhanced convenience would positively affect their perception of the system's usefulness. The results supported that lessened EE led to users positively increased PE of the system, meaning that user interface or user experience should be as user-friendly as possible.

The effect of self-regulation on behavioral intentions to use SR→ BIU was not statistically significant. According to a recent related study by van Deursen et al. (3), subjects with high self-regulation demonstrated a willingness to adopt various methods to fight against problematic smartphone use. On the contrary, our proposed research demonstrated that self-regulatory mentality had no significant impact on intentions to use the smartphone usage management app method as a means to intervene in problematic smartphone use.

Lastly, the statistical significance of PS as an important factor in determining users' intention to use the system was valid for both groups under a 95% confidence interval. Personal information, especially in medical fields, is considered to be highly sensitive information that should not be leaked at any cost. The recent findings of this paper are consistent with those of Cimperman et al. (56), who emphasized that PS is one of the three key factors that influence acceptance. Our recent findings were also supported by Ebert et al. (57), who stated that PS significantly affects acceptance of internet-based mental health interventions.

Difference Between NPSU and PSU

Among the common features discussed above, one hypothesis pathway of the proposed research showed an interesting difference between NPSU and PSU. That is, although the significance of PS as an important factor in determining users' intention to use the system was valid for both groups, the PSU group showed less need for the importance of security than the NPSU group. Related research specifically identifying this issue is extremely rare in the field of smartphone overuse. Similar research by Blachnio et al. (58) regarding the addictive use of the Internet found that Internet addiction was negatively related to PS. This may imply that the PSU group's proneness to addiction somewhat reduced their consciousness for PS. This logical pathway may have caused their statistically significant lower impact of PS on intention to use than the NPSU group.

CONCLUSIONS

This study has investigated the factors affecting users' BIU smartphone usage management apps. Participants were divided into NPSU and PSU groups for an in-depth investigation. Overall, the results showed common features between NPSU and PSU, with facilitating factors positively affecting PE for intentions to use smartphone usage management apps, and with perceived security positively affecting intentions to use smartphone usage management apps. One distinct difference between NPSU and PSU was that the latter attributed a lower importance to perceived security than the former.

A limitation of this research is that the population did not include adolescents, who are known to be heavy smartphone users and particularly susceptible to overusing these devices. Since this study data is from self-assessment information, it can cause recall bias and social satisfaction bias in response.

The results have been used to develop the core risk prediction model embedded in our developed smartphone overuse monitoring system app, which is currently being launched. Post-follow-up future research should be conducted among the served population for further survey investigation. The research results can also be flexibly applied to other medical systems. Some of our highlighted unique points are envisioned to provide intensive insights for broadening knowledge about technology acceptance in the field of e-Addictology (59), and a constant update of research is required to successfully reflect the quickly changing perceptions of adaptive smartphone users.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board of the Catholic University of South Korea, St. Mary's Hospital (MC18QESI0065) approved the study. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MC and S-JL: conceptualization, validation, and writing—original draft preparation. MC and MJR: methodology. MC: formal analysis, investigation, writing—review and editing, and visualization. MC and SL: software and data curation. IC: resources, supervision, and project administration. IC and D-JK: funding acquisition. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.571795/full#supplementary-material

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Altered Functional Connectivity of the Salience Network in Problematic Smartphone Users

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Smartphones provide convenience in everyday life. Smartphones, however, can elicit adverse effects when used excessively. The purpose of this study was to examine the underlying neurobiological alterations that arise from problematic smartphone use. We performed resting state seed-based functional connectivity (FC) analysis of 44 problematic smartphone users and 54 healthy controls. This analysis assessed the salience, central executive, default mode, and affective networks. Compared to controls, problematic smartphone users showed enhanced FC within the salience network and between the salience and default mode network. Moreover, we observed decreased FC between the salience and central executive network in problematic smartphone users, compared to controls. These results imply that problematic smartphone use is associated with aberrant FC in key brain networks. Our results suggest that changes in FC of key networks centered around the salience network might be associated with problematic smartphone use.

Keywords: probelmatic smartphone use, salience network, functional connectivity, fMRI, neuroimaging

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INTRODUCTION

For the past two decades, smartphones have radically changed human lives, becoming ubiquitous in everyday life (1, 2). Smartphones have brought about changes to various areas of life, such as productivity, information seeking, social information and interaction, diversion, relaxation, entertainment, monetary compensation, and personal status (3). However, with greater integration of smartphones into daily lives, concerns for psychological and behavioral dysfunction due to problematic smartphone use have begun to accumulate (4, 5).

The clinical characteristics of problematic smartphone use share conceptual similarities with typical addictive disorders (6). Lin et al. have suggested a diagnostic standard for smartphone addiction, with core symptoms of "impaired control" and withdrawal (7). According to the Interaction of Person-Affect-Cognition-Execution model, which lays the theoretical framework for addictive behaviors, an association between cue-reactivity/craving and diminished inhibitory control contribute to the development of addictive behaviors (8, 9). The frontoinsular cortex, which acts as a mediator between the limbic and prefrontal-striatal system, and an imbalance between hyperactive involvement of limbic structures and hypoactive involvement of prefrontal-striatal circuits are thought to play crucial roles in the pathophysiology of addictive behaviors (8, 9). While numerous attempts have been made to identify neural correlates undergirding behavioral addiction, most studies have been published on gambling and Internet gaming disorder; neural correlates responsible for problematic smartphone usage remain largely unknown.

Resting-state functional magnetic resonance imaging is a powerful tool that can be utilized to investigate correlates related to various neurological and psychiatric disorders. The salience network, central executive network, default mode network, and affective network play key functions in the human brain (10, 11). The salience network, comprising nodes in the right frontoinsular cortex and anterior cingulate cortex, facilitates orientation to stimuli and allocates attention (12). The central executive network, which is responsible for goal-directed behavior involving decision making, comprises the dorsolateral prefrontal cortex and posterior parietal cortex (12). The default mode network, which is responsible for stimulus-independent thought processes, comprises the medial prefrontal cortex, the rostral parts of the anterior cingulate cortex, the precuneus, and the posterior cingulate cortex (13). Lastly, the affective network, which is relevant for emotion perception and regulation, comprises a set of interconnected neural structures in the amygdala and subgenual anterior cingulate cortex (14, 15).

Research into changes in intrinsic connectivity networks in behavioral addiction has primarily been limited to Internet gaming disorders and has revealed aberrant functional connectivity (FC) between and within intrinsic connectivity networks in the brain (16–18). In Internet gaming disorder, deficient modulation of central executive network activity versus default mode network activity by the salience network has been suggested as a neurobiological mechanism in the maintenance of addictive behaviors (16). Furthermore, altered FC to the frontal lobe over the amygdala has been found to contribute to vulnerability to Internet gaming disorder (19). Meanwhile, a few neuroimaging studies on problematic smartphone use have also suggested changes in FC in brain regions related with cognitive control and emotional processing: One study reported altered neural deactivation of the prefrontal and cingulate cortex during facial emotion processing in problematic smartphone users, compared to controls (20). These results suggest that problematic smartphone use may affect cognitive control during emotional processing *via* altered integrity of functional brain networks. Another study reported that adolescent problematic smartphone users had reduced FC in brain regions related to cognitive control (21). Although these studies provide some insights into the neurobiological basis for problematic smartphone use, relatively few neuroimaging studies have focused on underlying neural correlates responsible for problematic smartphone use.

Thus, we aimed to identify changes in intrinsic connectivity networks in problematic smartphone use. We investigated alterations in FC among core intrinsic connectivity networks (salience network, central executive network, default mode network, and affective network) in problematic smartphone users based on regions of interest in these core networks.

MATERIALS AND METHODS

Participants

Ninety-eight subjects participated in this study: 29 males with excessive smartphone use, 15 females with excessive smartphone use, 32 healthy males, and 22 healthy females. All subjects were right-handed and between 16 and 54 years of age (mean: 23.6 ± 4.8 years). All participants were administered the Structured Clinical Interview from the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition to evaluate major psychiatric illness (22). The Korean version of the Wechsler Adult Intelligence Scale IV was used to assess intelligence quotient (23). Exclusion criteria for all subjects were major psychiatric disorder, intellectual disability, neurological or medical illness, and contraindications on magnetic resonance imaging (MRI) scan. None of the subjects included in this study received psychiatric treatment, including psychopharmacology.

Psychometric Measures

The Smartphone Addiction Proneness Scale (SAPS) test, developed by the Korean National Information Society Agency to assess problematic smartphone use (24), consists of 15 questions and includes the following four subscales: disturbance of adaptive functions, virtual life orientation, withdrawal, and tolerance. Subjects with the following SAPS scores were classified as high-risk smartphone users: (a) total SAPS score of $\geq$44 and (b) disturbance of adaptive functions, withdrawal, and tolerance subscale scores of $\geq$15, $\geq$13, and $\geq$13, respectively. In this study, subjects with the following SAPS scores were classified as potentially at-risk smartphone users: (a) total SAPS score of $\geq$40 and $\leq$43 or (b) disturbance of adaptive functions subscale score of $\geq$14. The high-risk or potentially at-risk users were classified as problematic smartphone users. The Cronbach's alpha of the SAPS was 0.932 in the present sample.

The Internet Addiction Test (IAT) was administered to assess Internet addiction status (25), with a Cronbach's alpha value of 0.933 in the present sample. The Barratt Impulsiveness Scale version 11 (BIS-11) was administered to test impulsivity (26), with a Cronbach's alpha in the present sample of 0.800. To evaluate comorbid psychiatric conditions of depression, anxiety, and alcohol use disorder, all subjects were administered the Beck Depression Inventory (BDI, Cronbach's alpha = 0.790), Beck Anxiety Inventory (BAI, Cronbach's alpha = 0.796), and Alcohol Use Disorder Identification Tests (AUDIT, Cronbach's alpha = 0.782), respectively.

FC Analysis

Brain MRI data were acquired using a 3T MRI scanner (Magnetom; Siemens, Munich, Germany) equipped with an eight-channel head coil. The structured MRI data were obtained through a T1-weighted spoiled gradient echo sequence (echo time = 2.19 ms, repetition time = 1,780 ms, flip angle = 9°, field of view = 256 mm, matrix = 256 × 256, transverse slice thickness = 1 mm). The functional MRI data were obtained through a single-shot T2-weighted gradient echo planar pulse sequence (echo time = 30 ms, repetition time = 2,500 ms, flip angle = 90°, field of view = 240 mm, matrix = 64 × 64, slice thickness = 3.5 mm). During the acquisition of functional MRI data, subjects were instructed to look at a white cross in the center of a black background for 6 min without any cognitive, lingual, or motor activities.

Imaging data were processed using a Microsoft Windows platform running MATLAB version 9.3 (R2020a) (The MathWorks Inc, Natick, MA, USA) and the MATLAB-based CONN-fMRI Functional Connectivity toolbox, version 19.c (Cognitive and Affective Neuroscience Laboratory, Massachusetts Institute of Technology, Cambridge, MA, USA). The default CONN preprocessing pipeline was applied. To correct motion across volumes, functional images were aligned to the first volume using a least-square minimization and a six-parameter rigid body spatial transformation. Unwarping and slice-timing correction were also applied.

Next, we ran the ART-based automatic outlier detection for later scrubbing. Specifically, functional volumes were deemed outliers if their signal intensity deviated more than five standard deviations from the mean signal intensity of the whole series or showed evidence of displacement superior to 0.9 mm in relation to the preceding volume. Subjects for whom more than 15% of frames were censored for scrubbing were excluded: all subjects were included in the FC analysis because none met these exclusion criteria. Both functional and structural images were then subjected to gray and white matter and cerebrospinal fluid segmentation, and a bias correction was performed to remove varying intensity differences across images.

Finally, structural and functional data were spatially normalized in parallel through non-linear transformations to the Montreal Neurological Institute space. Images were re-sliced to a 2-mm isotropic resolution and smoothed with an 8-mm full-width at half-maximum (FWHM) isotropic Gaussian kernel. After preprocessing, imaging data were denoised from residual movement and physiological noise (i.e., respiration, cardiac pulsations, slow involuntary head position motion, or "spike-like" movements) (27). Specifically, the denoising steps included a temporal de-spiking, regressing out confounding factors (i.e., BOLD signal small ramping effects at the beginning of each session, six rigid body realignment parameters and their first order derivatives), an anatomical component-based noise correction method (aCompCor, which reduces physiological and movement noise), the ART scrubbing protocol, linear detrending to remove linear signal drift, and band-pass filtering to restrict the analysis to a range of frequencies of interest (0.008–0.09 Hz).

Seed-to-voxel FC maps for each subject were constructed using the CONN-fMRI toolbox 19.c (http://www.nitrc.org/projects/conn). While configuring individual seed-to-voxel FC maps, movement parameters for each subject were preserved as confounders within the general linear model. For four networks, the following spherical seeds with a 6-mm radius were selected: the dorsal anterior cingulate cortex (6 45 9) (28) and the anterior frontoinsular cortex (left anterior frontoinsular cortex: −45 35 9; right anterior frontoinsular cortex: 45 3 15) (29) of the salience network; the bilateral frontal eye field (left frontal eye field: −24 −15 66; right frontal eye field: 28 −10 58) (29) and bilateral dorsolateral prefrontal cortex (left dorsolateral prefrontal cortex: −40 18 24; right dorsolateral prefrontal cortex: 40 18 24) (30) of the central executive network; the posterior cingulate gyrus (−5 −49 −40) (31), the medial prefrontal cortex (−1 47 −4) (31), and the bilateral rostral anterior cingulate cortex (left rostral anterior cingulate cortex: −5 34 28; right rostral anterior cingulate cortex: 5 34 28) (32) of the default mode network; and the bilateral amygdala (left amygdala: −24 −4 −16; right amygdala: 24 −4 −16) (33) and bilateral subgenual anterior cingulate cortex (left subgenual anterior cingulate cortex: −5 25 −10; right subgenual anterior cingulate cortex: 5 25 −10) (32) of the affective network were selected as regions of interest (ROIs). All seed regions were built using the MarsBaR toolbox in SPM to create 6-mm spherical ROI images. Signals from white matter and ventricular regions were also eliminated through linear regression (34). To reduce artifacts caused by head motion, estimated subject-motion parameters (35) implemented in CONN's default denoising guideline were applied to the linear regression model. Correlation coefficients were estimated and converted to z-values using Fisher's r-to-z transformation for the calculation of FC strengths. Afterwards, FC strength estimates were compared between groups using an analysis of covariance (ANCOVA) on each voxel, after controlling for age and sex. All imaging analyses were corrected for multiple comparisons using a combination of voxel-level thresholds ($p < 0.001$) and cluster extent threshold false discovery rate correction ($p < 0.05$).

Statistical Analysis

Statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS) version 25.0 (SPSS Inc., Chicago, IL, USA). Differences with p-values <0.05 were considered statistically significant. To compare demographic and psychological features, we employed independent Student's t-tests and χ^2 tests. We conducted correlation analyses to verify that FC strengths were correlated with clinical variables (smartphone usage times, SAPS score, and BIS score). In subsequent partial correlation analyses, parameters related to comorbidity conditions (age and gender) were added as covariates.

Ethics

This study was carried out in accordance with the latest version of the Declaration of Helsinki, and under the guidelines for human subject research established by the Institutional Review Board at Yonsei University. All protocols for this study were approved by the Institutional Review Board at Severance Hospital, Yonsei University. Written informed consent was obtained from all participants before enrollment.

RESULTS

Participant Characteristics

Problematic smartphone users and controls did not significantly differ with respect to age, sex, full scale IQ, or AUDIT scores

TABLE 1 | Demographics and clinical characteristics of study participants.

	Excessive smartphone users (n = 44) Mean (SD)	Healthy controls (n = 54) Mean (SD)	Test	*df*	Test
Age (years)	24.6 (6.1)	22.7 (3.3)	t = 1.871	96	t = 1.871
Sex (male), number (%)	29 (47.5%)	32 (52.5%)	χ^2 = 0.456	1	χ^2 = 0.456
Full-scale IQ[a]	110.5 (12.0)	109.7 (10.7)	t = 0.341	96	t = 0.341
SAPS	45.0 (4.7)	29.4 (6.3)	t = 13.983	95.299	t = 13.577
Disturbance of adaptive functions	15.3 (1.8)	9.6 (2.4)	t =13.454	95.391	t =13.070
Virtual life orientation	4.2 (1.3)	2.8 (1.0)	t = 6.055	96	t = 6.055
Withdrawal	11.8 (2.2)	8.1 (2.5)	t = 7.749	96	t = 7.749
Tolerance	13.6 (1.5)	8.9 (2.7)	t = 10.875	84.497	t = 10.279
IAT	48.8 (13.6)	36.8 (17.7)	t = 3.693	96	t = 3.693
BIS	55.5 (8.8)	49.8 (8.7)	t = 3.207	96	t = 3.207
BDI	8.7 (4.6)	6.2 (5.0)	t = 2.531	96	t = 2.531
BAI	8.5 (5.9)	5.0 (4.4)	t = 3.239	78.262	t = 3.333
AUDIT	9.6 (5.3)	7.7 (5.1)	t = 1.739	96	t = 1.739
Duration of smartphone use per day (hours)	6.9 (2.1)	2.6 (1.2)	t = 12.147	65.910	t = 12.783

AUDIT, alcohol use disorder identification test; BAI, Beck anxiety inventory; BDI, Beck depression inventory; BIS, Barratt impulsivity scale; IAT, Internet addiction test; IQ, intelligence quotient; SAPS, smartphone addiction proneness scale. SD, standard deviation.
[a] IQ was assessed using the Wechsler Adult Intelligence Scale.

TABLE 2 | Whole-brain seed-based functional connectivity analysis results.

	Region	BA	kE	Tmax	x	y	z	
Salience network - dorsal ACC								
Excessive smartphone users > control	Left	Anterior FIC	48	209	4.23	−40	24	2
Salience network – anterior FIC								
Excessive smartphone users > control	Left	Precuneus	5	207	3.82	−4	−42	58
	Right	Supramarginal gyrus	5	169	4.5	64	−34	26
	Right	Orbitofrontal cortex	34	266	5.3	24	8	−20
	Left	Dorsal ACC	24	354	4.76	−6	20	26
Control > excessive smartphone users	Left	DLPFC	9	190	4.01	−16	30	50
	Left	VLPFC	47	361	4.59	−38	38	−12
Central executive network - DLPFC								
Excessive smartphone users > control	Left	Postcentral gyrus	3	188	4.11	−66	−10	32
Default mode network - rostal ACC								
Excessive smartphone users > control	Left	Anterior FIC	48	169	4.31	−26	20	12
Affective network - Amygdala								
Excessive smartphone users > control	Left	DLPFC	9	563	5.25	−34	12	46
Affective network - subgenual ACC								
Control > excessive smartphone users	Left	Lingual gyrus	18	233	4.4	−26	−84	−14

ACC, anterior cingulate cortex; DLPFC, dorsolateral prefrontal cortex; FIC, frontoinsular cortex; VLPFC, ventrolateral prefrontal cortex. Brain regions showing a significant difference in functional connectivity between groups.

(**Table 1**). Psychometric self-repost scales showed significant group differences in SAPS ($p < 0.001$), IAT ($p < 0.001$), BDI ($p = 0.013$), BAI ($p = 0.001$), and BIS ($p = 0.002$) scores. Problematic smartphone users spent significantly more time daily using their smartphones than the control group ($p < 0.001$).

FC Analysis Results

Salience Network

Problematic smartphone users showed stronger FC between the dorsal anterior cingulate cortex and anterior frontoinsular cortex, as well as anterior frontoinsular cortex-based FC with the precuneus, supramarginal gyrus,

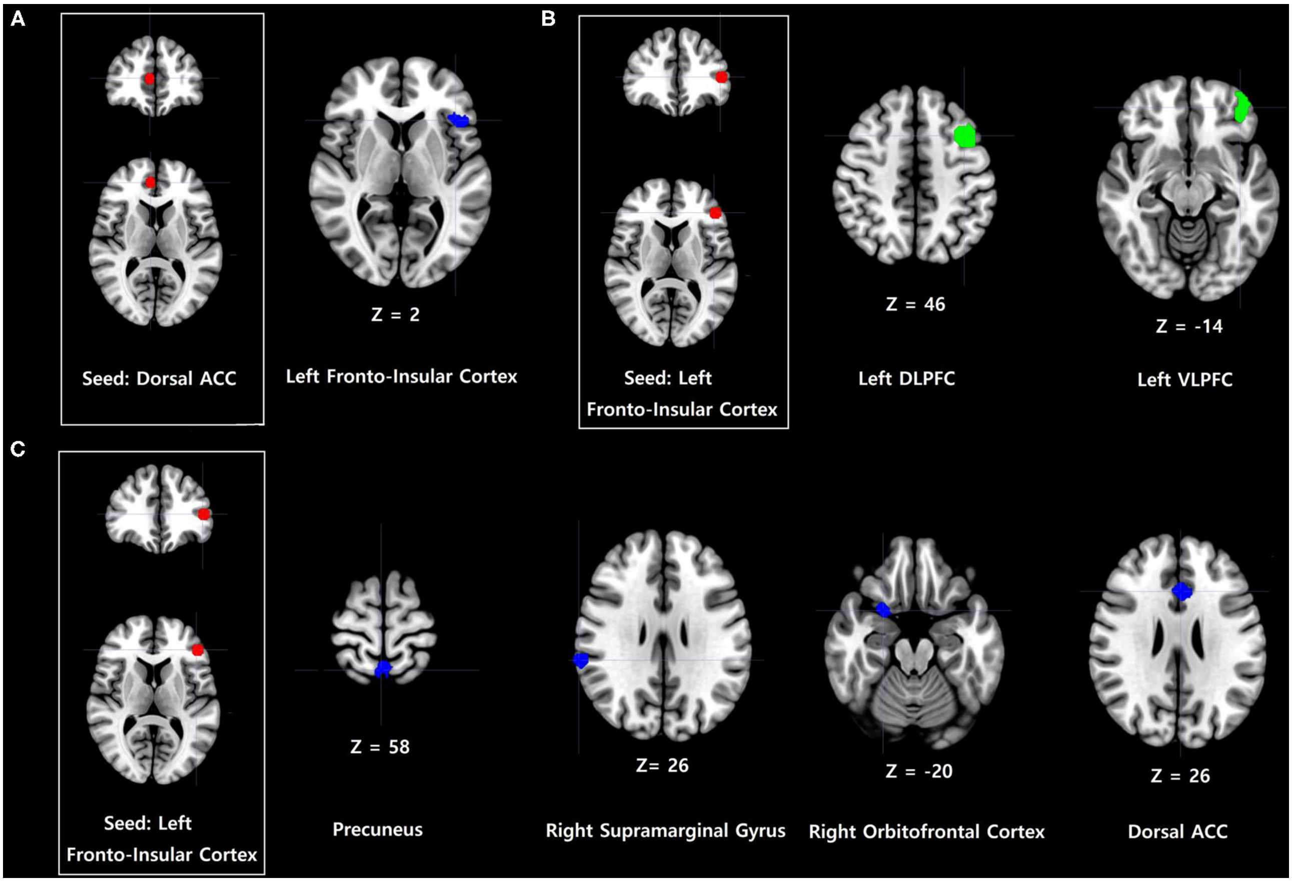

FIGURE 1 | Increases and decreases in dorsal anterior cingulate cortex (dorsal ACC) and frontoinsular cortex-based functional connectivity (FC) in problematic smartphone users, compared to controls. All imaging analyses were corrected for multiple comparisons using a combination of voxel-level thresholds ($p < 0.001$) and cluster extent threshold false discovery rate correction ($p < 0.05$). **(A)** Dorsal ACC-based FC was enhanced with the left anterior frontoinsular cortex in problematic smartphone users, compared to controls. **(B)** Left frontoinsular cortex-based FC was decreased with left ventrolateral prefrontal cortex (VLPFC) and left dorsolateral prefrontal cortex (DLPFC) in problematic smartphone users, compared to controls. **(C)** Left frontoinsular cortex-based FC was enhanced with precuneus, right supramarginal gyrus, right orbitofrontal cortex and dorsal ACC.

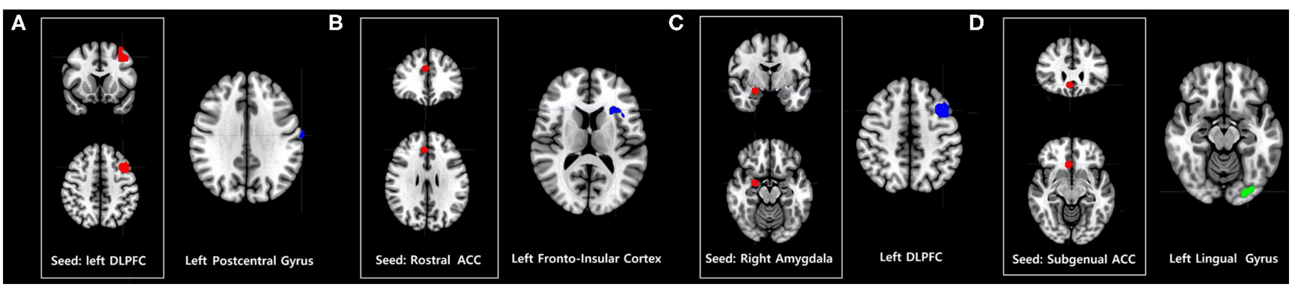

FIGURE 2 | Increases and decreases in seed-based FC among problematic smartphone users, compared to controls. All imaging analyses were corrected for multiple comparisons using a combination of voxel-level thresholds ($p < 0.001$) and cluster extent threshold false discovery rate correction ($p < 0.05$). **(A–C)** Brain regions with enhanced FC in problematic smartphone users, compared to controls. **(A)** Left dorsolateral prefrontal cortex (DLPFC)-based FC was increased with the left postcentral gyrus. **(B)** Right rostral anterior cingulate cortex (ACC)-based FC was increased with the left anterior frontoinsular cortex. **(C)** Right amygdala-based FC was increased with DLPFC. **(D)** Brain regions with decreased FC in problematic smartphone users, compared to controls. The right subgenual ACC and left lingual gyrus show differences in functional connectivity with right subgenual ACC-seeded analysis between the groups.

orbitofrontal cortex, and dorsal anterior cingulate cortex, relative to control users (**Table 2**, **Figure 1**). In contrast, problematic smartphone users demonstrated weaker anterior frontoinsular cortex-based FC with the dorsolateral prefrontal cortex, and ventrolateral prefrontal cortex than control users.

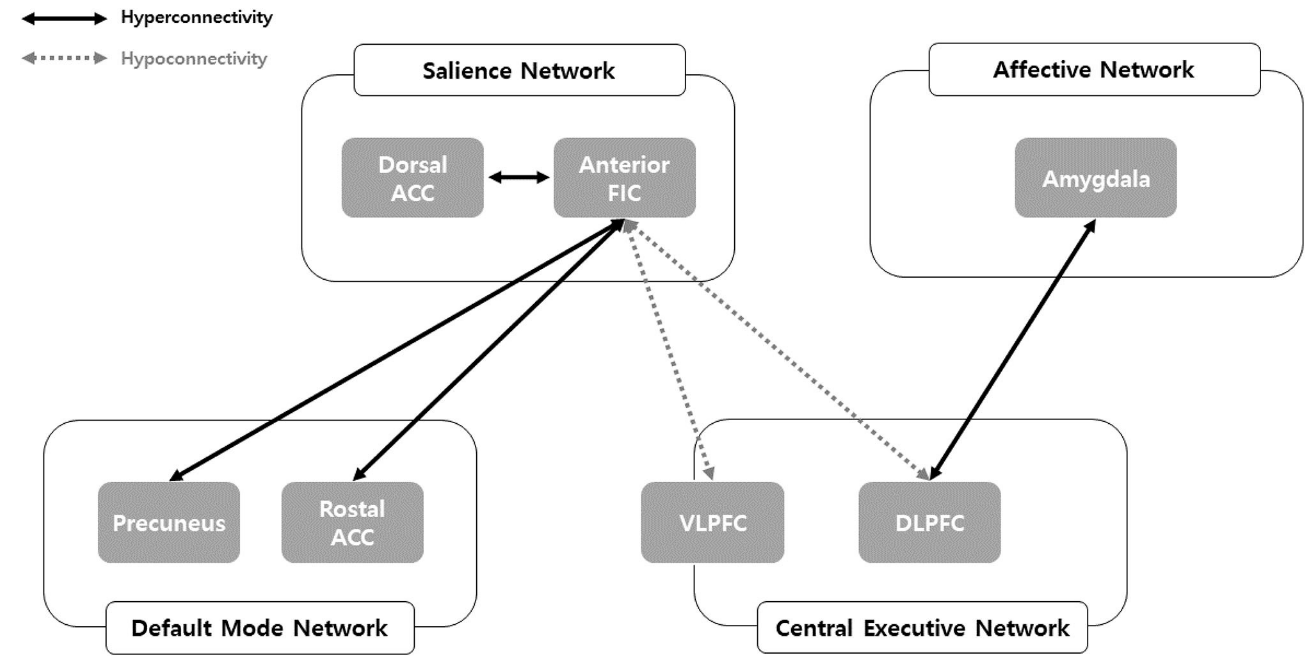

FIGURE 3 | Network model of problematic smartphone users. ACC, anterior cingulate cortex; DLPFC, dorsolateral prefrontal cortex; FIC, frontoinsular cortex; VLPFC, ventolateral prefrontal cortex.

Central Executive Network

Problematic smartphone users exhibited stronger dorsolateral prefrontal cortex FC with the left precentral gyrus than control users (**Figure 2**).

Default Mode Network

Problematic smartphone users showed greater right rostral anterior cingulate cortex FC with the anterior frontoinsular cortex than control users.

Affective Network

Compared to the control group, problematic smartphone users exhibited stronger FC between the amygdala and dorsolateral prefrontal cortex. Problematic smartphone users also showed weaker FC between the right subgenual anterior cingulate cortex and lingual gyrus.

Correlation Between FC Strengths and Psychometric Measures

We found no significant correlations between FC strengths and clinical variables (smartphone usage times, SAPS score, and BIS score).

DISCUSSION

Consistent with our hypothesis, we comprehensively identified FC changes in the salience, central executive, default mode, and affective networks among problematic smartphone users (**Figure 3**). We observed enhanced FC within the salience network and between the default mode network and salience network in problematic smartphone users, compared to controls. Meanwhile, we noted decreased FC between the salience network and central executive network among problematic smartphone users. Overall, neurobiological changes in FC of key networks centered around the salience network were observed in problematic smartphone users.

Enhanced FC within the salience network was observed among problematic smartphone users. In particular, we noted enhanced FC between the anterior frontoinsular cortex and dorsal anterior cingulate cortex during the resting state and enhanced FC between the anterior frontoinsular cortex and supramarginal gyrus. The salience network reacts to degrees of subjective salience and acts as a switch between the default mode network and the central executive network (10, 36). The anterior frontoinsular cortex and dorsal anterior cingulate cortex are the two key nodes of the salience network (10); the supramarginal gyrus is also known as a salience network node (37). The anterior frontoinsular cortex facilitates bottom-up detection of salient events and modulates access to attention and working memory resources. Strong neural functional coupling between the anterior frontoinsular cortex and dorsal anterior cingulate cortex has been shown to facilitate rapid access to the motor system (10). Enhanced interaction within the salience network in problematic smartphone users may represent enhanced salience for cues related to smartphones and may provoke more frequent use of smartphones in problematic users.

Our data highlighted enhanced FC between the salience network and default mode network in problematic smartphone users, as enhanced FC was found between the rostral anterior cingulate cortex and anterior frontoinsular cortex, as well as between the precuneus and anterior frontoinsular cortex. The rostral anterior cingulate cortex and precuneus are critical hubs of the default mode network (38), and enhanced FC between the salience and default mode networks in problematic smartphone users suggests decreased engagement of executive control or reflective system (39). Our findings are consistent with previous studies that reported enhanced FC between the frontoinsular cortex and default mode network in nicotine-dependent smokers (40) and Individuals with Internet gaming disorder (17). Aberrant FC between the frontoinsular cortex and default mode network is known to be involved in development and maintenance of addiction (41). Altogether, these results suggest a need to consider changes in resting state FC in problematic smartphone users as indicative of behavioral addiction. Additionally, we also noted enhanced FC between the anterior frontoinsular cortex and orbitofrontal cortex in problematic smartphone users. The orbitofrontal cortex is a major area of motivation, drive, and salience evaluation and has been found to be impaired in drug addiction (42) and behavioral addiction (43–45). Overall, our results are consistent with viewing problematic smartphone use from the perspective of behavioral addiction.

Interestingly, we recorded reduced FC between the salience network and central executive network, observing reduced FC between the anterior frontoinsular cortex and dorsolateral prefrontal cortex and between the anterior frontoinsular cortex and ventrolateral prefrontal cortex in problematic smartphone users, compared to healthy controls. The dorsolateral prefrontal cortex is a critical node of the central executive network (10), and the ventrolateral prefrontal cortex, which coactivates with the central executive network, is known to be involved in numerous cognitive operations (43). In a previous study of altered core brain network interactions in adolescents with Internet gaming disorder, abnormal functional and structural connections between the salience network and central executive network were deemed to be mediators of impaired cognitive control in adolescents with Internet gaming disorder (41). Also, one previous study proposed weakened cognitive control, which is related to function of the central executive network, as an important neurobiological basis of Internet gaming disorder (43). When using smartphones, individuals need to find a balance between the bottom-up smartphone-related salient stimuli and top-down inhibitory control of excessive usage, which negatively affects daily function. The reduced FC between the salience network and central executive network in problematic smartphone users observed in this study may suggest that these individuals are unable to control their smartphone usage and thus succumb to the temptation of pleasure from overuse.

Also noteworthy is that we were able to identify enhanced FC between the affective network and salience network and between the affective network and central executive network. We observed enhanced FC between the amygdala and dorsolateral prefrontal cortex during the resting state in problematic smartphone users. The amygdala is a key area responsible for generating and processing emotion that is involved in bottom-up attention to emotional stimuli (44, 44), and researchers have reported that levels of impulsivity were positively correlated with amygdala-dorsolateral prefrontal cortex connectivity (46). These results may indicate that aberrant FC between the affective network and central executive network might contribute to impulsivity in problematic smartphone users.

Lastly, we observed aberrant FC in brain regions responsible for sensory processing (e.g., the postcentral gyrus and lingual gyrus). Previous studies have demonstrated that patients with Internet gaming disorder and problematic smartphone users show aberrant FC in brain regions responsible for sensory processing (44, 45). Taken together, aberrant FC in brain regions responsible for sensory processing may reflect "bottom-up" neural processing in problematic smartphone users.

We acknowledge that this study has several shortcomings. Firstly, this study was designed as a cross-sectional analysis and thus limited in identifying causal relationships between changes in resting state FC and problematic smartphone use. Secondly, this study was limited in that problematic smartphone usage was evaluated only by self-reporting questionnaires and clinical interviews. Future studies with more precise measures of smartphone usage patterns are needed. Third, resting-state scan time was relatively short. Sufficient scan length can improve reliability and enable rigorous censoring for motion correction (46). Lastly, the age distribution of the subjects enrolled in this study was relatively large. As smartphone usage time was evaluated via self-reports, differences in smartphone usage time and smartphone usage pattern across different age groups might not be accurately reflected in the study. These limitations might account for why we found no significant correlation between FC strength and clinical variables. When related research is conducted in the future, stratification analysis according to age will be required.

Despite these limitations, we identified changes in underlying neural correlates of problematic smartphone users by analyzing key networks, including the salience, central executive, default mode, and affective networks, from the perspective of behavioral addiction. Overall, our results from multiple network analysis suggests that neurobiological changes centered around the salience network are associated with problematic smartphone use.

DATA AVAILABILITY STATEMENT

The completely anonymized raw data supporting the conclusions of this article will be made available by the authors upon request to the corresponding author, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board at Yonsei University.

The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

DL and Y-CJ conceived and designed the study. DL recruited participants. JA analyzed data and drafted the manuscript. KN and Y-CJ provided critical revision of the manuscript and important intellectual content. All authors had full access to all data in the study, take responsibility for the integrity of the data and the accuracy of the data analysis, and critically reviewed and approved the final version of this manuscript for publication.

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Relationship of Problematic Smartphone Use, Sleep Quality, and Daytime Fatigue Among Quarantined Medical Students During the COVID-19 Pandemic

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Background: The COVID-19 pandemic brought about great transformation to medical education mode. Although mobile communication devices played a crucial role in online learning among quarantined university students, the potential smartphone addition problems, negative health behaviors, and psychological symptoms need considerable attention. This study examined the relationship of problematic smartphone use (PSU), sleep quality, and daytime fatigue among medical students.

Methods: A web-based survey was conducted in six polyclinic hospitals in Beijing between February and May 2020. 1016 participants (26.01 ± 2.46 years, 65.16% female) completed self-report measurements including Short Version Smartphone Addiction Scale (SAS-SV), Athens Insomnia Scale (AIS), and Subjective Fatigue Scale (FS). Spearman correlation coefficients and multiple regression models were used to analyze the association among PSU, sleep quality, and daytime fatigue. We used structural equation modeling to test the mediating effect of sleep quality between PSU and daytime fatigue.

Results: 49.70% of the participants had PSU. Significant positive correlations were found among SAS-SV, AIS, and FS scores (r = 0.35–0.61, $P_S < 0.001$). Subjects with PSU were more likely to report sleep disturbance ($\beta = 1.07$, $P < 0.001$, OR = 2.91, 95%CI = 2.17–3.91), physical fatigue ($\beta = 1.16$, $P < 0.001$, OR = 3.18, 95%CI = 2.45–4.15), and mental fatigue ($\beta = 0.88$, $P < 0.001$, OR = 2.42, 95%CI = 1.86–3.14). The indirect effect of PSU on physical fatigue and mental fatigue mediated by sleep quality accounted for 50.03 and 45.43% of the total effect, respectively.

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Conclusions: PSU was significantly associated with sleep disturbance and fatigue among medical students during the COVID-19 pandemic. Sleep quality mediated the relationship between PSU and daytime fatigue. Our results provide valuable information for maintaining medical students' health status and constructing online education structures.

Keywords: problematic smartphone use, sleep quality, fatigue, mediating effect, COVID-19

INTRODUCTION

Since December 2019, an acute respiratory infectious disease caused by a novel coronavirus (SARS-CoV-2) broke out in Wuhan, China. The World Health Organization named it Coronavirus Disease 2019 (COVID-19) and declared on March 11 that the COVID-19 outbreak was a global pandemic (1). Recently emerged SARS-CoV-2 delta variants spreading in China and worldwide gave rise to a new wave of pandemics (2). The COVID-19 pandemic, a public health emergency, has had significant impacts on China's healthcare and medical education system (3), as governments adopted strict control measurements to require people to stay at home for social distancing (4). Many scholars have expressed their concerns about the online medical education in current and future pandemics (5, 6). One critical issue is that with the rapid development of communication technology, smartphone addiction and related clinical symptoms may surge among student populations. A cross-sectional online survey conducted by Chen and colleagues showed that primary school children who had psychological distress during the COVID-19 outbreak might spend longer time on Internet-related activities (7). The relationship between PSU and psychological distress has been influenced by the COVID-19, which has been confirmed by Chen's another longitudinal Study (8). Some scholars identified the overuse of smartphones as a hidden crisis during the pandemic (9), and this issue has been highlighted by recent literatures in China. A recent national survey among 746, 217 Chinese college students showed that the risks of developing depression and anxiety disorders increased with the exposure time to electronic devices (10). Another cross-sectional study showed that the level of COVID-19 related anxiety symptoms was correlated with the severity of problematic smartphone use (PSU) among Chinese adults (11). Many studies indicated that smartphone overuse directly impacts daytime functions and sleep quality (12–14), while the relationship has not been identified under the influence of the COVID-19 pandemic among medical students.

During the pandemic, medical students under quarantine relied heavily on the Internet and smartphone technology to complete heavy academic tasks and obtain the COVID-19 related information. Since medical students are more sensitive when tracking the pandemic information using smart deceives, their psychological patterns may differ from those of the general population (15). Thus, more studies about medical students are needed to cope with the transformation of the health care and education system. Colleges in Beijing have implemented measures to delay college students' return to school and required them to stay at home or in dormitories since January 2020. During an extended period of home isolation, university students' various living habits might change, among which the overuse of smartphones along with the resulting physical and mental health problems needs to be considered. Problematic smartphone use has been previously defined as excessive use of a smartphone that is accompanied by functional impairments in daily living, and substance addiction-like symptoms (16). PSU can cause many detrimental physical and psychological disorders and it has become a mental health threat to university students (17). A longitudinal study showed that the initial level of problematic use of smartphone/internet increased the psychological distress among university students in Hong Kong (18). Fatigue, defined as a subjective feeling of tiredness, weakness and discomfort, is now widely recognized as a premorbid state and causative factor (19). In clinical practice, physical fatigue and mental fatigue have specific symptoms.

Recent studies revealed that the intensity and time of electronic devices usage were relatively high during the COVID-19 pandemic, along with the increased incidence of smartphone addiction (20, 21), which could induce adverse behavioral and health outcomes (22, 23). Several studies have discussed the psychological and clinical mechanisms of the smartphone addiction issues, which are beneficial to support our hypotheses. In Billieux's pathway models, psychological, biological, social, and environmental factors play multiple roles in predicting PSU and are associated with various dysfunction symptoms (24). According to the Person-Affect-Cognition-Execution Model (I-PACE) of Internet addiction, individual factors such as physiology, personality, emotion, cognition, and executive function can significantly predict Internet addiction (25). In a study on undergraduate students, a combination of alexithymia, dissociative experiences, low self-esteem, and impulse dysregulation was confirmed to be a potential risk factor for Internet Addiction (26). As the Compensatory Internet Use Theory (CIUT) described, if individuals are in a negative situation, they may escape reality by surfing the internet, thus increasing the chance of addiction symptoms (27). The COVID-19 pandemic can be regarded as an unanticipated hostile incident, and people's mental health has been adversely affected, which further aggravates the possibility of dependence on smartphones (28). In addition to the above psychological models, clinical mechanisms are beneficial to support our theoretical model regarding the relationship of PSU, sleep quality, and daytime fatigue. Blue light and electromagnetic radiation emitted by smartphones directly cause harm to users' eyesight, neck, and spine (14, 29). Suppression of melatonin secretion caused by light stimulation at night is also a commonly recognized physiological pathway that results in sleep deprivation (30). As the skeletal muscle is a peripheral clock organ closely related to circadian rhythm, sleep disturbance may cause daytime physical symptoms by inhibiting mitochondrial activity (31). Besides, abnormal cortisol and hypothalamic-pituitary-adrenal cortex (HPA) axis functions have been confirmed as neuroendocrinology pathways of the association between sleep quality and mental fatigue (32). Based on the above mechanisms, we hypothesize that sleep disturbance is not only a direct adverse outcome of PSU, but also an important mediator of the relationship between PSU and daytime fatigue. Previous studies also showed that sleep quality played an intermediary role between smartphone overuse and various health issues (33–35). Thus, we built a theoretical partial mediation model and the following four hypotheses will be tested in the current study.

Hypothesis 01 (H01): PSU level is positively correlated with sleep disturbance.
Hypothesis 02 (H02): PSU level is positively correlated with daytime fatigue.
Hypothesis 03 (H03): Sleep quality is negatively correlated with daytime fatigue.
Hypothesis 04 (H04): Sleep quality mediate the relationship between PSU and daytime fatigue.

MATERIALS AND METHODS

Participants and Ethics

Participants were 1,016 full-time medical postgraduates from six polyclinic hospitals affiliated to Peking University Health Science Center or Peking Union Medical College in Beijing. Data was collected from the Beijing Hospital ($n = 208$), the First Hospital of Peking University ($n = 112$), the People's Hospital of Peking University ($n = 148$), the Third Hospital of Peking University ($n = 189$), the Peking Union Medical College Hospital ($n = 251$), and the Cancer Hospital of the Chinese Academy of Medical Sciences (108). In each hospital, more than 50% of the total graduate students were recruited. The Ethics Committee of Beijing Hospital approved the study protocol (2020BJYEC-231-01).

Procedures

Since college students in Beijing were quarantined at home or at school until July 2020, a cross-sectional online questionnaire survey was conducted between February and May 2020 through a widely used social network application, "WeChat." Data was collected by hospital administrators. The background and purpose of the survey, as well as the data consent were explained on the first page of the questionnaire. Each respondent could receive the feedback report *via* email and get compensation ranging from 3 to 10 *yuan* after submission. 1108 questionnaires were collected, and questionnaires with one of the following conditions were considered invalid: the response time was less than 5 min ($n = 28$); the individual's demographic information could not be identified ($n = 8$); all questions in the three scales used in this study were all answered repeatedly ($n = 56$). A total of 92 invalid questionnaires were excluded, and 1016 valid questionnaires were included in the final analysis, with an effective recovery rate of 91.70%. The education level was divided into master's and doctoral; the degree type was divided into academic and professional. An annual household income of <100,000 yuan was considered poor. The specialties were clinical medicine and others (including biology, preventive medicine, nursing, etc.). The student's relationship with the tutors was collected using a positive likert-5 single question (1–3 points = "bad"; 4–5 points = "good"). If the subjects self-reported regular exercise, they were defined as having exercise habits; and those who self-reported occasional exercise or no exercise were defined as having no exercise habit.

Measurements

Short Version Smartphone Addiction Scale

The 10-item Short Version Smartphone Addiction Scale (SAS-SV) developed by Kwon et al. was used to measure PSU (36). The scale consists of ten positive 6-point Likert questions describing the usage of smartphones, and the summed score ranges from 10 to 60. An example question was "Having my smartphone in my mind even when I am not using it." The subjects were asked how much they agreed with each question (1 point = "disagree"; 6 points = "agree"). According to the threshold recommended for student populations, males with a summed score $\geq$ 31 and females with a summed score $\geq$ 33 were identified with PSU. The SAS-SV is the most widely used instrument to assess PSU and has been proved to have good reliability and validity in the Chinese population (37). In this study, the Cronbach's α coefficient of the scale is 0.91.

Athens Insomnia Scale

Sleep quality was measured with the Athens Insomnia Scale (AIS), a self-assessment psychometric instrument including eight 6-point Likert items with a total score of 0–24. Eight items in the AIS are related to sleep induction, awakenings during the night, final awakening, total sleep duration, sleep quality, well-being, functioning capacity, and sleepiness during the daytime. The Chinese version of AIS has been confirmed to be reliable and valid among adolescents and adults (38). As previous studies suggested, individuals with a summed AIS score $\geq$ 6 were classified as having sleep disturbance (39). In this study, the Cronbach's α coefficient of AIS was 0.87.

Subjective Fatigue Scale

Daytime fatigue was measured with a 14-item subjective fatigue scale (FS) developed by Chalder et al. (40). The FS consists of 14 two-category fatigue symptom self-assessment items and the scale showed appropriate validity for Chinese populations (41). The answer "yes" is counted as 1 point, the answer "no" is counted as 0, and the total score ranges from 0 to 14. Higher summed FS scores indicate a higher risk of daytime fatigue. Considering the lack of consensus on the cutoff value of the FS, we regard a summed score higher than or equal to 7 as a threshold of daytime fatigue. In the FS, 8 items reflected physical fatigue, and subscale score $\geq$4 was used as a cutoff; the last 6 items reflected mental fatigue, and subscale score $\geq$3 was used as a cutoff. In this study, the Cronbach's α coefficient of the FS was 0.84.

Statistical Analysis

Continuous variables were described as the mean ± standard deviation (M ± SD), and categorical variables were described as numbers with percentage [n (%)]. Student's *t*-test and χ^2 test were used to compare the differences of SAS-SV scores across subgroups. Spearman correlation coefficient was used to analyze the association among SAS-SV, AIS, and FS scores. Multiple logistic regressions were used to analyze the association between PSU and the risk of fatigue and sleep disturbance. Subjects without PSU were used as the reference group and potential confounders were adjusted. We conducted a structural equation model (SEM) with robust weighted least squares estimation to test the mediating effect of sleep quality between PSU and daytime fatigue. A bias-corrected bootstrap method was used to test the significance of effect values in the SEM, and 1,000 random samples were put back from the original sample to calculate the 95% confidence intervals. Effect values were statistically significant if the 95% confidence interval did not include 0. Statistical analyses were performed using SPSS 24.0 version and Mplus 8.0 version. Statistical significance was accepted at the two-sided 0.05 level.

RESULTS

Demographic Characteristics

A total of 1016 graduate students completed the questionnaire with an average age of 26.01 ± 2.46 years. Among the participants, 65.16% were female, 61.81% were master's students, 55.02% had a professional degree type, 77.46% majored in clinical medicine, 31.69% were first-year graduate students, and 34.55% lived in rural areas.

Problematic Smartphone use Status

The mean SAS-SV score of the participants was 32.73 ± 9.85, and 49.70% had PSU. As **Table 1** showed, participants who had PSU were more likely to be male, have professional degree type, non-clinical medicine major, lower household income, live in rural areas, have a bad relationship with tutors, and have no exercise habits (*Ps* < 0.05).

Associations Among SAS-SV, AIS, and FS Scores

The mean score of AIS was 8.09 ± 4.59, and 70.57% of the subjects had sleep disturbance. The mean score of FS was 6.42 ± 3.74, and 40.06% had daytime fatigue. Specifically, 55.91% of the subjects had physical fatigue, and 43.60% had mental fatigue, respectively. As **Table 2** showed, the SAS-SV score was positively correlated with the AIS score ($r = 0.38$, $P < 0.001$) and fatigue scores ($r = 0.35$–0.41, $P < 0.001$). The AIS scores were positively correlated with fatigue scores ($r = 0.48$–0.61, $P < 0.001$).

In the multiple logistic regression analyses (**Table 3**), SAS-SV, AIS, and FS scores were involved as dichotomous variables according to corresponding cutoffs. Gender, degree type, household income, major, residence, relationship with tutors, and exercise habits were involved as co-variables. After adjusting for potential confounders, subjects with PSU were more likely to report sleep disturbance (β = 1.07, $P < 0.001$, OR = 2.91, 95%CI = 2.17–3.91), daytime fatigue (β = 1.10, $P < 0.001$, OR = 2.99, 95%CI = 2.29–3.90), physical fatigue (β = 1.16, $P < 0.001$, OR = 3.18, 95%CI = 2.45–4.15), and mental fatigue (β = 0.88, $P < 0.001$, OR = 2.42, 95%CI = 1.86–3.14) than those without PSU.

Mediation Effect of Sleep Disturbance Between PSU and Fatigue

According to the theoretical hypothesis, a partial mediation model of sleep disturbance between PSU and daytime fatigue was built (**Figure 1**). Since the ordinal SAS, AIS, and FS scores did not meet the multivariate normal distribution, the path coefficients in the model were estimated by a robust weighted least square method. In the SEM, all the measurement variables were involved as manifest variables. As described in **Table 4**, all the standardized path coefficients were statistically significant (*Ps* < 0.001). The effect value of PSU on sleep disturbance was 0.370. The total effect of PSU on physical fatigue was 0.385 including a direct effect of 0.177, and the indirect effect mediated by sleep disturbance was 0.208, which accounted for 54.03% of the total effect. The total effect of PSU on mental fatigue was 0.372 including a direct effect of 0.203, and the indirect effect mediated by sleep disturbance was 0.169, which accounted for 45.43% of the total effect. The bias-corrected bootstrap methods showed that all the 95% confidence intervals of the effect values did not include 0 indicating statistical significance. To test the stability of the mediating mode, we also involved the measurement variables as dichotomous scores according corresponding cutoffs and re-calculated the pathway coefficients. The parameter estimation results are summarized in **Supplementary Table 1**, and effect values were proved to be statistically significant.

DISCUSSION

In the current study, we identified the relationship of PSU, sleep quality, and daytime fatigue among medical university students during the COVID-19 pandemic. We obtained an unoptimistic incidence of PSU (49.70%) among quarantined medical students, which was higher than that of Chinese senior students (16.4%) from an online survey conducted on February 2020 (8). Consistent with our results, a cross-sectional study revealed a PSU prevalence of 59.42% in medical students from two provinces in China (42), and in another study the prevalence was 43.3% among Chinese adults (43). According to the I-PACE model and CIUT, the high prevalence of PSU among quarantined medical students was related to various factors (44). Firstly, Beijing has initiated a top-level response to major public health emergencies at the time of investigation and adopted social isolation policies. University students mainly relied on the Internet to communicate with the outside world, including social networking, shopping, learning, etc., which might aggravate smartphone overuse. Secondly, medical students had heavy academic burden during the pandemic. They needed to complete various learning and

TABLE 1 | Characteristics and PSU status of 1,016 medical students.

Characteristics		*N*	PSU (*n* = 505)	Non-PSU (*n* = 511)	t/χ^2	*P*-value
Age (mean ± SD)		1016	25.75 ± 2.35	26.25 ± 2.54	3.244	0.001
Gender [*n* (%)]	Male	354	191(53.95)	163(46.05)	3.929	0.048
	Female	662	314(47.43)	348(52.57)		
Education [*n* (%)]	Master	628	316(50.32)	312(49.68)	0.248	0.618
	Doctoral	388	189(48.71)	199(51.29)		
Degree [*n* (%)]	Academic	457	201(43.98)	256(56.02)	10.901	0.001
	Professional	559	304(54.38)	255(45.62)		
Residence [*n* (%)]	Rural	351	194(55.27)	157(44.73)	6.654	0.009
	Urban	665	311(46.77)	354(53.23)		
Household Income [*n* (%)]	Poverty	523	287(54.88)	236(45.12)	11.551	< 0.001
	Non-poverty	493	218(44.22)	275(55.78)		
Major [*n* (%)]	Clinical medicine	787	370(47.01)	417(52.99)	10.153	0.001
	Others	229	135(58.95)	94(41.05)		
Relationship with tutors [*n* (%)]	Good	860	415(48.26)	445(51.74)	4.718	0.029
	Bad	156	90(57.69)	66(42.31)		
Exercise habits [*n* (%)]	Yes	392	157(40.05)	235(59.95)	6.315	0.007
	No	624	393(62.98)	231(37.02)		
Sleep disturbance [*n* (%)]	Yes	717	411(57.32)	306(42.68)	57.607	< 0.001
	No	299	94(31.44)	205(68.56)		
Daytime fatigue [*n* (%)]	Yes	407	268(65.85)	139(34.15)	71.741	< 0.001
	No	609	237(38.92)	372(61.08)		
Physical fatigue [*n* (%)]	Yes	568	354(62.32)	214(37.68)	83.291	< 0.001
	No	448	151(33.71)	297(66.29)		
Mental fatigue [*n* (%)]	Yes	443	278(62.75)	165(37.25)	54.004	< 0.001
	No	573	227(39.62)	346(60.38)		

PSU, problematic smartphone use; SD, standard deviation.

TABLE 2 | Correlation coefficients among SAS-SV, AIS, and FS scores.

Measurement	α	Mean	SD	1	2	3	4	5
1. Problematic smartphone use	0.91	32.73	9.85	1.00				
2. Sleep disturbance	0.87	8.09	4.59	0.38*** (0.34***)	1.00			
3. Daytime fatigue	0.84	6.42	3.74	0.41*** (0.39***)	0.61*** (0.55***)	1.00		
4. Physical fatigue	0.81	4.16	2.45	0.37*** (0.35***)	0.58*** (0.54***)	0.92*** (0.90***)	1.00	
5. Mental fatigue	0.72	2.26	1.77	0.35*** (0.39***)	0.48*** (0.51***)	0.84*** (0.81***)	0.56*** (0.52***)	1.00

****P < 0.001.*

α: Cronbach's alpha coefficient.

Partial correlation coefficients are shown in parentheses, controlling for age, gender, degree type, household income, major, residence, relationship with tutors, and exercise habits.

SAS-SV, Short Version Smartphone Addiction Scale; AIS, Athens Insomnia Scale; FS, Subjective Fatigue Scale; SD, standard deviation.

research objectives through virtual education platforms. In addition, when in-person communication with tutors became less frequent, the pressure and anxiety level would also increase, which might be incentives of PSU. Researches have revealed that smartphone overuse was closely related to depression, anxiety, and other psychological disorders (12, 45), and these correlations have also been confirmed in several investigations conducted during the pandemic (11). Thirdly, with the continuous unfolding of the COVID-19 pandemic, college students are worried about the social stability and health status of their family and friends; thus, they have increased demand to browse online information through smartphones daily. A longitudinal ecological study from the United States showed that along with the unfold of COVID-19, college students used more smartphones, had less physical activity, and visited fewer outdoor places (20). In this study, we identified several types of college students who were more susceptible to have PSU during the pandemic, which was supported by the CIUT. Male, professional degree type, low income, living in rural, poor relationship with tutors and inactivity were potential risk factors. Among

TABLE 3 | Logistic regression analyses of PSU on sleep disturbance and fatigue.

Models		Crude model				Adjusted model$^{\Delta}$			
		β	SE	OR	95%CI	β	SE	OR	95%CI
Sleep disturbance	PSU	1.47	0.11	2.92	2.21–3.89	1.07	0.15	2.91	2.17–3.91
	Non-PSU	Ref.		1		Ref.		1	
Daytime fatigue	PSU	0.12	0.09	3.02	2.32–3.93	1.1	0.14	2.99	2.29–3.90
	Non-PSU	Ref.		1		Ref.		1	
Physical fatigue	PSU	0.85	0.09	3.25	2.51–4.21	1.16	0.13	3.18	2.45–4.15
	Non-PSU	Ref.		1		Ref.		1	
Mental fatigue	PSU	0.21	0.08	2.56	1.98–3.31	0.88	0.12	2.42	1.86–3.14
	Non-PSU	Ref.		1		Ref.		1	

$^{\Delta}$Adjusted model was adjusted for age, gender, degree type, household income, major, residence, relationship with tutors, and exercise habits.
β: Standardized regression coefficient.
Ref: Participants with non-PSU were reference category.
PSU, problematic smartphone use; SE, standard error; OR, odds ratio; CI: confidence interval.

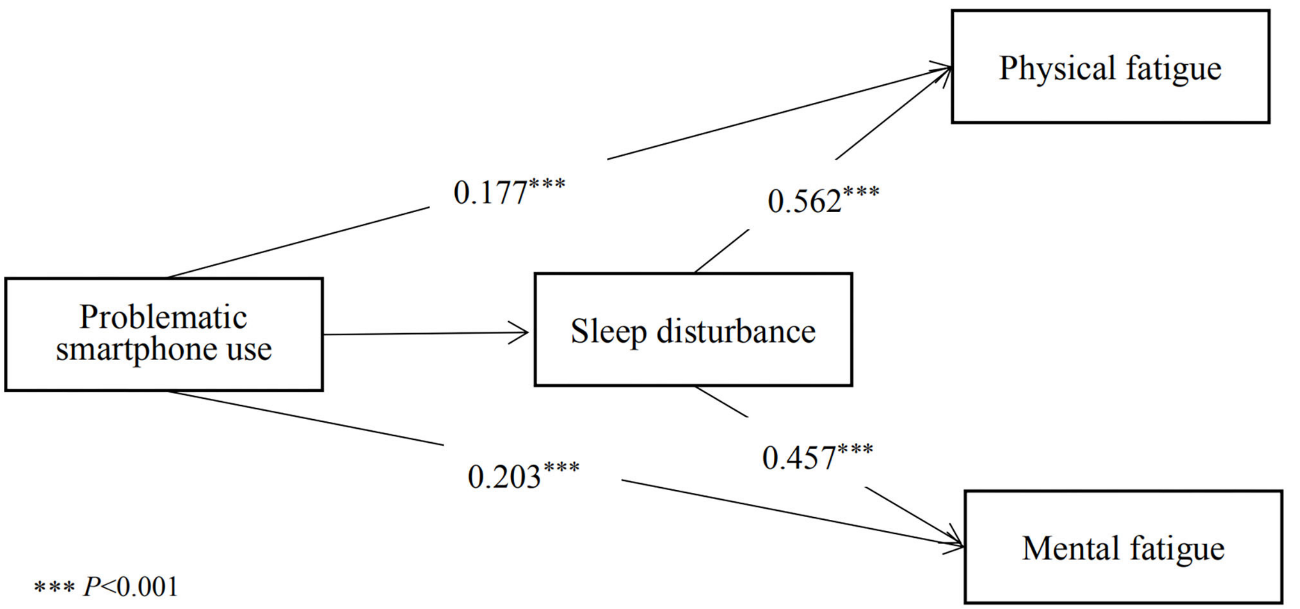

FIGURE 1 | Mediation models of problematic smartphone use, sleep disturbance, physical fatigue, and mental fatigue.

TABLE 4 | Path coefficients and effect values of PSU on sleep disturbance, physical fatigue, and mental fatigue.

Pathway	β	SE	*P*-value	Total effect (95% CI)	Direct effect (95% CI)	Indirect effect (95% CI)
PSU → sleep disturbance	0.37	0.014	< 0.001	0.370 (0.315, 0.420)	0.370 (0.315, 0.420)	–
PSU → physical fatigue	0.177	0.008	< 0.001	0.385 (0.331, 0.435)	0.177 (0.127, 0.228)	0.208 (0.174, 0.238)
PSU → mental fatigue	0.203	0.006	< 0.001	0.372 (0.322, 0.429)	0.203 (0.148, 0.259)	0.169 (0.143, 0.198)
Sleep disturbance → physical fatigue	0.562	0.018	< 0.001	0.562 (0.514, 0.604)	0.562 (0.514, 0.604)	–
Sleep disturbance → mental fatigue	0.457	0.014	< 0.001	0.457 (0.410, 0.505)	0.457 (0.410, 0.505)	–

β: standardized regression coefficient.
PSU, problematic smartphone use; SE, standard error; CI: confidence interval.

quarantined medical students, daytime fatigue was commonly observed (40.06%), of which the prevalence of physical and mental fatigue was 55.91 and 46.60%, respectively. In another cross-sectional study, the prevalence of fatigue was 67.3% among Chinese nursing students in post-COVID-19 era (46). We also found a high prevalence of sleep disturbance (70.57%) in this sample. A recent review study including 12,682 respondents showed that the pooled prevalence of insomnia was 30% in Chinese frontline healthcare workers during the COVID-19 pandemic (47). Several studies also reported various physical and mental health outcomes were associated with the pandemic among healthcare workers, adolescents, and adults (48–50). Similarly to this study, a recent web-based survey showed that Indian undergraduate and postgraduate medical students had high level of perceived stress and anxiety during the COVID-19 pandemic (51).

SAS-SV score was significantly correlated with AIS score ($r = 0.38$) and medical students with PSU were more likely to report sleep disturbance (OR = 2.91). Lateef and colleagues also found a statistically significant positive correlation between Internet addiction and insomnia among clinical medical students in Africa (52). We confirmed the *H-01* and the role of melatonin could account for the relationship between smartphone overuse and sleep deprivation, which has been confirmed by animal and human studies (29). Melatonin is one of the hormones secreted by the pineal gland, which helps sleep and regulates the circadian clock (53). The secretion of melatonin has an obvious circadian rhythm. Light stimulation during smartphone using at night will inhibit the activity of melatonin synthesis enzymes in the pineal gland, thus inhibiting the secretion of melatonin. We obtained significant correlations between SAS-SV score and FS score ($r = 0.41$), and *H-02* was supported. Subjects with PSU were more likely to experience physical fatigue (OR = 3.18) and mental fatigue (OR = 2.42). Compared with the previous review studies, we have obtained larger odds ratios in this study (16, 54), suggesting that the pandemic might exaggerate the excessive use of smartphones and the corresponding daytime fatigue and sleep disturbance. Overuse of smartphones can lead to worsen upper limb pain (14). People who have smartphone addiction are more susceptible to blurred vision, back pain, wrist pain, stiff neck, and other health issues (14, 55). A recent systemic review reported that excessive and frequent smartphone usage increases the risk of headaches by 38% (56). Previous studies have also confirmed that PSU is associated with fatigue and physical dysfunction in student and adult samples (37, 57). In addition, factors such as introversion personality and negative emotions highlighted by the I-PACE model also contribute to the association between Internet addiction behaviors and daytime dysfunction. We found sleep quality was significantly associated with both physical fatigue and mental fatigue, and *H-03* was supported. Firstly, although fatigue and sleep disturbance are defined as two independent, non-motor symptoms, they often overlap in clinical settings (58). People with fatigue often have difficulty in falling asleep and experience daytime sleepiness. In addition, the AIS and Pittsburgh Sleep Quality Index (PSQI), two most widely used sleep assessment scales, both contain components of daytime dysfunction, thus *H-03* was conceptually supported. Secondly, the AIS score was significantly correlated with physical fatigue ($r = 0.58$). Skeletal muscle is not only one of the most important motor organs, but also the peripheral clock organ closely related to circadian rhythm. More than 2300 genes in skeletal muscle are expressed with circadian rhythm (31). Laboratory studies have shown that when circadian rhythm is disrupted, skeletal muscle fiber type displacement, sarcomere structure changes, and mitochondrial dysfunction are observed (59). In particular, reduced mitochondrial biosynthesis ability is a key regulatory process leading to skeletal muscle dysfunction and reduced human endurance (60). Thirdly, abnormal cortisol and melatonin function might be the main physiological mechanism of the correlation between AIS score and mental fatigue ($r = 0.48$). Cortisol is a neuroendocrine hormone regulated by the hypothalamic-pituitary-adrenal cortex (HPA) axis, which can participate in body metabolism, activate the vitality of the nervous system, and regulate the function of the cardiovascular system (32). Circadian rhythm disorders can disrupt the secretion of cortisol, thereby weakening the body's ability to regulate the nervous system, leading to mental fatigue symptoms such as decreased daytime excitability, neurasthenia, and memory loss. Furthermore, *H-04* was confirmed in our SEM analysis. In the relationship of PSU and daytime fatigue, sleep quality mediated 50.03 and 45.43% of the total effect on physical and mental symptoms, respectively. The significance of path coefficients in the SEM model demonstrated the vital mediating role of sleep quality. The indirect effect of sleep quality in our hypothetical model could be supported by the above physiological mechanisms such as circadian rhythm and neurohormone secretion. Previous studies have also shown that sleep quality plays an intermediary role in PSU and physical and psychological illness such as eye symptoms, body dysfunction, and emotional problems in student samples (33, 61). Our findings have explored potential mechanisms of PSU on daytime function and are beneficial for health intervention among college students.

The emergence of new SARS-CoV-2 variants has dramatically increased the potential risk of future pandemics (62). Therefore, the government and colleges should alert to the adverse effects of excessive smartphone use on clinical health symptoms during the pandemic, and accessible psychological counseling services are necessary for quarantined university students. Tutors should strengthen the interaction with students, establishing timely and effective guidance on students' academic progress. While improving the virtual learning platforms, it is also feasible to monitor students' smartphone usage frequency during the lockdown. Establishing a monitoring network system that can send out reminders of smartphone overuse would benefit students' mental and physical wellness. Several limitations should be acknowledged. Firstly, the results did not indicate any causal inferences due to the cross-sectional design, and longitudinal studies are needed to further explore the COVID-19 pandemics' influence. Secondly, although the web-based survey and convenient sampling mode was the best option to reach subjects during the lockdown period, it inevitably led to selection bias and response bias. Thirdly, although we used standard measurements to identify the problematic use of smartphones, our data were not sufficient to discuss the duration and specific purpose of smartphones usage, which might overestimate the true incidence of PSU. Health-related information was collected from self-reports, which were less reliable than clinical diagnoses.

Fourthly, the subjects of this study were exclusively from one city, and the extrapolation of the results needs to be treated with caution. However, Beijing can be regarded as a representative city of outbreak prevention and control in China, which to some extent reflects the trend of the whole country.

CONCLUSIONS

In conclusion, during the pandemic of COVID-19, medical students in Beijing had serious smartphone overuse problems, which were associated with sleep disturbance, physical fatigue, and mental fatigue. Our study provided insights into the mechanism that sleep quality mediated the relationship between PSU and daytime fatigue, which was valuable evidence to suggest actions for maintaining university students' health status and constructing online education structures.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The Ethics Committee of Beijing Hospital. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CZ, PZ, DL, and JJ proposed the concept and design. CZ analyzed and interpreted the data and wrote the manuscript. JT, SS, MZ, JC, and GZ drafted and edited the manuscript. CZ, DL, and JJ supervised the study and obtained funding. All authors read and approved the final version of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.755059/full#supplementary-material

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Differences in the Effects of Reading and Aerobic Exercise Interventions on Inhibitory Control of College Students With Mobile Phone Addiction

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Although many previous studies have shown that short-time moderate-intensity aerobic exercise can improve one's inhibitory control, some researchers suggested that its effect on inhibitory control is small. Meanwhile, some studies have shown that reading has a positive effect on inhibitory control. Since many studies examining the effect of exercise on inhibitory control used reading as a filler task, it is important to compare their effects. The present study used the antisaccade task as a tool to examine the differences in the effects of aerobic exercise and reading on inhibitory control of college students with mobile phone addiction. Thirty healthy college students with mobile phone addiction (range: 17–20 years, mean: 19.2 years) took part in the experiment. Participants were randomly assigned to an aerobic exercise group and a reading group. For the aerobic exercise group, participants were asked to perform moderate-intensity aerobic exercise for 15 min. For the reading group, participants were asked to sit quietly and read articles from newspapers for 15 min. Each participant's inhibitory control was examined pre- and post-intervention using the antisaccade task. In the antisaccade task, they have to direct their gaze toward the mirror image location of the target appearing parafoveally as quickly and as accurately as possible. The results showed significant main effects of Time (pre-test vs. post-test) on antisaccade latency and error rate. More importantly, a significant interaction of Time (pre-test vs. post-test) and Group (aerobic exercise vs. reading) was found on antisaccade latency. Specifically, the antisaccade latencies in the post-test were significantly shorter than those in the pre-test for the reading group, but the antisaccade latencies in the post-test and pre-test were comparable for the aerobic exercise group. The results of the present study imply that although both exercise and reading have effects on inhibitory control of college students with mobile phone addiction, the effect of reading may be somehow superior to exercise. Moreover, the current results also imply that researchers should be cautious when using reading as a filler task in future studies regarding the effect of aerobic exercise. The limitations of the present study were discussed.

Keywords: inhibitory control, reading, aerobic exercise, college student, mobile phone addiction

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INTRODUCTION

Nowadays, the mobile phone is more than just a tool for communication. People use the Internet for consumption, entertainment, work, and study. It can be said that this is a mobile-phone-centered digital age. There are vast numbers of mobile phone users in the world (1, 2). Likewise, according to the latest Statistics of the 48th Statistical Reports on Internet Development in China, as of June 2021, the number of mobile phone Internet users in China reached 1.007 billion. 71.6% of people in China have access to the Internet via their mobile phones (3). Among these mobile phone users, college students make up a substantial portion. For college students, using mobile phones for communication, shopping, entertainment, and study is part of their daily life. However, although mobile phones bring much convenience and fun to college students, they also make college students suffer a large number of negative outcomes (4, 5). Among them, mobile phone addiction is one of the most common negative outcomes (6, 7). Mobile phone addiction would lead to poorer self-regulation, attentional control, and inhibitory control than normal individuals (8). Research has shown that about 21.3% of Chinese college students suffer from mobile phone addiction (9). Meanwhile, mobile phone addiction will cause significant impairments in academic performance and social relationships for college students (10–12). More seriously, college students with mobile phone addiction would suffer from severe mental disorders such as insomnia, anxiety, depression, and suicidal ideation (1, 2). Therefore, how to reduce the mobile phone addiction of college students has become the focus of researchers in recent years.

Inhibitory control is one of the three core components of executive functions (13). Inhibitory control enables individuals to focus on task-relevant information and suppress task-irrelevant information. Besides, inhibitory control helps individuals to control their emotions and behaviors (14). Of the three core components of executive function (i.e., inhibitory control, working memory, and cognitive flexibility), inhibitory control is most directly related to one's addiction or health behaviors. Study have shown that inhibitory control is a significant predictor of health behaviors (15). Neurobiological studies have shown that there is a intimate relationships between the circuits underlie inhibitory control and circuits disrupted by addiction behaviors. In fact, study do show that inhibitory control deficit is one of the critical factors contributing to mobile phone addiction (16). Previous studies have shown that individuals with higher levels of mobile phone addiction tend to have poorer inhibitory control, and increased inhibitory control is associated with a lower level of mobile phone addiction (16–18). Given the intimate relationship between inhibitory control and mobile phone addiction, we believe that it is important to explore effective ways to improve the inhibitory control function of college students with mobile phone addiction.

Moderate-intensity aerobic exercise refers to exercise with an intensity of 50–70% of one's maximum heart rate. Moderate-intensity aerobic exercise is deemed to be the most effective way to improve one's inhibitory control (19, 20) which were supported by many previous studies (21–24). Some studies found that 20 min of moderate intensity aerobic exercise can improve participants' performances on Stroop task (24, 25). More recently, researchers found that even 10 min moderate intensity aerobic exercise can improve participants' performance on antisaccade task (23). A newly published study conducted by Fan et al. (22) is most relevant to the present study. They found that 30 min acute aerobic exercise improved participants' performances on Go/no-go task. However, no significant improvement was found on participants' performances on Flanker task. However, there are some potential limitations in previous studies. **First**, most of the participants recruited in previous studies (except Fan et al.'s) were normal young adults rather than individuals with mobile phone addiction. Therefore, it remains unclear whether the results of previous studies could be generalized to individuals with mobile phone addiction. **Second**, previous studies used some cognitive tasks such as the Flanker task, Stroop task, and Go/no-go task to assess inhibitory control. However, some researchers argued that these tasks used to evaluate the inhibitory control require not only inhibitory control but also some other functions such as language, visual perception (Stroop task), and even perceptual-motor skill (Flanker task) (23, 26).Therefore, task involving both executive and non-executive components may not be able to detect subtle executive changes caused by short-time exercise. **Third**, in the study of Fan et al., which is the most relevant study of the present study, they assigned only 5 participants in each of the three groups of various intensity levels. This may result in somewhat less statistical power. Moreover, in Fan et al.'s study, the inhibitory control was assessed using the Flanker task and Go/no-go task. Yet, the pattern of the results obtained from the two tasks is incongruent. Therefore, the effect of moderate-intensity aerobic exercise on inhibitory control needs to be confirmed by further studies.

Furthermore, two studies using exercise interventions were brought to our attention. Wang et al. (27) used Wisconsin Card Sorting Test to investigate the effect of moderate-intensity aerobic exercise on executive function. Young adult participants were assigned to an aerobic exercise group or a reading control group. They failed to find the effect of the aerobic exercise effect on executive function. Heath et al. (28) used antisaccade task to investigate the effect of 10-min aerobic exercise with various intensities on executive function. Similarly, participants were assigned to exercise groups or reading control group. They found that antisaccade reaction times reduced significantly after aerobic exercise. Yet, the directional errors of antisaccade did not differ between exercise and control groups. These two studies both employed aerobic exercise as interventions and reading as filler tasks for participants in the non-exercise control group. Meanwhile, both studies obtained a null effect (either complete or partial). There are two possible reasons for these null effects. First, moderate-intensity aerobic exercise has no significant enhancement of executive function (or at least some aspects of it), as some previous studies have found (29–31). Second, reading as a filler task could improve executive function to some extent and act as a potential confound. For the first possibility, many previous studies have examined it extensively. Most of them revealed that aerobic exercise can improve executive function.

Additionally, two meta-analysis studies showed that aerobic exercise has a small but positive effect on executive function (32, 33). Therefore, the first possibility is very unlikely. However, few previous studies have examined the second possibility. Previous studies do find that reading as a mean of cognitive activities is significantly associated with cognitive functions such as executive function (34–37). Although the above studies indicate a positive correlation between reading and executive function, the acute effect of reading remain unclear. Considering that reading was used as a filler task for participants in control groups in many studies regarding the effect of exercise on executive function. It would be necessary to examine the effect of reading on inhibitory control.

Therefore, the goal of the present study was to examine the potential differences in the effects of aerobic exercise and reading on inhibitory control by antisaccade task. The antisaccade task is a well-known experimental paradigm that is used to examine inhibitory control (23, 38, 39). In a typical antisaccade task, participants are instructed to fix on a central dot. Then, they have to direct their gaze toward the mirror image location of the target appearing parafoveally as quickly and as accurately as possible. Based on previous studies, we predict that both moderate aerobic exercise and reading can improve inhibitory control of college students with mobile phone addiction, and the effects of aerobic exercise and reading on inhibitory control of college students with mobile phone addiction are comparable. Specifically, we hypothesized that (1) participants would exhibit shorter antisaccade latency and lower saccade error after either aerobic exercise or reading intervention, and (2) there were no significant differences in these three measures between participants who received aerobic exercise and reading interventions.

METHOD

Ethics Statement

This study was approved by the Ethical Committee of the Fujian Normal University. All participants provided their written informed consent to participate in this study. This study was performed in full compliance with the Declaration of Helsinki.

Participants

The G*Power tool (40) was used to calculate the sample size in the present study. Statistical Power analysis was conducted based on the reported effect size of aerobic exercise on antisaccade latency [mean Cohen's $d = 1.43$, from (28)]. The result indicated with an alpha level of 0.05, at least 24 participants are required to get a Power of 0.80 ($n = 12$ in each group). Therefore, we recruited 30 college students with mobile phone addiction from Fujian Normal University to participate in our experiment, which met the requirements of statistical power for replicating previous results. We used Mobile Phone Addiction Tendency Scale for College Student (MPATS) to screen participants. The MPATS consists of 16 items, each rated on a 5-point Likert scale, total of 80 points. A participant with a total score of 48 or above was classified as mobile phone addict (41). All these 30 participants scored over 48. Their ages and gender ranged from 17 to 20 years, with an average of 19.2 ± 0.88 years. The aerobic exercise group consisted of 15 participants (12 females and 3 males). The reading group consisted of 15 participants (11 females and 4 males). Each participant was paid ￥50 for their participation.

Apparatus

The antisaccade task was programmed in Experimental Builder (SR Research Ltd.). The materials were presented on a 17-inch DELL PC laptop (DELL VOSTRO 15; 149 resolution: 1,920 × 1,080 pixels; refresh rate: 150 Hz). Stimulus were displayed in black (RGB: 0, 0, 0) on a gray background (RGB: 153, 153, 153). Participants were seated at a viewing distance of ∼58 cm from the computer monitor. A chin rest was used to stabilize the participants' heads. Participants viewed stimulus binocularly while only their right eyes were monitored. Their eye movements were recorded using an Eyelink Portable Duo eye-tracking system with a sampling rate of 500 Hz.

Procedure

The experimental design of the present study is a two-factor mixed design with Group (aerobic exercise vs. reading) as a between-subject factor and Time (pre-test vs. post-test) as a within-subject factor. Thirty Participants were randomly assigned into two groups. For the aerobic exercise group, participants were asked to perform the moderate-intensity aerobic exercise using a bicycle ergometer (Ergoline, Germany) for 15 min. Participants' heart rates were monitored using a heart rate sensor (Polar, Finland) to ensure they were exercising at a moderate intensity. For the reading group, participants were asked to sit quietly and read articles from newspapers (which do not contain any pictures) for 15 min. The initial power of the bicycle was set to 50 W. Participants were asked to limited the revolution speed between 55–65 r/m. The resistance would be then adjusted to make sure each participant reach 60–70% of their maximum heart rate. Each participant's executive function was examined pre- and post-intervention using the antisaccade task. The antisaccade task comprised 75 trials. Five of them were practice trials. Each trial began with a fixation cross ($1^\circ \times 1^\circ$) at the center of the screen displayed for 1,000 ms. Then, the target circle ($1.2^\circ \times 1.2^\circ$) was displayed with an eccentricity of $\pm 10^\circ$ of visual angle in the horizontal plane for 1,500 ms (35 trials for each side), followed by an intertrial interval randomly varied between 800 and 1,200 ms. Participants were instructed to fixate at the cross to ensure that they were looking at the center of the screen when the target appeared peripherally. They were also instructed to direct their gaze toward the mirror image location of the target appearing parafoveally as quickly and as accurately as possible (see **Figure 1**). Participants were tested individually in a quiet room. After reading the experimental instructions and a brief description of the apparatus, the chair was adjusted to make them feel comfortable, and the eye tracker was calibrated using a nine-point calibration and validation procedure. The maximal error of validation was below 0.5° in the visual angle. At the beginning of each trial, a black circle ($0.5^\circ \times 0.5^\circ$) was presented on the center of the computer screen as drift correction. Once the participant successfully fixated on the black circle, the following stimuli were displayed. The antisaccade task lasted about 12 min.

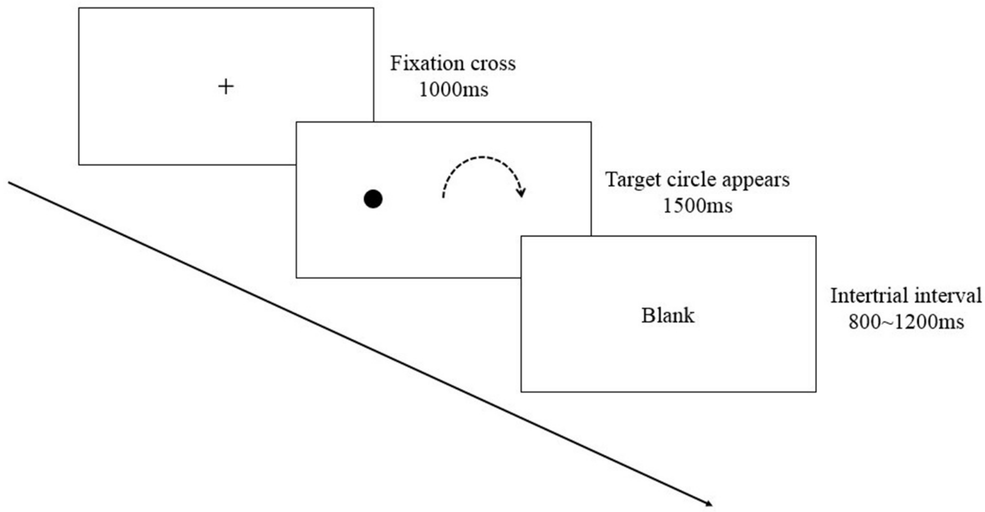

FIGURE 1 | The illustration of the antisaccade task.

TABLE 1 | Mean (SD) of eye movement measures in pre- and post-test antisaccade task for two groups.

Eye movement index	Reading group		Exercise group	
	Pre-test	Post-test	Pre-test	Post-test
Error rate	0.19 (0.21)	0.09 (0.11)	0.17 (0.09)	0.09 (0.05)
Antisaccade latency	248.58 (33.09)	227.98 (25.07)	223.58 (26.38)	218.77 (28.19)

Statistical Analysis

Data Viewer (SR Research Ltd.) was used to analyze the raw eye movement data. To ensure the including eye movement data are qualified, the following criteria for inclusion were adopted in analyses (42). (1) Saccades with a latency between 80 and 800 ms. (2) Saccade duration must be larger than 25 ms, and (3) saccade amplitude must be $>3°$. This resulted in a loss of $\sim$10% of the trials. Based on these criteria, the following saccade measures were derived: (1) Antisaccade latency, which was defined as the time elapsed from the onset of the target to the onset of the first saccade toward the mirror image location of the target after target onset. (2) Error rate, the probability that participant wrongly executes a prosaccade instead of an antisaccade.

RESULTS

Eye movement measures of two groups in pre- and post-test antisaccade task are reported in **Table 1**. A 2 (Group: aerobic exercise vs. reading) by 2 (Time: pre-test vs. post-test) repeated measure ANOVA was performed for each dependent variable separately (see **Figure 2** for detail).

Error Rate

The ANOVA revealed a significant main effect of Time, $F_{1,\,28} = 21.21$, $p < 0.001$, $\eta_p^2 = 0.43$, but not Group, $F_{1,\,28} = 0.12$, $p = 0.733$, $\eta_p^2 = 0.004$. The interaction of Time and Group was not significant, $F_{1,\,28} = 0.33$, $p < 0.573$, $\eta_p^2 = 0.01$. The main effect of Time showed that the participants produced fewer error in post-test than in pre-test.

Antisaccade Latency

The ANOVA revealed significant main effect of Time, $F_{1,\,28} = 16.13$, $p < 0.001$, $\eta_p^2 = 0.37$, but not Group, $F_{1,\,28} = 3.01$, $p = 0.094$, $\eta_p^2 = 0.09$. The interaction of Time and Group was significant, $F_{1,\,28} = 6.23$, $p < 0.019$, $\eta_p^2 = 0.18$. The main effect of Time showed that the post-test antisaccade latencies were shorter than their pre-test counterparts. Further analysis revealed that the antisaccade latencies in post-test were significantly shorter than those in pre-test for participants in reading group, $t_{28} = 14.38$, $p = 0.002$. However, the antisaccade latencies in post-test did not differ from those in pre-test for participants in aerobic exercise group, $t_{28} = 2.20$, $p = 0.160$.

DISCUSSION

In the current study, we examine the differences in the effects of aerobic exercise and reading on inhibitory control of college students with mobile phone addiction by antisaccade task. As we hypothesized, the current results showed that participants would exhibit shorter antisaccade latency and lower saccade error after either aerobic exercise or reading intervention. However, the hypothesis that the effects of aerobic exercise and reading on inhibitory control were comparable was not fully supported by current results.

The results showed significant main effects of Time on antisaccade latency and error rate. These results suggest that

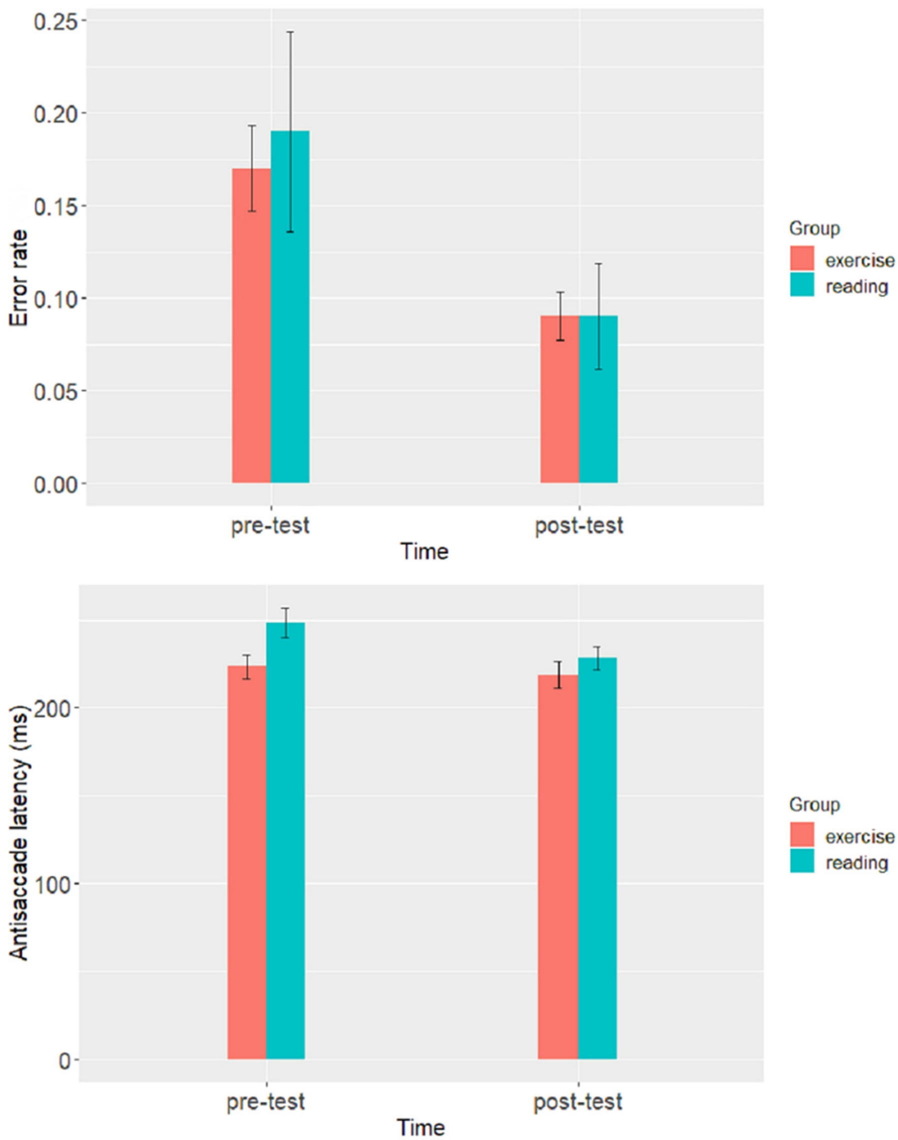

FIGURE 2 | Differences in saccadic eye movement measures in pre- and post-test antisaccade task for two groups of students.

both aerobic exercise and reading interventions can significantly improve the inhibitory control of college students with mobile phone addiction. This is consistent with previous studies finding that moderate-intensity aerobic exercise (21–24) or reading (34–37) can improve inhibitory control.

More importantly, the most critical and intriguing result of the present study is that a significant interaction of Time and Group was found on antisaccade latency. The antisaccade latencies in post-test were significantly shorter than those in pre-test for the reading group, yet, the antisaccade latencies in post-test did not differ from those in pre-test for the aerobic exercise group. This result suggests that reading has a positive effect on inhibitory control of college students with mobile phone addiction, and its effect was greater than that of aerobic exercise. This is consistent with previous studies concerning participating cognitive activities such as reading can improve one's inhibitory control (34–37). Yet, it is contrary to some other studies regarding the effect of aerobic exercise on inhibitory control (23, 28). These studies reported significant reductions in pre- to post-exercise antisaccade latency and non-significant changes in pre- to post-break (i.e., reading magazine) antisaccade latency. One thing we should note, however, is that the pattern of results varies across indicators. Specifically, we found a significant interaction on antisaccade latency, indicating that participants' antisaccade latency decreased after reading, whereas participants' antisaccade latency did not change significantly after aerobic exercise. However, no significant interactions were found on error rate. That is, a significant reduction in antisaccade latency after reading was not accompany with any significant change in error rate. Based on the explanation proposed by researchers in previous studies, this pattern indicates that participants did not decrease their post-test antisaccade latency at the cost of decreased accuracy (23, 28, 43). Additionally, we believe that this pattern of results may indicate that saccade latency is a more sensitive indicator which better reflects changes caused by intervention than error rate.

Previous evidence does indicate that reading can improve one's executive function (44, 45). There are several reasons why reading can improve inhibitory control. On the one hand, reading has some positive psychological effects. Pawlowski et al. (37) suggested that reading can improve performance on neuropsychological tasks. During the reading process, one must focus on the current visual input and suppress the interference from internal and external irrelevant information to absorb and comprehend reading materials. Therefore, inhibitory control plays an important role in the reading process, especially in inhibiting spontaneously generated information and behaviors within the individual. Thus, one's inhibitory control can be improved through reading. On the other hand, reading activates brain areas associated with inhibitory control. Previous neuroscience research has shown that some cerebral cortexes are involved in reading tasks, including: left medial extrastriate cortex, left middle temporal cortex, left frontal cortex, and left posterior temporal lobe (46). Meanwhile, researchers have revealed that inhibitory control associated with the execution of the antisaccade task involves the activations of prefrontal executive networks (47) and frontoparietal networks (23, 48). These studies above indicate that the reading process and inhibitory control both refer to some overlapping regions, supporting the view that reading can improve one's inhibitory control from the perspective of neuroscience. Yet, it is important to note that although the present study found an acute effect of reading, most of the previous studies only reported the chronic effect of reading. Considering that few previous studies have compared the chronic and acute effects of reading on executive functions or inhibited control functions, the potential differences between these effects are not clear. We should therefore be cautious when interpreting these results.

The null effect of aerobic exercise on antisaccade latency shows that exercise intervention does not significantly improve the inhibitory control of students with mobile phone addiction. This is consistent with previous studies which failed to find a significant effect of the exercise intervention on improving inhibitory control or cognitive functions (27, 28). However, it is inconsistent with previous studies showing that moderate-intensity aerobic exercise can improve inhibitory control (21–24). This discrepancy with previous literature may be due to some possible reasons. First, the duration of the exercise intervention in the present study may not be long enough. A meta-analysis study showed that the effect of short-time (<20 min) aerobic exercise on cognitive performance and executive control is generally small or negative while the aerobic exercise of more than 20 min has a positive effect (32). Second, the difference of participant populations in the present study and previous studies may contribute to the discrepancy. Although meta-analytic studies have shown the effect of short-time aerobic exercise on cognitive performance and executive control are generally small or negative, the previous study does find that 10-min moderate-intensity aerobic exercise can improve one's inhibitory control (23). Therefore, we believe that another possibility for the discrepancy is that the participant population in the current study differs from those in previous studies. Most of the participants in the previous studies were normal young adults or normal senior adults (22, 23, 26, 43), whereas the participants recruited for the present study were college students with mobile phone addiction, whose inhibitory control may differ from that of the normal population. Third, there are differences between the reading materials used in the current study and previous reading materials. In the previous studies, magazines and novels were used as reading materials (27, 28), but in the present study, newspapers are read. Serious newspapers covering daily global affairs were chosen as reading material to avoid causing emotional arousal which may influence one's inhibitory control (13). This difference might contribute to the discrepancy.

This result also suggests that there may be another possible explanation for the results of the two previous studies which did not find the effect of aerobic exercise on executive function (27, 28). That is, it may be because reading has an effect on improving executive function as aerobic exercise. Therefore, the current pattern of results supports the second possibility we raised at the beginning to explain the null effects of these two studies (i.e., reading as a filler task could improve executive function to some extent and act as a potential confound).

Another important issue is the causal relationship between mobile phone addiction and inhibitory control. Most of the previous studies focused solely on the relationship between mobile phone addiction and inhibitory control or examining the effect of some interventions on inhibitory control of populations with mobile phone addiction. However, the causal relationship between mobile phone addiction and inhibitory control has rarely been discussed in depth in these studies. One relevant literature may provide some inspirations for our understanding of the causal relationship between them. Gao et al. (16) examined the deficient inhibitory control problematic mobile phone use using Go/no-go task and electrophysiological technology. 20 problematic mobile phone users and 19 controls were included in this study. The results showed that problematic mobile phone users had a weaker NoGo P3 amplitude (which is related to inhibitory control) than controls on the mobile phone application background. It seemed that it was the presence of mobile phone-related stimuli or mobile phone use that caused the impairment of one's inhibitory control. Moreover, the authors suggested that the result might indicate that there is no general impairment of inhibitory control in problematic mobile phone users. The deficient inhibitory control appeared merely in mobile phone related background. Nevertheless, we should note that there was difference in inhibitory control between problematic mobile phone users and controls. Why the controls did not show lower P3 amplitude? Thus, does mobile phone addiction lead to the impairment in inhibitory control? Or are one with lower inhibitory control more likely to become addicted to mobile phones? We acknowledge that our study is not sensitive enough to answer this question; therefore, further psychobiological studies are needed to determine the causal relationship between mobile phone addiction and inhibitory control.

The findings of the present study shed some light on understanding the effects of short-time moderate-intensity aerobic exercise and reading on inhibitory control of college students with mobile phone addiction. The current results indicate that a single short-time reading can improve inhibitory control of college students with mobile phone addiction which extends previous research regarding that reading as a daily cognitive stimulation can improve executive function (34–37). Besides, considering that many previous studies examining the effects of various exercise interventions used reading as filler tasks for participants in control groups (23, 27, 28), some caution should be exerted when employing reading as a filler task in future studies. Additionally, the current study extends the findings of previous studies about the positive effect of reading on executive function of the normal population to a mobile phone addiction sample. Furthermore, the present study has some clinical and practical implications. The current results provide important supporting evidence on that reading is an effective way to improve the inhibitory control of people with mobile phone addiction. Although we do not know the causal relationship between mobile phone addiction and inhibitory control, the present study may imply that it is possible to help people with mobile phone addiction to reduce their levels of addiction by improving their inhibitory control. Hence, future research could test this view by examining the acute effects of reading on both the inhibitory control and level of addiction of people with mobile phone addiction. Moreover, many previous studies focused solely on the acute effects of aerobic exercise on inhibitory control while few studies focused on the acute effects of reading. The current study provides preliminary evidence for future research regarding the acute effects of reading on inhibiting control. Reading as a simple, convenient and economic activity, is less constrained by environment, such that it would be a promising way of intervention to improve one's inhibitory control and reduce one's level of mobile phone addiction.

Nevertheless, owing to the restriction of conditions, we should note that the present study has some limitations. For example, the majority of the current sample was female college students (23 out of 30) which makes it unclear whether the results could be fully generalizable to a wider range of populations with mobile phone addiction. In addition, the level of mobile phone addiction was assessed using a self-reported questionnaire in the present study, which may differ from the actual level of mobile phone addiction. Future studies could use some developed APPs to assess the participants' mobile phone usage more objectively and precisely. Additionally, there are only a reading group and an aerobic exercise group in the present study as we focus on examining the difference of effect on inhibitory control between reading and aerobic exercise. Future research should set a negative control group within which participants do nothing. By setting a baseline, the effects of reading and aerobic exercise on inhibitory control can be better assessed.

CONCLUSION

In summary, the results of the present study suggest that reading can improve inhibitory control of college students with mobile phone addiction and its effect may be better than short-time moderate-intensity aerobic exercise. Overall, the present findings are enlightening for understanding the effects of reading and aerobic exercise on inhibitory control in the young mobile phone addicted population.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethical Committee of the Fujian Normal University. Written informed consent to participate in this study was provided by participants or the participant' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

Both authors listed have made equal contribution to the work and approved it for publication.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2022.797780/full#supplementary-material

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A Network Analysis of the Relationships Between Behavioral Inhibition/Activation Systems and Problematic Mobile Phone Use

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Background: It is of great concern to society that individuals can be vulnerable to problematic mobile phone use (PMPU). However, there are a few studies in the field evaluating associations between behavioral inhibition/activation systems (BIS/BAS) and PMPU, and the results have been inconsistent. This study aimed to explore the relationships between BIS/BAS and PMPU by network analysis.

Methods: A total of 891 young adults participated in the study. BIS/BAS and PMPU were assessed by using the behavioral inhibition and activation systems scale and smartphone application-based addiction scale, respectively. The structure of the BIS/BAS-PMPU network was characterized using "strength," "closeness" and "betweenness" as centrality indices. Edge-weight accuracy and centrality stability were tested using a bootstrap procedure.

Results: The network analysis showed that "mood modification," "tolerance" and "withdrawal symptoms" had high centrality. In addition, the positive connection between BIS and "mood modification" or "tolerance" and between BAS-fun seeking and "mood modification" or "conflict" were also shown in the BIS/BAS-PMPU network.

Conclusion: These findings shed light on the central and bridge components between the BIS/BAS and PMPU communities, providing new evidence relevant to potential mechanisms that account for how high-BIS or high-BAS individuals develop PMPU, and inspiring component-based PMPU prevention or interventions.

Keywords: behavioral inhibition systems, behavioral activation systems, problematic mobile phone use, network analysis, components model of addiction

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INTRODUCTION

Broadly, problematic mobile phone use (PMPU) refers to an inability to regulate individual proper use of the mobile phone, which eventually involves negative consequences in daily life (1). It shares some key features of addictive behaviors (2), and has also been called "smartphone addiction" (3). In recent decades, PMPU has become a common problem among adolescents and young adults, and there is a burgeoning field of investigation owing to the significance of its consequences. A recent systematic review concluded that there are five categories of risky consequences of PMPU: cognitive control, emotional health problems, physical health problems, professional performance, and social performance (4). What is even more surprising is that individuals with PMPU showed lower brain volume and weaker intrinsic neural activity relevant for craving and inhibitory control (5). In addition, the prevalence of PMPU seems to have increased, especially during or after the COVID-19 pandemic [e.g., (6–9)]. In light of its consequences and prevalence, it is necessary to prevent individuals, especially susceptible people, from being addicted to mobile phones.

Previous studies have indicated that personality traits are associated with PMPU (10–13). The Big Five personality traits are of particular interest, and some of them are related to PMPU [see (14)]. From the perspective of physiological models of personality, some researchers have explored the relationship between behavioral systems and addiction (15–18). However, relatively few studies have focused on such a relationship in the field of PMPU, and the results have been inconsistent. More importantly, the relationships between behavioral systems and PMPU has traditionally been studied utilizing latent class analysis. A few studies, based on a systematic network perspective, have been conducted to understand these relationships, which could better explain the nature of the associations between behavioral systems and PMPU. Specifically, a systematic network perspective emphasizes the relationships between variables in the network system, which is more suitable for real situations (19). In addition, the visualization and dynamic study of the network enables us to more intuitively see the structure and dynamic evolution of the relationships between the behavioral systems and PMPU (19). Furthermore, network analysis can reveal the links between components of behavioral systems and PMPU by statistically punishing false correlations, which may solve the traditional issue of overrating the link strength of behavioral systems and PMPU (20). Finally, network analysis can provide multiple indices of nodes and edges to describe the relationships between behavioral systems and PMPU (19, 21).

Theoretical Background

Components Model of Addiction

Drug and behavioral addiction seem to have many commonalities (22, 23). Based on an eclectic approach to the study of addictive behaviors and the aim of increasing the general public's perception of addictive behaviors, the components model of addiction proposed that addictions need to present six distinct symptoms of behavior or psychological feelings (24). These symptoms of addiction are salience, mood modification, tolerance, withdrawal, conflict, and relapse. Specifically, salience refers to the fact that individual thinking, emotions, and behavior are almost dominated by a particular activity that becomes the most important activity in daily life. Mood modification refers to individual subjective experiences, such as provocation, excitement, or tension, followed by engaging in a particular activity. Tolerance refers to individual gradually increasing their time and investment in a particular activity to get the experience that the individual had before. Withdrawal symptoms refer to individuals tending to have unpleasant feeling states (e.g., extreme moodiness and irritability) and/or physical effects (e.g., nausea, sweats, headaches, insomnia and other stress-related reactions), when particular activities are interrupted. Conflict refers to particular activities that elicit conflicts between the individual and those around them (interpersonal conflict) or within the individual themselves (intrapsychic conflict). Relapse means that although there may be a period of control or abstinence, the particular activity can easily recur, and will show stronger tendencies when it occurs again. PMPU can be viewed from the perspective of this model and might also present these six symptoms.

Reinforcement Sensitivity Theory

Reinforcement sensitivity theory [RST (25)] attempts to explain individual differences from the perspective of human neurophysiological mechanisms. The theory suggests that there are some subsystems in the central nervous system that are sensitive to rewards and punishments, and regulate individual emotions and behaviors through reinforcement effects. The behavioral inhibition system (BIS) and behavioral activation/approach system (BAS) are two basic subsystems (26, 27). BIS is sensitive to conditional aversive stimuli. When a signal of punishment or termination of rewards is presented, the system is activated, accompanied by a negative emotional experience and withdrawal/avoidance behavior. BAS is sensitive to conditional appetitive stimuli. When a signal of reward or termination of punishment is presented, this system is activated to generate a positive emotional feeling and approach behavior. BAS consists of drive (BAS-D), reward responsiveness (BAS-R) and fun seeking [BAS-F (28)]. BAS-D refers to engaging strong and quick goal pursuit. BAS-R refers to receptivity to reward. BAS-F refers to the desire for new and potentially rewarding experiences. Because BAS is not a unified construct in relation to psychopathology, it is important to focus on each component of BAS carefully (29, 30).

The relationships between BIS/BAS and addiction have been supported by some evidence in the field of drug addiction. It was found that high reward (i.e., BAS) and low punishment sensitivity (i.e., BIS) were significantly related to drinking habits (31) Kambouropoulos and Staiger (32) also found that a higher BIS was associated with alcohol abuse. In addition, studies have shown that individuals with drug addictions had higher BIS and BAS-F scores than controls (15, 33).

Associations Between BIS/BAS and PMPU

With the rapid growth of network technology, problematic internet use behavior is becoming prominent (34–36). Researchers have started to pay attention to the causes of problematic internet use behavior. The relationships between BIS/BAS and problematic internet use behavior have captivated researchers' attention in recent decades. A recent study found that the BIS and BAS scores of people with internet gaming disorder (IGD) or internet addiction (IA) were higher than those of non-addicted people (37). Regarding specific dimensions of the BAS, BAS-F seems to have a stronger relationship with IA. Hierarchical regressions showed that the BIS emerged as a positive predictor of IA and that only BAS-F among the BAS components positively predicted IA (38). Individuals with IGD have higher BIS and BAS-F scores than non-IGD individuals (39). High BAS-F and high BIS scores have positively correlate with the severity of IA (18). A 1-year follow-up study has provided reliable evidence and revealed that individuals with higher BAS-F scores were more likely to develop IA (40). Similar results were also observed among adolescents with attention-deficit/hyperactivity disorder (41). Summarizing the above, it seems that an individual with high BAS-F or BIS scores was prone to IA. However, there have been inconsistent results. For example, some studies failed to observe that the BIS or BAS was related to IA (39, 42, 43). Regarding the specific dimensions of the BAS, low BAS-D scores were associated with severe IA (41). Another study showed that only BAS-D was a risk factor associated with IGD (44). Furthermore, there was a significant negative correlation between IA and BAS-R among high school students (39).

Recently, emerging studies have started to explore the relationships between BIS/BAS and PMPU. However, the number of relevant studies remains insufficient and the results have been mixed. To our knowledge, there are only four studies evaluating the relationship between BIS/BAS and PMPU. Kim et al. (45) found that BAS-D and BAS-R, not BAS-F and BIS, were predictors of PMPU. Jiang and Zhao (46) found that BIS was negatively correlated with PMPU. However, BAS was positively correlated with PMPU. Lee et al. (47) only reported BIS results and found a positive association between BIS and PMPU. Jeong et al. (48) found that the PMPU group had higher BIS and BAS scores than the normal group.

At present, these results are relatively confusing, which may be due to studies used different PMPU scales, and these different scales incorporated different symptoms of addiction. Thus, the BIS/BAS may be linked not only to PMPU, but also to the different symptoms of PMPU. In addition, many studies have not further analyzed the relationship between the dimensions of the BAS and PMPU, and therefore, the relationship between the BAS and PMPU have not been clarified.

Network Analysis

The method of network analysis involves presenting the characteristics and information of a system in interconnected network form. The system is composed of "nodes" and "edges" (49, 50). Nodes represent psychological variables such as mood states, symptoms, or attitudes, while edges (i.e., the links connecting two nodes) represent unknown statistical relationships that need to be estimated (20). Network analysis focuses on the relationship between variables and highlights their important aspects through statistical modeling. Therefore, network analysis can reveal the data patterns that are difficult to see in the latent variable model.

Some scholars have carried out research on PMPU by utilizing network analysis, with a focus on three aspects: the symptoms, associated comorbidities, and influencing factors of PMPU. First, regarding the symptoms of PMPU, Huang et al. (51) explored the PMPU network and found that loss of control was the key symptom. Another study found that compulsive use had higher centrality levels in the PMPU network (52). Second, regarding the comorbidities associated with PMPU, a recent study conducted an exploratory graph analysis and showed that PMPU and problematic WhatsApp use were heavily intertwined (53). Last, regarding the influencing factors of PMPU, Wei et al. (54, 55) explored network pathways and further discovered the "central" components and the "bridge" components between neuroticism and PMPU communities. Huang et al. (56) employed a network analysis approach to understand the interaction between PMPU and related influencing factors and found that there were several central influencing factors (such as self-control ability, loss of control, parent-child relationship, and peer attitudes toward smartphone use) and bridge factors (such as peer attitudes toward smartphone use, peer pressure for smartphone use, and fear of missing out).

Psychopathological network theory portrays mental disorders as causal systems of interacting symptoms (57). Symptoms cease to be passive indicators of the underlying common cause of illness and become dynamic components of the system (21). To our knowledge, there has been a lack of research on the symptoms of PMPU based on the addiction components model and on the relationship between BIS/BAS and PMPU by utilizing network analyses. This lack of research might obscure meaningful associations between BIS/BAS and addictive symptoms of PMPU and make it difficult to identify individual symptoms that may be more critical to the onset or maintenance of PMPU.

The Present Study

Through the above literature review, we identified the following limitations in the current research on the relationships between BIS/BAS and PMPU: First, the results describing the relationship between BIS/BAS and PMPU have been mixed and further clarification is needed. Second, the relationship between BIS/BAS and specific addictive symptoms of PMPU have not been explored. Finally, many studies have used latent variables for these analyses, which ignore the network structure of the relationship between variables. To bridge these gaps, this study attempted to explore the relationship between BIS/BAS and PMPU by using network analysis. We posed the following research questions:

R1: Which edges play the role of bridging the BIS/BAS community and PMPU community?

R2: Which symptoms are central in the BIS/BAS-PMPU network?

METHODS

Participants and Procedure

The ethics of all procedures in the research were approved by the ethics committee of the authors' research institution. A total of 914 university students from two provinces in China participated in the study by utilizing convenience sampling from December 2019 to January 2020 (before the COVID-19 epidemic). The survey was conducted by using the WeChat-based Wenjuanxing program. All participants received instructions and were told that their participation was voluntary and they could withdraw from the study at any time for any reason. To encourage honest responses, the anonymity of the survey was emphasized.

Participants who met the following criteria were included: (1) ability to understand Chinese; (2) consent to participate in the study; and (3) owned a mobile phone. We eliminated twenty-three participants who (1) completed the surveys, but indicated they did not respond at the appropriate times or (2) responded improperly or randomly on some of the essential study variables. The final sample was 891 students. Across the entire sample, 218 of the participants were men (24.47%), and 673 were women (75.53%); 485 were from rural areas (54.43%), and 406 were from urban areas (45.57%). The mean age of the participants was 19.09 years ($SD = 1.27$; range: 16–24 years).

Measurements

Smartphone Application-Based Addiction Scale

The smartphone application-based addiction scale (SABAS) is the most recently developed scale for assessing PMPU (2). The Chinese version of the scale, revised by Leung et al. (58), was used in this study. The scale was developed based on the addiction components model (24) and contained six items, such as "Over time, I fiddle around more and more with my smartphone," that corresponded to addiction components (i.e., salience, conflict, mood modification, tolerance, withdrawal symptoms, and relapse). A 6-point Likert-type scale from "1 = Strongly disagree" to "6 = Strongly agree" was used. Higher scores on the SABAS related to greater risk of PMPU. Cronbach's α coefficient was 0.76 in our sample.

Behavioral Inhibition and Activation Systems Scale

The BIS/BAS scale was utilized to assess sensitivity to punishment and rewards (28). The Chinese version of the BIS/BAS scale was revised by Li et al. (59), which deleted the items "Even if something bad is about to happen to me, I rarely experience fear or nervousness" and "I have very few fears compared to my friends" considering the low item discrimination of the two in Chinese sample. The Chinese version of the scale has 18 items in total. The BIS scale contained 5 items (e.g., "If I think something unpleasant is going to happen. I usually get pretty 'worked up"'). The BAS scale consisted of 13 items, "If I think something unpleasant is going to happen, I usually get pretty 'worked up"' (BAS-R; e.g., "When I get something I want, I feel excited and energized"), 4 items assessing drive for goals (BAS-D; e.g., "I go out of my way to get things I want"), and 4 item assessing fun-seeking (BAS-F; e.g., "I will often do things for no other reason than that they might be fun."). The Cronbach's α coefficients of the BIS, BAS, BAS-R, BAS-D and BAS-F were 0.82, 0.85, 0.85, 0.74, and 0.73, respectively, in our sample.

Statistical Analysis

Descriptive statistics, Pearson correlations, and Cronbach's α were performed by using SPSS 25. Cohen's d and network analysis were conducted by using JASP (Jeffrey's Amazing Statistics Program). Edge-weight accuracy and centrality stability were tested by using R (Version 4.1.2).

A visualized network analysis was performed in the present study. A graphical LASSO [glasso (55)] estimated least absolute shrinkage and selection operator (LASSO) regularization. A regularized Gaussian graphical model [GGM; (60, 61) was estimated by utilizing glasso in combination with the extended Bayesian information criterion [EBIC (62)] model (i.e., EBICglasso model). The EBICglasso model was calculated by using JASP. The tuning parameter was set to 0.5 for a more parsimonious and easily explainable network (i.e., fewer edges, higher specificity and sensitivity). The connection of nodes was described using edges. Edge thickness was used to indicate the strength of the association between nodes. Blue edges indicate positive correlations and red edges indicate negative correlations. The centrality of nodes in the network, which represented study variables, were calculated using measures of betweenness (degree of connectivity), closeness (distance centrality), and strength [degree centrality (63)]. Centrality measures are reported as standardized values (z-scores).

Edge-weight accuracy and centrality stability were used by the R-package bootnet (Version 1.4.3). Bootstrapped 95% confidence intervals were utilized for estimating the accuracy of edge-weight (the number of bootstrap samples was 1,000) and fewer overlaps indicated higher stability/accuracy. The stability of node attributes was estimated by using the case-dropping bootstrap procedure. If most samples can be excluded from the dataset without observing significant changes in the centrality index of the node, the network is considered to be stable. Centrality stability is represented graphically and quantified by calculating the correlation stability coefficient (CS-coefficient), which was suggested to preferably be above 0.5 and should not be below 0.25 for interpretability and stability (49). The small-worldness index (SWI) was calculated by considering both the average shortest path length and the global aggregation coefficient, SWI = (C/C') / (L/L'), where L and C are the shortest path length and the global aggregation coefficient of the network, and L' and C' are ER random networks [Erdos-Rényi model (64)] with the same number of nodes and connections. If the SWI is >1, it means that the network has small-world characteristics, i.e., high connection strength, short average paths between nodes, and strong overall connections (57).

RESULTS

Descriptive Statistics and Correlation Analyses

Sample characteristics and group comparisons for the study variables are shown in **Table 1**. The PMPU, BIS and BAS-R scores were significantly different by sex. Women all had higher PMPU, BIS and BAS-R scores than men. In addition, the BAS-D and BAS-F scores were significantly different by residence. The participants from urban areas had higher BAS-D and BAS-F scores than the participants from rural areas.

Descriptive statistics and correlation analyses for the study variables are shown in **Table 2**. PMPU was significantly positively associated with BIS ($r = 0.22$, $p < 0.001$) and BAS-F ($r = 0.20$, $p < 0.001$) scores. Similarly, the six components of PMPU were all significantly positively associated with BIS and BAS-F scores and the correlations among them ranged from small to medium.

TABLE 1 | Sociodemographic characteristics.

		n (100%)	PMPU M ± SD	t	d	BIS M ± SD	t	d	BAS-R M ± SD	t	d	BAS-D M ± SD	t	d	BAS-F M ± SD	t	d
Gender	Male	218 (24.47%)	3.48 ± 0.92			2.86 ± 0.48			3.12 ± 0.49			2.85 ± 0.51			2.79 ± 0.48		
	Female	673 (75.53%)	3.66 ± 0.88			2.97 ± 0.48			3.21 ± 0.46			2.80 ± 0.50			2.79 ± 0.49		
				2.49*	0.20		3.06**	0.23		2.40*	0.19		1.19	0.10		0.12	0.00
Residence	Rural areas	485 (54.43%)	3.58 ± 0.87			2.94 ± 0.47			3.17 ± 0.47			2.77 ± 0.47			2.75 ± 0.49		
	Urban areas	406 (45.57%)	3.65 ± 0.90			2.94 ± 0.49			3.22 ± 0.48			2.87 ± 0.53			2.84 ± 0.48		
				1.18	0.08		0.04	0.00		1.52	0.11		2.80**	0.20		2.77**	0.19
Only child	Yes	365 (40.97%)	3.56 ± 0.85			2.93 ± 0.46			3.17 ± 0.48			2.85 ± 0.51			2.78 ± 0.50		
	No	526 (59.03%)	3.66 ± 0.92			2.95 ± 0.49			3.20 ± 0.46			2.79 ± 0.49			2.80 ± 0.48		
				1.64	0.11		0.44	0.04		0.92	0.06		1.88	0.12		0.45	0.04

** <0.05, ** <0.01. PMPU, Problematic mobile phone use; BIS, Behavioral inhibition systems; BAS-R, Behavioral activation systems-reward responsiveness; BAS-D, Behavioral activation systems-drive for goal; BAS-F, Behavioral activation systems-fun seeking.*

In addition, BAS-R scores were significantly positively associated with salience (r =0.07, p =0.048) and mood modification ($r = 0.12$, p <0.001) scores.

Network Analysis

Characteristics of Edges

The EBICglasso network including BIS, BAS-R, BAS-D, BAS-F and six components of PMPU is presented based on the domain-level network in **Figure 1A**. There are 10 nodes and 27 non-zero edges in the domain-level network. Edges between nodes BIS and BAS-R and between BAS-R and BAS-D had the strongest edge intensity ($r = 0.34$ for each). In addition, nodes BIS and BAS-F had positive associations with mood modification and tolerance scores. In addition, edge weights' accuracy was relatively high and reliable based on the results of the bootstrapped network analysis (**Supplementary Figure 1**). The bootstrap difference test showed that most of the comparisons between edge weights were statistically significant (**Supplementary Figure 2**). The domain-level network is characterized by high connection strength, short paths between nodes, and overall tighter connections (SWI = 1.01).

Item-level BIS, BAS-R, BAS-D, BAS-F, and PMPU data are shown in **Figure 1B**. There were 22 nodes and 106 non-zero edges in the item-level network. Node BAS-F4 ("I often act on the spur of the moment") was positively related to node PMPU2 ("Conflicts have arisen between me and my family (or friends) because of my smartphone use"; $r = 0.09$), followed by the connection between node BIS4 ("I feel pretty worried or upset when I think or know somebody is angry at me") and node PMPU4 ("Over time, I fiddle around more and more with my smartphone"; $r = 0.08$). In addition, edge weights' accuracy was relatively accurate and reliable based on the results of the bootstrapped network analysis (**Supplementary Figure 3**). The bootstrap difference test showed that most of the comparisons between edge weights were statistically significant (**Supplementary Figure 4**). The item-level network is characterized by high connection strength, short paths between nodes, and overall tighter connections (SWI = 1.38).

Characteristics of Nodes

Table 3 and **Figure 2** show the study variables' betweenness, closeness, strength (degree) and expected influence in the domain-level network. Mood modification [betweenness = 1.65 (rank = 1); closeness = 2.20 (rank = 1); strength = 0.86 (rank = 3)], BIS [betweenness = 1.65 (rank = 1); closeness = 0.52 (rank = 2); strength = −0.88 (rank = 9)], BAS-R [betweenness = 0.65 (rank = 3); closeness = −0.30 (rank = 8); strength = 0.50 (rank = 4)], tolerance (betweenness = 0.15 (rank = 4); closeness = 0.27 (rank = 4); strength = 1.44 (rank = 2)] and withdrawal symptoms [betweenness = −0.35 (rank = 4); closeness = 0.38 (rank = 3); and strength = 1.52 (rank = 1)] exhibited extremely high centrality. Among them, mood modification was the most central node. We also analyzed the stability of the network and found an excellent level of stability (i.e., *CS*-coefficient for strength = 0.67), indicating that 67% of the sample could be dropped without the network structure changing a significant extent compared to the original structure

TABLE 2 | Correlation analysis of the study variables.

	M ± *SD*	1	2	3	4	5	6	7	8	9	10
1 PMPU	3.62 ± 0.89	-									
2 Salience	3.94 ± 1.33	0.63***	-								
3 Conflict	3.37 ± 1.48	0.61***	0.20***	-							
4 Mood modification	4.11 ± 1.26	0.68***	0.37***	0.31***	-						
5 Tolerance	3.84 ± 1.27	0.73***	0.38***	0.26***	0.42***	-					
6 Withdrawal symptoms	3.13 ± 1.29	0.76***	0.34***	0.40***	0.40***	0.45***	-				
7 Relapse	3.30 ± 1.25	0.68***	0.28***	0.24***	0.29***	0.50***	0.51***	-			
8 BIS	2.94 ± 0.48	0.22***	0.10**	0.13***	0.23***	0.20***	0.12***	0.13***	-		
9 BAS-R	3.19 ± 0.47	0.05	0.07*	0.01	0.12***	0.06	−0.04	0.01	0.44***	-	
10 BAS-D	2.81 ± 0.50	−0.02	0.06	−0.02	0.003	−0.06	−0.03	−0.03	0.11**	0.47***	-
11 BAS-F	2.79 ± 0.49	0.20***	0.12***	0.16***	0.17***	0.13***	0.12***	0.10**	0.18***	0.31***	0.39***

** <0.05, ** <0.01, *** <0.001. PMPU, Problematic mobile phone use; BIS, Behavioral inhibition systems; BAS-R, Behavioral activation systems-reward responsiveness; BAS-D, Behavioral activation systems-drive for goal; BAS-F, Behavioral activation systems-fun seeking.*

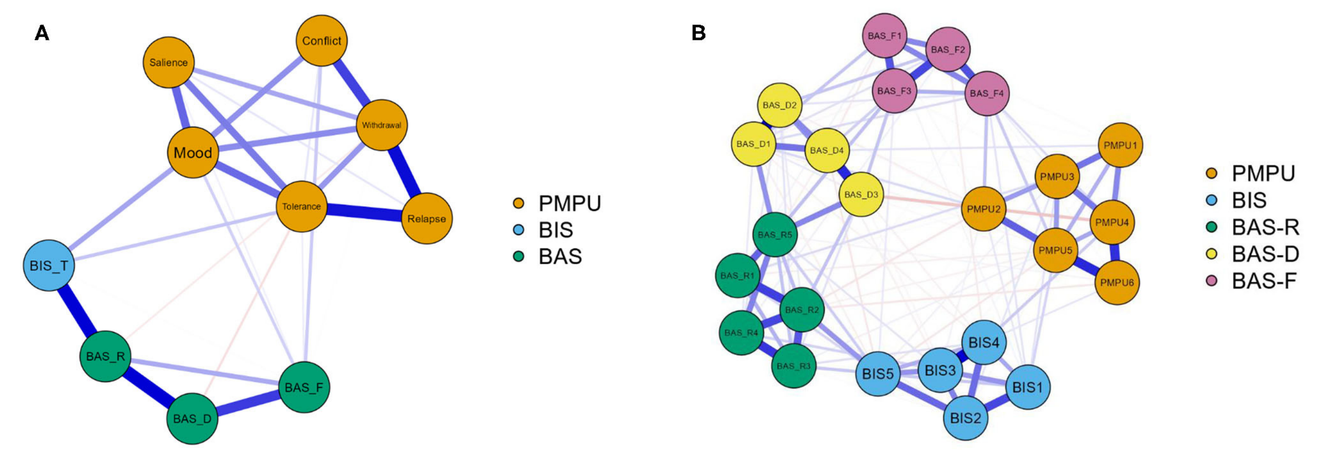

FIGURE 1 | EBICglasso model based on the domain-level **(A)** and the item-level **(B)** network analysis according to the relationships between BIS, BAS-R, BAS-D, BAS-F and PMPU. PMPU, Problematic mobile phone use; BIS-T, Behavioral inhibition systems; BAS-R, Behavioral activation systems-reward responsiveness; BAS-D, Behavioral activation systems-drive for goal; BAS-F, Behavioral activation systems-fun seeking; B: PMPU1-PMPU6, Problematic mobile phone use (PMPU).

(**Supplementary Figures 5, 6**). The centrality stability of nodes in the network was considered to be in the preferable range (i.e., *CS*-coefficient ≥ 0.5).

In the item-level network, the item PMPU3 ["Preoccupying myself with my smartphone is a way of changing my mood (I get a buzz, or I can escape or get away, if I need to)"] had higher levels of betweenness, closeness, and strength (betweenness = 1.93; closeness = 0.94; strength = 0.70) in PMPU. Item BIS4 ("I feel pretty worried or upset when I think or know somebody is angry at me") had a higher level of strength (strength = 0.70) in BIS, and item BIS5 ("I feel worried when I think I have done poorly at something. I have very few fears compared to my friends") had higher levels of betweenness and closeness (betweenness = 1.17, closeness = −0.10) in BIS. Item BAS-R5 ("When I see an opportunity for something I like, I get excited right away") had higher levels of betweenness and closeness (betweenness = 2.88, closeness = 2.30) in BAS-R, and item BAS-R2 ("When I'm doing well at something, I love to keep at it") had a higher level of strength (strength = 1.96) in BAS-R. Item BAS-D3 ("When I want something, I usually go all-out to get it") had higher levels of betweenness and closeness (betweenness = 1.55, closeness = 2.09) in BAS-D, and item BAS-D1 ("If I see a chance to get something I want, I move on it right away") had a higher level of strength (strength = 1.03) in BAS-D. Moreover, item BAS-F3 ("When I want something, I usually go all-out to get it") had higher levels of betweenness, closeness, and strength (betweenness = 0.60; closeness =-0.56; strength = 0.002) in BAS-F (**Supplementary Table 2**). We also analyzed the stability of the network and found an excellent level of stability (i.e., *CS*-coefficient for strength = 0.75), indicating that 75% of the sample could be dropped without the network structure changing to a significant extent compared to the original structure (**Supplementary Figures 7, 8**). The centrality stability of nodes in the network was considered to be in the preferable range (i.e., *CS*-coefficient ≥ 0.5).

TABLE 3 | Centrality study variables relationship network.

	Between	Closeness	Strength
Salience	−1.10	−0.18	−0.87
Conflict	−0.60	−0.06	−1.07
Mood modification	1.65	2.20	0.86
Tolerance	0.15	0.27	1.44
Withdrawal symptoms	−0.35	0.38	1.52
Relapse	−0.60	−0.21	−0.25
BIS	1.65	0.52	−0.88
BAS-R	0.65	−0.30	0.50
BAS-D	−0.60	−1.12	−0.39
BAS-F	−0.85	−1.50	−0.87

BIS, Behavioral inhibition systems; BAS-R, Behavioral activation systems-reward responsiveness; BAS-D, Behavioral activation systems-drive for goal; BAS-F, Behavioral activation systems-fun seeking.

DISCUSSION

To the best of our knowledge, this is the first study to use network analysis to explore relationships between BIS/BAS and PMPU. First, this study clarified which specific symptoms of PMPU are related to BIS/BAS and identified which dimension of the BAS is related to PMPU. Second, this study also revealed core symptoms of PMPU among the components of the BIS/BAS-PMPU network. The network perspective adds novel characteristics about which symptoms of PMPU are most related to BIS/BAS and how specific symptoms interconnect with each other in the specific network, which may help in the better design of precise and effective interventions.

Associations Between the BIS and PMPU

The domain-level network showed connections between mood modification, tolerance, and BIS. The item-level network further revealed a more detailed relationship, in which BIS4 ("I feel pretty worried or upset when I think or know somebody is angry at me") was connected with PMPU4 ("Over time, I fiddle around more and more with my smartphone"). These findings are consistent with some previous studies that reported that individuals with high BIS are more likely to be addicted to mobile phones (47, 48).

The results indicated that individuals who were sensitive to punishment or termination of rewards were susceptible to become addicted to mobile phone. This may be because they are more prone to develop specific addictive symptoms such as mood modification and tolerance. A possible explanation for these results may be that those who score highly on BIS would be more likely to experience negative emotions [e.g., anxiety and depression; (65)], and attempt to escape into the virtual world provided by mobile phones to regulate moods (i.e., mood modification; 24; Csibi et al., (2)). Park and colleagues (38) also found that the association between the BIS and IA was mediated by anxiety and depression. This also dovetails with the view of RST (25) that BIS is usually activated and accompanied by avoidance behavior (e.g., to avoid the distress of daily life by mobile phone use). Additionally, tolerance is a result of a reinforcement process that increases the degree of mobile phone use to experience a mood-modifying effect that was initially obtained with a much smaller degree of use (24). Mood modification reflects the purpose of PMPU, while tolerance reflects the result of PMPU. Individuals with a high BIS are more likely to preoccupy themselves with mobile phones as a way of changing their moods and to increasingly fiddle with mobile phones.

Associations Between the BAS and PMPU

The current study found that BAS-F has a relatively strong connection with mood modification and conflict in the domain-level network. The item-level network further revealed a more detailed relationship, in which BAS-F4 ("I often act on the spur of the moment") and PMPU2 ("Conflicts have arisen between me and my family (or friends) because of my smartphone use") had a positive connection. These findings are in line with the findings that fun seeking has been reported to be the only BAS subscale associated with IA (18, 38–40).

The results indicated that individuals who were sensitive to rewards or termination of punishment, especially the desire for novel rewarding experiences (i.e., BAS-F), more easily develop addictive symptoms such as mood modification and conflict. A possible explanation for the association between BAS-F and mood modification might be that BAS-F is associated with immediate gratification (66) and active hedonistic seeking (28). Mobile phones are tools providing individual entertainment, which might help individuals enjoy a positive experience (i.e., mood modification). Existing research has found that more hedonistic activities are undertaken on smartphones than on other technological devices (67).

The positive connection between BAS-F and conflict may partly be explained by the impulsive characteristics of BAS-F individuals. Gray (68) suggested that individuals with heightened impulsivity were more sensitive to reward signals. Empirical evidence has also revealed that fun seeking is associated with impulsivity (69). Impulsivity typically pertains to behaviors that are rash and spontaneous (70), which might lead to conflicts with family and friends. Park and colleagues (38) found that BAS-fun seeking predicted IA and was mediated by impulsivity. Thus, individuals with high BAS-F are also more likely to preoccupy themselves with mobile phones as a way of having fun, which may lead to conflict with family (or friends) because of mobile phone use.

Core Symptoms of PMPU Among Specific Networks

A homeostatic network of mental disorders (e.g., PMPU) might be developed by interactions of symptoms that are no longer independent of each other. Among such homeostatic networks, central symptoms are more likely to activate other symptoms. Thus, central symptoms are thought to play a major role in causing the onset and/or maintenance of mental disorders [e.g., PMPU (71)]. Our results indicated that "preoccupying

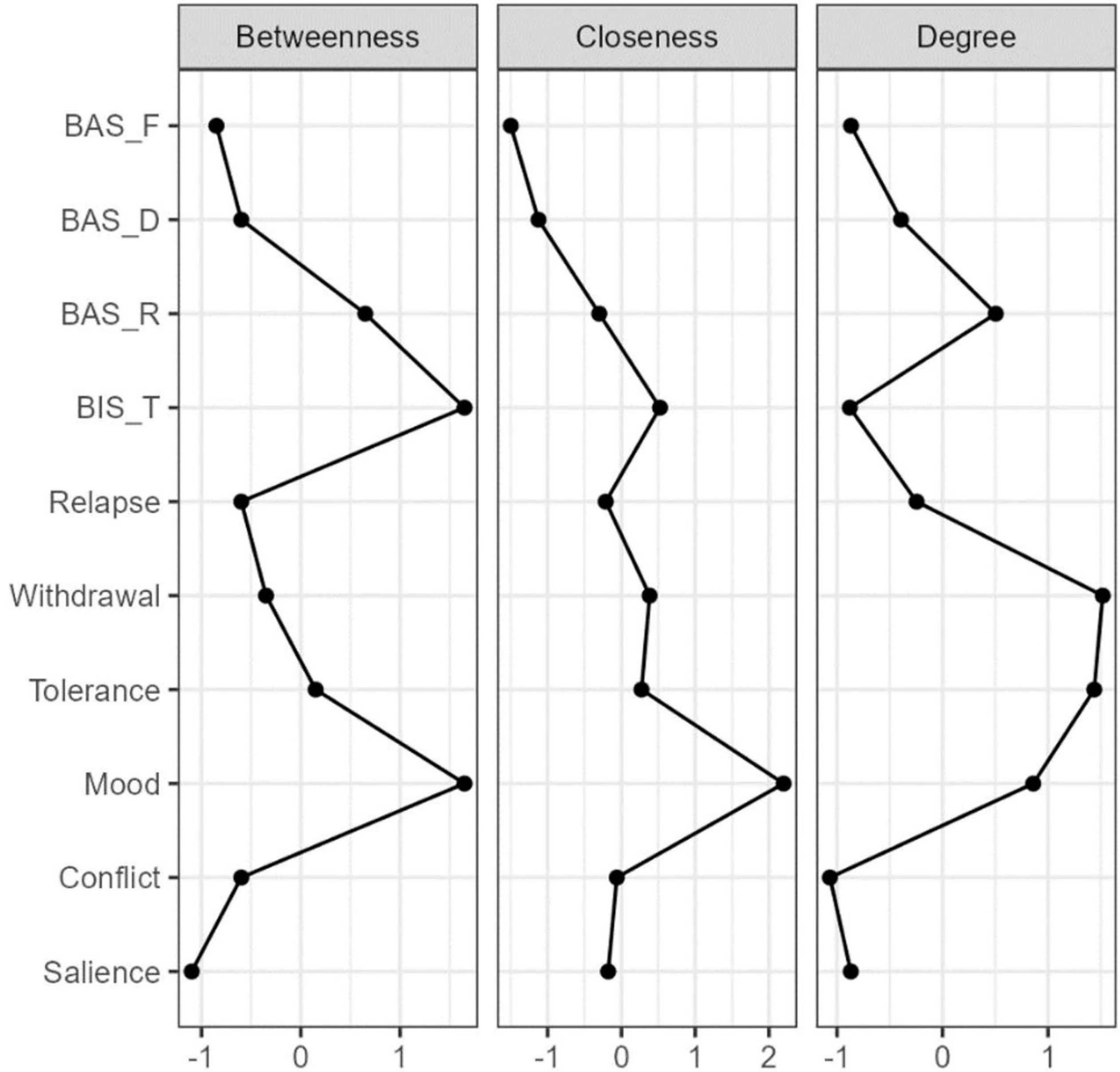

FIGURE 2 | Centrality Plots for EBICglaaso network depicting the betweenness, closeness, and degree (strength), expected influence of each node (variable). BIS-T, Behavioral inhibition systems; BAS-R, Behavioral activation systems-reward responsiveness; BAS-D, Behavioral activation systems-drive for goal; BAS-F, Behavioral activation systems-fun seeking.

myself with my smartphone is a way of changing my mood" (i.e., mood modification) was one of the central symptoms that might play a key role in the development, persistence, remission, and relapse of PMPU, and another two indicators were "over time, I fiddle around more and more with my smartphone" (i.e., tolerance) and "if I cannot use or access my smartphone when I feel like, I feel sad, moody, or irritable" (i.e., withdrawal symptoms). These findings echo the compensatory internet use model (72), which suggests that people probably use mobile phones to reduce their painful emotions, which may result in overuse or even dependence on mobile phones. These three symptoms are more likely to activate other symptoms which finally leads to the onset and/or maintenance of PMPU.

Our results are different from Huang et al., (51) and (52), who reported that either loss of control or compulsive use was the core symptom of PMPU. There may be two explanations. One explanation for these results could be that the researchers used different measurement tools for PMPU. Huang et al., (51) adopted the smartphone addiction proneness scale (73) and took a single item as the symptom index in the network analysis. Andrade et al. (52) adopted a smartphone addiction inventory (74) and analyzed four dimensions (i.e., compulsive behavior, functional impairment, withdrawal, and tolerance) of node characteristics. Because different researchers adopted different addiction models, the core symptoms of PMPU were also different. Another possible explanation is that the core symptoms of PMPU may be different in specific relationship networks. From the perspective of analysis method, network analysis calculates the relationship strength of two nodes after considering other nodes (49). This means that the centrality of nodes will change with the increase in nodes. Therefore, the core symptoms of PMPU among the relationship network might be specific to the relationship [e.g., (54, 75)]. Certainly, the network specificity of core symptoms of PMPU needs further exploration.

Limitations and Future Directions

The present study has several limitations that should be considered. One of the main limitations is the use of cross-sectional data and presentation of a static network, which unfortunately fails to provide dynamic information and causal relationships between variables. Therefore, it is important to explore the dynamic development of PMPU symptoms caused by BIS/BAS based on time series data. When a node in the symptom network is activated by BIS/BAS, it may further activate other symptoms "adjacent" to it in the network.

Moreover, the network analysis in this study incorporated only personality variables, ignoring the role of environment, cognition, and emotion [which are thought to play an important role in the development and maintenance of IA (22)], and may provide only a limited picture of the development and maintenance of PMPU symptoms. Future studies may consider the different levels of physiological, psychological, and environmental factors as part of the overall system and integrate these factors into a unified framework to examine the network of development and maintenance of PMPU symptoms.

Third, after the update of RST (76), different understandings of the BIS have been generated. This study was still based on the previous understanding of the BIS without considering the new role of the BIS. Future research can further explore the relationship between revised BIS and PMPU.

Last, this study did not specifically examine the content of mobile phone use. Previous studies have called for PMPU to investigate the specific contents of mobile phone use (77), which will help us to further compare the similarities and differences between different subtypes of PMPU. Future research can include types of mobile phone use in network analyses.

Implications

The aforementioned findings contribute to PMPU research both theoretically and practically. Regarding to theoretical contributions, first, to our knowledge, our study is one of the first works to show the network of the relationships between BIS/BAS and PMPU. Emerging evidence that the BIS and BAS-F are connected with tolerance and mood modification, which are the core symptoms of PMPU, in the BIS/BAS-PMPU network, has been provided. Second, these findings might help us identify new ways in which PMPU forms and gain a better understanding of the components model of addiction. The traditional SEM/latent variable analysis approach focuses on the relationship between individual factors and PMPU [e.g., (45–48)], while ignoring the interaction between symptoms of PMPU and the dynamic network of how individual factors are related to specific symptoms of PMPU. Based on the network analysis approach, our study indicated that individuals with high BIS and BAS-F scores might develop mood modification and tolerance symptoms. These two sets of symptoms may activate one or more symptoms of PMPU that in turn activate another based on the strength of the edge linking them. The interaction among these symptoms may be the cause or result of PMPU. Last, these findings also offer a novel bridge between RST (25) and the components model of addiction (24). Based on a theoretical integration of the field in personality and addiction, the understanding of BIS/BAS is specifically related to what kind of PMPU symptoms are expanded upon, and a harmonious orientation to resolving the contradictory results of existing studies might be provided.

The current research also provides important practical contributions concerning the object and content of prevention. Regarding the object of prevention, our findings highlight the importance of centering on individuals with a high BIS or high BAS-F when formulating PMPU prevention for vulnerable individuals. Regarding the content of prevention, our findings suggest that when intervening in the addictive behavior of specific individuals with a high BIS or high BAS-F, it is necessary to intervene not only in their behaviors but also in their behavioral motivations, especially their motivation for emotion regulation. Inventions could replace PMPU by guiding these individuals to adopt appropriate emotional regulation methods (e.g., mindfulness-based cognitive-behavioral intervention (78). In turn, PMPU prevention may also consider increasing the punishment for mobile phone use and decreasing rewards associated with mobile phone use.

CONCLUSION

The relationship between BIS/BAS and PMPU were examined by using network analysis. These results indicated that mood modification, tolerance, and withdrawal symptoms are central symptoms in the BIS/BAS-PMPU network. In addition, edges between mood modification, tolerance, and BIS and edge between mood modification, conflicts, and BAS-F bridge the BIS/BAS community and PMPU community. Furthermore, a new perspective on PMPU prevention is suggested by these findings. More specifically, practitioners developing interventions to overcome PMPU should consider aspects focusing on individuals who are sensitive to punishment and fun and their behavioral motivation.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of Institutional Review Board of School of Psychology, Central China Normal University. Written informed consent from the participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

LG executed the study and wrote the paper. HC and WL collaborated with the design. XC and WZ collaborated in the writing and editing of the final manuscript. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

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Psychometric Properties of the Smartphone Distraction Scale in Chinese College Students: Validity, Reliability and Influencing Factors

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Aim: The objective of this study was to evaluate the Chinese version of the Smartphone Distraction Scale (C-SDS), which is an easy-to-use tool for screening the risk of smartphone distraction in Chinese college students.

Methods: The C-SDS, Smartphone Addiction Scale - Short Version (SAS-SV), Fear of Missing Out scale (FoMO) and Metacognition about Smartphone Use Questionnaire (MSUQ) were used in a sample of 1,002 Chinese college students to test smartphone distraction and its influencing factors. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were performed to test measurement properties and factor structures of the C-SDS. Multi-variable linear regressions examined the relationships of sex, age, education level, the purpose of using a smartphone, usage of smartphone (hours per day), fear of missing out, smartphone addiction and positive and negative metacognitions about smartphone use with the C-SDS.

Results: The EFA showed a 3-factor structure, which consisted of attention impulsiveness, multitasking and emotion regulation. The CFA showed that the 3-factor demonstrated an overall better model fit ($RMSEA$ = 0.07, $SRMR$ = 0.05, CFI = 0.94, TLI = 0.93). The C-SDS showed internal consistency (Cronbach's α = 0.88, McDonald's Omega ω = 0.88). Findings included that negative metacognition about smartphone use was most correlated with the C-SDS (b = 0.73; $p < 0.001$). Smartphone addiction, positive metacognition about smartphone use and fear of missing out also correlated with the C-SDS (b = 0.66, $p < 0.001$; b = 0.53, $p < 0.001$; b = 0.40, $p < 0.001$, respectively). The study shows that males compared to females (b = –1.65; p = 0.003), had a higher C-SDS score.

Conclusion: The C-SDS was valid and reliable for assessing the distraction of using smartphones in the Chinese context. Being female, the purpose of using a smartphone, smartphone usage (hours per day), fear of missing out, smartphone addiction and positive and negative metacognitions about smartphone use were positively correlated to the C-SDS.

Keywords: distraction, smartphone use, smartphone distraction scale, reliability, validity

INTRODUCTION

With the rapid development of information technology and wireless communication, people are developing an inseparable relationship with the Internet. According to a report generated by the China Internet Network Information Center in 2021, the number of mobile Internet users had reached 1.007 billion and 99.6% of them used a smartphone (1). People aged between 10 and 29 years accounted for 29.7% of all Internet users in China (1). Today, almost every college student owns a smartphone, and they use this digital medium frequently on a daily basis (2). Digital media has many convenient and positive activities in education and entertainment of college students including online searching, accessing academic resources, communicating with instructors and peers, online payments and online shopping. However, increasing concerns exist about the negative effects of long-term use and over-reliance on digital devices.

An increasing reliance on smartphones among college students may signal the evolution of smartphone use from a habit to an addiction. To date, smartphone addiction is not currently a formally accepted diagnostic construct. However, terms like "problematic smartphone use" have been used in many studies (3, 4). Problematic smartphone use (PSU) has been defined as a non-substance or behavioral addiction that results in impaired physical, mental and social functioning (5). It typically manifests as excessive usage of a phone while undertaking other activities such as studying, driving, social gatherings and even lying on the bed before bedtime (6). The PSU rate among college students in China ranges from 28.00 to 58.33% (7, 8). For college students who use smartphones, distraction has become frequent and common. Distraction is due to a lack of interest in the topic; the absence of attention; and the great intensity, novelty or attraction of something other than the object of interest (9). It derives from both internal and external sources. Internal distractions include hunger, tiredness, illness, anxiety and daydreaming. While external distractions include factors like visual triggers, social interactions, music, text messages and telephone calls (10). The smartphone has made distraction easier, due to its portability and the diversity of entertaining features. These inattention activities can have many undesirable consequences. In 2014, 47.2% of all traffic accidents in China were caused by distracted attention when using mobile phones while driving (11). Disruption from smartphone use is even more prominent within classroom environments. Available evidence suggests that smartphone use in the classroom might be an important source of distraction (12, 13). Increasing numbers of studies have shown that the use of smartphones may interrupt main tasks, further interfering with cognitive processes and ability (14, 15), cognitive functioning (e.g., thinking, memory, attention, and regulating emotions) (16, 17) and result in poor academic outcomes among college students (18).

Attention factors related to smartphone distraction are the focus of current research. Previous research has emphasized that distraction among college students was related to multitasking and executive control abilities (19). Metacognitions refer to higher order cognitive states and coping mechanisms to regulate those cognitions (20). Metacognitions can be further divided into two domains: (a) positive metacognitions about the benefits of engaging in addictive behavior as a means of cognitive and affective regulation, such as "When I get upset Smartphone use comforts me" (21); and, (b) negative metacognitions concerning the uncontrollability and dangers of thoughts and outcomes relating to the addictive behavior employed, such as "My Smartphone use persists no matter how I try to control it" (21). In recent years, the mediating role of positive and negative metacognitions between addictive behaviors and emotion regulation has also been confirmed (20–25). Metacognitive processes were chosen for construct validity due to metacognitions having been shown to play a central role in motivating individuals to participate in smartphone addictive behaviors (26). They may also serve as a potential pathway to controlling PSU (20) through positive beliefs about cognitively controlling attention (27).

According to reports, the most important interference factor when college students use smartphones is the social media platform (28). Smartphone distraction may be caused by external triggers, such as notifications. If one receives a message or call, most people will reply in time (16). The fear of missing out is a psychological state in which other people might be having rewarding experiences from which one is absent, can become an issue (29). Previous research has shown that this fear increases the desire to remain in touch with others and is the main driver of PSU (30). Problematic smartphone use reflects a prolonged pathological engagement involving use of a smartphone, which may be mediated by distraction and constant checking (31–34). With smartphone use, distraction reflects a salient cognitive and emotive coping strategy, mediating or facilitating other potentially problematic processes (e.g., checking behaviors) (31). The Smartphone Distraction Scale (SDS) not only expresses PSU behaviors, but also expresses the psychology of college students' frequent engagement with social content (18, 35). The use of smartphone measures (metacognitions and PSU) and fear of missing out were deemed appropriate to support the validity of the C-SDS.

To the best of the researchers' knowledge, previous studies have developed several instruments for assessing smartphone distraction. These scales are limited to a few items that assess distraction and include the mobile phone distraction scale (10) and the Social Media Disorder (SMD) scale (36). While some items can assess distraction, they are neither comprehensive nor able to assess the cognitive and emotional processes of distraction. Since there is currently no tool to measure distraction caused by using a smartphone and social media in China, Feng, S et al. measured Internet use and Facebook usage to assess distraction (37). Throuvala et al. (38) recently developed the SDS to assess smartphone distraction. The SDS includes 16 items, and factor analyses revealed a four-factor solution: attention impulsiveness, online vigilance, multitasking and emotion regulation. The author of the original version found that the SDS had good reliability and validity, and recommended further research on the factorial structure of the SDS in different populations (38). The reliability and validity of the SDS has not been tested in other populations. Given the obvious dependence of performance on attention engagement, it is important to accurately assess, identify and mitigate distractions in the context of smartphones that might capture attention and undermine performance. Therefore, the current study explored the reliability and validity of the Chinese version of the SDS (C-SDS). The purpose of this study is to evaluate the reliability, validity and influencing factors of the C-SDS in order to provide psychometric tools for evaluating distraction among Chinese college students.

MATERIALS AND METHODS

Participants

According to the rough estimation of sample size, the number of participants needed to be five to ten times the number of items (39). Since the total number of items in the survey was 60, the sample size of this study should reach 300∼600. Taking a 20% dropout rate into account, at least an estimated 375∼750 participants are required. In this study, a relatively large sample size was investigated taking into account the diversity of the participants. Data collection began in September 2021 using offline and online methods and a total of 1,100 students were recruited from seven universities in Wuhan, Hubei Province to participate in this research. Offline data recruited 426 students through convenience sampling. Educators at these universities distributed the questionnaires and asked students to complete them in exchange for college credit. The online survey recruited 674 students and was administered by the Questionnaire Star platform. Participants were not allowed to submit the questionnaires until all questions were answered. The platform randomly allocated 50% of the participants to receive a small monetary reward. Inclusion criteria of participants were: (1) experience using a smartphone and (2) college student. The exclusion criteria were: (1) the inability to complete the online survey and (2) not reading a question carefully and answered the item in less than 3 min. The survey took approximately 7 min to complete. The final sample size was 1,002 participants after deleting invalid questionnaires with missing data.

Using SPSS 24 software, the final 1,002 participants were randomized into two sub-samples by a random number generator. The mean age in years for the total sample, sub-sample 1, and sub-sample 2 was 20.28 $\pm$ 1.54, 20.27 $\pm$ 1.60, and 20.30 $\pm$ 1.49, respectively. The first sub-sample (sample 1, $n = 501$) was evaluated using EFA, and the second sub-sample (sample 2, $n = 501$) was evaluated using CFA to assess population construct validity. The two sub-samples showed no difference in socio-demographic variables. Sample characteristics are shown in **Table 1**.

Procedure

The SDS was authorized by the author of the original scale and independently translated into Chinese by two nursing postgraduates who had obtained a College English Test-6 Certificate. After translation, an associate professor of nursing who had a three-year visit experience in the United States reviewed the content of the scale and proposed revisions. Back translation was performed independently by researchers who spoke fluent Chinese. One was a professor of global health in the United States and the other was a doctor of nursing in the United States.

Using convenience sampling method, 38 students (44.70% female, mean age = 20.32 $\pm$ 1.21 years) from Hubei University of Chinese Medicine were selected for pre-testing and interviews to determine if the C-SDS scale was suitable for the Chinese cultural context. The students were asked if there were any unclear and difficult choices and if each item was clear and easy to understand. The Cronbach's alpha for the total scale was 0.88 (McDonald's Omega ω = 0.89).

Measures

Socio-Demographic Characteristics and Smartphone Usage

Participants were asked their age, sex, education level and purpose of using a smartphone. According to a recent study (40), participants' reported time of daily smartphone use was coded as follows: 1 = "less than 3 h", 2 = "3–9 h", 3 = "over 9 h".

They were also asked to describe their usage of the numerous functions of smartphones, such as frequent or infrequent instant messaging, frequent or infrequent access to social media, frequent or infrequent access to music, frequent or infrequent gaming, frequent or infrequent use for learning and frequent or infrequent shopping.

Chinese Version of the Smartphone Distraction Scale

The 16-item SDS was developed by Throuvala et al. (38). This scale assesses the distraction of young people due to social media content, including four dimensions: attention impulsiveness, online vigilance, multitasking and emotion regulation. It uses a 5-point Likert scale, from 1 (almost never) to 5 (almost always), and the higher the score, the more distracted the user. This scale has evidenced adequate internal consistency, good reliability and validity (38). The C-SDS was a reliable measure (Cronbach's $\alpha = 0.88$, McDonald's Omega ω = 0.88).

Smartphone Addiction Scale-Short Version

The 10-item SAS-SV developed by Kwon et al. (41) was used in the study, and is a self-report measure of problematic smartphone usage. Items are rated using a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). This scale has shown effective reliability and validity in a sample of Chinese adults in Hong Kong (41). The SAS-SV showed good internal consistency (Cronbach's $\alpha = 0.86$, McDonald's Omega ω = 0.87).

Metacognitions About Smartphone Use Questionnaire

The 24-item MSUQ was developed by Casale et al. (21). It uses self-report measures to assess the metacognition of addictive behaviors in using a smartphone. Items are rated on a 4-point Likert scale ranging from 1 (do not agree) to 4 (agree very much). The scale has sufficient internal consistency and validity of positive metacognition concerning emotional and cognitive regulation and social advantages of smartphone use (MSUQ-PM) and negative metacognition about the uncontrollability and cognitive harm of smartphone use (MSUQ-NM). The higher the score, the higher the degree of metacognitive dysfunction

TABLE 1 | Comparison between the two samples.

	Total sample (n = 1002)	Subsample 1 (n = 501)	Subsample 2 (n = 501)	$\chi^{2/t}$	p
Male (%)	40.02%	38.10%	41.90%	1.50	p = 0.221
Female (%)	59.98%	61.90%	58.10%		
Freshman	28.80%	28.30%	29.30%	4.65	p = 0.325
Sophomore	22.80%	25.00%	20.60%		
Junior	35.00%	32.50%	37.50%		
Senior	10.20%	10.60%	9.80%		
Postgraduate	3.20%	3.60%	2.80%		
Age (M ± SD)	20.28 ± 1.54	20.27 ± 1.60	20.30 ± 1.49	–0.27	p = 0.790
C-SDS (M ± SD)	49.12 ± 8.56	48.89 ± 8.57	49.34 ± 8.56	–0.84	p = 0.403
Attention impulsiveness (M ± SD)	23.22 ± 5.14	22.96 ± 5.06	23.49 ± 5.21	–1.64	p = 0.101
Multitasking (M ± SD)	12.41 ± 2.63	12.40 ± 2.71	12.41 ± 2.55	–0.07	p = 0.943
Emotion regulation(M ± SD)	13.49 ± 2.97	13.53 ± 3.03	13.44 ± 2.91	0.49	p = 0.625
MSUQ-PM	35.37 ± 8.04	35.26 ± 8.23	35.49 ± 7.86	–0.45	p = 0.652
MSUQ-NM	23.03 ± 5.94	22.82 ± 5.91	23.25 ± 5.96	–1.15	p = 0.251
SAS-SV (M ± SD)	37.35 ± 8.17	37.05 ± 8.31	37.65 ± 8.02	–1.16	p = 0.245
FoMO (M ± SD)	28.62 ± 8.15	28.28 ± 7.94	28.96 ± 8.35	–1.33	p = 0.185

Subsample 1 = The first subsample obtained by randomly dividing the sample data into two halves; Subsample 2 = The second subsample obtained by randomly dividing the sample data into two halves. C-SDS = Chinese smartphone distraction scale; MSUQ-PM = Positive Metacognitions about Smartphone Use Questionnaire; MSUQ-NM = Negative Metacognitions about Smartphone Use Questionnaire; SAS-SV = Smartphone addiction scale-short version; FoMO = Fear of missing out scale. χ^2/t = descriptive statistical differences of variables between sample 1 and sample 2.

associated with the use of smartphones. The scale has good reliability and validity in a sample of college students in China (42). In the present sample, using the Chinese MSUQ, the Cronbach's alpha for the total scale was 0.94 (McDonald's Omega ω = 0.94), for the MSUQ-PM it was 0.94 (McDonald's Omega ω = 0.94), and for the MSUQ-NM it was 0.90 (McDonald's Omega ω = 0.90).

Fear of Missing Out Scale

The 10-item FoMO scale was developed by Przybylski et al. (29). The scale reflects current anxiety of missing out on social events and getting along with friends. Items are rated on a 4-point Likert scale ranging from 1 (not at all true of me) to 4 (extremely true of me). The scale has evidenced adequate internal consistency and good reliability and validity in multiple studies (29, 43, 44). In the present sample, the Cronbach's alpha for the FoMO was 0.90 (McDonald's Omega ω = 0.90).

Data Analyses

Descriptive statistics were used to delineate the participants' characteristics. The associations between the collected normal distribution variables were analyzed using Pearson's correlation and non-normal distribution of data using Spearman 's correlation. Internal consistency was shown by a Cronbach's alpha $\geq$ 0.70 (45) and McDonald's Omega $\geq$ 0.70 to 0.90 (46). A value of item-total correlation > 0.4 was considered acceptable (47). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (KMO, > 0.80) and Bartlett's test of sphericity ($p < 0.05$) were used to assess the suitability of the participants' data (48). *Chi-square* test, independent sample t-test, assessment of skewness and kurtosis levels, EFA, convergent validity and multi-variable linear regressions were used for data analysis. All data were analyzed using SPSS 24. The CFA was performed using MPLUS 8.0. The CFA with maximum likelihood estimator was applied to test the factorial structures.

Ethical Considerations

This study was approved by the Ethics Committee of Hubei University of Chinese Medicine (2021-ICE-015). All participants received an explanation about the purpose of the study and provided written informed consent prior to their participation.

RESULTS

As shown in **Table 1**, participants had a mean age of 20.28 (range = 17–28 years, SD = 1.54) and were primarily female (59.98%), males (40.02%). A total of 289 participants (28.80%) were freshman, 228 were sophomores (22.80%), 351 (35.00%) were juniors, 102 (10.20%) were seniors and 32 (3.20%) were postgraduates.

Participants were asked to estimate the time they spend on their smartphones each day and the smartphone applications they frequently used. Daily use time of smartphones by participants was: (3.80%) less than 3 h, more than half (69.40%) three to 9 h, and (26.80%) more than 9 h. The smartphone applications most used by participants were social media (86.90%), followed by music (73.20%), learning (40.20%), shopping (37.80%), game (36.60%) and instant messaging (22.90%).

Item Analysis of Chinese Version of the Smartphone Distraction Scale

Table 2 shows that correlation coefficients between the C-SDS and the total score ranged from 0.47 to 0.70. All results exceeded the acceptable cut-off of 0.40, indicating statistical significant ($p < 0.01$).

Construct Validity

Exploratory Factor Analysis

According to measurement of the *KMO* it was found that sampling adequacy was 0.89 for the C-SDS and Bartlett's test of

TABLE 2 | Factor loadings for the C-SDS items.

	M(SD) (*n* = 501)	Skewness (Kurtosis) (*n* = 501)	F1 (*n* = 501)	F2 (*n* = 501)	F3 (*n* = 501)	Item-total correlations (*n* = 1002)	Alpha if item deleted (*n* = 1002)
Attention impulsiveness							
4.I get distracted by my phone even when my full attention is required on other tasks.	2.70 (0.97)	0.07 (–0.63)	0.80			0.62**	0.88
3.I get distracted by just having my phone next to me.	2.81 (0.90)	0.29 (–0.26)	0.78			0.59**	0.88
7.I get distracted with what I could post while doing other tasks.	2.88 (0.86)	–0.03 (–0.48)	0.73			0.69**	0.87
1.I get distracted by my phone notifications.	3.25 (0.82)	–0.41 (0.14)	0.64			0.60**	0.88
2.I get distracted by my phone apps.	3.22 (0.81)	–0.27 (0.08)	0.63			0.62**	0.87
8.I get distracted thinking how many likes and comments I will get while doing other tasks.	2.63 (0.97)	0.12 (–0.57)	0.63			0.61**	0.88
6.I think a lot about checking my phone when I can't access it.	2.86 (0.93)	0.08 (–0.49)	0.57			0.70**	0.87
5.I get anxious if I don't check messages immediately on my phone.	2.60 (0.93)	0.37 (–0.15)	0.61			0.62**	0.88
Emotion regulation							
14.Using my phone distracts me from negative or unpleasant thoughts.	3.39 (0.88)	–0.21 (–0.12)		0.86		0.62**	0.87
16.Using my phone distracts me when I'm under pressure.	3.40 (0.92)	–0.28 (–0.18)		0.79		0.64**	0.87
15.Using my phone distracts me from tasks that are tedious or difficult.	3.36 (0.88)	–0.38 (0.08)		0.79		0.62**	0.87
13.Using my phone distracts me from doing unpleasant things.	3.39 (0.89)	–0.38 (–0.09)		0.78		0.63**	0.87
Multitasking							
12.I often talk to others while checking what's on my phone.	2.84 (0.91)	0.13 (–0.54)			0.75	0.52**	0.88
11.I often walk and use my phone at the same time.	2.98 (0.90)	0.03 (–0.41)			0.66	0.58**	0.88
10.I can easily follow conversations while using my phone.	3.27 (0.91)	–0.30 (–0.37)			0.67	0.47**	0.88
9.I use several applications on my phone while working.	3.31 (0.87)	–0.25 (–0.20)			0.55	0.51**	0.88
Total Variance Explained (%)				58.88%			
KMO				0.89			
$\chi 2(df)$				3293.93 (120)			
p				< 0.01			

$^{**}p < 0.01$.

TABLE 3 | The CFA of the C-SDS (*n* = 501).

		χ^2 *(df)*	*RMSEA [CI]*	*TLI*	*CFI*	*AIC*	*BIC*	*SRMR*
Model 1	3-factor model	440.84 (101)	0.08 [0.07–0.09]	0.88	0.90	17641.41	17856.46	0.06
Model 2	4-factor model	357.33 (98)	0.07 [0.07–0.08]	0.91	0.92	17563.90	17791.60	0.05
Model 3	3-factor model	309.54 (98)	0.07 [0.06–0.07]	0.93	0.94	17516.11	17743.80	0.05

TLI = Tucher-Lewis index; CFI = Comparative fit index; RMSEA = Root mean square error of approximation. CI = Confidence Interval; SRMR = Standardized root mean square residual.

sphericity was significant $\chi^2 = 3293.93$ ($df = 120$, $p < 0.01$). These findings indicated that the C-SDS had common factors and was suitable for factorial analysis.

When orthogonal rotation was applied and a suppressed value of < 0.50, EFA revealed a three-factor structure solution in which all factors had an eigenvalue above 1.0. After restricting the extraction of four factor structures according to the original SDS structures, the eigenvalue of the fourth factor was 0.96. The explained variances of the three-factor and four-factor structures were 58.88% and 64.85%, respectively. Parallel analysis indicated a three-factor solution. After comparison, the three-factor structure was chosen and factor loading of 16 items was

TABLE 4 | The correlations between C-SDS and other variables.

	Sex	Instant messaging	Social media	Music	Gaming	Shopping	Learning	Attention impulsiveness	Multitasking	Emotion regulation	C-SDS	FoMO	SAS-SV	MSUQ-PM	MSUQ-NM	Age	Education level	Time on smartphone
Sex	1.00																	
Instant messaging	–0.06*	1.00																
Social media	0.15**	0.08*	1.00															
Music	0.09**	0.10**	0.13**	1.00														
Gaming	–0.17**	0.13**	0.02	0.06*	1.00													
Shopping	0.26**	0.28**	0.19**	0.23**	0.15**	1.00												
Learning	0.09**	0.27**	0.08**	0.12**	0.07*	0.28**	1.00											
Attention Impulsiveness	0.08*	0.04	0.10**	0.05	0.03	0.06	–0.04	1.00										
Multitasking	0.06	0.05	0.10**	0.03	0.05	0.11**	–0.02	0.42**	1.00									
Emotion regulation	0.08*	–0.05	0.03	0.05	0.06	0.004	–0.08*	0.43**	0.45**	1.00								
C-SDS	0.09**	0.04	0.11**	0.05	0.04	0.068*	–0.07*	0.88**	0.71**	0.74**	1.00							
FoMO	–0.01	0.06	0.07*	0.02	0.08*	0.05	–0.01	0.36**	0.26**	0.25**	0.38**	1.00						
SAS-SV	0.10**	0.01	0.11**	0.08*	0.07*	0.06	–0.07*	0.61**	0.35**	0.43**	0.63**	0.32**	1.00					
MSUQ-PM	–0.03	0.00	0.04	0.06*	0.06	0.02	–0.09**	0.38**	0.34**	0.49**	0.50**	0.35**	0.43**	1.00				
MSUQ-NM	–0.07*	0.08**	0.02	0.00	0.10**	0.03	–0.03	0.52**	0.31**	0.27**	0.50**	0.44**	0.48**	0.58**	1.00			
Age	0.01	0.05	0.03	–0.08*	–0.10**	0.02	0.05	0.00	–0.04	–0.03	–0.02	–0.12**	–0.04	–0.06*	–0.07*	1.00		
Education level	0.11**	0.04	0.06	–0.04	–0.12**	0.05	0.07*	0.02	–0.03	0.01	0.00	–0.10**	–0.043	–0.06	–0.08**	0.79**	1.00	
Time on smartphone	0.05	0.00	0.02	0.10**	0.15**	0.13**	0.01	0.13**	0.16**	0.17**	0.20**	0.13**	0.19**	0.18**	0.13**	–0.11**	–0.11**	1.00

$^{*}p < 0.05$, $^{**}p < 0.01$.

TABLE 5 | Associations of variables with C-SDS score (*n* = 1002).

	Mean (SD) C-SDS score	b [95% CI]	*p*
Sex			
Female	49.78 (8.23)	Ref.	
Male	48.12 (8.96)	–1.65 [–2.73, –0.58] **	$p = 0.003$
Age		–0.12 [–0.47,0.22]	$p = 0.486$
Freshman	49.23 (8.56)	Ref.	
Sophomore	48.96 (8.27)	–0.26 [–1.75,1.23]	$p = 0.729$
Junior	49.09 (8.92)	–0.14 (–1.75,1.23)	$p = 0.834$
Senior	48.81 (8.35)	–0.42 (–2.35,1.52)	$p = 0.675$
Postgraduate	50.50 (7.76)	1.27 (–1.86,4.41)	$p = 0.426$
The purpose of using a smartphone			
Non- instant messaging	48.89 (8.46)	Ref.	
Instant messaging	49.65 (8.80)	0.76 [–0.40,1.92]	$p = 0.198$
Non-social media	46.40 (9.17)	Ref.	
Social media	49.53 (8.40)	3.13 [1.57,4.69] ***	$p < 0.001$
Non-music	48.28 (8.59)	Ref.	
Music	49.42 (8.54)	1.14 [–0.06, 2.34]	$p = 0.062$
Non-game	48.79 (8.44)	Ref.	
Game	49.68 (8.77)	0.88 [–0.22, 1.98]	$p = 0.116$
Non-shopping	48.58 (8.43)	Ref.	
Shopping	50.00 (8.73)	1.42 [0.33,2.51] *	$p = 0.011$
Non-learning	49.54 (8.54)	Ref.	
Learning	48.48 (8.57)	–1.06 [–2.14, 0.02]	$p = 0.054$
Time on smartphone (hours per day)			
$<$ 3h	45.21 (7.37)	Ref.	
$\geq$ 3 and $<$ 9h	48.35 (8.38)	3.14 [0.39,5.89] *	$p = 0.025$
$\geq$9h	51.66 (8.64)	6.45 [3.59,9.31] ***	$p < 0.001$
FoMO		0.40 [0.34,0.46] ***	$p < 0.001$
SAS-SV		0.66 [0.61,0.71] ***	$p < 0.001$
MSUQ-PM		0.53 [0.47,0.59] ***	$p < 0.001$
MSUQ-NM		0.73 [0.65,0.80] ***	$p < 0.001$

*SD = Standard deviation; CI = Confidence interval; *p < 0.05. **p < 0.01. ***p < 0.001.*

between 0.55 and 0.86 (see **Table 2**). It was found that the first factor (attention impulsiveness) measured the distraction of the smartphone itself and the distraction caused by checking online content, and explained 23.41% of the variance. The second factor (emotion regulation) measured distraction as an individual would use to relieve tension, stress and anxiety, and explained 19.69% of the variance. The third factor (multitasking) measured the simultaneous use of smartphone devices at work or walking, and explained 15.78% of the variance.

Confirmatory Factor Analysis

For the CFA, sub-sample 2 was used to compare the structural validity of the three-factor model and the four-factor model derived from the EFA conducted in sub-sample 1. In model 1, the C-SDS was defined as a three-factor model. In model 2, the C-SDS was defined as a four-factor model. To evaluate the overall model fit, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and conventional criteria was followed (49): *CFI* and *TLI* values of $>$ 0.90; *SRMR* and *RMSEA* value of $<$ 0.08 indicated a good fit. Notably, as *Chi-square* is known to be highly influenced by the sample size (50), it was not considered as a fit index in the present study. The three-factor model derived from the EFA of subsample 1 did not achieve a satisfactory fit. In model 3, a modification index (MI) that correlated item uniqueness was used for the instruments. Specifically, the uniqueness of item 1 was correlated to that of items 2, the uniqueness of item 9 was correlated to that of items 12, the uniqueness of item 14 and 16 were correlated to improve the fit indices. Finally, the modified C-SDS model 3 showed satisfactory fit indices [χ^2 = 309.54, df = 98, p < 0.01; TLI = 0.93; CFI = 0.94; $SRMR$ = 0.05; $RMSEA$ = 0.07; 90% CI (0.06, 0.07)] (see **Table 3**).

Convergent Validity Analysis

Spearman's correlation was used to analyze the correlation between the C-SDS and sex, education level, usage of smartphone (hours per day), instant messaging, social media use, music, gaming, shopping and learning applications. Pearson's correlations between the C-SDS and age, attention impulsiveness, multitasking, emotion regulation, FoMO, SAS-SV, MSUQ-PM, and MSUQ-NM are shown in **Table 4**. The C-SDS scores were positively correlated with the SAS-SV scores, the MSUQ-PM, MSUQ-NM scores and the FoMO scores. Correlation coefficients ranged from 0.38 to 0.63.

Reliability Analysis

According to some scholars, McDonald's Omega (ω) provides more accurate reliability results for applied research (51, 52). Cronbach's alpha (α) and McDonald's Omega (ω) were used to assess the internal consistency of each scale. The Cronbach's alphas of the scale were 0.88 (C-SDS), 0.87 (attention impulsiveness), 0.71 (multitasking) and 0.87 (emotion regulation). McDonald's Omega was highest for emotion regulation (ω = 0.87), followed by attention impulsiveness (ω = 0.87), and multitasking (ω = 0.71).

Correlation Between Related Variables and Chinese Version of the Smartphone Distraction Scale Score

Table 5 shows that males have lower C-SDS scores than females (b = −1.65; 95% CI = −2.73, −0.58; p = 0.003). Compared with those who used social media infrequently, respondents who used social media frequently had higher C-SDS scores (b = 3.13; 95% CI = 1.57, 4.69; $p < 0.001$); participants who shopped frequently had higher C-SDS scores than those who shopped infrequently (b = 1.42; 95% CI = 0.33, 2.51; p = 0.011). This study also showed that using a smartphone for " ≥ 3h/d and < 9h/d" (b = 3.14; 95% CI = 0.39, 5.89; p = 0.025) and " ≥ 9h/d" (b = 6.45; 95% CI = 3.59, 9.31; $p < 0.001$) had a higher C-SDS score than using a smartphone for " < 3h/d". In addition, it was found that fear of missing out (b = 0.40; 95% CI = 0.34, 0.46; $p < 0.001$), SAS-SV (b = 0.66; 95% CI = 0.61, 0.71; $p < 0.001$), positive metacognition about smartphone use (b = 0.53; 95% CI = 0.47, 0.59; $p < 0.001$), and negative metacognition about smartphone use (b = 0.73; 95% CI = 0.65, 0.80; $p < 0.001$) were related to the high risk of the C-SDS. However, it was found that age, education level, instant messaging, music, games and learning applications had no significant effect on C-SDS.

DISCUSSION

This is the first study to examine the psychometric properties of the C-SDS in a sample of Chinese college students. The C-SDS showed good internal consistency (Cronbach's α = 0.88). A three-factor C-SDS model and a four-factor C-SDS model were also compared. However, according to model fitting indicators, the three -factor model with attention impulsiveness, multitasking and emotion regulation was considered as a better fit for evaluating smartphone distraction.

The model of this study was different from the parent version (38). The EFA results showed that attentional impulsiveness and online vigilance were on the same dimension. There are two possible reasons. First, there may be differences among the participants themselves. Second, this may be due to the distraction of the smartphone device itself and checking social media content in common. A previous study showed that college students' use of smartphones was mainly due to checking social media content (28). Ultimately, the authors chose attentional impulsiveness as the first factor.

As a cognitive mechanism in a digital environment, distraction has been only partially evaluated in previous scales, such as the attention and executive function rating inventory scale (53) and problem Internet use scale (54). Since many existing psychometric scales are limited to a few items, they are neither comprehensive nor can they represent the complexity of a smartphone use experience or the frequent lack of attention and related processes experienced by smartphone users. For example, the recently introduced SMD scale is able to assess social media addiction. Since it was originally developed for teenagers, in the Chinese context, some items may not apply to most college students whose parents rarely supervise their smartphone use (36). The C-SDS not only assesses cognitive and emotional processes of distraction and PSU, but also applies to college students. Future research should focus on different age groups. The findings of this study supported the C-SDS as a useful tool to measure smartphone distraction in Chinese college students, which can further be used to measure the psychological experience of PSU. The C-SDS will facilitate its assessment in academic institutions and work-related environments, generating further multidisciplinary scientific knowledge about this disruptive construct and its relation to mental health in smartphone use.

The results of this study showed that fear of missing out, smartphone addiction and metacognitions about smartphone use are positively correlated with smartphone distraction. These results further support the psychopathology of smartphone distraction. In fact, earlier studies linking distraction and metacognition were based on auditory distraction (55). This finding supports recent studies that positive and negative metacognitions about smartphone use could predict PSU levels (20, 21, 42). The current study results also add to the evidence about the relationship between metacognition and distraction (38). It is worth noting that the MSUQ-NM is more strongly related to smartphone distraction than the MSUQ-PM. Previous studies used the attention control scale to assess the resistance to distraction and ability to prioritize attention. It was found that the MSUQ-NM would be negatively correlated with dimensions of attentional control (attention focusing and attention shifting) (56). This may be due to the reduced self-regulation ability of the MSUQ-NM, which further promotes distraction (27). In addition, a previous study showed that positive metacognition appears to mediate the relationship between fear of missing out and problematic social media use (25). Similarly, this result supports previous research that fear of missing out is related to PSU and social media use (57, 58). This may be due to the fear of missing out causing people to frequently keep in touch with others through social networks (57). Consistent with previous research results, smartphone addiction caused by frequent use of smartphones can distract us (59). This may be a common result of smartphone use related to cognitive interference and interruptions (60–62).

Consistent with previous studies, it was found that females were more susceptible to smartphone distraction than males (38, 63, 64). A possible reason is that women are more attached to their smartphones than males in order to establish contact and maintain social connections (63). In this study, no significant effects were found in terms of age and education level. This is inconsistent with the results of previous studies, which have shown that age was a negative predictor of PSU (41, 65). These results need to be interpreted cautiously since the current sample was composed of college students.

This study showed that increased time spent on smartphones was positively related to smartphone distraction. It is inconsistent with the previous result that the relationship between distraction and smartphone use was not significant (32). This may be due to the fact that previous studies did not measure the scale of distraction and used mindfulness measures to measure distraction through reverse scores.

The current study also found that participants who frequently used social media and shopping were more distracted than those who did not use it often. Compared with shopping, social media has a greater relationship with smartphone distractions. This may be due to the fact that social media content has largely contributed to the attention drift caused by the frequent and prolonged use of smartphones among students (66). In the future, more studies including the elderly are needed to clarify these points.

Limitations

This study had some limitations. First, it is not certain whether the distraction scores of smartphone users are different in various age groups due to using a convenience self-selected sample of college students. Therefore, future studies should explore distraction in varied age groups, such as drivers, workers, retired older adults and clinical samples. Second, the results obtained from self-reported questionnaires may have biases of social desirability and recall. Third, the sex invariance and retest reliability of the C-SDS should be examined in future studies. Sex invariance would provide important support for the validity of the C-SDS because it would indicate that the measurement model is comparable for men and women. Lastly, more longitudinal studies or experimental studies are needed to further explore the causal relationship between smartphone distraction and metacognition for PSU.

CONCLUSION

In conclusion, the C-SDS was found to be valid and reliable among Chinese college students. This study not only identified that sex, the purpose of using a smartphone, smartphone usage (hours per day), fear of missing out, PSU and positive and negative metacognitions about smartphone use were related to smartphone distraction, but also added arguments for applying distraction theory to understanding smartphone addiction. Future investigations are needed to assist in developing potential prevention programs for college students' smartphone distraction.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

This study was approved by the Ethics Committee of Hubei University of Chinese Medicine (2021-ICE-015). Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

FY and XZ designed the study and wrote the protocol. TH, CL, and MW conducted literature searches and provided summaries of previous research studies. XZ, TH, and JZ conducted the statistical analysis. XZ wrote the manuscript. JZ and GQ provided language help. All authors have contributed to the manuscript and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2022.859640/full#supplementary-material

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