ADVERSE HEALTH CONSEQUENCES OF EXCESSIVE SMARTPHONE USAGE, VOLUME II

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ADVERSE HEALTH CONSEQUENCES OF EXCESSIVE SMARTPHONE USAGE, VOLUME II

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Editorial: Adverse health consequences of excessive smartphone usage, volume II

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KEYWORDS

excessive smartphone usage, problematic smartphone usage, adverse health consequences, anxiety and negative emotion, emotional and physical wellbeing problems

Editorial on the Research Topic
Adverse health consequences of excessive smartphone usage, volume II

Excessive smartphone usage has diverse negative social, emotional, and physical wellbeing consequences and may lead to self-control and productivity problems as reviewed in Buscha and McCarthy (1). This special topic on *Adverse health consequences of excessive smartphone usage, volume II* covers the latest research results on anxiety, negative emotion, and physical health issues.

Anxiety

Problematic smartphone use is related to anxiety and depression. Jiang's work in this collection investigated college students' anxiety during COVID-19 pandemics. This work identified the positive relationship between problematic social media usage and anxiety, and the mediating role of psychological capital (e.g., self-efficacy and resilience). Students' level of academic burnout moderated this relationship, with a stronger correlation among burnt-out students. Dai et al.'s work deepened our understanding of social anxiety by conducting a qualitative study. They offered detailed patterns of how college students experienced nomophobia (fear of being disconnected), phubbing (preferring online communications to face-to-face communications), and fear of missing out on social media usage. Among these anxiety-inducing factors, Servidio et al. studied how self-construal (i.e., independent vs. interdependent) is related to the fear of missing out, and its relationship with problematic phone usage. Their findings showed that interdependent self-construal was positively related to the fear of missing out and problematic phone usage.

Emotional wellbeing

Bai et al. studied the relationship between social media usage and subjective wellbeing (e.g., emotion, satisfaction) and the mediating role of boredom proneness. They found that problematic social media usage has a negative impact on a user's subjective wellbeing, and boredom proneness mediated the relationship between problematic social media usage and subjective wellbeing. Park further studied people with visual impairment and showed that types of smartphone use are related to emotion and loneliness; for example, leisure or information search are positively related to negative emotion, but communication showed the opposite effect. Wang et al. studied the mediating role of negative emotion on the relationship between perceived stress and problematic smartphone usage among medical college students in China. Their study revealed that perceived stress and negative emotions were positively related to problematic smartphone usage.

Physical wellbeing

This topic collection also includes two papers that reported the negative consequences of physical wellbeing (e.g., headaches, sleep disturbances, gastrointestinal problems, and dry eye symptoms). Reer et al. studied the relationship between problematic phone usage and emotional wellbeing (i.e., stress, anxiety, and loneliness) and the relationship between emotional wellbeing and physical symptoms such as headaches and sleep disturbances. Their work clearly showed that problematic smartphone usage is positively associated with both negative emotional wellbeing (i.e., higher loneliness, stress, and anxiety) and physical wellbeing (i.e., frequent headaches, and sleep disturbances). Abusamak et al. examined digital eye strain symptoms during the COVID-19 pandemics. Their findings showed that digital device usage has significantly increased during pandemics, which are positively related to physical symptoms such as headaches and neck/shoulder pain. Furthermore, usage duration is positively related to the severity of eye symptoms and the possibility of developing new eye complaints.

While problematic phone usage has various negative consequences as reported in this collection, Moshe et al. showed that mobile phone sensing offers new opportunities to proactively deal with various wellbeing issues. Recent smartphones are equipped with various sensors (e.g., GPS, sound, light) and interaction logging features (e.g., phone usage). Their work showed that applying data mining and machine learning techniques allow us to infer and predict potential negative consequences (e.g., depression and anxiety). This kind of smartphone sensing offers new opportunities for enabling just-in-time intervention for negative social, emotional, and physical wellbeing situations as illustrated in Lee et al. (2).

Author contributions

UL wrote the draft. PL reviewed and provided feedback. 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.

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BRIEF RESEARCH REPORT
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The Relationship Between the Use of Mobile Social Media and Subjective Well-Being: The Mediating Effect of Boredom Proneness

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Objective: This study took users of short-form mobile videos as research participants to explore the role of their boredom proneness in mediating the relationship between the use of mobile social media (UMSM) and subjective well-being (SWB).

Methods: A sample of 656 users was evaluated by the Problematic Mobile Social Media Usage Assessment Questionnaire, General Well-Being Schedule, and Boredom Proneness Scale.

Results: Firstly, significant interactions were found between monthly living expenses and the UMSM of the participants, which were recognized as factors affecting SWB. Secondly, the level of living expenses had little effect on the high-level and low-level groups of the UMSM but imposed a significant impact on the medium-level group. Thirdly, the UMSM showed an influence that could positively predict boredom; both the UMSM and boredom demonstrated a negative predictive effect on SWB.

Conclusion: The findings indicate that the inappropriate use of mobile social media negatively affects users' subjective well-being; boredom partially mediated the relationship between the use of mobile social media and SWB.

Keywords: short video, problematic use of mobile social-media, subjective well-being/SWB, the boredom proneness, network environment

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INTRODUCTION

In recent years, mobile social media have been used by more and more people due to its convenience. Although online social activities have become a supplement to the offline social life to a certain extent, excessive dependence on the Internet would inevitably induce more or less negative effects on the users (Jiang, 2018a). For instance, a decrease in subjective well-being was reported in individuals with Internet addiction (AFROZ, 2016; Mei et al., 2016; Nie et al., 2016; Koç, 2017; Suresh et al., 2018).

Subjective Well-Being and the Use of Mobile Social Media

Subjective well-being (SWB) is a subjective, holistic, and relative indicator, which is widely used in psychological research as an overall assessment of the quality of life (Diener, 1984). SWB is also regarded as one of the standards for measuring mental health. People with high-level SWB could experience a higher level of self-esteem (Joshanloo and Daemi, 2015) and be more tolerant of others (Datu, 2013). Several factors have been reported to be effective to influence SWB (Yamaguchi et al., 2013), such as individual personality traits, style of attribution, physical health, socioeconomic status, social support, etc. (Diener et al., 2013; López Ulloa et al., 2013; Zhang et al., 2014). Among the affecting factors, the critical role of social support has been repeatedly verified (Khan and Husain, 2010; Wang, 2014; Tian et al., 2015). When people obtained more social support, they experienced less loneliness and more happiness (Q. Tian, 2014). In contrast, people with less social support are likely to turn to mobile social media to get noticed (e.g., by posting a tweet and attracting comments). Some studies have shown that using mobile social media can strengthen the connection with others and provide social support, to help people enhance their SWB (Boyd and Ellison, 2007; Koroleva et al., 2011; Wenninger et al., 2018). However, with the advancement of research, it has been demonstrated that individuals who use mobile social media frequently are more inclined to develop addictive behaviors, which may cause a series of negative effects such as anxiety, depression, etc. (Labrague, 2014). The improper use of mobile social media imposes negative impacts on people both physically and psychologically, thereby affecting their SWB (Hanprathet et al., 2015; Hawi and Samaha, 2016). A negative correlation has been found between the levels of SWB and problematic use of the Internet (AFROZ, 2016; Mei et al., 2016; Nie et al., 2016; Koç, 2017; Suresh et al., 2018).

Boredom Proneness and SWB

Boredom is a state of being weary and restless through lack of interest. Also, boredom proneness refers to a persistent personality trait reflecting how easy an individual is apt to feel bored (Farmer and Sundberg, 1986; Eastwood et al., 2012). The individual feels bored when the environment cannot provide enough emotional stimuli. One with higher boredom proneness is more possible to generate negative emotions, which may lead to depression, anxiety, loneliness, and lower levels of SWB (German and Latkin, 2012). Thus, individuals tend to look for something new and exciting from the environment to alleviate boredom (Skues et al., 2015). Once an individual becomes overdependent on a stimulus that was novel, the adaptation to the novelty can reduce the interest and lead to new boredom. On the contrary, boredom proneness also acts as a predictor of the overdependence on a certain object. It was suggested that individuals whose personality trait is easy to feel bored are more possible to indicate Internet addiction (Chaney and Blalock, 2006). Titilope (2014) examined the use of mobile phones from a psychosocial dimension and found that boredom proneness could significantly predict the degree of dependence on mobile phones in adolescents. Leung (2008) found that people who were more likely to be bored used mobile phones more frequently. So, the interplay between boredom proneness and excessive reliance on certain specific activities or tools appears mutual and complex. In the latest decade, the use of mobile social media keeps rising, owing to the increasing interest of people in the new product that integrates features of the Internet and mobile phone. Nevertheless, to answer the question whether the gradually unfolding dependence on mobile social media is associated with boredom proneness, further investigations are still necessary.

In addition, a negative correlation between boredom proneness and SWB has been revealed. Individuals manifesting a high degree of boredom tended to show negative emotions and a lower level of SWB (German and Latkin, 2012). The study by Wang et al. (2014) confirmed that boredom proneness could negatively predict SWB. Combined with the aforementioned evidence indicating the links between the use of mobile social media and SWB, the two variables and boredom proneness constitute a new psychological framework. Rosen et al. (2013) suggested that bored people utilized social networks to relieve their boredom. In the Internet environment, it seems feasible to reduce the boredom by using the Internet appropriately and consequently improve SWB (Rosen et al., 2013; Greyling, 2018). A number of investigations have also been carried out focusing on the relationship between Internet-based utility and negative emotions (Bozoglan et al., 2013; Banjanin et al., 2015; Chen et al., 2019), whereas few studies have explored the role of boredom in the interrelationship between Internet use and SWB.

Aims and Hypotheses

Some evidence has proven that social media imposed a significant effect on SWB (Uysal et al., 2013; Brooks, 2015). However, the mechanism underlying the interactions remains ambiguous (Nie et al., 2016). In our study, we surveyed users of short video who had habitual use of Internet-based social media, to figure out the pathways on how the individuals' well-being is influenced by the improper use of social media and boredom proneness in the cyber world.

Given that boredom proneness is related to the use of social media and enables the prediction of the level of SWB, the current study raised the following hypotheses: (1) correlations exist among the use of mobile social media, boredom proneness, and SWB; (2) boredom proneness is a mediator variable between the problematic use of mobile social media and SWB, which means that the problematic use of mobile social media affects SWB *via* boredom proneness.

MATERIALS AND METHODS

Ethics

The recruitment of participants for this study was approved by the Ethics Committee of the Department of Psychology, Beijing Forestry University. A survey was carried out with all the participants online or offline. All data were collected with the consent of the participants. Before the survey, the participants were informed about the research content and their rights.

Participants

In this study, an online questionnaire survey platform called "Questionnaire Star"[1], as well as offline questionnaires, was used to collect data on the use of mobile social media from

[1] https://www.wjx.cn/

short-video users. Due to the COVID-19 pandemic and the restriction of close social contact, the offline data collection could not continue. As a result, a mix of online and offline data collection was adopted.

After eliminating unqualified questionnaires (e.g., questionnaires that were filled out randomly), a total of 656 valid samples were collected, including 237 male samples (36.1%) and 419 female samples (63.9%).

Measures

Problematic Use of Mobile Social Media

The Problematic Mobile Social Media Usage Assessment Questionnaire developed by Jiang (2018b) was used in this study. This questionnaire includes 20 questions, divided into five subdimensions, which are used to measure five different aspects of the use of mobile social media (UMSM). (1) *Viscosity increase* is used to measure the time length, frequency, and intensity of the use of mobile social media. For example, "Always extend the time of using mobile social-media without awareness" and "I have a certain dependence on mobile social-media, and sometimes cannot control the using time." A higher score on this factor means that individuals use mobile social media for a longer time and more frequently and individuals are more dependent on mobile social media. (2) *Physiological damage* refers to the negative physical responses of individuals after excessive use of mobile social media, such as impaired vision, lack of sleep, shoulder pain, etc. A higher score on this factor means that the use of mobile social media has caused more serious physiological damage to individuals. To some certain extent, the improper use of mobile social media can be reflected by a physical condition. (3) *Omission anxiety* refers to the anxiety caused by individuals' concerns about missing messages due to their inability to check their mobile social media in time. A higher score on this factor indicates a higher level of anxiety caused by an individual's uncontrollable worry about missing information. This emotion could affect people's concentration on their ongoing tasks. (4) *Cognitive failure* refers to the negative consequences of using mobile social media for cognition, such as memory loss and thinking stagnant. "Due to the convenience of mobile phones and mobile networks, I rarely remember things by myself, which made my memory gradually decline." "Because of excessive dependence on the mobile social media, a great amount of information is no longer needed to be thought and processed by individuals, which dulls our mind and causes memory loss." This is also a manifestation of excessive reliance on mobile social media. (5) *Guilt* is the feeling of being unable to complete an individual's work or study schedule on time due to using mobile social media for a long time, for example, "I often regret wasting too much time on mobile social media." This feeling may make the individual fall into constant self-blame and compunction. A higher score on this factor indicates that an individual feels guiltier for not completing a task on schedule due to unreasonable arrangement of using mobile social media. All items are scored from "1 = not at all" to "5 = completely true." The higher total score of the UMSM represents the higher tendency in the problematic use of mobile social media. In this study, the internal consistency coefficient of the scale was 0.93, showing that this scale was highly reliable in the survey.

Subjective Well-Being

The Overall Happiness Scale revised by Duan (1996) was used in this study. The scale has 18 items, covering satisfaction and interest of life, energy, concerns about health, depressed or positive emotions, and control of emotions and behavior, as well as tension and relaxation. A higher score on this scale means a higher level of SWB. In this study, the internal consistency coefficient of the scale was 0.84, revealing its high reliability.

Boredom Proneness

The Boredom Proneness Scale was developed by Huang et al. (2010). The questionnaire has a total of 30 items, including two dimensions—external stimuli and internal stimuli. The external stimuli include four factors, and they are monotony, loneliness, tension, and restraint. On the other hand, the internal stimuli include two factors, and they are self-control and creativity. All items are scored from "1 = not at all" to "5 = completely true." In this study, we only used the total score to measure the individual's boredom proneness. Individuals showing a higher total score of boredom proneness are characterized by higher boredom proneness and the tendency to be bored easily. The internal consistency coefficient of the scale was 0.92 in the current study.

Data Processing

All data were processed and analyzed by using statistical software SPSS 24.0. A series of analyses were implemented to check the systematic errors and explore the relationship among various psychological variables.

A common method bias test was conducted to find out whether the properties of the data in this study affected the results. The common method bias is a systematic error which can be attributed to several environmental factors, such as the experimental settings, the way how the participants answer the questionnaires, and so forth. These factors can enlarge the errors and bias the final results of the study. Therefore, the aim of the implementation of the common method bias effect testing was to confirm whether such systematic error exists in our collected dataset. According to the test method introduced by Zhou and Long (2004), the method of "separating the first common factor" was used to compare the model fitting degree before and after controlling the deviation of the common method.

After we eliminated the possibility of common method biases, we performed the variance tests to explore the significance in the use of mobile social media, SWB, and boredom proneness, influenced by differences in gender, age, daily short-video viewing duration, and daily mobile social media usage time.

The Pearson correlation analysis was conducted to examine the correlations between pairs of variables, followed by a stepwise regression analysis to explore the linear relationship between the five factors of the use of mobile social media and SWB.

We also used a two-factor ANOVA to analyze whether the main effects of demographic variables and the use of mobile social media exist to influence SWB, as well as the potential interaction

TABLE 1 | The results of difference analysis on UMSM.

Variable	Number	UMSM	t/F	p
Gender				
Male	237	3.28 ± 0.82	2.825**	0.005
Female	419	3.10 ± 0.78		
Age				
Under the age of 18	95	2.84 ± 0.78	11.382***	0.000
Aged 18–24	426	3.25 ± 0.76		
Aged 24 and above	135	3.10 ± 0.80		

*UMSM, use of mobile social media; **correlation is significant at the 0.01 level (two tailed); ***correlation is significant at the 0.001 level (two tailed).*

TABLE 2 | The results of difference analysis on SWB.

Variable	Number	SWB	t/F	p
Gender				
Male	237	4.25 ± 0.70	−1.986*	0.047
Female	419	4.37 ± 0.77		
Age				
Under the age of 18	95	4.38 ± 0.78	2.418	0.09
Aged 18–24	426	4.28 ± 0.75		
Aged 24 and above	135	4.44 ± 0.74		

*SWB, subjective well-being. *Correlation is significant at the 0.05 level (two tailed).*

between the two factors. Notably, among the demographic variables of the participants, we focused on the "monthly living expenses," as we considered it an indicator of an individual's economic status, which might be related to SWB. Finally, the PROCESS 2.1 program and bootstrap method were employed to verify the mediating effect of boredom proneness.

RESULTS

Common Method Bias Test

The results of the single-factor test showed that for the 12 factors with eigenvalues greater than 1, the first factor explained 26.04% of the variation, which was lower than the critical value of 40%. Therefore, the common method deviation had little effect on the following analyses (see **Supplementary Table 1**).

Descriptive Statistics and Difference Tests

Gender, age, daily viewing duration of short videos, and daily usage time of mobile social media were utilized as grouping variables for the short-video users in the t-tests or one-way ANOVA analyses, which were carried out to examine the differences caused by the demographic factors in UMSM, SWB, and boredom proneness. The results are shown in **Tables 1–3** and **Supplementary Tables 2–4**.

Males' total scores of the UMSM and boredom proneness were higher than those of females (t = 2.825, p < 0.005; t = 4.377, p < 0.000); males' SWB score was significantly lower than that of females (t = −1.986, p < 0.047).

TABLE 3 | The results of difference analysis on BP.

Variable	Number	BP	t/F	p
Gender				
Male	237	3.62 ± 0.92	4.377***	0.000
Female	419	3.29 ± 0.90		
Age				
Under the age of 18	95	3.66 ± 0.92	8.366***	0.000
Aged 18–24	426	3.43 ± 0.88		
Aged 24 and above	135	3.17 ± 0.99		

*BP, boredom proneness. ***Correlation is significant at the 0.001 level (two tailed).*

Significant differences among different age groups were found in scores of both UMSM and boredom proneness (F = 11.382, p < 0.000; F = 8.366, p < 0.000). The following multiple comparisons showed that, regarding the UMSM scores, the group "Under the age of 18" had lower scores than the group "Aged 18–24" and the group "Aged 24 and above."

For the scores of boredom proneness, the group "Under the age of 18" had higher scores than the group "Aged 18–24," and the group "Aged 18–24" had higher scores than the group "Aged 24 and above." That is, boredom proneness decreased with age.

Correlation Among Boredom Proneness, UMSM, and SWB

This study used the Pearson correlation to analyze the relationship among boredom proneness, UMSM, and SWB. In **Table 4**, it suggested that SWB showed a significantly negative correlation with the UMSM; boredom proneness showed a significantly positive correlation with the UMSM and a significantly negative correlation with SWB.

According to the total score of the UMSM, participants were divided into the high-level group (the top 27%), medium-level group (the middle 46%), and low-level group (the bottom 27%). The independent sample test was used to compare SWB and boredom proneness between groups of high and low levels. The results showed that the SWB of the low-level group was significantly higher than that of the high-level group (t = 9.996, p < 0.001), and the low-level group had significantly lower boredom proneness than the high-level group (t = −10.807, p < 0.001).

In the group with low-level UMSM, the Pearson correlation coefficient (PCC) between the UMSM and SWB was −0.200 (p < 0.01), and the PCC between the SWB and boredom proneness was −0.446 (p < 0.001). In the high-level group, the PCC between the UMSM and SWB was −0.162 (p < 0.05), the PCC between the UMSM and boredom proneness was 0.244 (p < 0.01), and the PCC between SWB and boredom proneness was −0.575 (p < 0.001). In the medium-score group, there was no correlation between the UMSM and SWB, and the PCC between the SWB and boredom proneness was −0.576 (p < 0.001) (**Supplementary Tables 5–7**).

Main Effects and Interaction Analysis

A two-factor ANOVA analysis was implemented to explore the main effects of the UMSM and monthly living expenses

TABLE 4 | Correlation between variables.

	M	*SD*	1	2	3	4	5	6	7	8
(1) SWB	4.33	0.75	1							
(2) UMSM	3.16	0.80	−0.392***	1						
(3) Viscosity increase	3.49	0.93	−0.260***	0.801***	1					
(4) Physiological damage	2.99	0.95	−0.346***	0.847***	0.547***	1				
(5) Omission anxiety	3.06	0.99	−0.354***	0.851***	0.636***	0.635***	1			
(6) Cognitive failure	3.07	0.95	−0.343***	0.837***	0.527***	0.647***	0.652***	1		
(7) Guilt	3.17	1.19	−0.295***	0.698***	0.426***	0.528***	0.492***	0.610***	1	
(8) BP	3.41	0.92	−0.604***	0.420***	0.307***	0.341***	0.368***	0.383***	0.313***	1

*UMSM, use of mobile social media; SWB, subjective well-being; BP, boredom proneness; ***correlation is significant at the 0.001 level (two tailed).*

on SWB, as well as the possible interaction between the two factors. Multiple levels of each factor were taken into the analysis. As a result, the main effect of the UMSM on SWB was significant (F = 43.77, p < 0.001); the main effect of monthly living expenses on SWB was not significant (F = 0.02, p > 0.05), whereas the interaction between the UMSM and monthly living expenses was significant (F = 3.943, p < 0.05).

Further simple effect analysis revealed that for the groups with high- and low-level UMSM, living expenses had no significant effect on SWB; for the group with medium-level UMSM, the SWB of participants reporting high living expenses (more than CNY 2,000) was higher than that of participants reporting low living expenses (less than CNY 2,000) (p < 0.05). The results demonstrated that different levels of living expenses are related to discrepancies in SWB, which is valid only for the group showing medium-level UMSM (see **Figure 1**).

Regression Analysis of the UMSM and SWB

Multiple stepwise regression analysis was performed based on the correlation analysis. The SWB was used as the dependent variable, and the five factors constituting the UMSM were used as the predictor variables. As shown in **Table 5**, three of the five factors—omission anxiety, physiological damage, and guilt—exerted negative predictive effects on the SWB of short-video users (β = −0.148, p < 0.001; β = −0.128, p < 0.01; β = −0.072, p < 0.01); the contribution rates reached 12.4, 14.8, and 15.5%, respectively.

The Mediating Effect of Boredom Proneness

On basis of the test method proposed by Ye and Wen (2013), we examined the mediating effect of boredom proneness on the relationship between the UMSM and SWB. The result showed

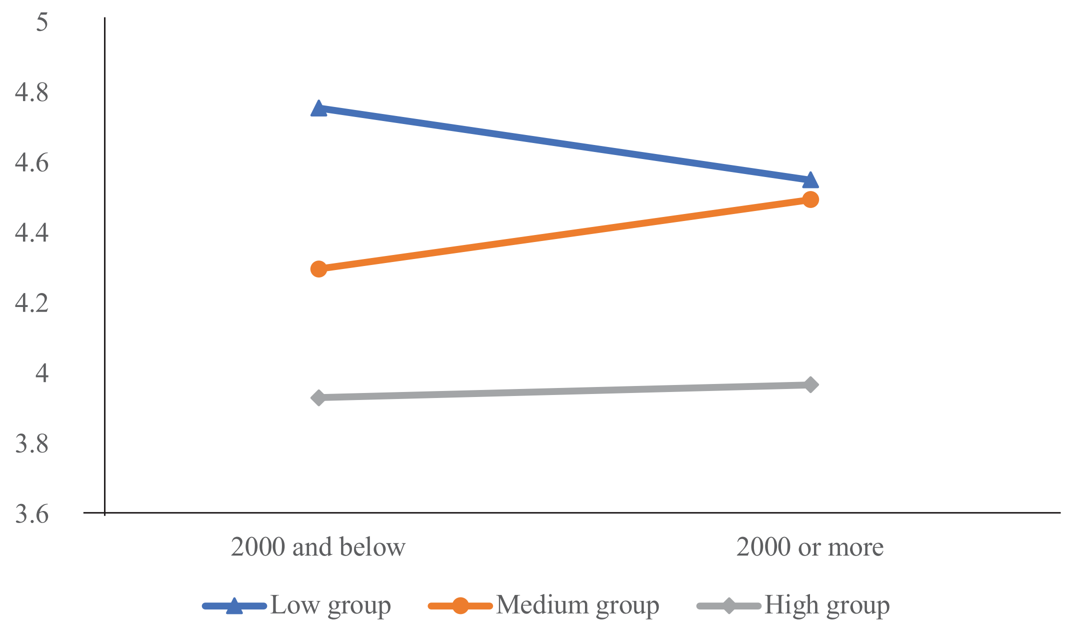

FIGURE 1 | Interaction between living expense and mobile social media use on SWB. A 3 (use of mobile social media) * 2 (living expense) analysis of variance to show the interaction between the two factors.

TABLE 5 | Regression analysis of the use of mobile social media and SWB.

Dependent variable	Independent variable	R	R^2	ΔR^2	F	β	Beta	t
SWB	Omission anxiety	0.354	0.124	0.126	93.877	−0.148	−0.195	−4.085***
	Physiological damage	0.388	0.148	0.025	57.717	−0.128	−0.162	−3.309**
	Guilt	0.399	0.155	0.009	41.081	−0.072	−0.113	−2.605**

*SWB, subjective well-being; **correlation is significant at the 0.01 level (two tailed); ***correlation is significant at the 0.001 level (two tailed).*

that the UMSM enabled a significantly negative prediction of SWB (β = −0.1683, $p < 0.001$). Boredom proneness allowed a significantly negative prediction of SWB as well (β = −0.5334, $p < 0.001$). The UMSM gave rise to a significantly positive prediction of boredom proneness (β = 0.4202, $p < 0.001$), indicating that boredom proneness played a partial mediating role in the interplay between the UMSM and SWB. In summary, the mediation model hypothesized in this study was supported (see **Figure 2**).

In order to verify the model, this study used the PROCESS program compiled by Hayes to conduct the bootstrap test (5,000 times). The result showed that the confidence interval of 95% for the UMSM to influence SWB through boredom proneness was [−0.2848, −0.1728] (see **Table 6**).

DISCUSSION

Demographic Analysis of the UMSM, SWB, and Boredom Tendency

Results of the descriptive statistics showed that there were gender differences in the UMSM. Males' scores on the UMSM were significantly higher than females' scores. That is to say, males tend to have more problematic use of mobile social media than females. This was consistent with the result of previous research (Tomaszek and Muchacka-Cymerman, 2019). On the overall score of SWB, females' score was significantly higher than that of males, which may be caused by the different motivations of males and females on using mobile social media and their different preferences on specific functions when using it. Males are more inclined to use mobile social media for work-related instrumental purposes, while females use it more as a way to communicate

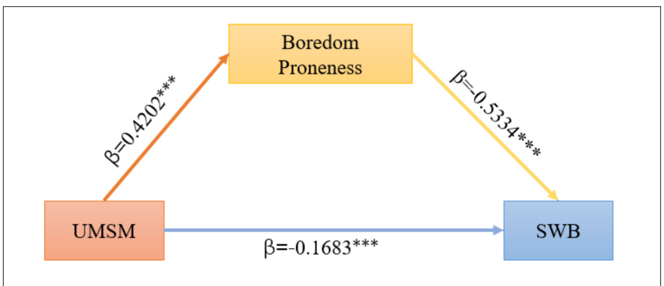

FIGURE 2 | The mediating effect of boredom proneness. Test of the mediating role of boredom proneness between the use of mobile social media and subjective well-being. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. UMSM, use of mobile social media; SWB, subjective well-being; *correlation is significant at the 0.05 level (two tailed); **correlation is significant at the 0.01 level (two tailed); ***correlation is significant at the 0.001 level (two tailed).

with important people, maintain contact, or perform some entertainment activities to achieve satisfaction (Walsh et al., 2011). This is the reason why females' SWB is higher. At the same time, this study found that the longer time individuals use mobile social media, the lower SWB they could perceive.

Moreover, there were differences in the scores of the UMSM and boredom proneness of different age groups. There was no difference in SWB among different age groups, which showed that SWB of short-video users was not affected by age. That is, in the long run, SWB is a relatively stable measure (Diener, 1984). For the scores of the UMSM, the users in the "Under the age of 18" group showed lower scores than those in the "Aged 18–24" group, and the users in the "Aged 18–24" group presented lower scores than those in the "Aged 24 and above" group. Overall, the tendency of problematic use of mobile social media increases with age. As to the scores of boredom proneness, the "Under the age of 18" group had higher scores than the "Aged 18–24" group, and the "Aged 18–24" group had higher scores than the "Aged 24 and above" group. That is, boredom proneness decreases with age. In China, most of the teenagers under the age of 18 are trapped in academic stress and do not have enough time for extracurricular activities out of school, particularly using mobile phones, which is usually limited under the supervision of parents. When staying in a highly constrained environment, people often feel more bored (Chin et al., 2017). Besides, numerous students feel caught by rigid routines from which they cannot escape (Daschmann et al., 2011). As the students grow up, the time at their disposal increases proportionally, by which they are able to engage in more activities according to their own ideas, to enrich their lives.

The result of the main effect and simple effect analyses showed that after dividing the tendency of problematic use of mobile social media into three groups of high, medium, and low level, it can be found that there were significant differences in the impact of living expenses on SWB among the different groups. In this study, most of the short-video users were from 18 to 24 years old, accounting for 64.93% of the total sample. This group of participants was primarily comprised of college students, who had limited income, so the CNY 2,000 was determined as the standard for dividing samples into high- and low-level economic status. An interaction effect influencing SWB was found in our study between two factors—the UMSM and the economic status of the participants. In general, a co-variation was exhibited between economic status and SWB in the medium-level UMSM group, where the SWB level of people with living expenses above CNY 2,000 was higher than that of people with living expenses below CNY 2,000. It is consistent with the findings of the positive correlation between income and SWB (Clark et al., 2005; Carroll et al., 2007). However, an inconformity was revealed in the low-

TABLE 6 | Test of the mediating effect of the use of mobile social media, boredom proneness, and SWB.

Mediator	Effect	Effect size	Effect ratio	Boot SE	BootCI LL	BootCI UL
Boredom proneness	Total effect	−0.3924***		0.0360	−0.4630	−0.3218
	Direct effect	−0.1683***		0.0337	−0.2345	−0.1021
	Indirect effect	−0.2241***	57.11%	0.0284	−0.2848	−0.1728

****Correlation is significant at the 0.001 level (two tailed).*

and high-level UMSM groups, in which the SWB of participants was independent of their economic status. Within the low-level UMSM group that showed the greatest SWB, no significant difference was identified between the high-expense and low-expense subgroups in this degree of SWB. This might be caused by the "marginal utility" which implies that the benefit to one of an additional unit of happiness is inversely related to the number of units of happiness he already owns. The satisfaction derived from higher income barely progresses further in the people who are already satisfied with their economic status (Kahneman, 2006). Therefore, the change in SWB was not significant when economic status was taken as the independent variable for the high-SWB (low-UMSM) group. Within the high-level UMSM group demonstrating the lowest SWB, no apparent difference was revealed between the subgroups with discrepant economic status. This result is inconsistent with previous evidence showing that lower-level economic status exacerbated the distress of people with poorer SWB caused by life events, such as divorce, illness, and being alone (Kahneman and Deaton, 2010). In the present study, differences in economic status did not affect the degree of SWB in the individuals showing less happiness that was associated with their problematic use of mobile social media. The result implies that low-level SWB linked to the UMSM differs from that induced by stress events or life pressure, which reflects the complexity among the UMSM, economic status, and SWB. To unveil the panorama, more in-depth investigations are needed.

Impact of UMSM on SWB

This study confirmed that mobile social media was an important variable for predicting SWB. The higher the tendency of the problematic use of mobile social media, the lower the SWB which was perceived by individuals. This result showed that the use of mobile social media imposed a significant effect on SWB and enabled a significantly negative prediction of SWB. This was consistent with previous research results (Uysal et al., 2013; Brooks, 2015). On the one hand, the social comparison theory points out that the happiness of an individual results from comparing himself with other individuals. It will reduce an individual's subjective happiness when he/she compares himself/herself with a happier person (Festinger, 1954). The convenience of mobile social media makes it easier for individuals to access information about what is happening in their social community by browsing social media platforms. People are more inclined to post interesting and delightful life stories *via* mobile social media to build up popular personal images. When such stories are captured by the audience, the unconscious comparison of themselves with the "leading characters" in stories may make them feel gloomy, which consequently reduces their level of SWB. More than 50% of social media users think that their friends are happier than themselves (Tamir and Mitchell, 2012). On the other hand, when individuals need to handle negative life events, they are more likely to adopt a coping style of avoidance (Wu et al., 2014) and gain more positive emotions through mobile social media. However, the prolonged use of mobile social media is more likely to cause individuals to feel guilty and fall into self-blame. This negative emotional experience can also reduce an individual's sense of well-being (Katana et al., 2019).

Furthermore, three of the five subdimensions constituting the UMSM—physiological damage, omission anxiety, and guilt—had negative predictive effects on SWB, which was revealed by the stepwise regression analysis. This might be due to the fact that physiological damage caused individuals to develop excessive worries about their health. Both emotional distress and physical discomfort can affect quality of life (Estévez-López et al., 2015). Therefore, the worries resulted in a decline of SWB. Omission anxiety refers to unrest when one is unable to view the information in time and worry about missing messages. This emotion could reduce the individual's level of SWB (Malone and Wachholtz, 2017). When individuals are immersed in mobile social media, they might unconsciously increase the time and frequency of the use of mobile social media, and this results in failure to complete relevant work or achieve study goals. This is a situation that can lead to self-blame and self-criticism, which can also decrease well-being (Przybylski et al., 2013). These results suggest that when individuals have more awareness of their discomfort related to the use of mobile social media, whatever it is from the physical aspect (e.g., physical damage) or the psychological aspect (e.g., guilt), the level of SWB tends to decrease. On the contrary, if the individuals are not aware of these, their SWB level will not be affected.

The Mediating Effect of Boredom Proneness

This study showed that boredom proneness played a partial mediating role in the interaction between the UMSM and SWB. Our findings provide evidence to explain the mechanism underlying the interplay between the inappropriate use of the Internet and SWB reported in previous researches (Boyd and Ellison, 2007; Koroleva et al., 2011; Wenninger et al., 2018). The fundamental reason why boredom proneness is involved in mediation is that boredom *per se* influences SWB. Another explanation is the weakened attention induced by the improper use of social media.

The excessive use of the Internet has been linked to attention deficits (Kawabe et al., 2019). When a person is overly reliant on the use of mobile social media, his/her attentiveness is vulnerable.

Meanwhile, boredom is sometimes led by the absence of attention to the current goals (Hunter and Eastwood, 2016). Individuals with high boredom proneness are more inclined to experience boredom. In a state of boredom, a lack of attention drives negative emotions, and when attention is not fully engaged, the activities would be negatively treated, which results in a negative emotional state and affects the level of SWB (Fahlman et al., 2011).

LIMITATIONS

This study also has some limitations. Firstly, according to the collected questionnaire results, most of the short-video users were from 18 to 24 years old. In future research, the age range of the participants could be expanded, and more in-depth research could be conducted based on a population with different age groups. Secondly, according to the results, this study divided the monthly living expenses into above CNY 2,000 and below CNY 2,000. In future studies, the impact of living expenses on mobile social media could be further explored by considering people from different occupations and collecting more detailed data related to living expenses. Thirdly, the survey adopted the self-reported approach, which may be affected by the social desirability effect, resulting in biases in the measurement results. Fourthly, this study is a preliminary exploration, and the factor *usage style* of short-video users could be taken into consideration in the future study. Finally, this study showed that omission anxiety, physical damage, and guilt involved in the use of mobile social media imposed a negative predictive effect on SWB. In future research, more effort could be made to explore the mechanism underpinning the relations among the relevant factors.

CONCLUSION

Previous investigations have revealed the negative impact of the inappropriate use of mobile social media on one's SWB. However, the mechanism underlying the relationship between the two variables is unclear. The current study focused on another variable—boredom proneness, and figured out its mediating role between the use of mobile social media and SWB. This study not only provides new evidence to verify the influence path proposed in previous studies but also demonstrated the principle of how the dynamic model works.

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 involved human participants, and has been reviewed and approved by Ethics Committee of Department of Psychology, Beijing Forestry University. The ethics committee waived the requirement for written informed consent. However, written informed consent was implied via completion of the questionnaire.

AUTHOR CONTRIBUTIONS

JB, XL, and YY designed the study. JB, KM, and YP collected the data. JB, WH, and YQ analyzed the data. JB and YY wrote the manuscript. JB, YY, XL, KM, YP, WH, and YQ revised the manuscript. 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/fpsyg.2020.568492/full#supplementary-material

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Predicting Symptoms of Depression and Anxiety Using Smartphone and Wearable Data

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Background: Depression and anxiety are leading causes of disability worldwide but often remain undetected and untreated. Smartphone and wearable devices may offer a unique source of data to detect moment by moment changes in risk factors associated with mental disorders that overcome many of the limitations of traditional screening methods.

Objective: The current study aimed to explore the extent to which data from smartphone and wearable devices could predict symptoms of depression and anxiety.

Methods: A total of $N = 60$ adults (ages 24–68) who owned an Apple iPhone and Oura Ring were recruited online over a 2-week period. At the beginning of the study, participants installed the *Delphi* data acquisition app on their smartphone. The app continuously monitored participants' location (using GPS) and smartphone usage behavior (total usage time and frequency of use). The Oura Ring provided measures related to activity (step count and metabolic equivalent for task), sleep (total sleep time, sleep onset latency, wake after sleep onset and time in bed) and heart rate variability (HRV). In addition, participants were prompted to report their daily mood (valence and arousal). Participants completed self-reported assessments of depression, anxiety and stress (DASS-21) at baseline, midpoint and the end of the study.

Results: Multilevel models demonstrated a significant negative association between the variability of locations visited and symptoms of depression (beta = −0.21, p = 0.037) and significant positive associations between total sleep time and depression (beta = 0.24, p = 0.023), time in bed and depression (beta = 0.26, p = 0.020), wake after sleep onset and anxiety (beta = 0.23, p = 0.035) and HRV and anxiety (beta = 0.26, p = 0.035). A combined model of smartphone and wearable features and self-reported mood provided the strongest prediction of depression.

Conclusion: The current findings demonstrate that wearable devices may provide valuable sources of data in predicting symptoms of depression and anxiety, most notably data related to common measures of sleep.

Keywords: digital phenotyping, predicting symptoms, depression, anxiety, mobile sensing

INTRODUCTION

Depression and anxiety are leading causes of disability worldwide, with estimated lifetime prevalence rates of 20% (1). Whilst the majority of individuals with depression and anxiety are treated in primary care settings, over 50% of people are not recognized or adequately treated (2, 3). Given the adverse health outcomes and costs associated with untreated conditions and the recent increase in the prevalence of common mental disorders (4–6), adequate diagnosis and timely treatment of depression and anxiety has become an urgent priority.

Traditionally, researchers have relied on questionnaire data administered by a clinician or self-reported to assess an individual's mental health. However, these methods may be limited in their ability to detect the moment-by-moment changes in psychological factors that is required for preventative measures and rapid interventions. First, questionnaires often take place sporadically, with long intervals between them, during which time symptoms may change considerably. Second, these questionnaires often rely on retrospective evaluations and, as such, are prone to recall bias (7, 8). Third, there may be a tendency for respondents to provide socially-desirable answers (9, 10). Finally, patients typically only meet with a clinician or undertake assessments once the symptoms have already progressed to a certain level of severity, making prevention far more challenging.

Smartphone devices may offer a unique opportunity to overcome some of these limitations. Equipped with an array of sensors, smartphones unobtrusively provide a continuous stream of data related to an individual's mental health, including location, smartphone usage behavior, physical activity and social interactions (11, 12). This moment-by-moment quantification of the individual-level human phenotype *in situ* using data from personal digital devices is referred to as "digital phenotyping" (13, 14). There is now a growing body of research demonstrating that digital phenotyping data may enable the identification of people suffering from or at risk of developing mental disorders, in some cases even before symptoms are visible (or detectable) using traditional methods (11, 15–18).

One source of data that has yielded promising results in identifying those suffering from mental disorders is location data derived from smartphone global positioning systems (GPS). Saeb et al. (19), e.g., found that regularity of participants' 24-h movement patterns ($r = -0.63$), the variance of locations visited ($r = -0.58$) and the proportion of time spent at home ($r = 0.49$) were related to depressive symptom severity in a non-clinical population (19). Beiwinkel et al. (20) found that the total distance traveled had a significant negative relationship with clinical manic symptoms in patients diagnosed with bipolar disorder (beta $= -0.37$). Finally, in a meta-analytic review of studies assessing the correlation between smartphone and wearable device data and affective disorders, Rohani et al. (15) revealed that the association between time spent at home and depressive symptoms was the most consistently significant finding of any smartphone-derived feature in the analysis.

Yet, whilst GPS may provide a valuable source of data to predict symptoms of mental ill-health, there may be certain situations in which GPS data is not available (e.g., due to technological limitations or privacy concerns) or when movement is limited (e.g., due to physical ill-health), requiring us to establish other digital phenotyping data sources to aid the identification of symptoms or risk factors associated with mental disorders.

One plausible source of these additional data points may be consumer wearable devices, such as the Apple Watch (www.apple.com/watch), Fitbit (www.fitbit.com) or Oura Ring (www.ouraring.com). In recent years, the number of connected wearable devices worldwide has proliferated and is expected to exceed 1 billion by 2022 (21). Whilst wearable devices differ in the type and quality of data they collect, common measures include activity (e.g., number of steps and energy expenditure), heart rate and sleep. Individually - and combined - these data points may offer the opportunity for a richer digital phenotyping data set and alternative digital biomarkers in the absence of, or in addition to, valid GPS location data.

The most widely used sensor in wearable devices is the accelerometer, most commonly used to measure an individual's physical activity. There is a large body of research demonstrating the relationship between physical activity and mental health (22–26). In one of the largest studies conducted to-date using wrist-worn devices to measure physical activity in a population-based sample of 2,862 participants, Vallance et al. (27) found a strong association between accelerometer-based activity and decreased rates of depression. In a clinical study of older adults diagnosed with depression, O'Brien et al. (28) found that physical activity was significantly reduced in individuals diagnosed with depression compared to healthy controls.

Decades of research has also demonstrated that sleep alterations are highly prevalent in mental disorders (29–31). A number of sleep markers, including total sleep time, sleep onset latency, sleep efficiency (the ratio of total sleep time to time in bed), and rapid eye movement (REM) have consistently been found to be associated with measures of mental health (32).

Finally, a growing number of wearable devices are now available measuring heart rate variability (HRV). HRV is the variation in time interval between adjacent heart beats (the R-R interval). Typically recorded by an electrocardiogram (ECG) (33), HRV indexes neurocardiac function and is a validated measure of balance in the activity of the autonomic nervous system (ANS) (34, 35). In addition to associations with general cardiovascular health and being a significant predictor of mortality (36), several studies have demonstrated that lower HRV is also associated with increased symptoms of depression (37), anxiety (38), and later stages of bipolar disorder (39). Taken together, consumer wearable devices may therefore provide a valuable source of additional data to help identify moment by moment changes in risk factors associated with mental disorders.

The aim of the current study was to assess to what extent data from smartphone and wearable devices may be used to predict symptoms of depression, anxiety and stress during periods of restricted movement. The study was conducted during the first wave of the coronavirus disease 2019 (COVID-19) pandemic as governments across the world instated widespread restrictions on individual movement and social interaction intended to reduce the incidence of the virus. This provided an opportunity to assess the role of GPS in predicting symptoms of depression and anxiety during periods of limited movement and examine the predictive power of other digital phenotyping data sources.

We sought to answer the following questions:

(1) Can location features derived from smartphone GPS data be used to predict symptoms of depression and anxiety? i.e., do previous findings replicate during periods of restricted movement?
(2) Can measures of physical activity, sleep and HRV derived from consumer wearable devices predict symptoms of depression and anxiety?
(3) Which digital phenotyping variables have the strongest predictive power?
(4) What is the difference in predictive power between digital phenotyping data and a daily self-report mood measure in predicting depression and anxiety symptoms?

MATERIALS AND METHODS

Study Design

The current study was a longitudinal observation study with repeated measurements over a 30-day period. Measurements consisted of baseline (day 1), a midpoint (day 16) and endpoint questionnaire (day 31) and daily assessed digital phenotyping variables extracted from smartphone data and wearable data (Oura Ring).

Participants and Procedure

Participants ($N = 60$) were recruited via posts on online communities and social media sites. Recruitment started on 12 April and was closed on 29 April 2020. Interested individuals were included in the study if they (a) were at least 18 years of age, (b) were able to read and speak English, (c) owned an iPhone with access to the internet, (d) owned an Oura Ring. All participants signed a consent form agreeing with the data collection and analysis. According to the local ethical guidelines in the conduct of research (40), the study was exempt of a formal ethical committee approval since: (1) the study does not deviate from the informed consent; (2) the research does not intervene in the physical integrity of the participants; (3) all our participants are above 15 years old; (4) our study does not expose participants to strong stimuli; (5) there is no intervention nor there is a foreseeable potential for mental harm to the participants that exceed the limits of participants' normal daily life or those around them. As compensation for participating in the study all participants received a personalized mental health and well-being report reviewed by a clinical psychologist (L.B.S.) at the end of the study.

Following completion of the online consent form, participants were emailed an online link to download a custom smartphone application called "Delphi" developed for Apple (iOS) smartphones. The Delphi app was used to gather all study data, including baseline, midpoint and endpoint questionnaire data and data related to participants' daily mood, activity, sleep, HRV, smartphone usage, and context throughout the duration of the study. Participants were required to provide Delphi with permission to access location data at all times, Apple Healthkit and enable notifications from the app. To monitor data collection and compliance during the study period, a secure web-based dashboard was developed displaying the data gathered for all participants, updated at 15-min intervals. Cases of missing data were resolved via email. At the end of the study, participants were requested to uninstall the app.

The present study used methods from a previous study (19) investigating the correlation between GPS variables and depressive symptom severity with a sample size of $N = 40$. However, as dropout rates in longitudinal observation studies using digital phenotyping data are typically high, recruitment was continued for 2 weeks after reaching the required sample size to compensate for dropout.

Assessment

Mental Health Outcomes

Mental health outcomes were assessed at baseline (T0), the midpoint of the study (16 days; T1) and the end of the study (31 days; T2). Symptoms of depression, anxiety and stress were assessed with the Depression Anxiety Stress Scales (DASS-21). The DASS-21 is a 21-item short form of the DASS (41). It measures depressive mood, anxiety, and chronic tension/stress during the past week (e.g., "I was aware of dryness of my mouth"; "I couldn't seem to experience any positive feeling at all."). All items are rated on a 4-point Likert scale ranging from 0 ("did not apply to me at all") to 3 ("applied to me very much or most of the time"). The subscores range from 0 to 21, with higher subscores indicating more severe symptoms of depression, anxiety and stress. The DASS21 has demonstrated high internal consistency for the three subscales of depression, anxiety, and stress in previous administrations (42).

To further quantify the baseline severity of participants we used the standard cut-off values for the DASS. The subscale "depression" was categorized as normal 0–4, mild 5–6, moderate 7–10, severe 11–13, or extremely severe 14+; the subscale "anxiety" as normal 0–3, mild 4–5, moderate 6–7, severe 8–9, or extremely severe 10+; and the subscale stress as: normal 0–7, mild 8–9, moderate 10–12, severe 13–16, extremely severe 17+ (41, 42).

Ecological Momentary Assessment (EMA) of Mood

To assess participant mood, notifications were sent by the Delphi app asking participants to report their mood 3 times per day, randomized within a 30-min window during the morning, afternoon and evening (i.e., ∼09:00, 14:30, and 20:00). Mood was assessed through the circumplex model of affect (43), which conceptualizes mood as a two-dimensional construct comprising different levels of valence (positive/negative) and arousal (low/high). We used a single item question, "How are you feeling right now?" and 2 response scales, representing the two dimensions. Levels on both dimensions were tapped on a 9-point scale scored from −4 to 4 (low to high). The default mode was set to zero.

Smartphone Sensor Data

Delphi uses the AWARE open source framework (44, 45) to collect raw data from smartphone sensors. Sensors enabled in the current study included Battery, GPS, Screen (on and off), and Timezone. In addition, we used the ESM Scheduler plugin to deliver the EMAs. **Supplementary Table 1** provides a detailed list of sensors used in the study, the data collected by each sensor and the sampling frequency.

Data collected by Delphi is first stored locally on the participant's device and then uploaded onto a secure server in the cloud when a WiFi connection is established. To ensure privacy and data protection AWARE obfuscates and encrypts the data using a one-way hashing of logged personal identifiers, such as phone numbers. Increased security is achieved with application permissions, certificates, user authentication, and the use of secure network connections to access and transfer the logged data between the client and the dashboard. For further information on the AWARE framework see Ferreira et al. (44) and Nishiyama et al. (45).

Activity, Sleep, and HRV Data

We used the Oura Ring to measure participants' activity, sleep and HRV. Activity measures included number of steps ("step count," measured via the device's 3D accelerometer) and metabolic equivalent for task (MET). MET is a standardized measurement of the amount of energy used by the body during physical activity, as compared to resting metabolism (46). One MET is defined as the energy the body uses at rest. In the current study we used an average score to determine the energy expenditure during a 24-h period.

To measure sleep, the Oura Ring uses a combination of accelerometer data, heart rate, HRV and pulse wave variability amplitude in combination with machine learning models to calculate deep (N3), light (N1+N2) and rapid-eye-movement (REM) sleep in addition to sleep/wake. The Oura Ring has been shown to have high agreement with polysomnography (PSG; the gold-standard for measuring sleep) in the whole night estimation of total sleep time (TST), sleep onset latency (SOL) and wake after sleep onset (WASO) (47). For the current study we measured participants' TST, SOL, WASO and time in bed (TIB).

We also used the Oura Ring to measure participants' average night-time heart rate variability (HRV). The Oura Ring calculates HRV using the root mean square of successive differences between normal heartbeats (RMSSD). Although the R-peak detection typical of ECG is not directly available via the Oura Ring, the device has been shown to have high agreement ($r^2 = 0.98$) with ECG (the gold standard for measuring HRV) (48).

Data Processing

Data Preprocessing

We converted the UNIX timestamps of each sensor data into a human-readable local date and time format using each participant's timezone data. We then aggregated the data at the "day" level. To ensure location accuracy, we removed all duplicate entries in the database as well as GPS coordinates with accuracy > 80th percentile of all participants' GPS accuracies and GPS coordinates with latitude 0.0 and longitude 0.0 that arose due to sensing errors.

Preprocessing and extraction of the location features were computed according to Saeb et al. (19). Prior to feature extraction we established whether each GPS location data sample represented a stationary state (e.g., at home) or transition state (e.g., walking outside). This was determined by calculating the movement speed at each location sample using its time derivative. A movement speed > 1 km/h was defined as a transition state. We then applied a K-means clustering algorithm (49) to the stationary state data samples to identify the locations where participants spent the majority of their time.

Location Feature Extraction

We extracted five location features from the GPS data: Total Distance, Location Variance, Entropy, Normalized Entropy and Time at Home.

Total Distance was defined as the total number of kilometers traveled by the participant during the specified time period. It was calculated as the sum score of the distances between the location samples.

Location Variance was defined as the variability in participants' GPS locations. It was calculated from the logarithm of the sum of the variance in latitude and longitudinal coordinates of the stationary states.

Location Entropy was defined as the variability of the time participant spent at the location clusters. It was computed as: $[Entropy = -\sum_i p_i \log p_i]$ where each $i = 1, 2, \ldots, N$ represented a location cluster, N represented the total number of location clusters, and p_i represented the percentage of time spent at the location cluster. Higher entropy reflected the fact that the participant spent similar amounts of time at different clusters (e.g., 50% of time at home and 50% of time at work), lower entropy reflected that participants spent significantly more time at certain clusters than others (e.g., 70% of time at work, 30% of time at home).

Normalized Location Entropy was computed to provide a measure of entropy that is invariant to the number of clusters a participant spent time at. It was calculated by dividing the entropy by its maximum value, which is the logarithm of the total number of clusters. The resulting value ranges from 0 to 1, where 0 represents that all location data points belong to the same cluster and 1 indicates that they are uniformly distributed across all clusters.

Time at Home was defined as the proportion of time a participant spent at home relative to other location clusters. To calculate it we first defined the home cluster as the cluster with the most GPS coordinates between the hours of 00:00 and 06:00. We then computed the percentage of time by dividing the total time spent in the home cluster by 24 h.

Phone Usage Feature Extraction

We extracted two features related to phone usage. First, *Phone Usage Frequency* was defined as the number of times a participant interacted with their phone during the specified time period. Interactions were calculated based on a screen unlocking event. Second, *Phone Usage Duration* was defined as the total number of minutes a participant interacted with their phone during the specified time period. The usage session duration was calculated as the time from when phone is unlocked until it was locked.

Statistical Analysis

Before beginning the analyses, study dates were converted into the study day (1–30) specific to each participant. The extracted smartphone features, wearable data, EMA data (independent variables) and scores on the DASS-21 subscales (depression, anxiety, stress; dependent variables) were then synchronized according to the study day.

Correlation Analysis

To ensure that all variables in the analyses reflected the same time period, the daily smartphone and wearable feature data was pooled for the first 2 weeks and second 2 weeks of the study to align with the timing of the DASS-21 measurements. For example, we calculated the average Total GPS Distance during days 1–15 and correlated this with the DASS-21 scores at T1 (day 16) and calculated the average Total GPS Distance during days 16–30 and correlated this with the DASS-21 scores at T2 (day 31). According to this, all features were pooled and correlations with the respective DASS-21 were investigated (average feature data from day 1–15 with T1 DASS-21 and average feature data from day 16–30 with T2 DASS-21). Correlations were calculated using the Spearman's correlation coefficient, since the data was not normally distributed. *P*-values were adjusted for multiple testing based on the Bonferroni Holm method (50) with a false discovery rate of 0.05. To avoid biases introduced by missing values we used full information maximum likelihood as the estimator (51, 52). However, *p*-value adjustment methods are sensitive and since the present study is of an exploratory nature, adjustment was only performed cluster-wise (e.g., separately for GPS features and wearable features) to avoid an overcorrection by *p*-value adjustment leading to a false-rejection of findings.

Predicting Mental Health Symptom Severity From Smartphone and Wearable Data

To account for the hierarchical structure of the data we used a multilevel model (MLM) to predict the influence of smartphone and wearable data on mental health scores (53–55). MLMs take into account that data is nested within persons, i.e., the observations are not independent (56) and reduce the likelihood of Type I errors (57). In the current study, the repeated measures (level 1) are nested within the person (level 2). Intra-class correlations (ICC) underlined the necessity of a MLM (all ICC > 0.05).

To investigate whether mental health symptom severity can be predicted from smartphone and wearable device data, we pooled the data in the same manner as the correlation analyses and applied the MLM with random intercepts and random slopes to four sets of independent variables: GPS features (total distance, location variance, entropy, normalized entropy, and time at home); smartphone usage features (usage duration and usage frequency); wearable device data (step count, MET, TST, SOL, WASO, TIB, and HRV); and EMA mood data (valence and arousal). Variables were z-standardized.

The intercept represents the average depression, anxiety, stress scores across the study and the slope represents the association between mental health scores and the smartphone and wearable data. Two-sided $p < 0.05$ were considered statistically significant.

In a first step, regression models were built separately for each predictor to investigate its predictive power on depression, anxiety and stress scores. In a second step we explored whether the combination of multiple predictors could outperform single predictor models. Only predictors showing predictive power in single predictor models were included in the combined model. All models were fitted using maximum likelihood. Combined models with different predictors were compared to each other to investigate whether more complex models with more predictors were superior. For the comparison of the models, likelihood ratio tests were used (51, 58, 59).

Missing Data Handling

Missingness only occurred in the DASS-21 assessment (10%) and the sensing variables (9.1%) and was assumed to be missing at random (MAR), meaning missingness depended on observed data (51, 52). To avoid bias introduced by missingness we used multiple imputations to handle missing values in the correlation and regression analysis. The imputation model took the nested structure of the data into account and followed guidelines for multilevel multiple imputations (58). To make the MAR assumption hold, variables related to non-response and explaining variance in observed variables were included in the imputation model. Predictive mean matching for multilevel was used as imputation method. The number of imputed data sets was set to 20 and the number of iterations to 15. Convergence was visually assessed and confirmed (58). Regression analysis was performed on each imputed data set and results were pooled using the Rubin's rule (60).

Software

The pre-processing and feature extraction were performed using Python (version 3.7.6), R (version 4.0.2) (61), snakemake (version 5.20) (62) and following workflow examples from RAPIDS (63). All analyses were conducted in R. Correlations were calculated using the "psych" package (52). MLM was carried out using the packages lme4 (64) and lmerTest (65). For multiple imputations the "MICE" package was used (58).

RESULTS

Participant Characteristics and Adherence

Of the 60 participants at intake, 1 participant (1.7%) dropped out of the study due to concerns over privacy, 2 participants (3.4%) dropped out due to burden of self-report and 2 (3.4%) participants dropped out for unknown reasons. Of the remaining 55 participants, 47 (85.5%) completed the midpoint questionnaire and 54 (98.2%) completed the endpoint questionnaire.

Of the 55 participants, 30 (54.5%) were female and 25 (45.5%) were male. Their ages ranged from 24 to 68 with a mean of 42.8 (SD 11.6). There were 2% with no secondary education, 17% with high school as the highest education, and 80% with bachelor's degree or a higher degree. The mean depression severity was M = 3.78, SD = 3.48 (normal: 67.3%, mild-moderate: 25.4%, severe: 7.3%), the mean anxiety severity was M = 2.73, SD = 2.68 (normal: 70.9%, mild-moderate: 23.7%, severe: 5.5%), and the mean stress level was M = 6.00, SD = 3.82 (normal: 65.5%, mild-moderate: 29.1%, severe: 4.4%). **Table 1** provides a detailed summary of all participants included in the final analysis.

The majority of participants (66%) were from Finland. During the time of the study, the restrictions in Finland were such that the government strongly recommended that individuals maintain social distancing, companies adopt remote work wherever possible and the majority of public and private facilities (e.g., libraries, museums, bars and sports facilities) were temporarily closed. A multi-level model predicting the daily distance traveled (using categorized country Finland vs. other as predictor) revealed no significant distance between the average daily distance traveled between participants from Finland and those from other countries ($\beta = -922.9$ [in meters], $p = 0.943$).

Correlations Between Smartphone and Wearable Data and Mental Health Symptoms

Table 2 presents Pearson's correlation matrixes of the four sets of independent variables (GPS, smartphone-usage, wearable, and EMA features) and mental health symptom severity.

For all three mental health outcomes, significant small-to-medium correlations with the obtained EMA data – valance and arousal - were found (see **Table 2**). In contrast, none of the wearable or smartphone usage features were associated with mental health symptom severity in the correlation analysis ($p>0.05$). Also, for GPS features only the location variance and the entropy showed a significant correlation with depression. All other GPS features as well as variance and entropy for anxiety and stress were non-significant (see **Table 2** for more details).

Predicting Symptom Severity From Smartphone and Wearable Data

Analyses of the GPS-derived location features showed that location variance had a negative association with subsequent depressive symptom severity (beta = −0.21, SE = 0.10,

TABLE 1 | Participant characteristics.

Variable	%/M (SD)	*n*
Age	42.8 (11.6)	55
Gender		
Female	54.5	30
Male	45.5	25
Ethnicity		
Asian/Pacific Islander	1.8	1
Hispanic or Latino	3.6	2
White	92.7	51
Other	1.8	1
Education		
Less than a high school diploma	1.9	1
High school degree or equivalent	16.7	9
Bachelor's degree (e.g., BA, BS)	44.4	24
Master's degree (e.g., MA, MS)	33.3	18
Doctorate (e.g., PhD, EdD)	1.9	1
Prefer not to say	1.9	1
Employment		
Employed full-time (35+ h a week)	49.1	27
Employed part-time (< 35 h a week)	7.3	4
Unemployed (currently looking for work)	1.8	1
Unemployed (not currently looking for work)	3.6	2
Student	5.5	3
Retired	1.8	1
Self-employed	21.8	12
Unable to work	7.3	4
Prefer not to say	1.8	1
Marital status		
Single (never married)	25.5	14
Married	49.1	27
In a domestic partnership	20.0	11
Divorced	5.5	3
Mental health status at baseline		
Depression	3.78 (3.48)	–
Normal	67.3%	37
Mild	12.7%	7
Moderate	12.7%	7
Severe	5.5%	3
Extremely severe	1.8%	1
Anxiety	2.73 (2.68)	–
Normal	70.9%	39
Mild	16.4%	9
Moderate	7.3%	4
Severe	1.8%	1
Extremely severe	3.6%	2
Stress	6.00 (3.82)	–
Normal	65.5%	36
Mild	18.2%	10
Moderate	10.9%	6
Severe	3.6%	2
Extremely severe	1.8%	1

Values are based on observed data.

TABLE 2 | Correlations between smartphone and wearable data and mental health scores.

	Depression		Anxiety		Stress	
	r	*p*	*r*	*p*	*r*	*p*
GPS features						
Location variance	−0.31	0.035*	−0.26	0.110	−0.28	0.077
Total distance	−0.26	0.110	−0.28	0.077	−0.17	0.572
Location entropy	−0.30	0.035*	−0.17	0.572	−0.22	0.251
Normalized location entropy	−0.26	0.100	−0.13	0.788	−0.20	0.298
Homestay	0.12	0.788	0.13	0.788	0.07	0.788
Smartphone usage features						
Usage time	0.09	> 0.99	0.05	> 0.99	0.07	> 0.99
Usage frequency	0.15	0.716	0.24	0.079	0.12	0.971
Wearable device data						
Steps	−0.23	0.516	−0.16	> 0.99	−0.19	> 0.99
Metabolic equivalent for task	−0.21	0.99	−0.07	> 0.99	−0.06	> 0.99
Total sleep time	0.15	> 0.99	0.04	> 0.99	0.12	> 0.99
Sleep onset latency	0.08	> 0.99	0.06	> 0.99	0.04	> 0.99
Wake after sleep onset	0.20	> 0.99	0.14	> 0.99	0.16	> 0.99
Time in bed	0.15	> 0.99	0.03	> 0.99	0.11	> 0.99
Heart rate variability	0.08	> 0.99	0.12	> 0.99	0.09	> 0.99
Mood						
Arousal	−0.30	0.003*	−0.35	0.001*	−0.36	0.001*
Valence	−0.48	< 0.001*	−0.44	< 0.001*	−0.48	< 0.001*

*All p-values are adjusted cluster-wise for multiple testing; * indicates significance.*

$t(81) = -2.13$, $p = 0.037$), but no significant relationship with symptoms of anxiety or stress. No significant association between the other GPS-derived features (total distance, location entropy, normalized location entropy and time at home) and symptoms of depression, anxiety or stress were found.

With regards to smartphone usage features, we found no significant relationship between smartphone usage duration or smartphone usage frequency and symptoms of depression, anxiety and stress.

The analyses of wearable device data showed no significant association between any of the physical activity measures (MET and steps) and depression, anxiety, and stress. From the sleep measures, we found a significant relationship between total sleep time and depression [beta = 0.24, SE = 0.11, $t(73) = 2.33$, $p = 0.023$], time in bed and depression [beta = 0.26, SE = 0.11, $t(59) = 2.39$, $p = 0.020$] and WASO and anxiety [beta = 0.23, SE = 0.11, $t(90) = 2.13$, $p = 0.035$]. Additionally, we found a significant association been HRV and anxiety [beta = 0.26, SE = 0.12, $t(71) = 2.15$, $p = 0.035$]. None of the sleep measures were significantly related to stress.

The EMA data (valence and arousal) showed that valence was significantly related to depression [beta = −0.39, SE = 0.11, $t(55) = -3.43$, $p = 0.001$], anxiety [beta = −0.30, SE = 0.12, $t(57) = -2.54$, $p = 0.014$], and stress [beta = −0.39, SE = 0.11, $t(74) = -3.64$, $p < 0.001$]. There was no significant relationship between arousal and depression, anxiety or stress. **Supplementary Tables 2–4** provide the full set of results from single predictors.

Combined Predictions

Depression could be predicted by EMA and smartphone and wearable data. EMA performed better than smartphone and wearable data models, but the combination yielded the best fit (see **Table 3**). For anxiety and stress, EMA-only data models were the strongest predictors (see **Tables 4**, **5**).

DISCUSSION

The current study assessed whether data from smartphone and wearable devices could predict symptoms of depression and anxiety during periods of limited movement. We found that GPS (location variance on depression) and wearable device data (total sleep time and time in bed on depression; wake after sleep onset and HRV on anxiety), were able to predict mental health. Furthermore, a combined model of GPS and wearable data significantly increased the ability to predict symptoms of depression and anxiety compared to GPS data alone.

The finding that greater diversity in visited locations predicted lower depression severity supports previous research demonstrating that participants who move about more through geographic space are less depressed (19, 67). Furthermore, it indicates that, despite limited movement and social interaction, GPS may still provide a valuable source of data for the identification of individuals at risk of developing mental disorders. However, contrary to previous findings (19, 67–69), we did not find a significant relationship between the other smartphone features (total distance, location entropy,

TABLE 3 | A comparison of MLM model performance on the prediction of depression.

Model	Fixed effects					Goodness of fit and Comparison*		
	Estimate	SE	*t*-value	Df	*p*-value	F	df1, df2	*P*-value
Baseline model								
Intercept	0	0.13	0	105	> 0.999			
EMA model								
Intercept	0	0.11	0.00	104	> 0.999	10.52	1, 172	0.001[a]
Valence	−0.39	0.11	−3.49	55	0.001			
GPS model								
Intercept	0	0.12	0	104	> 0.999	4.574751	1, 568	0.033[a]
Variance	−0.21	0.10	−2.15	81	0.035			
Extended digital phenotyping model: GPS and wearable data								
Intercept	0	0.11	0.00	103	> 0.999	5.23	1, 136	0.024[b]
Variance	−0.21	0.10	−2.17	78	0.033			
Time in bed	0.25	0.10	2.43	58	0.018			
Combined model: EMA and digital phenotyping model								
Intercept	0	0.10	0.00	102	> 0.999	11.47	1, 176	0.001[c]
Variance	−0.21	0.09	−2.32	72	0.023	5.42	2, 560	0.005[d]
Time in bed	0.24	0.09	2.54	59	0.014			
Arousal	−0.38	0.10	−3.61	52	0.001			

**For more details on the likelihood ratio test see chapter 5.3.1 in Van Buuren (66). [a]Comparison against baseline, [b]Comparison against GPS, [c]Comparison against extended sensing model, [d]Comparison against EMA model.*

TABLE 4 | A comparison of MLM model performance on the prediction of anxiety.

Model	Fixed effects					Goodness of fit and comparison*		
	Estimate	SE	t	df	*p*-value	F	df1, df2	*P*-value
Baseline model								
Intercept	0	0.12	0.00	105	> 0.999			
EMA model								
Intercept	0	0.11	0.00	104	> 0.999	5.63	1, 191	0.019[a]
Valance	−0.30	0.12	−2.60	57	0.012			
GPS model								
No predictors identified								
Wearable data model								
Intercept	0	0.12	0.00		> 0.999	4.45	1, 997	0.035[a]
WASO	0.23	0.11	2.16		0.034			
Combined model: EMA and digital phenotyping model								
Intercept	0	0.11	0.00	103	> 0.999	5.03	1, 240	0.026[c]
Valence	−0.27	0.11	−2.41	59	0.001	3.67	1, 2,655	0.055[d]
WASO	0.19	0.10	1.90	90				

**For more details on the likelihood ratio test see chapter 5.3.1 in Van Buuren (66).*
[a]Comparison against baseline, [b]Comparison against GPS, [c]Comparison against extended sensing model, [d]Comparison against EMA model.

normalized location entropy and time spent at home) and mental health measures. This may be explained by weaker associations found in the current study compared to previous studies or by abnormal movement patterns during COVID-19. As such, it highlights the importance of further research on the role of context and other moderating variables that may influence the relationship between different GPS-derived features and mental health.

From the physiological data derived from the wearable device, we found total sleep time and time in bed to be significant predictors of depressive symptom severity. One explanation for this may be the lack of motivation and fatigue exhibited by individuals suffering from depression. The additional finding that longer periods of wakefulness after falling asleep significantly predicted symptoms of anxiety may be explained by the hyper-vigilance or hyperarousal characteristic of anxiety disorders

TABLE 5 | A comparison of MLM model performance on the prediction of stress.

Model	Fixed effects					Goodness of fit and comparison*		
	Estimate	SE	t	df	*p*-value	*F*	df1, df2	*P*-value
Baseline model								
Intercept	0	0.12	0.00	105	> 0.999	282.3	290.4	–
EMA model								
Intercept	0	0.10	0.00	104	> 0.999	11.09	1, 434	0.001[a]
Arousal	−0.39	0.11	−3.71	74	< 0.001			
GPS model								
No predictors identified								
Wearable data model								
No predictors identified								
Combined model: EMA and digital phenotyping model								
Not applicable								

For more details on the likelihood ratio test see chapter 5.3.1 in Van Buuren (66).
[a]*Comparison against baseline.*

causing individuals to wake up more frequently during their sleep (70). Similar findings to these have been reported in previous studies using polysomnography in a laboratory setting (32), however this is the first study to use validated consumer wearable devices to provide sleep data in real-life settings. Given the transdiagnostic nature of sleep disturbances (30) and that insomnia has been identified as a precursor to the development of full clinical syndromes (71), sleep data from consumer wearables may thus provide valuable tools to identify early warning signs of mental disorders, thereby facilitating time-sensitive preventative measures (72).

Finally, the superior performance of the combined GPS and wearable data model compared to the GPS-only model in predicting symptoms of depression and anxiety demonstrates the value of wearable data during times of restrictive movement such as COVID-19. Furthermore, our finding that adding smartphone and wearable data to EMA data had the highest predictive power of all models in the analysis suggests that a combination of passive sensing and active assessment may provide the greatest predictive power in identifying people suffering from symptoms of depression and anxiety.

A number of limitations of the study should be taken into account. First, it is important to highlight that this is a longitudinal observational study, thus the current findings do not necessarily represent a causal relationship between the behavior measured by smartphone and wearable devices and symptoms of depression and anxiety, nor can they explain the direction between them. For example, an increase in total time in bed may be a cause or effect of the increase in depressive symptom severity or it may be explained by another third variable (73). Furthermore, as pooling data prevented us from exploring high-frequency processes (e.g., the relationship between movement and mood), we were unable to establish temporal precedence (74). Second, the small sample size meant that the study was likely underpowered to find statistically significant results for a number of predictors exhibiting small effect sizes. Forthcoming, studies should therefore assess whether the current findings are replicated in a larger sample size. Third, there were some sample biases. The sample was heavily skewed toward white, employed individuals who were more educated than the general population. Related to this, the study was open only to participants with an Apple (iOS) smartphone. Research has shown that sociodemographic status and smartphone usage behavior may differ between iOS and Android users (75, 76). Future studies should therefore assess the relationship between digital phenotyping data and mental health across both platforms and in populations with more diverse backgrounds. Forth, participants were a non-clinical sample recruited from the general population. This was intentional as the focus of the current study was related to the detection of depression across a continuous spectrum and in a naturalistic setting. Although participants scored highly on the depression subscale in particular (over 25% of participants had at least mild-to-moderate depression severity), clinical diagnosis was not an inclusion criterion. Future research would therefore benefit from examining the relationship between the current smartphone and wearable device data and mental health in a clinical population. Finally, individual responses to restrictions on movement during the COVID-19 pandemic are likely to have varied considerably. As the study commenced after the onset of the pandemic, we were unable to provide any data comparing participants' movement before and during the study to confirm that their movement was indeed more limited during the study period.

Notwithstanding these limitations, the current study provides promising indications of digital phenotyping data derived from consumer wearable devices for the identification of individuals suffering from or at risk of developing a mental health condition. Future research would benefit from assessing how data from additional sensors [e.g., speech and voice (77), keyboard interactions (78), bio-sensing (79), and smartphone app usage (80)], combined with machine learning models may be used to further improve predictive accuracy (81–85). Given the issues quantifying explained variance in multilevel models (86, 87), future research would also benefit from understanding the amount of variance explained in symptomatology by smartphone and wearable sensing data. Studies with larger samples sizes, conducted over longer periods of time are also needed, both to ensure adequate power as well as to assess how digital phenotypes may be used to predict changes in symptomatology over time (88, 89). Such research may also provide valuable insights into the causal mechanisms underlying mental disorders (e.g., behavioral activity, loneliness) and thereby enable the development of early mental health warning systems and more effective, timely interventions targeted to the individual based on personalized models of psychopathology (90, 91).

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because the data we report are from unique patients and therefore identifiable when the full set of data is provided. However, the code used to generate the data may be provided upon reasonable request to the corresponding author.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

IM, LP-R, DM, DF, KA, LS, and YT contributed to the study conceptualization and design. IM, KA, DF, and YT participated in data collection. YT, LS, KA, and IM contributed to the creation of participant reports. KA, DF and IM contributed to feature extraction. YT, IM, KA, DF, DM, LS, and LP-R contributed to the methods and analysis. IM, YT, and KA prepared the original draft. LP-R, DM, HB, DF, and LS critically reviewed and edited the draft. All authors read and approved the final manuscript and account for all aspects of the work.

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ADDITIONAL INFORMATION

Correspondence and requests for materials should be addressed to IM.

CODE AVAILABILITY

The code used to process and analyze the findings of this study may be made available to an investigator upon reasonable request.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.625247/full#supplementary-material

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Problematic Social Media Usage and Anxiety Among University Students During the COVID-19 Pandemic: The Mediating Role of Psychological Capital and the Moderating Role of Academic Burnout

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The outbreak of COVID-19 has greatly affected university students' studies and life. This study aimed to examine the possible mediating role of psychological capital and the moderating role of academic burnout in the relationship between problematic social media usage and anxiety among university students during COVID-19. A total of 3,123 undergraduates from universities in Shanghai participated in an online survey from March to April 2020. The results showed that problematic social media usage among university students predicted their levels of anxiety. Mediation analysis indicated that psychological capital mediated the relationship between problematic social media usage and anxiety. Furthermore, for university students whose academic performance had been affected by the COVID-19 pandemic, the effects of both problematic social media usage and the psychological capital on anxiety were moderated by academic burnout. For university students whose academic performance was not affected by the COVID-19 pandemic, academic burnout moderated the effects of psychological capital but not the effects of problematic social media usage on anxiety. The results highlighted the underlying mechanisms in the relationship between problematic social media usage and anxiety. These findings provide practical insights into the development and implementation of psychological interventions when facing a pandemic.

Keywords: problematic social media usage, anxiety, academic burnout, epidemic, psychological capital, COVID-19, university students

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INTRODUCTION

The COVID-19 pandemic that began in December 2019 has spread to more than 200 countries and regions and infected 79,094,442 patients globally (96,074 in China) as of 24 December 2020. The pandemic brought not only the threat of physical health but also psychological stress, such as anxiety, depression, and fear among the public (Song, 2020). Previous studies have demonstrated the negative effects of infectious outbreaks and subsequent quarantine orders on both posttraumatic stress disturbance (Hawryluck et al., 2004) and psychological stress (Lau et al., 2005; Brooks et al., 2020) experienced in the general population. Given the wide social impact of the pandemic and the governmental response, including physical distancing measures and quarantine, the COVID-19 pandemic might have psychiatric consequences. The results from a recent meta-analysis documented high levels of both posttraumatic (26.2%) and psychological (23.1%) stress associated with COVID-19 (Cooke et al., 2020). Furthermore, patients diagnosed with COVID-19 in the isolation ward and/or with general pneumonia in the observation ward had different degrees of anxiety, depression, and sleep problems (Yang et al., 2020). Sizable proportions of the public not infected with COVID-19 reported panic and anxiety (Islam et al., 2020; Wang et al., 2020). For both the infected and non-infected population, anxiety may be particularly prevalent and devastating during this pandemic due to uncertainty, reduction in economic income, and the accompanying lack of a sense of security.

As a result of the COVID-19 pandemic, the learning and lifestyle of university students in China have undergone drastic changes. To curb the spread of the pandemic, universities delayed the spring semester and students were, in advance, asked not to return to university and stay at home as much as possible. Consequently, long periods of isolation at home and uncertainty about when to return to university may increase the risk of anxiety among university students (Wang et al., 2020). Additionally, universities have started using internet platforms to develop different types of online courses, for example, requiring students to complete their study tasks at home via social media. Although previous studies reported a positive influence of social media usage on mental health and well-being (Clark et al., 2018; Glaser et al., 2018), many studies have found that the excessive use of social media has negative effects on users (Steers et al., 2014; Muench et al., 2015; Nesi and Prinstein, 2015; Hormes, 2016). During the pandemic, university students who were forced to stay at home had to learn, communicate, and obtain the latest information about the pandemic from social media, thus increasing the time and frequency of mobile social media usage. Given that preoccupation and the excessive amount of time spent on social media are symptoms of problematic use, excessive social media use among Chinese university students may easily turn into problematic use (Andreassen et al., 2012). Therefore, the present study focused on university students' problematic social media usage during the pandemic. Overuse and problematic social media usage have been linked to poor psychological well-being (Huang, 2017) and symptoms of depression (Twenge et al., 2018), and anxiety (Vannucci et al., 2017; Elhai et al., 2020). Therefore, changes in the learning style, lifestyle, and problematic social media usage have become possible risk factors for university students' anxiety.

Thus far, the extent to which the COVID-19 pandemic and problematic social media usage affect the levels of anxiety among university students in this context have not been empirically addressed. To fill this gap, this study recruited students from universities in Shanghai as participants. After the COVID-19 pandemic was effectively controlled in China (from the end of March to the beginning of April 2020), an online questionnaire was distributed to systematically investigate the relationship between problematic social media usage and anxiety. Concurrently, this study focused on the mediating role of psychological capital between levels of anxiety and problematic social media usage, as well as the moderating effect of university students' academic burnout on the effect of problematic social media usage on anxiety and related behavioral mechanisms. Although prior studies had found a close relationship between problematic social media usage, anxiety, and psychological capital, the pattern of the relationships may be changed during COVID-19. In the following paragraphs, I introduce the theoretical background and then propose the hypotheses.

Theoretical Framework and Hypotheses Development

The Relationship Between Problematic Social Media Usage and Anxiety Among University Students During the COVID-19 Pandemic

Anxiety refers to an unpleasant sense of fear and apprehension, which is characterized by uneasiness derived from anticipating danger, the unknown, or unrecognized (Allen et al., 1995). The COVID-19 pandemic is an example of such a situation, in which the outbreak is sudden and highly infectious, and the current knowledge or treatment of the disease is limited, which can have devastating effects on the mental health of people and produce anxiety (Ho et al., 2020). For university students, the outbreak has had two main effects on their studies and life. First, university campuses were closed, thus students could not attend classes or continue to complete research in the laboratory as usual, which might have disrupted their original study plans and added more uncertainty to their future academic development (Liu et al., 2020). In addition, with the introduction of long-term home quarantine, most university students and their families had to study or work at home while living together in a confined space. This scenario could lead to an increase in the likelihood of family conflict and, thereby, increase individual anxiety levels (Chen et al., 2020; Wu et al., 2020). Therefore, the academic performance of some students, which refers to "how students deal with their studies and how they cope with or accomplish different tasks given to them by their teachers" (Masrek and Zainol, 2015, p. 3,604), will be affected by the pandemic. Recently, the breakdown from the Office for National Statistics (2020) showed that young adults' anxieties during the pandemic often revolved around the effect on their university and the impact on the quality of education in the United Kingdom. Similarly, research by Cao et al. (2020) found that higher levels of anxiety were associated with factors strongly related to COVID-19 among Chinese medical university students. For these reasons, university students may be particularly vulnerable to anxiety during the pandemic. Based on the above literature review, Hypothesis 1 is proposed:

Hypothesis 1 (H1):The levels of anxiety will increase among the university students whose academic performance has been affected by the COVID-19 pandemic.

The second major impact among university students was from the problematic social media usage, which refers to being preoccupated with social media, having a strong motivation to use social media, and spending too much time on social media, which leads to impairments in their social, personal, and/or professional life, as well as psychological health and well-being (Andreassen and Pallesen, 2014). Most universities have developed online courses to deal with the impact of the COVID-19 pandemic on the curriculum plans. The use of social media has been forced to be prolonged, which may lead to the emergence of problematic use of social media, and thus hurt university students' mental health. Previous studies have shown that excessive use of social media can increases anxiety (Lepp et al., 2014). Especially during the pandemic, people who frequently use social media may receive a lot of negative information, even fake news, related to the situation, which may, in turn, increase the levels of anxiety (Gao et al., 2020). Moreover, the internet platform has become the only way to attend classes, receive notices from universities, and attend meetings, so the passive use of social media, such as browsing content, has increased among university students. Thorisdottir et al. (2019) investigated social media use and symptoms of anxiety among 263 Icelandic adolescents and suggested that passive use of social media was related to greater anxiety symptoms for both genders. Both active and passive excessive use of social media by university students is likely to develop into problematic use of social media. Previous studies have demonstrated a close relationship between problematic social media usage and anxiety (Hussain and Griffiths, 2018; Wong et al., 2020). Against this background, I propose the following hypothesis:

Hypothesis 2 (H2): During the pandemic, problematic social media usage predicts the anxiety levels of university students.

The Mediating Effect of Psychological Capital

Psychological capital refers to an individual's positive psychological state, which consists of four psychological resources: self-efficacy, optimism, hope, and resilience (Luthans et al., 2007a). According to key resource theories, these resources, and thus psychological capital, can help individuals successfully cope with, alleviate, or eliminate the negative effects of stress and maintain mental health (Thoits, 1994; Bandura, 1997; Wright et al., 1998; Hobfoll, 2002). Several studies have revealed that psychological capital is an important psychological mechanism relating stress and health. For example, Fang et al. (2014) found that negative life events decreased mental health by reducing psychological capital among university students. Furthermore, Yang (2016) suggested that an increase in stressful events leads to a decrease in individuals' well-being, and psychological capital plays a mediating role between stressful events and well-being. In the context of COVID-19, Mubarak et al. (2020) suggested that psychological capital effectively alleviated individuals' fear. Therefore, psychological capital may be an important psychological mechanism for university students to deal with COVID-19 pandemic and maintain their mental health.

The growth of psychological capital depends on the development of positive resources and finding new ways to deal with psychological problems (Simsek and Sali, 2014). However, excessive social media usage or smartphone addiction is regarded as an escape behavior (Kwon et al., 2011), which is harmful to cultivating psychological capital. Specifically, excessive internet usage would provide a virtual world where individuals seem to control everything and generate a virtual state of strength that does not enable them to cope with problems in reality (Boellstorff, 2008; Simsek and Sali, 2014). Furthermore, spending much time and energy on the internet reduces the investment of time and energy in cultivating psychological capital (Simsek and Sali, 2014). Some studies also suggested that excessive internet or smartphone usage was closely correlated with psychological capital. For example, Zhang and Jin (2015) found that smartphone addiction negatively correlated with psychological capital and Simsek and Sali (2014) revealed that internet-addicted students were more likely to have lower psychological capital. Furthermore, many university students who were asked to complete study tasks through mobile phones increased their time and frequency of mobile social media usage during COVID-19 (Dong et al., 2020; Prakash and Yadav, 2020), which enhances the chances of problematic use of mobile social media, giving rise to various negative effects (Duan et al., 2020; Elhai et al., 2020). Thus, I speculate that problematic social media usage may impede the development of psychological capital and propose the following hypothesis:

Hypothesis 3 (H3): During the pandemic, problematic social media usage can significantly negatively predict individuals' psychological capital.

Psychological capital is also significantly correlated with anxiety (Dian et al., 2020). According to the ego depletion theory (Muraven and Baumeister, 2000), psychological capital comprised of positive psychological resources may be limited. If individuals lack psychological capital, they cannot effectively cope with stressful events and suffer from negative emotions, such as anxiety and depression (Baumeister et al., 1998; Rahimnia et al., 2013). In other words, individuals with high psychological capital have more positive resources to cope with stress, thereby reducing anxiety, whereas individuals with low psychological capital have fewer positive resources to cope with stress, thereby increasing anxiety. Many empirical studies have verified that psychological capital is beneficial in dealing with stress and eliminating anxiety. For example, Wu et al. (2019) found that an increase in psychological capital effectively alleviated university students' anxiety. Liu et al. (2013) revealed that psychological capital could help reduce anxiety symptoms among employees diagnosed with HIV/AIDS. Dian et al. (2020) found that high psychological capital, especially self-efficacy, and optimism reduced the levels of anxiety for market fire victims. Moreover, it has also been shown that enhancing youth's psychological capital could reduce their social anxiety during the COVID-19 pandemic outbreak (Li, 2020). Therefore, it is conceivable that psychological capital would negatively predict anxiety among university students.

Based on the literature review above, problematic social media usage negatively predicts individuals' psychological capital, and decreases in psychological capital can exacerbate anxiety. Therefore, the following hypothesis is proposed:

Hypothesis 4 (H4): Psychological capital plays a mediating role in the relationship between problematic social media usage and individuals' anxiety.

The Moderating Effect of Academic Burnout

In addition to the negative effect of problematic social media usage on anxiety and the mediation role of psychological capital, another concern is that during the COVID-19 pandemic, the effect of the problematic social media usage on anxiety will be stronger. In particular, the learning-related variables would interact with problematic social media usage, thus jointly influencing the general anxiety of university students during the pandemic. In this study, given its close connection with psychological capital and anxiety, I focused on the role of academic burnout, a common negative psychological trait among university students, in the relationship between problematic social media usage and anxiety, as well as its mechanism.

Academic burnout was defined as a negative psychological syndrome caused by long-term, excessive academic pressure. Facing academic burnout, students gradually lose energy and have reduced enthusiasm for learning, a lower sense of achievement, and a lack of positive attitudes owing to long-term academic burden (Meier, 1983). Researchers have suggested that academic burnout consists of three dimensions: emotional exhaustion, cynicism, and a low sense of accomplishment (Lee and Ashforth, 1996; Houkes et al., 2011). Some researchers have found that burnout may be a significant moderator, and different levels of burnout tend to have beneficial or detrimental effects on a series of outcomes (Baba et al., 2009; Akanni et al., 2019). For instance, individuals with higher burnout levels are less likely to be engaged in their job, even though their emotional intelligence is high (Akanni et al., 2019). According to Kao and Chang (2017), the interaction effect of burnout and job stress can affect the well-being of individuals. Additionally, emotional exhaustion, a dimension of burnout, plays a moderating role in the relationship between proactive personality and individual performance. That is, individuals with less proactive personalities performed worse under circumstances of high levels of emotional exhaustion (Baba et al., 2009). Therefore, it is reasonable to consider academic burnout as a moderating variable in this study.

In addition, during the outbreak of the COVID-19 pandemic, universities closed their doors and students had to attend classes and take examinations by using social media, which increased their levels of academic burnout (Zis et al., 2020). Learning online poses a great challenge to students, which can easily result in excessive usage of social media. Moreover, social media overuse may easily turn into problematic social media usage, which can result in emotional problems for people (Yildiz Durak and Seferoğlu, 2019). In the case of the COVID-19 pandemic, it remains unclear what effects learning-related variables may have on the relationship between problematic social media usage and general anxiety. Besides, according to the model of job resources-demand, similarly, academic burnout is the result of the constant consumption of psychological resources (Demerouti et al., 2001). In this case, when university students with a high level of academic burnout are faced with academic stress, the association between problematic social media usage and anxiety may be increased, owing to individuals' lack of psychological resources. Although psychological capital acted as a moderator in previous studies (Shaheen et al., 2016; Guo et al., 2018), I mainly focus on the moderating role of the learning-related variable in the current research, and academic burnout can be considered as the consumption of psychological resources. Thus, academic burnout, instead of psychological capital, may act as a moderator in my research.

More specifically, it has been shown that anxiety is more likely to be the result of academic burnout (Chang et al., 2012). This means that the higher the levels of burnout, the higher the levels of anxiety. According to Han's (2017), students with high academic burnout were more likely to be dependent on social media, possibly to avoid studying. Additionally, the overuse of social media was linked to students' anxiety (Woods and Scott, 2016); thus, I proposed that students with high academic burnout levels would strengthen the relationship between problematic social media usage and students' anxiety.

Furthermore, in terms of the relationship between burnout and psychological capital, most researchers agreed that the higher the level of psychological capital, the lower the level of burnout (Wang et al., 2012; Laschinger and Fida, 2014; Estiri et al., 2016). This is because psychological capital, as a kind of positive mental status, affects the ways students respond to difficulties. To be more accurate, students with higher levels of psychological capital are less likely to have symptoms of academic burnout. Simultaneously, as mentioned above, students' anxiety also increased with an increase in burnout (Chang et al., 2012).

In general, according to Pluess (2015), the interaction between the environment and the individual has different developmental effects based on their sensitivity to the environment. That is, if one is sensitive to changes in the environment, they may experience extreme emotions. Social media usage is deemed an environmental factor, and psychological capital and academic burnout are deemed psychological factors. The interactions among these factors can influence individuals in different ways. Previous research has found that excessive mobile social media usage may result in anxiety (Woods and Scott, 2016); therefore, when academic burnout, as a coordinator, interacts with other factors, it also influences students' anxiety. In addition, in the context of the pandemic, academic burnout may interact with the pandemic and, thus, affect students' anxiety. Students who are affected by the pandemic are more sensitive to environmental changes and more prone to academic burnout. Therefore, the moderating effect of academic burnout may be different among students based on whether their academic performance is affected by the pandemic or not. Consequently, the following hypothesis is proposed.

Hypothesis 5 (H5): Academic burnout moderates the relationship between problematic social media usage and students' anxiety (H5a) and between psychological capital and students' anxiety (H5b), and moderated effects are different among students based on whether their academic performance is affected by the pandemic or not.

The Present Study

In this study, Chinese university students were recruited as participants, and an online questionnaire was administered during the COVID-19 pandemic. It is well known that COVID-19's outbreak at the beginning of 2020 changed people's life. To avoid the further spread of the pandemic, the Chinese Ministry of Education postponed the start of school and notified students about the need to complete their studies in the form of online classes at home. This form is very different from traditional learning methods and is an academic challenge for many students. Some students could not adapt to this methodology. The lack of group discussions and the weakening of the interactive learning environment greatly reduced their learning efficiency and enthusiasm. Therefore, subjectively, they believed that the pandemic negatively affected their academic performance. However, other students who had orderly planned their studies felt that the changes in the external environment and learning methods could not hinder their learning process and academic enthusiasm. They were in the same state as before. These students did not believe that the pandemic affected their academic performance. Only those students who subjectively believed that they were affected by the pandemic were truly victims of the pandemic. The pandemic did not affect the academic performance or mental health of students who considered themselves unaffected. Given the different subjective feelings of individuals, the pandemic had different effects on the psychological structure of individuals and these effects should be discussed separately. Therefore, I divided the students into two groups according to their subjective perception and explored the psychological structure of the two groups of students to reveal the more comprehensive impact of the pandemic. In the actual investigation, the students needed to answer a question about whether the pandemic affected their academic performance. According to their answers, they were divided into two groups: university students who reported that they were affected by the pandemic (Group 1) and those who reported not being affected by the pandemic (Group 2). First, I compared the differences in problematic social media usage, psychological capital, anxiety, and academic burnout between the two groups. Then, I integrated problematic social media usage, anxiety, psychological capital, and academic burnout into a model to examine the mediating and moderating mechanisms underlying the relationship between problematic social media usage and anxiety. **Figure 1** illustrates the proposed model.

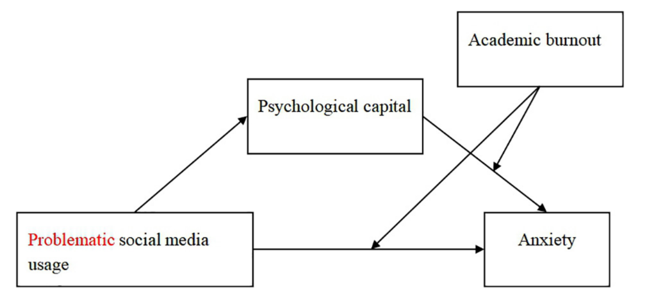

FIGURE 1 | The proposed moderated mediation model.

MATERIALS AND METHODS

Participants

The questionnaire was distributed online during the spring semester of 2020. A total of 3,123 undergraduates from universities in Shanghai participated in the survey. To distinguish between students whose academic performance was affected by the pandemic and students whose academic performance was not affected, I included the following item: "Whether COVID-19 has affected your academic performance or not." The responses were coded as: "yes" or "no". Then, I recoded the responses into two categories: 1 (affected) and 2 (not affected). According to participants' self-reports, 2,056 students (816 males, 1,240 females) believed that their academic performance was affected by the COVID-19 pandemic (Group 1) and 1,067 (739 males, 328 females) students believed that their academic performance was not affected by the COVID-19 pandemic (Group 2).

Measures

Anxiety

Anxiety was measured using the GAD (Generalized Anxiety Disorder, GAD-7) self-report scale (Spitzer et al., 2006). Qu and Sheng (2015) tested the Chinese version of the scale and proved its reliability and validity. The scale consisted of seven items (e.g., "Over the past 2 weeks, have you often worried too much about different things?"). Each item was rated on a 4-point Likert-type scale, ranging from 0 (not at all) to 3 (nearly every day). The scale had no reverse scoring, and all items were added to obtain a total score. The higher the total score, the more serious the anxiety symptoms. Cronbach's α coefficient was 0.93 in the current sample.

Psychological Capital

The Positive Psychological Capital Questionnaire was used to assess participants' psychological capital (Zhang et al., 2010). The scale contains 26 items, each assessed using a 7-point scale that ranges from 1 (very inconsistent) to 7 (very consistent). Items such as "I have great confidence in my ability" were included in the scale. Five items required reverse scoring before calculating the total score. After reverse scoring the negative items and summing the item results, a higher score indicated that individuals have more psychological capital. The Cronbach's α coefficient for the scale was 0.93 in the current study.

Problematic Social Media Usage

The problematic social media usage of the participants was assessed using the Problematic Mobile Social Media Usage Assessment Questionnaire (Jiang, 2018). The questionnaire consisted of 20 items (e.g., "I have a certain dependence on mobile social networks, and sometimes I cannot control my playing time.") mainly related to the duration, frequency, and intensity of mobile social media use and the negative impact of excessive use on the individual's physiology, psychology, and cognition. Each item was rated on a 5-point Likert-type scale, ranging from 1 (totally inconsistent) to 5 (totally consistent). The scale had no reverse scoring. Summing the items, higher scores indicate greater problematic social media use. In the current study, Cronbach's α coefficient was 0.93.

Academic Burnout

Academic burnout levels were measured using the Maslach Burnout Inventory-Student Survey (MBI-SS) (Schaufeli et al., 2002). The Chinese version was revised by Fang et al. (2009) and had good reliability and validity. The scale had 15 items measuring three aspects of academic burnout: exhaustion, cynicism, and efficacy related to academic work. A sample item was "I feel burned out from my studies." Each item was assessed using a 7-point Likert-type scale, with responses ranging from 1 (very inconsistent) to 7 (very consistent). After reverse scoring six items, all the items were added to calculate the total score. A high score indicated high academic burnout, and the Cronbach's α coefficient was 0.90.

Data Analysis

First, to examine the difference between Groups 1 and 2, an independent sample t-test was computed using SPSS 25.0. A P-value of less than 0.05 was considered statistically significant. Second, I calculated the correlation between the four variables of the two groups. Third, regression analysis was used to examine the relationships between problematic social media usage and anxiety and test hypothesis 2. Then, to examine hypotheses 3 and 4, the PROCESS macro (Model 4), which provides indirect effects of problematic social media usage on anxiety with 95% bias-corrected confidence intervals obtained from 1,000 bootstrap resamples, was used to test the mediation effect of psychological capital. The mediation effect was significant when the 95% confidence interval did not include zero. Finally, I used the PROCESS (Model 15) to test the moderated mediation effect, which allowed us to investigate whether the mediation process was moderated by academic burnout. The moderation effect was regarded as significant if the bootstrapped 95% confidence interval did not contain zero. If the moderation effect was significant, a simple slope analysis was also conducted using the PROCESS macro to further explore the nature of the moderation effect. This allowed us to verify hypotheses 5a and 5b. In addition, a previous study revealed that gender might affect anxiety (Xu et al., 2012). Therefore, in all analyses, participants' gender was included as a covariate.

RESULTS

Descriptive Statistics and Correlation Analysis

The descriptive statistics and correlations for all measures are presented in **Table 1**. According to the t-test, students of Group 1 and Group 2 differed significantly in terms of their problematic social media usage, psychological capital, academic burnout, and anxiety. These results supported hypothesis 1, indicating that the levels of anxiety increased among the university students who believed that their academic performance had been affected by the COVID-19 pandemic.

TABLE 1 | Means, standard deviations, bivariate correlations, and t-test of variables.

Variables	M	SD	1	2	3	4	t
(1) Anxiety	5.46 (3.94)	4.28 (3.91)	–				9.95***
(2) Problematic social media usage	59.74 (53.57)	14.51 (15.38)	0.39** (0.32**)	–			11.05***
(3) Psychological capital	124.73 (129.33)	20.02 (21.54)	−0.43** (−0.45**)	−0.30** (−0.33**)	–		−5.93***
(4) Academic burnout	44.62 (40.03)	12.93 (13.41)	0.44** (0.42**)	0.40** (0.39**)	−0.65** (−0.71**)	–	9.18***

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, all tests were two-tailed. The data outside the brackets were for university students whose academic performance had been affected by the pandemic ($n_1 = 2056$), and the data inside the brackets were for university students whose academic performance had not been affected by the pandemic ($n_2 = 1067$).

Based on the correlation test, problematic social media usage had a significant positive correlation with anxiety in both groups. For these students, psychological capital was significantly negatively correlated with anxiety and problematic social media usage. Academic burnout had a significantly positive correlation with anxiety and problematic social media usage and a significantly negative correlation with the psychological capital of students.

Problematic Social Media Usage and Anxiety

I used linear regression to test hypothesis 2. The results showed that problematic social media usage was positively associated with the anxiety level of participants in Group 1 ($b = 0.39$, $SE = 0.02$, $p < 0.001$) and Group 2 ($b = 0.32$, $SE = 0.03$, $p < 0.001$). This means that regardless of what the students reported on their academic performance, problematic social media usage predicted university students' anxiety levels. Therefore, hypothesis 2 was supported.

Mediation Analysis

To examine hypotheses 3 and 4, a mediation analysis was conducted on both groups using PROCESS (Model 4). Among university students whose academic performance had been affected by the COVID-19 pandemic, there was a significant negative effect of problematic social media usage on psychological capital ($b = -0.30$, $SE = 0.02$, $p < 0.001$) and of psychological capital on anxiety ($b = -0.35$, $SE = 0.02$, $p < 0.001$). The indirect effect of psychological capital on the relationship between problematic social media usage and anxiety was significant ($b = 0.10$, $SE = 0.01$, 95% CI = [0.082, 0.125]). In addition, the residual direct effect of problematic social media usage on anxiety was also significant ($b = 0.29$, $SE = 0.02$, $p < 0.001$) (see **Table 2**).

TABLE 2 | Testing the mediation effect of psychological capital.

Predictor	Model 1			Model 2		
	Psychological capital			Anxiety		
	b	*se*	*t*	*b*	*se*	*t*
Gender	0.11 (0.11)	0.04 (0.06)	2.66** (1.79)	0.07 (0.03)	0.04 (0.06)	1.73 (0.46)
Problematic social media usage	−0.30 (−0.33)	0.02 (0.03)	−14.03*** (−11.34***)	0.29 (0.19)	0.02 (0.03)	14.58*** (6.61***)
Psychological capital				−0.35 (−0.39)	0.02 (0.03)	−17.57*** (−13.76***)
R^2		0.09 (0.11)			0.26 (0.24)	
F		106.08*** (68.11***)			246.22*** (109.88***)	

*Gender was dummy coded such that 1 = male and 0 = female. Model 1 regressed psychological capital on problematic social media usage and gender; Model 2 regressed anxiety on problematic social media usage, psychological capital, and gender, respectively; the b values were standardized coefficients. The data outside the brackets were for university students whose academic performance had been affected by the pandemic (n_1 = 2056), and the data inside the brackets were for university students whose academic performance had not been affected by the pandemic (n_2 = 1067). *p < 0.05, **p < 0.01, ***p < 0.001.*

Similarly, among university students whose academic performance was not affected by the COVID-19 pandemic, there was also a significant negative effect of problematic social media usage on psychological capital ($b = -0.33$, $SE = 0.03$, $p < 0.001$) and of psychological capital on anxiety ($b = -0.39$, $SE = 0.03$, $p < 0.001$). The indirect effect of problematic social media usage on anxiety via psychological capital was also significant ($b = 0.13$, $SE = 0.02$, 95% CI = [0.092, 0.170]). In addition, the direct relationship between problematic social media usage and anxiety was also significant ($b = 0.19$, $SE = 0.03$, $p < 0.001$) (see **Table 3**). Thus, irrespective of whether students' academic performance was affected by the pandemic, psychological capital played a mediating role between problematic social media usage and anxiety.

Moderation Effects

I used the PROCESS macro (Model 15) by Hayes (2017) to examine the moderating effects of academic burnout on the path from problematic social media usage to anxiety as well as the path from psychological capital to anxiety. A moderated mediation analysis was conducted on the two groups of participants. The results are summarized in **Table 3**.

For university students whose academic performance had been affected by the COVID-19 pandemic, problematic social media usage positively predicted anxiety, which was moderated by academic burnout ($b = 0.08$, $SE = 0.02$, $p < 0.001$). I further tested the interaction effect at high and low levels of academic burnout (i.e., one standard deviation above and below the mean of academic burnout) to investigate the moderating effects. The results showed that the association between problematic social media usage and anxiety was stronger for participants with a high level of academic burnout ($b_{simple} = 0.35$, $SE = 0.03$, $p < 0.001$) compared to those with a low level ($b_{simple} = 0.17$, $SE = 0.03$, $p < 0.001$). In addition, university students' psychological capital negatively predicted anxiety, and these effects were moderated by academic burnout ($b = -0.06$, $SE = 0.02$, $p < 0.001$). The simple tests showed that the relationship between psychological capital and anxiety was stronger for participants with high levels of academic burnout ($b_{simple} = -0.33$, $SE = 0.03$, $p < 0.001$) than for those with low levels of academic burnout ($b_{simple} = -0.19$, $SE = 0.03$, $p < 0.001$).

For university students whose academic performance was not affected by the COVID-19 pandemic, the relationship between problematic social media usage and anxiety was not moderated by academic burnout ($b = 0.03$, $SE = 0.02$, $p = 0.13$). However, the relationship between psychological capital and anxiety was moderated by academic burnout ($b = -0.06$, $SE = 0.02$, $p < 0.05$). The simple tests showed that the relationship between psychological capital and anxiety was stronger for participants with high levels of academic burnout ($b_{simple} = -0.37$, $SE = 0.04$, $p < 0.001$) compared to those with low levels of academic burnout ($b_{simple} = -0.25$, $SE = 0.04$, $p < 0.001$). The above results suggest that hypothesis 5 was partially supported.

DISCUSSION

The present study investigated the relationship between problematic social media usage and anxiety among university students during the COVID-19 pandemic. It also aimed to test a moderated mediation model in which the effects of problematic social media usage on anxiety were contingent on the intervening processes of psychological capital and academic burnout.

The results suggested that levels of anxiety were significantly higher among university students who perceived their academic performance to be affected by the COVID-19 pandemic compared to those who did not share this perception. Previous studies have also shown that pandemics of severe infectious diseases present the loss of resources, uncontrollable stress, and a crisis in mental and psychosocial health (Leone et al., 2014). As a recurring feature of human history, large-scale pandemics of emerging infectious diseases likewise presents not only the challenges of the disease itself but also the risk of anxiety symptoms. This is consistent with a previous study, which indicated that the population became more pessimistic after experiencing the pandemic of the severe acute respiratory syndrome (SARS) (Neuner et al., 2006). Except for the anxiety caused by the COVID-19 virus itself, the pandemic has disrupted university students' lives and study schedules, which may have further increased their anxiety.

Another lifestyle change triggered by the pandemic that may increase anxiety levels among university students is the

TABLE 3 | Testing the moderated mediation effect of problematic social media usage on anxiety.

Predictor	Model 1			Model 2		
	Psychological capital			Anxiety		
	b	*se*	*t*	*b*	*se*	*t*
Gender	0.11 (0.11)	0.04 (0.06)	2.66** (1.78)	0.03 (0.01)	0.04 (0.06)	0.81 (0.80)
Problematic social media usage	−0.30 (−0.33)	0.02 (0.03)	−14.03*** (−11.34***)	0.26 (0.17)	0.02 (0.03)	12.60*** (5.91***)
Academic burnout				0.17 (0.13)	0.03 (0.04)	6.58*** (3.38***)
Problematic social media usage × Academic burnout				0.08 (0.04)	0.02 (0.02)	4.32*** (1.53)
Psychological capital				−0.25 (−0.30)	0.02 (0.04)	−10.16*** (−7.87***)
Psychological capital × Academic burnout				−0.06 (−0.06)	0.02 (0.02)	−3.78*** (−2.57*)
R^2		0.09 (0.11)			0.30 (0.26)	
F		106.08*** (68.11***)			146.99*** (61.27***)	

*Gender was dummy coded such that 1 = male and 0 = female. Model 1 regressed psychological capital on problematic social media usage and gender; Model 2 regressed anxiety on problematic social media usage, academic burnout, problematic social media usage × academic burnout, psychological capital, psychological capital, academic burnout, and gender, respectively; the b values are standardized coefficients. The data outside the brackets were for university students whose academic performance had been affected by the pandemic ($n_1 = 2056$), and the data inside the brackets were for university students whose academic performance had been not affected by the pandemic ($n_2 = 1067$). *p < 0.05, **p < 0.01, ***p < 0.001.*

use of mobile social media. In the present study, I found that problematic social media usage during the COVID-19 pandemic was significantly associated with anxiety among university students. Prior research also revealed that adults who put more effort and time into mobile social media had poorer sleep quality, lower self-esteem, and higher levels of anxiety and depression (Vannucci et al., 2017). These findings can be explained by the displacement hypothesis, which states that the use of the internet, especially to connect with people online, displaces face-to-face social relationships and the quality of social support given and received. These aspects negatively impact an individual's mental health (Huang, 2010). Moreover, during public health crises, mobile social media spreads disinformation, thus aggravating public fear and panic. The prevalence of the pandemic has forced university students' social capital to turn toward online connections. During the pandemic, mobile social media has played a pivotal role in the learning, living, and leisure activities of university students. Due to the long hours at home, e-learning has become the primary mode of learning for university students, whereas face-to-face social relationships have been kept to a minimum, both of which have created conditions and opportunities for social media usage and resulted in a significant increase in the amount of time university students spend on social media. Overreliance on social media certainly leads to higher anxiety among university students. A recent study also supported that during the COVID-19 pandemic, young adults who used social media frequently reported greater symptoms of depression and loneliness (Lee et al., 2020).

In addition, my study found that problematic social media usage affected the levels of anxiety through the mediation of psychological capital during the pandemic. Specifically, when university students use more social media, they typically have lower levels of psychological capital and, thus, higher levels of anxiety. These results are consistent with a recent study, which found that psychological capital had a mediation effect between coping style and anxiety among university students (Wu et al., 2019). An increase in internet and social media use time increases the possibility of internet addiction. Previous studies have also shown that individuals using the internet for social communication were more likely to be addicted to the internet than those who used the Internet for entertainment/news (Simsek and Sali, 2014). However, excessive internet use presupposes individuals to adopt negative coping styles of escapism, resulting in a sense of hopelessness and loss of control in life, which reduces psychological capital (Fincham et al., 2009). More specifically, the concept of psychological capital emphasizes the development of positive attributes to cope with psychological problems, which requires individuals to solve problems, rather than escape them. As a developmental structure, psychological capital requires an investment of time and energy (Fincham et al., 2009). For university students, spending too much time and energy on social media may deplete the internal mechanisms needed to cope with challenges and maintain a higher level of psychological capital.

Moreover, the negative predictive effect of psychological capital on mental health has been demonstrated in previous studies across cultures and populations (Krasikova et al., 2015; Tan, 2016; Xiong et al., 2020). Rahimnia et al. (2013) found that high psychological capital reduced destructive emotions, such as stress and anxiety, and eventually increased well-being. Specifically, when individuals have high psychological capital, they are equipped with extra resources to cope with stress, expect good things to happen, quickly "bounce back" after setbacks, and are more hopeful about negative situations (Shen et al., 2014). Therefore, university students with high psychological capital might have some control over their lives and have positive psychological capacities and motivation to cope with obstacles (Luthans et al., 2007b), which partly counteracts the effects of negative life events and stressors on mental health and reduces anxiety and depression. In sum, psychological capital played a mediating role in the relationship between social media usage and anxiety among university students.

This study also assessed whether university students perceived that their academic performance was affected by the pandemic. As mentioned above, I believe that for the students who perceived their academic performance to be affected, there were interactions between the pandemic and variables such as individual mobile media usage. However, the relationship between problematic media usage and other psychological constructs in the group who did not perceive any significant change in their academic performance was stable and less affected by the pandemic. By comparing the different patterns of relationships between these variables in the two groups, I hope to shed some light on the individual-specific effects of the pandemic. In the current study, I found that for the students who did not perceive their academic performance to be affected by the pandemic, the effects of problematic media use on anxiety and the mediation of psychological capital were also significant, similar to those who perceived their academic performance to be affected by the pandemic. This may be because for students who perceived their academic performance to be affected by COVID-19, the effect of problematic mobile social media usage on anxiety through psychological capital was the reflection of the external environment and a product of special situations (First et al., 2020; Lin et al., 2020). However, students who perceived their academic performance not to be affected by the pandemic but used mobile media more frequently, were not immune to the negative effects of overuse of social media. These students were likely to have already problems with excessive usage of mobile social media as a substitute for real-life face-to-face social networking in their daily lives (Glaser et al., 2018). In other words, these students were already at risk for fragile relationship networks, low offline social capital, and high internet addiction in non-pandemic periods, while being minimally affected by the pandemic. Moreover, for university students who perceived that they were not affected by the pandemic, psychological capital also had a strong role in mediating the relationship between problematic social media usage and anxiety.

Finally, the present study found that academic burnout moderated two pathways among university students: the influence of problematic social media usage on anxiety and that of psychological capital on anxiety. That is, problematic social media usage was more predictive of anxiety among university students with high levels of academic burnout than those with low levels. Specifically, students with high academic burnout feel exhausted because of study demands, have a detached attitude toward schoolwork, and have lower self-efficacy as a student (Zhang et al., 2007; Rahmati, 2015). In this case, social media overuse is more likely to be an approach to escape academic tasks, which increases the risk of internet addiction, resulting in higher levels of anxiety (Fincham et al., 2009). For students with low academic burnout, the sensitivity of the relationship between problematic social media usage and mental health may be relatively weak. Thus, students with low academic burnout were less affected by the influence of problematic social media usage on anxiety. Moreover, academic burnout also moderated the effects of psychological capital on anxiety. Students with high academic burnout similarly strengthened the relationship between psychological capital and anxiety. High academic burnout leads to university students being in a state of exhaustion, cynicism, and low efficacy, which brings to the fore the negative impact of low psychological capital on mental health outcomes (Schaufeli et al., 2002). In contrast, when individuals experience low academic burnout, the protective role of psychological capital in reducing anxiety may not be sufficiently realized (Shen et al., 2014).

Interestingly, the current study also found that academic burnout moderates different patterns of the relationship between problematic social media usage, psychological capital, and anxiety in the two groups of students. Our results demonstrated that for university students who perceived their academic performance to be unaffected by the pandemic, academic burnout only moderated the effects of psychological capital on anxiety but not the effects of problematic social media usage on anxiety. This could be interpreted considering another finding of this study, that is, the students who perceived their academic performance to be unaffected by the pandemic had lower levels of academic burnout compared to the other group, which is also consistent with the study of Peinado and Anderson (2020). Thus, the moderating role of academic burnout was also relatively weak in the former group of students. Furthermore, for the university students who perceived their academic performance to be affected by the pandemic, their problematic mobile social media usage was largely influenced by external stressors, such as COVID-19 exposure, fear of COVID-19, and COVID-19 misunderstanding (First et al., 2020; Lin et al., 2020). Conversely, for those who thought that their academic performance was unaffected by the pandemic, the high frequency and problematic mobile social media usage was attributed to preexisting factors, such as their personality (Correa et al., 2010), self-esteem (Bányai et al., 2017), attachment style (Blackwell et al., 2017), and a variety of other factors. Thus, the role of problematic social media usage on anxiety was more stable, leading to a more limited and insignificant moderating effect of academic burnout.

Limitations and Implications

The present findings have both theoretical and practical implications. First, to the authors' knowledge, this is the first systematic exploration of the relationships between problematic social media usage, psychological capital, anxiety, and academic burnout among university students during the COVID-19 pandemic. The findings of this study enhance the understanding of how and when problematic social media usage affects anxiety among university students. They further show that psychological capital was an important psychological mechanism among university students and enrich the research related to psychological capital and anxiety among university students. Second, the findings provided a new perspective on how to alleviate university students' anxiety determined by the use of mobile social media. Furthermore, the mediating role of psychological capital and the moderating role of academic burnout suggest that I may be able to alleviate anxiety by improving students' psychological capital or reducing their academic burnout so that these can counteract the negative effects of problematic media usage.

However, the study has some limitations. First, this study adopted a self-report method, in which participants reported whether they were affected by the pandemic. It is worth noting that these effects may be influenced by other factors, such as personality. Therefore, further research should collect data from multiple perspectives to reveal the relationships more accurately among these variables in different backgrounds. Second, I used a cross-sectional design to explore the mechanism of problematic social media usage on university students' anxiety. Further studies should use a longitudinal-based design to establish causal relationships between problematic social media usage, psychological capital, academic burnout, and anxiety. Finally, prior research has revealed that the negative effect of social media usage was mediated by internet addiction, whereas when individuals use social media to build on preexisting offline social capital, their mental health is improved (Glaser et al., 2018). However, in the current study, I focused only on the problematic mobile social media usage among university students, using the problematic mobile social media usage assessment questionnaire; thus, we did not explore the positive effect of social media use on university students during the pandemic. Further studies should adopt multidimensional and comprehensive social media usage questionnaires to assess both the positive and negative effects of mobile social media usage on university students during the pandemic.

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 Tongji University. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

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

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BRIEF RESEARCH REPORT
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Relation Between the Degree of Use of Smartphones and Negative Emotions in People With Visual Impairment

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The use of smartphones has become commonplace, even among people with disabilities. The purpose of this study was to investigate the effect of smartphone use on the negative emotions of people with visual impairment. This study analyzed data from 30 respondents with visual impairments obtained from the 2016 Internet Overdependence Survey in South Korea. The analysis was based on partial least squares regression with information search, leisure, communication, and online transactions as independent variables, and negative emotions comprising depression, anxiety, and loneliness as the dependent variables. Among people with visual impairment, the use of smartphones as a means of communication decreased negative emotions while their use for leisure or information search was related to an increase in negative emotions such as depression and loneliness. Use for information retrieval was found to be associated with a low level of anxiety, and use for online transactions was associated with low loneliness. The results of this study showed that the use of the Internet can be a means of providing interaction opportunities and reducing negation emotions for people with visual impairment.

Keywords: smartphone, people with visual impairment, depression, anxiety, loneliness

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INTRODUCTION

According to a survey conducted in 2015, there are more than 1.5 billion smartphone users worldwide and, overall, more than 1 billion smartphones are estimated to have been sold (Demirci et al., 2015). Smartphone ownership was 56% in 2013 in the United States (Smith, 2013) and 79% in 2012 in Switzerland (Suter et al., 2015). Based on a survey conducted in South Korea, about 9 out of 10 people own a smartphone and the usage time is steadily increasing (Jeong et al., 2020). More than 2.23 billion people use Facebook monthly, and appear to share their thoughts on social issues and details of friends through this platform (Wiese et al., 2020). In addition, more than 90% of adults in the United States visit social media websites, and in the United Kingdom people spend an average of 136 min a day on social media; such people make social comparisons through their use of social network services (SNS) and their behavior is significantly influenced by these social comparisons (Oh et al., 2014).

The 2018 Digital Information Gap Survey Report published by the National Information Society Agency (NIA) comprehensively measured the level and characteristics of the information gap occurring in the digital environment of South Korea and found that, taking the level of the general public as 100, the level of digital informatization of people with disabilities was 74.6% as of 2018. This was higher than the average (68.9%) of people with disabilities, low-income, farmers, fishermen, and the elderly, which comprised the information-vulnerable groups in the digital information gap survey and was the second highest after the low-income group (86.8%). Even relative to other groups, this information gap for people with disabilities has been increasing every year (National Information Society Agency, 2019).

Quantitative growth and the narrowing of the gap in accessibility are the result of policy measures, such as the information and communication assistive device distribution project and development projects for people with disabilities who have difficulty accessing information due to physical and economic conditions (Baxter et al., 2012; Duplaga, 2017). The use of the Internet can provide opportunities for people with disabilities to enhance their independence, access online services such as e-banking and Internet shopping, and communicate with family and friends through e-mail or video conferencing. Through such ways, it can greatly improve their daily lives (D'Aubin, 2007; Duplaga, 2017). The Internet can be a viable way to promote social participation for people with disabilities (Raghavendra et al., 2013) who can use information and communication assistive devices to overcome their physical limitations and to engage in socio-economic activities to expand their rights and interests (Jin, 2013). Therefore, there is a need for an empirical study on how the use of digital smartphones affects the psychology of individuals, beyond the accessibility gap issue.

In recent years, with the global increase in smartphone use, studies on the relationship between this usage and emotional risk behaviors, such as depression, anxiety, and suicide-related behaviors, have been continually conducted (Lemola et al., 2015; Sueki, 2015; Twenge et al., 2018). Previous research on people with disabilities has confirmed that digital use influences life satisfaction and satisfaction with policies (Lee and Lee, 2018; Hwang, 2019). In a study that investigated the relationship between social media use and well-being in people with physical disabilities, it was reported that the higher the intensity of SNS use and online community use, the lower the level of depression through intervention tools and information support. It was reported that social media use played a positive role in building social support and strong psychological tendencies (Lee and Cho, 2019). In other words, there is a possibility that people with disabilities experience a positive impact on their lives through online activities.

Studies involving Internet use and individuals with visual impairments have generally focused on issues related to barriers to access and use (Williamson et al., 2001; Gerber, 2003). Among these barriers are the difficulties associated with accessibility, cost, and assistive technology; while the perceived benefits of using the Internet include access to new information, ability to use the Internet in the workplace, and improved social participation. However, the relationship between Internet use and the psychosocial well-being of individuals with visual impairments has not yet been investigated. Initially, visually impaired people could not use mobile phones for other purposes than making calls; however, with the advent of the iPhone in 2009 and the improvement of services such as the voice over function, people with visual impairments were able to expand their mobile phone usage beyond just making phone calls. However, studies related to the use of smartphones among people with visual impairment have not been actively conducted. Therefore, it is necessary to investigate the impact of smartphone use on the lives of people with visual impairment and its effect on negative emotions in order to obtain basic data to plan future mobile device-related research projects for this population. Accordingly, this study aims to investigate the relationship between the degree of use of smartphones and negative emotions in people with visual impairment.

MATERIALS AND METHODS

Data

This study utilized the data from the 2016 Internet Overdependence Survey conducted by NIA from September to November 2016 in South Korea. The survey covered a sample of 24,386 people (100,000 households) aged between 3 and 69, who resided in 17 cities and provinces nationwide, with a resulting sampling error of ±0.63 at a 95% confidence level. This study analyzed a subset of the overall data, covering 30 people with visual impairments. For the survey, a trained professional investigator personally visited the sample households and wrote down the subject's responses to each question. **Table 1** summarizes the general characteristics of the participants.

TABLE 1 | General characteristics of people with visual impairment.

Category	Sub-category	*n*	%	At high risk	At potential risk	General user
Sex	Male	18	60.0	2	1	15
	Female	12	40.0	0	2	10
Age	18–29	2	6.7	0	0	2
	30–49	18	60.0	1	3	14
	Above 50	10	33.3	1	0	9
Education level	Graduate middle school	5	16.7	0	0	5
	Graduate high school	8	26.7	2	0	6
	Above college	17	56.7	0	3	14
Income level+	Below 2,000	3	10.0	0	0	3
	2,000–3,999	9	30.0	1	1	7
	4,000–5,999	11	36.7	0	0	11
	6,000–7,999	4	13.3	1	1	2
	8,000–9,999	2	6.7	0	0	2
	Above 10,000	1	3.3	0	1	0
Employment	Yes	29	96.7	1	3	15
	No	1	3.3	1	0	10

+*Income levels in 10,000 South Korean won (USD 1 = KRW 1,126.50).*

Measure

The purpose of smartphone use was measured by classifying it into information search, leisure, communication, and online transactions, and using a seven-point Likert scale. Information search comprised searching for information related to news, academic/business, education/learning, product/service, and traffic/location. Leisure was defined as the use of smartphones for games, adult content, movies, TV and video content, music, e-books, web cartoons and web novels, and speculative games (sports betting, online gambling, etc.). Communication covered the use of e-mail, messenger, and SNS. Lastly, online transactions covered product/service purchases and product/service sales.

Negative emotions can be defined in various ways. The questions related to negative emotions presented in representative emotion scales are as follows. The Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) includes questions with negative emotions such as "frightened," "hostile," "nervous," "sensitive," "impatient," "painful," "broken heart," "guilty," and "shameful." The Intensity and Time Affect Scale (ITAS; Diener et al., 1995) includes negative emotions such as "fear," "anger," "irritation," "anxiety," "worry," "guilty," "shame," "disgusting," "regret," "sadness," "loneliness," "unhappy," and "depression." The Scale of Positive and Negative Experience (SPANE; Diener et al., 2009) includes negative emotions such as "sad," "unpleasant," "bad," "negative," "afraid," and "angry."

The emotional problems experienced by people with visual impairments were measured by a scale developed by National Information Society Agency (2019). This scale includes questions aimed at measuring emotions similar to the questions suggested by the emotion measurement tools used in previous research. The Cronbach's α was reported as.880 (Bae, 2015). The emotional mood in the respondent's daily life was assessed through several statements. The statement "I am depressed and de-motivated" was used to measure depression, "I am anxious" was used to measure anxiety, and "I am lonely" was used to measure loneliness. The responses to these statements were measured on a 4-point rating scale where one represented "I do not feel like this at all" and four represented "I feel this way often."

Statistical Analysis

Descriptive statistics were used to describe the characteristics of people with visual impairment. A one-sample Kolmogorov-Smirnov test was performed to check whether the continuous data used in our study was normally distributed, which is a prerequisite for conducting parameter estimations. Negative emotions such as depression, anxiety, and loneliness were not normally distributed ($p < 0.05$). In terms of smartphone use purposes, information search, leisure, and communication use were found to be normally distributed ($p > 0.05$) while the degree of online transaction utilization was not normally distributed ($p < 0.05$). In regression analysis, since both the independent and the dependent variables must follow normal distributions, this study conducted a partial least squares (PLS) regression analysis.

Interpretation of PLS analysis results can determine the magnitude of influence through variable importance in the projection (VIP). In general, if the VIP value is close to or exceeds 1, the coefficient of the variable can be considered statistically very significant. Even a VIP of 0.8 or higher would imply that the variable plays a significant role in estimating the causal relationship (Nash and Chaloud, 2011). This study used an empirical criterion that if the VIP value of a particular variable was less than 0.8 and the absolute value of all regression coefficients was very small (close to 0), it could be removed as a meaningless explanatory variable when extracting latent factors or estimating the causal relationship (Sawatsky et al., 2015). This study applied a PLS regression analysis using five potential factors, which are basic set values, to observe the change in explanatory power of the derived model according to a change in the number of potential factors. The explanatory power of the model can be determined by the cumulative y variance of the response variable Y. This explanatory power generally increases as variables are added until a specific point where the explanatory power decreases upon adding the next variable. This point is deemed as the cutoff and the number and specific factors included until this newly added variable are used to define the statistical characteristics of the model (Sawatsky et al., 2015).

All analyses were performed using SPSS 21.0 (SPSS Inc., Chicago, IL, United States) at a significance level of $\alpha = 0.05$.

Ethics Approval and Consent to Participate

This study did not require formal ethical approval under national laws. It used publicly available data from NIA, which did not contain any personally identifiable data. Ethical and governance approvals were granted by the Ministry of Science and ICT in South Korea. All participants gave written informed consent for participation before completing the survey.

RESULTS

Explained Variance in Negative Emotion

Table 2 shows the effect of smartphone usage on the three negative emotions analyzed in this study.

As shown in **Table 2**, the variance of the explanatory variables through each latent factor (Cumulative *X* Variance) was analyzed to explain 72.3% of the variance of all nine explanatory variables through five latent factors in depression, 73.6% in the case of anxiety, and 74.1% in the case of loneliness.

The explanatory power of the model can be determined by the cumulative y variance of the response variable Y, and the difference in explanatory power was reduced upon adding the third latent factor; hence, the explanatory power at this point and the number of potential factors (two) were determined as the statistical characteristics of the model. The explanatory power of the model constructed to determine the influence of smartphone use on the negative emotion of depression was therefore, 19.2%, which corresponds to the second potential factor. Similarly, the explanatory power of the model constructed for the effect of smartphone usage on anxiety and loneliness can be interpreted as 24.4 and 34.5%, which correspond to the second and third potential factors, respectively.

TABLE 2 | Explained variance in negative emotions.

Negation emotion	Latent factors	Cumulative *X* variance	Cumulative *Y* variance (R-square)	Adjusted R-squared
Depression	1	0.251	0.141	0.110
	2	0.379	**0.192**	0.132
	3	0.469	0.212	0.121
	4	0.631	0.214	0.088
	5	0.723	0.216	0.053
Anxiety	1	0.230	0.187	0.158
	2	0.387	**0.244**	0.188
	3	0.477	0.266	0.181
	4	0.615	0.271	0.154
	5	0.736	0.273	0.121
Loneliness	1	0.209	0.277	0.251
	2	0.370	0.332	0.283
	3	0.551	**0.345**	0.269
	4	0.679	0.349	0.245
	5	0.741	0.351	0.215

Bold means the explanatory power of model.

The Results of PLS Regression Analysis

The models determining the effect of smartphone use on the negative emotions of depression and anxiety were analyzed based on the importance value of the second latent factor, while the model for loneliness was based on the importance value of third latent factor. **Table 3** lists the resulting importance of the explanatory variables for each potential factor through the VIP values of the five potential factors.

As a result of the PLS regression analysis, the most important factor influencing the negative emotion of depression was leisure with the highest importance (VIP) of 1.694. Information search (1.489) and communication (1.347) were other factors that were considered important as their VIP values were 1.0 or higher.

Regarding anxiety, leisure was estimated as an important factor with the highest importance (VIP) at 1.608. Based on a VIP value exceeding 1.0, other factors deemed important variables were information search (1.297) and communication (1.608). In addition, the variables with VIP values between 0.8 and 1.0 were sex (0.837) and leisure (0.940).

Lastly, in the case of loneliness, the variable that was determined to be the most important influencing factor was online transactions, with the highest importance (VIP) at 1.824. Leisure (1.045) and income (1.139) were other important factors with VIP values exceeding 1.0. In addition, the variables with VIP values ranging between 0.8 and 1.0 were gender (0.823) and information search (0.902).

DISCUSSION

To determine whether the use of smartphones affected negative emotions such as depression, anxiety, and loneliness in people with visual impairment, this study analyzed the data from the 2016 Internet Overdependence Survey of South Korea.

First, it was found that the use of smartphones for leisure, information search, and communication purposes by people with visual impairment significantly influenced their negative emotions. Regarding depression, the non-standardized coefficient of communication was negative (-) indicating that the more that smartphones were used for communication, the lower the negative emotion of depression. Second, the use of smartphones for information search and communication was associated with lower anxiety in people with visual impairment. Third, regarding the effect of the use of smartphones by people with visual impairment on the negative emotion of loneliness, it was found that income, leisure, and online transactions had significant effects. Among these, the coefficients for income and leisure were positive, indicating that the higher the income or the greater the use of smartphones for leisure, the greater was the negative emotion of loneliness. The coefficient of online transactions was negative indicating that the use of smartphones for online transactions was associated with lower loneliness levels.

Just as it cannot be denied that the Internet and the use of smartphones have made our lives more convenient than before, not all aspects of using smartphones have a positive impact (Demirci et al., 2015; Elhai et al., 2016). Studies that show that smartphone use is related to negative emotions such as depression and anxiety have been reported steadily. In particular, research results on the effect of problematic smartphone use have been reported (Rozgonjuk et al., 2018). Social smartphone use is negatively associated with anxiety and depression symptoms severity (Elhai et al., 2017). This indicates that using a smartphone for communication is associated with lower depression and anxiety. The aforementioned findings are consistent with the results of this study, which showed a negative relationship between the use of smartphones for communication and the negative emotions of depression and anxiety. A possible explanation for this negative relationship is that the proportion of people at risk of developing smartphone addiction among people with visual impairments (16.7%; National Information Society Agency, 2019) was lower than that of the total survey group (20.0%; National Information Society Agency, 2019). The use of online chat or instant messaging by people with visual impairment has been reported to have a positive effect on their psychological well-being while information retrieval has been reported to have a negative effect (Smedema and McKenzie, 2010). The social use of smartphones and the low ratio of addiction associated with their usage in people with visual impairment might have an effect on the negative relation between communication and depression and anxiety.

It has been argued that the use of social networks has a negative impact on emotions. An excessive use of Facebook not only caused a phenomenon of "Facebook depression" among teenagers (O'Keeffe and Clarke-Pearson, 2011), but the literature also uncovered a high correlation between the frequent use of Facebook and depression (Pantic et al., 2012; Oh et al., 2014). This is because many people participate in social comparison behaviors through social network sites like Facebook, and their behaviors are significantly influenced by such social comparisons (Zhang and Centola, 2018). SNS have also been shown to negatively affect an individual's emotional state (Sagioglou and Greitemeyer, 2014). In other words, while communication through direct conversation on Facebook

TABLE 3 | The PLS regression analysis results.

Negative emotion	Variables	B	Latent factors				
			1	2	3	4	5
Depression	Constant	2.616					
	Sex	0.047	0.478	0.536	0.665	0.663	0.665
	Age	−0.136	0.816	0.701	0.870	0.870	0.886
	Education level	−0.134	0.618	0.532	0.509	0.542	0.541
	Income	−0.080	0.597	0.514	0.584	0.583	0.584
	Information search	0.043	1.719	**1.489**	1.440	1.438	1.447
	Leisure	0.277	1.810	**1.694**	1.641	1.633	1.629
	Communication	−0.200	0.000	**1.347**	1.377	1.371	1.366
	Online transactions	0.027	0.369	0.353	0.336	0.386	0.394
Anxiety	Constant	2.635					
	Sex	−0.248	0.716	0.837	0.803	0.807	0.805
	Age	0.239	0.407	0.507	0.660	0.655	0.667
	Education level	−0.014	0.309	0.396	0.418	0.447	0.446
	Income	0.021	0.099	0.278	0.455	0.452	0.471
	Information search	−0.106	1.480	**1.297**	1.270	1.261	1.257
	Leisure	0.017	1.033	0.940	0.907	0.932	0.941
	Communication	−0.322	1.174	**1.608**	1.573	1.563	1.558
	Online transactions	0.105	0.190	0.711	0.704	0.700	0.701
Loneliness	Constant	0.864					
	Sex	0.301	0.867	0.815	0.823	0.824	0.828
	Age	0.228	0.165	0.416	0.499	0.498	0.505
	Education level	−0.043	0.561	0.587	0.675	0.671	0.670
	Income	0.266	1.003	1.160	**1.139**	1.132	1.130
	Information search	−0.012	0.904	0.912	0.902	0.932	0.943
	Leisure	0.232	1.158	1.058	**1.045**	1.039	1.037
	Communication	0.012	0.279	0.596	0.593	0.603	0.611
	Online transactions	−0.418	1.914	1.831	**1.824**	1.821	1.816

Bold means variable importance in the projection.

increases bonding social capital and reduces loneliness, the longer one uses Facebook without any interaction, the lesser the social capital and greater the loneliness (Burke et al., 2010). This is because information such as vacation photos of other people on Facebook induces envy in viewers, which in turn negatively affects life satisfaction (Krasnova et al., 2013). By replacing strong connections with weak connections through social media use and reducing direct face-to-face contact with people close to us, we become unhappy by creating emotions such as "alone while together" or "solitude in a crowd." In the case of people who use the Internet for communication, it was reported that the depression score decreased at the follow-up after 6 months (Bessière et al., 2008). In addition, using the Internet for communication purposes is a predictor of low depression while using the Internet for purposes other than communication has been reported to predict high levels of depression and social anger (Selfhout et al., 2009). The results of this study, which showed that the use of smartphones for leisure and information search was positively related with the negative emotions of depression and loneliness among people with visual impairment, are consistent with these previous studies.

Information search can be motivated by the aim of reducing uncertainty when a problem occurs; it has been reported that provision of information relieves anxiety in situations such as when facing surgery (Sjöling et al., 2003). Moreover, the pursuit of security through information search can be an important issue in online health-related searches (Starcevic and Berle, 2013). Since previous studies are related to health-related information retrieval and hepatic anxiety, it is difficult to directly compare them with the results of this study; in this sense, this study can be said to be different. Therefore, further research on the relationship between the use of smartphones for information retrieval and anxiety is necessary.

Partial least squares regression analysis can capture the influence of factors regardless of the sample size. Moreover, since each independent variable is modeled using least squares, the analysis is free from the problem of multicollinearity. In addition, it has the advantage that the predictive power is superior to the principal component regression analysis because the dependent variable and the independent variable are considered simultaneously when the principal component is extracted. For all its methodological advantages, this study conducted a PLS regression analysis, using panel data with systematic sampling.

Nonetheless, this study has several limitations. First, the sample size was relatively small. Future research should increase the number of participants so that the effects of degree of smartphones use on negative emotions in people with visual impairment can be verified through various methods such as path analysis. Second, the questionnaire to measure emotional mood is too simple to capture all emotional well-being. The information available for this study was limited to what was provided by the panel data. In future studies, it is necessary to obtain more detailed information about relation between the degree of use of smartphones and negative emotions in people with visual impairment. Third, the data analyzed were from 2016. Although this is the most recent data on Internet use and negative emotions from the national information gap survey, as a result of improvements on the usage restrictions since then, the present impact on negative emotions may be less. Therefore, research is needed to assert the current relationship between the use of smartphone's features and negative emotions.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://eng.nia.or.kr/site/nia_eng/main.do.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

E-YP contributed to project administration, data analysis, and writing.

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Perceived Stress and Smartphone Addiction in Medical College Students: The Mediating Role of Negative Emotions and the Moderating Role of Psychological Capital

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Background: Many studies have confirmed the existence of an extremely close relationship between smartphone addiction and perceived stress. However, the mediating and moderating mechanisms underlying the association between perceived stress and smartphone addiction in medical college students remain largely unexplored.

Methods: A questionnaire was distributed among a total of 769 medical college students in Heilongjiang Province, China. Participants completed measures of perceived stress, smartphone addiction, negative emotions, and psychological capital. Pearson's correlation analysis was used to test the correlations between variables. The analysis of a moderated mediation model was performed using Hayes's PROCESS macro.

Results: Pearson's correlation analysis indicated that perceived stress ($r = 0.18$, $p < 0.01$) and negative emotions ($r = 0.31$, $p < 0.01$) were positively correlated with smartphone addiction, and psychological capital was negatively correlated with smartphone addiction ($r = -0.29$, $p < 0.01$). The moderated mediation analysis indicated that negative emotions partially mediated the association between perceived stress and smartphone addiction [mediation effect accounted for 33.3%, $SE = 0.10$, 95% CI = (0.10, 0.24)], and the first stage of the mediation process was significantly moderated by psychological capital [moderated mediation = −0.01, $SE = 0.01$, 95% CI = (−0.01, −0.00)].

Conclusion: Negative emotions play a mediating role between perceived stress and smartphone addiction, and psychological capital plays an important moderating role in the first stage of the mediation process.

Keywords: perceived stress, smartphone addiction, medical college students, psychological capital, negative emotion

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INTRODUCTION

The smartphone has become an important tool for accessing information, interaction, and entertainment in modern society. However, excessive use of smartphones has accumulating adverse influences on individuals, which has aroused great concern within society. Smartphone addiction, also known as problematic smartphone use or mobile phone dependence (Gao et al., 2017), is essentially behavioral addiction. It refers to the individual behavior being out of control because of the use of mobile phones, resulting in a state of obsession (Gao et al., 2017). The studies reported that smartphone addiction in adolescence ranges from 20 to 40%. Especially, a recent Filipino study found that the incidence of smartphone addiction is as high as 60% (Buctot et al., 2020). The individual's physiological, psychological, and social functions are significantly impaired (Yen et al., 2009). Specifically, a large number of studies have shown that smartphone addiction can cause a variety of maladjustment, including physical health difficulties (Kim et al., 2015), sleep disturbances (Liu et al., 2017), academic failures (Samaha and Hawi, 2016), and emotional and behavioral problems (Chen et al., 2016, 2020).

The general strain theory is originally used for explaining criminal behaviors (Agnew, 1992), and now it has been well used for analyzing addictive behaviors (Eitle et al., 2013; Jun and Choi, 2015). According to the general strain theory, strains or stressors increase the likelihood of negative emotions like anger and frustration (Agnew, 2001). These emotions cause corrective behavior (Agnew, 2001), and addictive behavior may be a method for reducing strain or alleviating negative emotions. Medical college students, as a special group of college students, have high levels of stress that could be due to academic burden, frequency of examinations, lengthy academic curriculum, and worrying about the future (Gazzaz et al., 2018). When faced with this stress, they are more likely to use smartphones as a way to relieve stress (Yang et al., 2020). Perceived stress refers to the degree to which an individual perceives an external event as stress (Cohen et al., 1984). Whether the objective stress affects the individual depends on the individual interpretation and perception of the stress event (Cohen et al., 1984). Perceived stress could make an individual believe they are in a stress situation, which is considered to be a risk factor in the occurrence and recurrence of many addictions, such as problematic online gaming (Snodgrass et al., 2014), substance abuse (Sinha, 2008; Tavolacci et al., 2013), internet addiction (Jun and Choi, 2015), and so on. Particularly, some studies have confirmed that stress could effectively predict smartphone addiction (Chiu, 2014; Kuang-Tsan and Fu-Yuan, 2017). Individuals who perceive more stress are more inclined to engage in smartphone addiction (Liu et al., 2018).

Unfortunately, previous studies have made valuable contributions to the relationship between stress and smartphone addiction; however, the mediating (i.e., how perceived stress relates to medical college students' smartphone addiction) and moderating mechanisms (i.e., when the relation is most potent) underlying the association between perceived stress and smartphone addiction in medical college students remain largely unexplored. Confirming its mediating and moderating mechanisms could be critical to advance our understanding of smartphone addiction in medical college students and to develop an effective intervention as well.

The Mediating Role of Negative Emotions

Abundant studies have shown that perceived stress is positively correlated with negative emotions (Spada et al., 2008; Anitei and Chraif, 2013). Stress is one of the most important risks leading to mental health problems. To some extent, the existence of stress can break the balance between the individual and the environment. The imbalance makes it difficult for the individual to adapt to the impact of objective events on themselves, which leads to some negative emotions such as anxiety and depression. Negative emotions have an important impact on individual cognition and behavior. Previous studies have found a positive correlation between negative emotions and problematic behavior. On the one hand, negative emotions can cause substance problematic use, such as drug abuse (Ketcherside and Filbey, 2015). Apart from substance problematic use, a large number of studies have shown that negative emotions are related to nonmaterial problematic use, such as internet addiction (Young and Rogers, 1998; Scimeca et al., 2014) and smartphone addiction (Ghasempour and Mahmoodi-Aghdam, 2015; Matar Boumosleh and Jaalouk, 2017). For example, one study pointed out that anxiety and depression scores emerged as the independent positive predictors of smartphone addiction (Matar Boumosleh and Jaalouk, 2017). Individuals with high depression scores are more likely to become addicted to their smartphone. Relevant studies have shown that mood regulation (defined as reducing negative feelings such as loneliness, anxiety, depression, stress) could reduce the occurrence of smartphone addiction among a convenient sample of 394 Chinese university students (Zhang et al., 2014; Stanković et al., 2021). Furthermore, some studies have indicated that individuals are prone to eliminate negative emotions accumulated in daily life through negative means including substance abuse, dependence, and addiction (Ketcherside and Filbey, 2015). Considering that smartphone addiction behavior is problematic behavior, we could speculate that negative emotions are significantly positively correlated with smartphone addiction based on the mentioned studies.

Therefore, we assume that negative emotions will play a mediating role in the relationship between perceived stress and smartphone addiction. This hypothesis could be corroborated by similar studies. For example, many researchers have found that negative emotions mediated the relationship between stress and problematic behaviors, including eating disorders (Goldschmidt et al., 2013) and problematic use of marijuana (Ketcherside and Filbey, 2015). To our knowledge, the mediated effect in the relation of perceived stress and smartphone addiction in medical college students remains largely unexplored.

The Moderating Role of Psychological Capital

Psychological capital is an important personal resource, defined by Luthans et al. (2004) as "a positive psychological state that an individual performs in the process of growth and development." It is composed of four psychological resource capacities, namely, self-efficacy, hope, optimism, and resilience (Luthans et al., 2004). According to Bandura's Social Cognitive Theory (Bandura, 1986; Bandura, 2002), efficacy is defined as "having the confidence to undertake and make the necessary effort to succeed at challenging tasks"; hope means persevering toward goals and when necessary, redirecting paths to goals in order to succeed; optimism refers to "a mood or attitude"; resilience is defined as "sustaining and bouncing back and even beyond to attain success when beset by problems and adversity" (Luthans et al., 2008). Resilience could help an individual cope with stress effectively and achieve good adaptation and development (Dyrbye et al., 2010; Hu et al., 2015). The general strain theory incorporates conditioning factors into the theory to explain individual differences in adaptations to strain (Jang and Johnson, 2003). Agnew proposed that an individual's internal and external factors condition the effects of strain on negative emotions, which in turn affects deviant coping (Agnew, 1992). That is, the conditioning factors influence an individual's selection of deviant or non-deviant coping by decreasing or increasing the likelihood that the individual will experience negative emotions in response to strain. For example, an angry adolescent high in self-efficacy is less likely to turn to delinquency than an equally angry adolescent low in self-efficacy (Jang and Johnson, 2003). Particularly, some studies have revealed the moderating effect of resilience (Wingo et al., 2010). Wingo et al. (2010) found that resilience moderated depressive symptom severity in a cross-sectional study of 792 adults; that is, individuals high in resilience had lower levels of depression. In a survey of Chinese physicians, psychological capital moderates the association between occupational stress and depressive symptoms in female physicians. Psychological capital could be a positive resource for combating depressive symptoms (Shen et al., 2014). To our knowledge, no studies have examined psychological capital as a moderator of the direct and/or indirect associations between perceived stress and smartphone addiction.

Based on the literature reviewed above, we put forward the following hypotheses:

> *Hypothesis* 1: Negative emotions will mediate the link between perceived stress and smartphone addiction in medical college students.
> *Hypothesis* 2: The direct and/or indirect associations between perceived stress and smartphone addiction *via* negative emotions will vary as a function of psychological capital. **Figure 1** illustrates the proposed model.

MATERIALS AND METHODS

Participants

An online survey including the purpose of the study and an informed consent form was used to collect data in Harbin Medical University, China. The online survey was disseminated using a hyperlink and a QR code. Only after providing informed consent could participants continue with the online

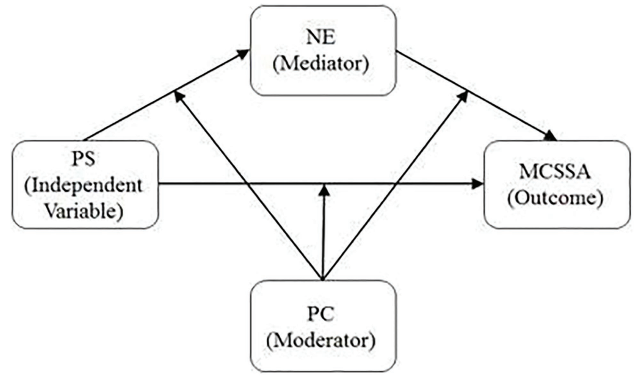

FIGURE 1 | The proposed moderated mediation model. PS, perceived stress; NE, negative emotion; PC, psychological capital; MCSSA, medical college student smartphone addiction.

survey. A total of 769 students were recruited using a convenience sampling method, with an effective rate of 81%.

The mean age of the participants was 20.46 years ($SD = 1.40$, range = 17–29 years). Of the participants, 19% were men, and 81% of the participants were women. Of the participants, 467 (61%) were from cities and 302 (39%) were from rural areas. Finally, 58% of medical college students came from one-child families, and 42% of them came from non-only child families.

Measures

Mobile Phone Addiction Index Scale

Smartphone addiction was measured by the Mobile Phone Addiction Index Scale (Leung, 2008). The scale consists of 17 items that measure four dimensions of smartphone addiction: inability to control cravings, anxiety and feeling lost, withdrawal and escape, and productivity loss. Participants answered these items on a 5-point scale (ranging from 1 = never to 5 = always). Previous studies have shown that the MPAI had good reliability and validity in Chinese adolescents and young adults (Lian et al., 2016). For the current study, the measure demonstrated a good reliability ($a = 0.88$).

The Perceived Stress Scale

Perceived stress was assessed using the Perceived Stress Scale (González-Ramírez and Hernández, 2007). This scale consists of 14 items (e.g., "Feeling nervous and stress?"). The participants rated each item on a 5-point scale ranging from 1 = never to 5 = very much, with higher scores indicating a higher level of perceived stress. For the current study, the measure demonstrated a good reliability ($a = 0.82$).

The Positive and Negative Affect Scale

Negative emotions were measured by the Positive and Negative Affect Scale (Watson et al., 1988). The scale consists of 20 items that measure two dimensions of emotions: positive emotions and negative emotions. This scale was measured in a 5-point scale (ranging from 1 = almost none to 5 = very much), with higher negative emotional scores indicating individuals were puzzled and in pain. The survey asked medical students to tick behind each adjective according to the actual situation in the last week. There were five options after each adjective: almost none, less, medium, more, and very much. The Cronbach's α in this study was 0.88.

Positive Psychological Capital Questionnaire

The Psychological Capital Questionnaire consists of 26 items, and there are four dimensions: self-efficacy, resilience, hope, and optimism (Luthans et al., 2007). There are seven items for the self-efficacy dimension, seven items for the resilience dimension, six items for the hope dimension, and six items for the optimistic dimension. This questionnaire was measured on a 7-point scale (ranging from 1 = not at all to 7 = completely suitable), with higher scores indicating that medical college students had a higher psychological capital level. The Cronbach's α in this study was 0.84.

Procedure

The data were collected in university classrooms between April and May 2017. Trained postgraduate students administered the measures using scripts and a manual of procedures to ensure the standardization of the data collection process. Informed consent was obtained from college students before the data collection. Students were informed that their participation was completely voluntary, and they could decline participation at any time. Participants received a gift as an incentive after they completed all questionnaires.

Statistical Analysis

All statistical analyses were conducted using SPSS 23.0. First, descriptive statistics (i.e., M, SD) were calculated for all variables, followed by bivariate associations among these variables. Second, we followed MacKinnon's four-step procedure to establish a mediation effect (MacKinnon and Tofighi, 2012). Third, we further examined whether the mediation process was moderated by psychological capital. Moderated mediation is often used to examine whether the magnitude of a mediation effect is conditional on the value of a moderator (Muller et al., 2006). The analysis of the moderated mediation model was performed using Hayes's PROCESS macro (Model 59; Hayes, 2013). All continuous variables were standardized, and the interaction terms were computed from these standardized scores. In addition, the bootstrapping method was applied to examine the significance of all the effects to obtain robust standard errors for parameter estimation (Hayes, 2013). The bootstrapping method produces 95% bias-corrected confidence intervals of these effects from 1,000 resamples of the data. Confidence intervals that do not include zero indicate the effects that are significant.

RESULTS

Preliminary Analyses

The incidence of mobile phone addiction was 17.8 and 19.1% in male and female students, respectively. The gender differences in the incidence were not significant in our study. Means, SD, and correlations for all variables are presented in **Table 1**. Correlation analyses showed that perceived stress was positively associated with smartphone addiction, $r = 0.18$, $p < 0.01$, indicating that perceived stress was a risk factor for smartphone addiction in medical college students. Psychological capital was negatively associated with smartphone addiction, $r = -0.29$, $p < 0.01$. In addition, negative emotions were positively related to smartphone addiction, $r = 0.31$, $p < 0.01$, indicating that medical college students with high negative emotions were more likely to become addicted to their smartphone. Finally, perceived stress was positively related to negative emotions, $r = 0.20$, $p < 0.01$.

Testing for Mediation Effect

In Hypothesis 1, we anticipated that negative emotions would mediate the relationship between perceived stress and smartphone addiction in medical college students. To test this hypothesis, we followed MacKinnon's four-step procedure to establish the mediation effect (MacKinnon and Tofighi, 2012), which requires (a) a significant relation between perceived stress and smartphone addiction in medical college students; (b) a significant association between perceived stress and negative emotions; (c) a significant relation between negative emotions and smartphone addiction after controlling for perceived stress; and (d) a significant coefficient for the indirect path between perceived stress and smartphone addiction through negative emotions. The bias-corrected percentile bootstrap approach determines whether the last condition is satisfied.

TABLE 1 | Means, standard deviations, and correlations of the main study variables.

Variable	1	2	3	4	5	6	7	8
1. Gender	—							
2. Age	−0.13*	—						
3. Only child	0.11*	0.01		—				
4. Home location	0.04	0.13*	0.46*		—			
5. Perceived stress	−0.01	−0.07	0.01	0.01	—			
6. Negative emotions	−0.03	0.06	−0.02	0.00	0.20*	—		
7. Psychological capital	0.15*	−0.05	−0.01	−0.04	0.03	−0.42*	—	
8. Smartphone addiction	−0.04	0.05	0.04	0.05	0.18*	0.31*	−0.29*	—
M	1.81	20.5	1.42	1.39	31.96	22.14	123.55	39.08
SD	0.40	1.40	0.50	0.49	3.45	6.31	16.73	9.89

N = 769. SD, standard deviation. *$p < 0.01$.

Regression analyses indicated that in the first step, perceived stress positively predicted smartphone addiction in medical college students, $b = 0.18$, $p < 0.01$ (see Model 1 of **Table 2**). In the second step, perceived stress positively predicted negative emotions, $b = 0.20$, $p < 0.01$ (see Model 2 of **Table 2**). In the third step, when we controlled for perceived stress, negative emotions significantly and positively predicted smartphone addiction, $b = 0.31$, $p < 0.01$ (see Model 3 of **Table 2**). Finally, the bias-corrected percentile bootstrap method indicated that the indirect effect of perceived stress on smartphone addiction through negative emotions was significant, $ab = 0.06$, $SE = 0.10$, 95% CI = [0.10, 0.24]. The mediation effect accounted for 33.3% of the total effect. Overall, the above four criteria for establishing the mediation effect were fully satisfied. Therefore, Hypothesis 1 was supported.

Testing for Moderated Mediation

As noted, Hypothesis 2 predicted that psychological capital would moderate the direct and/or indirect associations between perceived stress and smartphone addiction *via* negative emotions. To examine this hypothesis, we used the PROCESS macro (Model 59) developed by Hayes to test for moderated mediation (Hayes, 2013). Specially, we estimated the parameters for three regression models. In Model 1, we estimated the moderating effect of psychological capital on the relation between perceived stress and smartphone addiction in medical college students. In Model 2, we estimated the moderating effect of psychological capital on the relation between perceived stress and negative emotions. In Model 3, we estimated the moderating effect of psychological capital on the relation between negative emotions and smartphone addiction. The specifications of the three models are shown in **Table 3**.

Moderated mediation was established if either or both of the two patterns existed (Muller et al., 2006; Hayes, 2013): (a) the path between perceived stress and negative emotions was moderated by psychological capital (first-stage moderation), and/or (b) the path between negative emotions and smartphone addiction was moderated by psychological capital (second-stage moderation).

As **Table 3** illustrates, in Model 1, there was a significant effect of perceived stress on smartphone addiction, $b = 0.18$, $p < 0.01$, but this effect was not moderated by psychological capital, $b = -0.04$, $p > 0.05$. Model 2 showed that the effect of perceived stress on negative emotions was significant, $b = 0.20$, $p < 0.01$, and more importantly, this effect was moderated by psychological capital, $b = -0.07$, $p < 0.05$. For descriptive purposes, we plotted the predicted negative emotions against perceived stress, separately for low and high levels of psychological capital (1 SD below the mean and 1 SD above the mean, respectively; **Figure 2**). Simple slope tests indicated that for medical college students with high levels of psychological capital, perceived stress was not significantly associated with negative emotions, $b_{simple} = 0.145$, $p = 0.15$. However, for medical college students with low levels of psychological capital, perceived stress was significantly associated with negative emotions, $b_{simple} = 0.22$, $p < 0.05$. That is, in the low psychological capital group, perceived stress had a significant positive predictive effect on negative emotions. This shows that the influence of

TABLE 2 | Testing the mediation effect of perceived stress on smartphone addiction.

Predictors	Model 1 (MCSSA)		Model 2 (NE)		Model 3 (MCSSA)	
	b	t	b	t	b	t
S	0.18	5.09**	0.20	5.63**	0.12	3.55**
NE					0.31	9.08**
R2	0.03		0.04		0.10	
F	25.88**		31.73**		82.42**	

*N = 769. Each column is a regression model that predicts the criterion at the top of the column. PS, perceived stress; NE, negative emotions; MCSSA, medical college student smartphone addiction.**p < 0.01.*

TABLE 3 | Testing the moderated mediation effect of perceived stress on medical college student smartphone addiction.

Predictors	Model 1 (MCSSA)		Model 2 (NE)		Model 3 (MCSSA)	
	b	t	b	t	b	t
PS	0.18	5.43**	0.20	6.39**	0.14	4.18**
PC	–0.29	–8.65**	–0.42	–13.21**	–0.21	–5.77**
PS × PC	–0.04	–1.21	–0.07	–2.04*	–0.03	–0.75
NE	—	—	—	—	0.19	4.88**
NE × PC	—	—	—	—	–0.03	–0.72
R2	0.12	—	0.22	—	0.15	—
F	35.40**	—	73.80**	—	27.01**	—

*N = 769. Each column is a regression model that predicts the criterion at the top of the column. PS, perceived stress; NE, negative emotion; PC, psychological capital; MCSSA, medical college student smartphone addiction. *p < 0.05; **p < 0.01.*

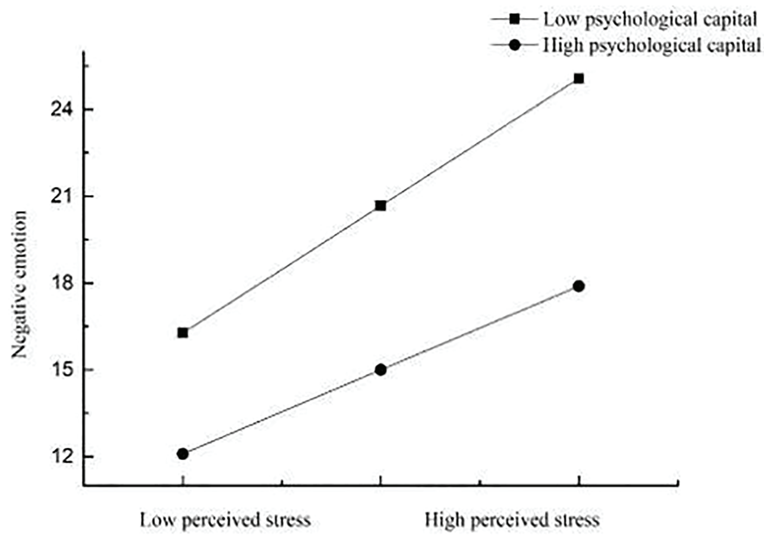

FIGURE 2 | Plot of the relationship between perceived stress and negative emotions at two levels of psychological capital.

perceived stress on negative emotions decreases with the increase in psychological capital. In other words, the indirect influence of perceived stress on smartphone addiction through negative emotions decreases with the increase in psychological capital. Model 3 indicated that there was a significant effect of negative emotions on smartphone addiction, $b = 0.19$, $p < 0.01$, but this effect was not moderated by psychological capital, $b = -0.03$, $p > 0.05$.

The bias-corrected percentile bootstrap method further indicated that the indirect effect of perceived stress on smartphone addiction through negative emotions was moderated by psychological capital, with the index of moderated mediation $b = -0.01$, $SE = 0.01$, 95% $CI = [-0.01, -0.00]$. For medical college students low in psychological capital, perceived stress had an adverse impact on smartphone addiction through increased negative emotions, $b = 0.16$, $SE = 0.05$, 95% $CI = [0.08, 0.27]$. In contrast, the indirect effect was much weaker for medical college students high in psychological capital, $b = 0.06$, $SE = 0.03$, 95% $CI = [0.02, 0.13]$. Thus, Hypothesis 2 was partially supported.

DISCUSSION

The incidence of smartphone addiction in our study is lower compared to other studies. The reason for this result is that there are more female subjects in this study. Precious studies reported that men are more likely to be addicted to smartphones than women (Chiang et al., 2019; Su et al., 2019; Buctot et al., 2020).

The influence of perceived stress on smartphone addiction has begun to gain empirical support (Chiu, 2014; Yang et al., 2020). However, questions concerning the underlying mediating and moderating mechanisms remain largely unknown. Our study adds to the literature by examining the mediating role of negative emotions and the moderating role of psychological capital in the relationship between perceived stress and smartphone addiction. The results indicated that the impact of perceived stress on smartphone addiction can be partially explained by negative emotions. That is, perceived stress could positively predict negative emotions, and negative emotions could positively predict smartphone addiction. Furthermore, this indirect relation was moderated by psychological capital in the first stage of the mediation process. The following sections will discuss each of the hypotheses according to the research results.

The Mediating Role of Negative Emotions

In line with previous studies (Chiu, 2014; Kuang-Tsan and Fu-Yuan, 2017; Liu et al., 2018), we found that perceived stress was positively correlated with smartphone addiction in medical college students. The more stress medical college students perceived, the more likely they were to become addicted to their smartphone. This is consistent with the general strain theory (Jun and Choi, 2015) proposing that all kinds of strain or stress experienced by an individual would cause negative emotions, which subsequently causes problem behaviors. Many studies have shown that stress is an important risk factor for individual addictive behaviors (Lam et al., 2009; Li et al., 2010; Mai et al., 2012). For example, Mai et al. (2012) found that stress is positively associated with adolescent internet addiction. These findings suggest that stress plays an important role in addictive behavior.

In addition, our study showed that negative emotions partially mediated the link between perceived stress and smartphone addiction. For the first stage of the mediation process (i.e., the links between perceived stress and negative emotions), we revealed that negative emotions increased with perceived stress. Our result supports the views of Coyne and Downey (1991). They believed that stressors could cause emotional changes, and these stressors mainly come from the various life events experienced in daily life (i.e., study, peers, and family for university students). These multiple stressors could lead to negative emotions in medical college students. Moreover, some studies have shown that perceived stress is a strong predictor of negative emotions (Bergdahl and Bergdahl, 2002; Spada et al., 2008; Jun and Choi, 2015). For example, Spada et al. (2008) found a positive and significant correlation between perceived stress, anxiety, and depression. For the second stage of the mediation model (i.e., the links between negative emotions and smartphone addiction), this study revealed that negative emotions were positively associated with smartphone addiction in medical college students. This finding is in line with the cognitive-behavioral model of pathological internet use proposed by Davis (2001), which postulates that addiction behavior is the result of a predisposed vulnerability including negative emotions. In addition, many studies have confirmed the relationship between negative emotions and addictive behaviors (Caplan, 2007; Gámez-Guadix et al., 2012; Özdemir et al., 2014). For example, one study showed that there is a significant positive relationship between depression and smartphone addiction and also indicated that depression is able to predict and account for smartphone addiction among students (Ghasempour and Mahmoodi-Aghdam, 2015). Furthermore, Jun and Choi (2015) found that negative emotions play a mediating role in the link between academic stress and internet addiction. Based on the above theories, it clarifies the link between perceived stress and negative emotions (Bergdahl and Bergdahl, 2002; Spada et al., 2008) as well as the link between negative emotions and smartphone addiction (Matar Boumosleh and Jaalouk, 2017; Stanković et al., 2021). In this study, we integrated these two relationships with a mediation model approach. Our study goes one step further by uncovering that individuals who perceive more stress have more negative emotions, and they are more likely to engage in smartphone addiction.

This finding has important implications for policymakers who develop means to prevent and intervene in smartphone addiction among medical college students. The results suggest that it is particularly important for counselors to deal with medical college students' negative emotions in the context of smartphone addiction. The findings also suggest that the early prevention of stress is important in halting the development of negative emotions that subsequently influence smartphone addiction. In addition, for clinical practitioners, we not only pay attention to the symptoms of internet addicts themselves, but also stress and negative emotions.

The Moderating Role of Psychological Capital

Our findings confirmed the moderating role of psychological capital in the indirect association between perceived stress and smartphone addiction. Specifically, we found that psychological capital attenuated the link between perceived stress and negative emotions. No significant correlation between perceived stress and negative emotions was found in medical college students with higher levels of psychological capital. However, perceived stress is more likely to lead to negative emotions in medical college students with lower levels of psychological capital. Our findings are in line with the research of Li-Feng and Hua-Li (2009), which suggests that not all people who are exposed to stressful conditions feel negative emotions to the same degree. Perceived stress depends not only on the effects of stressors but also on how the individual appraises the situation—one of the students' positive psychological states such as psychological capital may attenuate the negative effects of stress on negative emotions. Moreover, Hobfoll (1989) proposed a conservation of resources theory, and Hobfoll (2012) considered that valuable resources played a positive role in the process of the individual stress response. These resources included material, power, interpersonal relationships, and positive psychological factors (Hobfoll, 1989). This theory provides a reliable perspective to explain that psychological capital could protect individuals from the adverse effects of stress, and it is a protective factor for mental health (Collishaw et al., 2007; Wingo et al., 2010; Goldstein et al., 2013). Our results also support the opinion that individuals with higher levels of psychological capital may view stress as a controllable factor and are able to recover from stressful experiences quickly and efficiently (Fredrickson et al., 2003; Tugade and Fredrickson, 2004; Tugade et al., 2004). When faced with stress, medical college students with higher levels of psychological capital might bounce back from adversity or failure with positive psychological capacity (resilience), preserve the will to accomplish a learning task or goal (hope), have more confidence and exert greater effort in the pursuit of success (self-efficacy), and have positive expectations and attributes regarding outcomes (optimism).

This finding indicates that psychological capital is a positive personal trait and an important protective factor. It prevents individuals from being affected by perceived stress, reducing their negative emotions and the likelihood of developing smartphone addiction. Our findings suggest that we should pay attention to psychological capital when helping medical college students to deal with the negative effects of perceived stress in the future. And our findings also suggest that we should enhance students' psychological capital in their daily life to keep them from developing addiction behavior when faced with stress.

Limitations

Several limitations must be considered when interpreting the findings of this study. First, this study was cross-sectional and cannot infer causality. For example, smartphone addiction is used as a result variable in this study, but smartphone addiction may also have a reverse effect on risk factors (such as perceived stress, negative emotions) and protective factors (such as psychological capital). Therefore, further studies should apply longitudinal or experimental designs to confirm the causal assumptions in this study. Second, the representative of the sample may restrict the general validity of our results, because our participants were from the same university. Future research may explore the proposed model among diverse populations.

Third, most of the participants were female students in our study. Therefore, the results of the present study may not generalize to other university students with more male students, other age populations such as middle school students, and people of older age. Fourth, medical college students' self-reported data on perceived stress and smartphone addiction could not be independently verified. The understanding of each questionnaire item measuring an abstract concept varies from one participant to another. Future research should use multiple informants (e.g., parents, teachers, and peers) to collect data to ensure its accuracy.

CONCLUSION

In summary, this study is among the first to uncover the mediation role of negative emotions and the moderation role of psychological capital in the relation between perceived stress and smartphone addiction. It explains how, when, and how perceived stress is related to smartphone addiction. These results deepen the work of previous studies by clarifying the mediation and moderation factors in the link between perceived stress and smartphone addiction. In this study, negative emotions serve as one potential mediation mechanism between perceived stress and smartphone addiction in medical college students. Moreover, the mediation mechanism was moderated by psychological capital, and the adverse impact of perceived stress on smartphone addiction through decreased negative emotions appears to be weaker for medical college students with higher levels of psychological capital. Our findings demonstrate the importance of the moderated mediation model in understanding the mechanism linking perceived stress and smartphone addiction in medical college students.

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 Ethics Committee of Harbin Medical University. Written informed consent from the participants was not required for them to participate in this study in accordance with the national legislation and institutional requirements.

AUTHOR CONTRIBUTIONS

YY and PL conceived and designed the study. AM and ZY collected the data. HC and WW participated in statistical analysis and interpretation of data. ZQ and XQ interpreted the data and wrote the preliminary manuscript. JZ and XY revised the content of the manuscript. PL and JN compiled the data and wrote the preliminary manuscript. All authors contributed to the article and approved the submitted version.

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Smartphone Use and Psychological Well-Being Among College Students in China: A Qualitative Assessment

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Background: Problematic smartphone use is widespread, and college-age youth faces an especially high risk of its associated consequences. While a promising body of research has emerged in recent years in this area, the domination of quantitative inquiries can be fruitfully and conceptually complemented by perspectives informed through qualitative research. Toward that end, this study aimed to interrogate the myriad behavioral, attitudinal, and psychological tendencies as a side effect of college students' engagement with the smartphone in their everyday lived experience through in-depth interviews.

Methods: We recruited 70 participants from seven college campuses hailing from different geographic regions in China, and conducted semi-structured in-depth virtual interviews via WeChat in November and December 2020. Subjective experiences, personal narratives and individual perceptions in the context of routine interaction with the smartphone were thematically analyzed through a reiterative process in an effort to detect prevailing threads and recurring subthemes.

Results: The smartphone has established a pervasive presence in college students' everyday life. Time-based use characteristics generated a typology of four distinct user groups: hypo-connected antagonists, balanced majority, hyper-connected enthusiasts, and indulgent zealots. Habitual usage falls on predictable patterns matched onto temporal, locale-based and contextual cues and triggers. Students' dependency relationships with the smartphone have both functional and emotional dimensions, as prominently manifested in occasions of detachment from the device. Self-regulatory effort in monitoring and limiting use is significantly impacted by mental focus and personal goal setting. Perspectives from our qualitative data suggest the need for taking into account a variety of contextual cues and situational factors in dissecting psychological and emotional outcomes of smartphone use and abuse.

Keywords: smartphone use disorder, smartphone dependency, mobile lifestyle, problem smartphone use, digital wellbeing

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INTRODUCTION

The rapid and widespread penetration of mobile technologies into the fabric of everyday life has fundamentally changed the landscape of human communication. This mobile revolution has been amplified by two landmark developments in the 21st century: mobile phone subscription surpassed fixed-line use in 2002 (Srivastava, 2005), and Apple launched its first iPhone in 2007 (followed by

Google's Android devices in 2008). By incorporating multifunctional applications and multifaceted traits into an all-in-one device, smartphones have nourished "an [sic] historical movement toward a personal communication society" (Campbell and Park, 2008, p. 381). Thanks to their boundary-spanning nature, portable convenience and all-encompassing affordances, smartphones function as integrated environments of polymedia (Madianou, 2014), and have turned into the "fourth screen" (coming after but emulating the historical role of the cinema, television, and computers) (Miller, 2014).

The pervasiveness of mobile media in general and smartphones in particular with the adolescent population is a hallmark of contemporary youth culture. As "mobile natives," Vanden Abeele (2016) argues that immersive engagement with the smartphone has engendered heterogeneous "mobile lifestyles" among the current youth generation. Smartphone technology conforms to the *Apparatgeist* of "perpetual contact" – "the spirit of the machine that influences both the design of the technology as well as the initial and subsequent significance accorded them" (Katz and Aakhus, 2002, p. 305). The always-on mode of the smartphone, coupled by its portability and multilayered functionality, has triggered concerns about its addictive potential, especially among the adolescent and youth population. Against this backdrop, an expanding body of academic inquiries in recent years has linked excessive smartphone use to a variety of addiction-like behavioral and psychometric symptoms such as decrease in productivity and daily interruptions (Duke and Montag, 2017), stress, social anxiety and loneliness (Vahedi and Saiphoo, 2018), neuroticism and impulsivity (Carvalho et al., 2018).

The term "smartphone addiction" has been prevalently used and frequently studied in conceptual frameworks commonly adopted for substance abuse and pathological gambling in contextualizing its antecedents as well as myriad negative physical and physiological outcomes and consequences (Mahapatra, 2019; Sahu et al., 2019; Yu and Sussman, 2020). However, we concur with Panova and Carbonell (2018) that, even though there is mounting evidence to associate smartphone use with various problems and negative outcomes, "addiction" is not an accurate or correct term to diagnose a set of psychological or physical consequences that are not comparable to the severity and/or associated health problems caused by substance addiction. In a similar vein, as De-Sola Gutiérrez et al. (2016) point out, the diversity of perspectives encapsulated in the umbrella term and the failure to differentiate between addiction, problematic use and abuse has caused confusion and muddied comparability of findings.

It is worth noting that different terms – among them smartphone addiction, smartphone use disorder, pathological smartphone use, excessive smartphone use, maladaptive smartphone use, smartphone dependence, and problematic smartphone use – have been used interchangeably or synonymously in most academic literature. We support the call (De-Sola Gutiérrez et al., 2016; Panova and Carbonell, 2018) for a more precise conceptualization of terms, which is more constructive in promoting academic deliberations in investigating symptoms and pondering corresponding corrective actions. We therefore adopt the term problematic smartphone use (PSU) in our research, which aims to examine the myriad behavioral, attitudinal, and psychological tendencies as a side effect of college students' engagement with the smartphone in their lived experience. We resorted to semi-structured in-depth interviews with 70 college students in disentangling the variety of nuanced pathological habitual patterns and psychological predispositions in the context of students' daily interaction with the smartphone.

Problematic Use of the Smartphone: Psychological and Behavioral Dimensions

By consolidating computing, portability, and mobility into one interface, the smartphone has the potential to fulfill a variety of communication needs from information to entertainment and interaction. The all-in-one nature of smartphone technologies has drastically enhanced the ever-expanding repertoire of available functionalities and applications. However, availability of services is not tantamount to adoption by the end users. As is the case with most other media technologies, usage and adoption of mobile applications and services has been a well-trodden area of academic research in the new millennium (e.g., Park and Chen, 2007; Verkasalo et al., 2010; Kang and Jung, 2014). The continuous advancement of smartphone technologies calls for constant update of this line of research in various national contexts.

Research Question 1: What are the most frequently used smartphone-based apps in college students' daily routine engagement?

Design of the smartphone succeeds on a variety of habit-forming technologies and compulsive human tendencies (Eyal, 2014). As a result, habitual use of the smartphone has the potential to develop into certain patterns of compulsive behaviors, including repetitive checking (brief sessions of touching), context-dependent triggered acts, and quick access of dynamic content, all of which may induce habit formation on users (Oulasvirta et al., 2012). Psychology of habit theory posits that a variety of cues, exposure to which may be intentional or inadvertent, can trigger habit performance; in the case of substance use, addiction results when motivation shifts from goal-directed (voluntary) to habitual drug use (Wood and Rünger, 2016). It stands to reason that the same process applies to pathological smartphone use, although more research is needed in support of this mechanism. We therefore pose the following research question:

Research Question 2: What are the temporal and venue-based cues and triggers driving patterns of habitual use of the smartphone?

In terms of psychological consequences, a meta-analysis of 30 independent samples by Vahedi and Saiphoo (2018) confirms a positive association between PSU and stress and anxiety. A survey of college students in Turkey by Enez Darcin et al. (2016) found that social anxiety and feeling of loneliness are associated with vulnerability to smartphone addiction. In a similar vein, Yang et al.'s (2020) meta-analytic review of 14 studies points to a significant correlation of PSU with poor sleep quality, depression, and anxiety. Recent research has started to pay attention to NOMOPHOBIA or NO MObile phone PHOBIA, which is a psychological condition caused by the mental disorder over fear of being disconnected from the smartphone (Yildirim and Correia, 2015; Bhattacharya et al., 2019). Another behavioral tendency, especially among adolescent and young users, is called "phubbing," defined as the practice of "an individual halting face-to-face communication with another person to interact with their telephone" (Erzen et al., 2021, p. 57). Moreover, problematic smartphone behavior can be exacerbated by FOMO, or Fear of Missing Out – the perceived need to be constantly connected over the apprehension of missing important information, especially that over social networking sites (Wolniewicz et al., 2018; Elhai et al., 2020). We are thus interested in finding out:

Research Question 3: What are the college students' self-reported symptoms and motivating factors with regard to NOMOPHOBIA, Phubbing and FOMO?

There is a growing awareness among the general public about the excessive amount of time the smartphone consumes and its possible negative consequences on personal health and well-being. In response to the concerns of deepening dependency on the smartphones, digital detox has been proposed as one viable solution to promote planned abstinence from electronic devices such as the smartphone. A synthesis of existing evidence from the body of detox scholarship published between 2008 and 2020 as it relates to smartphone use shows mixed results, with no consistent findings between detox interventions and subsequent cognitive and physical performance measures (Radtke et al., 2021). We would like to contribute to this emerging line of research by asking:

Research Question 4a: What detox measures, if any, do students undertake to mitigate smartphone (over)use?

Research Question 4b: What is the efficacy of these detox interventions?

It is worthy to highlight that the majority of the research on smartphone use and addiction has been inspired by quantitative studies. For instance, an extensive review of current research on phubbing by Al-Saggaf and O'Donnell (2019) led them to bemoan the paucity of qualitative studies and prompted them to call for more qualitative interviews in offering rich descriptions on why people phub. What we aim to contribute to the expanding body of literature through our qualitative semi-structured interviews is to supplement and complement the sizable body of quantitative findings with in-depth, personal and situated perspectives to the diverse dimensions of PSU.

MATERIALS AND METHODS

We recruited university students from seven college campuses in China, hailing from different geographic locations and representing diverse academic disciplines. Interviewees were briefed on the overall purpose of the study as well as the voluntary nature of participation, and these who agreed to proceed were asked to sign an informed consent to take part in the study. Participants were assured of the anonymity of the interview data. We resorted to a semi-structured interview design in an effort to "understand themes of the lived daily world from the subjects' own perspectives" (Brinkmann and Kvale, 2018, p. 14) with regard to their daily encounters with the smartphone. Because the interviews were conducted in November and December 2020 when the Covid-19 pandemic was still a threat, we adapted to a virtual interview modality conforming to the overall strategies and suggestions in Gray et al. (2020) and Khalil and Cowie (2020) from subject recruitment to rapport building to question handling and use of verbal/non-verbal cues, the main rationale of which was driven by concern for the participants' health and well-being. However, one major difference is that, instead of using Zoom or Skye, we adopted WeChat, the most popular real-time chat app in China, to conduct the interviews. The reason is that all students have a high level of familiarity and comfort with video-chatting on WeChat, a routine engagement in their daily communication. Our overall WeChat interview experience corroborates the observation by Jenner and Myers (2019), who conclude after comparing Skye and in-person interviews that virtual interviews are conducive to more sharing of personal information, and does not compromise rapport or reduce the efficacy of the interview methods. As a result, we did not sense any loss or inferiority of the data thus obtained.

The questions cover a range of activities and user characteristics, with most of them open-ended in nature so as to capture the nuanced variations and diverse meanings each interviewee might assign while describing their everyday engagement, but all questions maintained a focus on themes pertaining to the various aspects of PSU mentioned in the above literature review. Specifically, we developed a few clusters of questions focusing on topics framed in our research questions, such as most-often used apps (RQ1), patterns of habitual use and responses to situated cues (RQ2), symptoms of NOMOPHOBIA, phubbing behavioral tendencies, how they would respond to leaving their smartphones behind, and FOMO (RQ3), and whether they had taken detox measures (RQ4a), and (if yes) to what effect (RQ4b). Each interview typically took 30 to 40 min to complete, with a few having gone more than 1 h. Follow-up questions were asked whenever necessary for the sake of clarification or data enhancement.

Data were analyzed by following the well-established qualitative content analysis and thematic analysis approaches in dissecting manifest content into categories and latent content into thematic threads (Guest et al., 2011; Vaismoradi et al., 2016). Our analysis is also inspired by the grounded theory method through immersing ourselves in the data corpus in pinpointing key concepts via microanalysis of specific topical areas as well as identifying salient patterns and thematic threads at the level of general analysis (Brinkmann and Kvale, 2018). Conforming to the often-adopted practice of processing the data through a reiterative process in analyzing qualitative interview data, we went through multiple rounds of analysis in first detecting core discrete concepts at the local/individual level and then deciphering dominant, tacit thematic alignments regarding broad perspectives from integrating the totality of the data.

RESULTS

Interviewee Demographics and User Typology

The interviewees comprised 52 female and 18 male students. The disproportionate male/female makeup largely reflects the distribution of the gender differences in the disciplines in the host universities, which are dominated by humanities, social and management sciences, although the number is slightly skewed to the female line.

Of necessity, smartphone dependency first manifests itself in the amount of time one engages with the device on a daily basis. We asked each interviewee to offer an estimate on how much time the smartphone consumes them every day by turning on the Screen Time feature on their smartphone. The majority of the students were able to offer pretty precise answers, typically to the hour with some indicating a clear range (e.g., 6–7 h); moreover, about a quarter of the students reported the exact time as revealed on the Screen Time, such as 5 h 36 min on weekdays by one student. Based on their estimations, the average number of hours on the smartphone approximates to about 6 h (5.7 vs. 5.9 along male/female line) per day on weekdays. There is a sizable increase to the weekend hours (7.7 for male and 7.9 for female). There is, however, significant variation among the individuals, as the reported daily smartphone hours ranged from just 50 min to 10 h on an average weekday, and from 20 min to 12 h on weekend days. For the vast majority of students, there is a consistent pattern in the weekday-weekend variation; we therefore arrived at the daily average use amount in terms of hours by adopting the respective mean of weekday and weekend hours for each interviewee. Our tabulation of users in conformity to the daily amount of smartphone engagement yields four types of users, as reported in **Table 1**: below average (disciplined) users (less than 4 h on the phone per day); average (balanced) users (spending 4–7 h on the phone per day); above average (heavy) users (being on the phone for 8–9 h every day); and excessive (problematic) users (using 10 h or more for smartphone-related activities).

TABLE 1 | Typology of users.

Gender	Below average (disciplined user) less than 4 h		Average (balanced majority) 4–7 h		Above average (heavy user) 8-9 h		Excessive (problematic user) 10 h and above		Total
Male	1	5.6%	10	55.6%	4	22.2%	3	16.7%	18
Female	3	5.7%	26	50.0%	17	32.7%	6	11.5%	52
Male and Female	4	5.7%	36	51.4%	21	30.0%	9	12.9%	70

Total percentage may not add up to 100% for some columns due to rounding errors.

Among the four individuals (three in the female group and one from the male group) who said they spent less than 4 h on an average day, all indicated the exercise of self-imposed control as an intentional effort to reduce the amount of time on the phone. On the opposing end, the nine students (making up about 12.9% of the total) who reported excessive smartphone use consented to symptoms of problematic or pathological dependency by explicitly admitting an urge to get onto the smartphone whenever possible. The following quote illustrates the all-consuming nature well by one interviewee: "I get onto my phone whenever I am free. Especially when it comes to the weekend, I stay on my phone all the time except for eating meals or taking the bath."

For ease of cross-type comparison, we summarized time-based pattern of smartphone use in association with psycho-attitudinal responses to the interview questions into four distinct groups, as presented in **Table 2**. First, the *hypo-connected antagonists* (5.7% of the total) recognize the utilitarian aspects of the smartphone, and their engagement is driven by a highly goal-oriented approach in that they mostly know what they are looking for and go directly to the respective app, dominated by informational and social networking needs, accomplished in short sessions. They are also quite cautious about the negative potentials of the smartphone and exercise appropriate self-control. Second, the *balanced majority* (51.4%) maintain a conspicuous presence on the smartphone by spending 4–7 h on it. Their use is more expansive, as a significant amount of time is consumed in activities such as listening to music, video-sharing, and mobile shopping beyond information-seeking and social networking. They typically spend half to 1 h browsing the phone before bed and display more noticeable tendencies than hypo-connected antagonists symptomatic of NOMOPHOBIA, phubbing, and FOMO.

The third user type, which we name *hyper-connected enthusiasts*, comprises 30% (22.2% male vs. 32.7% female) of the participants. Hyper is indicated by the level of smartphone engagement as measured in the amount of smartphone time (averaging 8–9 h per day), and enthusiasm is embodied in the palpable craving we detected in their interview conversations while discussing smartphone activities as well as their related emotional dispositions therein. Compared with the two previous groups, entertainment use (e.g., watching teledramas, reading online fiction, viewing movies and using TikTok) is an important part of their regular engagement with the smartphone.

The fourth cohort – who we call *indulgent zealots* – spend almost all their time outside of class and free from other required duties on the smartphone (averaging about 10 h per day). Although amount of time alone should not be the sole criterion, it is one of the most dependable benchmarks in diagnosing PSU in extant research (Duke and Montag, 2017; Vahedi and Saiphoo, 2018; Sahu et al., 2019). The statistical distribution of this group (12.9%) fits well-nigh the overall estimate by Eichenberg et al. (2021) in evaluating the prevalence rate of PSU at 15.1% in their study of college students in Vienna. Besides the prevailing tendency to stay longer on a variety of activities that the previous groups also engage in, close to one-half of them specifically mention mobile gaming as one of the most frequently accessed apps on their smartphone. Of particular note is that

TABLE 2 | Psycho-attitudinal traits of different user types.

User type responses	Below average users (hypo-connected antagonists)	Average users (balanced majority)	Heavy users (hyper-connected enthusiasts)	Excessive users (Indulgent zealots)
Most used apps	Social networking; news and informational browsing	Social networking; news and informational browsing; video-sharing services; music; shopping	Social networking; news and informational browsing; video-sharing services; music; shopping; entertainment	Social networking; news and informational browsing; video-sharing services; music; shopping; entertainment; gaming; live streaming
Bedtime and Wake-up Use	20–30 min before bed; 5–20 min after wake-up	30-60 min before bed; 10-20 min after wake-up	0.5-1.5 h before bed; 10-20 min after wake-up	0.5 – 2 h before bed; 10-30 min after wake-up
Phone out of sight	Feel calm (50%); Lose sense of safety (50%)	Feel uneasy, anxious or unsafe (73%);	Feel disconnected, insecure Cannot concentrate; Don't feel myself (85%)	Feel anxious, a sense of loss, agitated (100%)
Think about the smartphone during class	Sometimes (25%)	Often or sometimes (52.8%)	Often or sometimes (76.2%)	Often or sometimes (77.8%)
Phubbing	Occasionally (25%)	Sometimes or often (51%)	Sometimes or often (75%)	Sometimes or often (78%)
When leaving smartphone behind	Feel unsafe (50%); Feel just fine or even happy (50%); Must go back and get it (25%)	Feel agitated, unsafe, antsy, bored (81%); Must return and find it (65%)	Feel edgy, bored, unfocused, isolated (95%); Must go back and get it back (45%)	Feel uneasy, disconnected from the world (89%); Must go back to pick it up before doing anything else (89%)
Worry about smartphone time and tried to reduce	Yes (25%)	Yes (51.4%)	Yes (38.1%)	Yes (77.8%)

these students consistently display a set of psych-behavioral traits commonly associated with PSU, such as NOMOPHOBIA, FOMO, and worrying about the amount of time consumed by the smartphone.

The fact that gaming has been mentioned the most prominently among the indulgent zealots is noteworthy, as gaming has been consistently pinpointed as a primary addictive tendency associated with compulsive smartphone use (Liu et al., 2016; Derevensky et al., 2019). However, PSU symptoms are not just limited to indulgent zealots only, as similar patterns (albeit to a slightly lesser extent) can be observed with hyper-connected enthusiasts. With regard to content type, the reported use pattern among our cohorts is highly congruent with research findings linking entertainment use and gaming to problematic smartphone dependency (Jeong et al., 2016; Bae, 2017; Park et al., 2021).

The overall patterns of differences across the four user categories can be found in **Table 2**. Detailed symptomatic manifestations among the interviewees are discussed in the sections that follow along the topical lines of the research questions.

TABLE 3 | Top 10 most often-used smartphone apps.

Rank	App
1	WeChat
2	QQ
3	Alipay
4	NetEase Cloud Music
5	Taobao
6	Sina Weibo
7	Eleme
8	Baidu Cloud
9	Bilibili
10	Xiaohongshu

Smartphone Utilities (RQ1)

We asked each participant to name five to six apps that they used the most frequently. Among the most mentioned are a total of about 20 apps encompassing four broad areas of functions and affordances. Ranked in the degree of their popularity, the first category serves to carry out variegated tasks of socializing functions via instant video and text messaging, as seen in WeChat, QQ, and Sina Weibo. The second type of apps pertains to multiple ways of news sharing and information seeking (e.g., WeChat, QQ, Toutiao, Zhihu). Closely aligned with the second type is an assortment of apps – for example, Xiaohongshu, Taobao, Alipay, Elema – that facilitate the delivery of utilitarian transactions and tasks ranging from online shopping, mobile payment, photo-taking, and time-keeping to navigational services. Trailing not far behind, the fourth category of apps cater to students' entertainment needs, as exemplified by NetEase Cloud Music, QQ Music, blibli, Youku, and mobile games led by *King of Glory* (also known as *Wangzhe Rongyao* in Chinese) and *Counter-Strike*.

Table 3 lists the top 10 apps students reported using the most. Of particular note is the role of WeChat in the routines of everyday communications among the participants. WeChat offers multifunctionalities that crosscut boundaries typically found in the first and second types of apps as mentioned above – its text messaging, audio and video chat features are widely used for one-on-one interpersonal communications, while the group chat and one-to-many broadcast capabilities make it the platform of choice for getting messages out to groups of varying sizes.

The latter affordances make WeChat a hugely popular venue for information sharing, as evidenced in the avowed use of WeChat by the students as a major channel of information seeking.

Along gender lines, we noted a striking difference: male students express an unmistakable appetite for games, whereas female students are much more inclined to use the built-in camera. *King of Glory* dominates mobile gameplay. Conversely, almost all female students admitted to using the built-in camera as one of their favorite habitual undertakings while only about half male students acknowledged doing this. The most common cited motive for photo-taking is to chronicle daily life, as revealed in this quote: "Shooting pictures is my favorite pastime. I send photos of my every meal to my parents. I will take photos of the scenery or objects I like whenever I take a stroll."

One notable development in China during the past years has been its quick transformation into a cashless environment enabled by the widespread adoption of mobile payment technology. This is resonated soundly in the interviews, and it comes as no surprise that e-payment via the smartphone is one of the most sought-after features among the students. This is well illustrated by the following statement:

> "One cannot be separated from the smartphone nowadays, mainly because it fulfills the daily need of paying bills. Like most everyone else, I used to pocket cash a few years ago. Now that's no longer necessary thanks to the smartphone. I can almost do any transaction with the phone, such as buying stuff, paying fees and purchasing tickets. So the smartphone is indeed all-capable!"

Indeed, many students specifically mention e-wallet as one of the major causes of their anxiety when asked about how they feel when they don't have their smartphone with them. This is elaborated in the ensuing discussion on NOMOPHOBIA.

Habituation (RQ2)

As mentioned in the previous literature review, checking behaviors comprise a large part of repetitive habitual use of the smartphone (Oulasvirta et al., 2012), and smartphone-related habits are closely associated with external situations or internal states (Wood and Rünger, 2016; Park et al., 2021). Research also indicates that process-oriented smartphone use may develop into habits, which may in turn automatically trigger problem behaviors activated by internal or external cues (Van Deursen et al., 2015). We asked the students about their habitual routines, rituals, and general tendencies in using their smartphones. The following thematic lines stand out across the interviewees.

A clear pattern emerges characterizing students' interaction with the smartphone: almost all indicated that the time they spent on the phone surges during weekend or holidays; and smartphone is the primary medium of choice when fragments of time are available, such as during intervals between routine tasks, and moments of non-essential or leisure activities. Smartphones are the unrivaled choice for casual browsing, as students typically opt for "swiping" at most chunks of time available. As far as gender is concerned, female students display no significant deviation percentagewise in these behavioral patterns.

The venue that smartphone consumes the most uninterrupted chunk of time is the dorm for most students. The most extensive block of concentrated smartphone time on each day for virtually everyone is the pre-bedtime hours, although the specific amount of time varies from about half an hour to more than 2 h. The next routinized allocation of smartphone time prevalent among the students is the early morning hour, when the students typically idle on bed from 15 min to close to 1 h browsing the smartphone. Besides the difference in length of time, the late-evening and early-morning rituals tend to focus on different tasks and accomplish different purposes. Late-evening smartphone use is primarily entertainment-oriented (e.g., video, online teledramas, music, gossipy tabloid hearsays, gaming), although socializing (e.g., personal communication) maintains a noticeable presence. Early-morning smartphone checking uniformly centers on updating news of the day and attending to personal messages. As result, students mentioned gravitation toward different apps during these two daily periods. It is also worthy of note that the pre-bed period shows a distinct pattern of variation among the different types of users (from below average to excessive users) in the amount of time they expense. Especially among heavy and excessive users, many confess that this has become a basic routine as a necessary precursor to sleep every night. In contrast, the early-morning time immediately after wake-up, which is typically followed with some smartphone browsing, does not vary much with user types, with each student spending anywhere between 10 and 20 min doing this. This is understandable in that morning is not the time for most students to loaf around in bed, as they are rushed to get ready to embark on the errands of the day.

Besides the pre-bed hour, the next block of time of concentrated smartphone use for the students is during meal (i.e., lunch and dinner) time, when casual, entertainment use dominates. This is confirmed both from self-revealed narratives and alleged observations of habitual behaviors by others. This behavior is aided by the design of the smartphone for one-handed holding and swiping, as some students acknowledged. Another favorite way for the students to engage is to place the smartphone on the table and browse content on the smartphone while dining. Ease of single-handed actions such as flicking, tapping and dragging is something that many students fondly describe and have become very adept in doing.

Regarding the question whether they turn their smartphones off while going to sleep at night, only two out of the 70 informants answered positively, while the rest confirmed that they always keep their phone on at night. Of the two who turned their smartphones off, one student indicated doing this as a habit formed years ago, and the other student who turns off the phone at night said she does this due to health concerns:

> "I used to turn the phone to airplane mode, but I was told that would not totally eliminate radiation [from the phone]. In order to avoid radiation, I now completely switch the phone off."

As to why they keep their smartphones on at night, the most-cited reason (by 83% of the students) is to use its alarm and time-keeping function. Ninety percent of the interviewees said they placed the phone within grab distance, while about a quarter of the students mentioned checking the time on the smartphone at night. Psychologically, about a quarter made a point that opening eyes to see the smartphone makes them feel safe.

In response to the question whether they would check on the phone while waking up in the middle of the night, 32 (constituting 45.7% of the total) students admitted doing this. The type of content consumed late into the night varies quite a bit from looking at the current time, checking on friends' WeChat "Moments" posts and Weibo updates to viewing short videos. When asked whether the late-night smartphone feeds had any negative impact on their sleep quality, 44% said no but 56% answered in affirmation. Similarly, the aftereffect of this midnight smartphone perusing is diametrically perceived by the two groups: the former group claimed that doing this helps sooth them back to sleep whereas the latter group alleged smartphone checking during bed hours often produces some type of arousal effect on them, thus prolonging the time they need to go back to sleep. Some students in the latter group, albeit not specifically acceding to being addicted to the smartphone, alluded to the potential nature as shown in these quotes:

> "Checking my smartphone at night affects my sleep. Oftentimes, once flipping the screen on, it keeps me in a state of arousal, and delays my time to go back to sleep."

> "If I get onto sites such as Zhihu [a popular question-and-answer site like Quora] and Weibo, my sleep will suffer, because these sites are highly addictive. Related content through links on these pages is very seductive to thoughtless, mechanical strolling."

College students' social life mainly consists of moments such as hanging up with peers during class breaks, meal times, or weekend hours. Smartphone has been invariably cited as the most-sought-for companion for various purposes – kill time, fool around, idle away, or finish fragments of academic assignments. The campus lifestyle dictates a lot of in-transit moments when students move around between the dorm, classroom, cafeteria, and other places in attending to daily tasks and events. Listening to music is a popular activity for these students, as well as some occasional "virtual strolling" into quick informational checking via various apps of personal preferences. Fifty-six percent of the students acknowledged that they are in the habit of checking their smartphones on a regular basis while walking. As corroborating evidence for its popularity, in response to our interview question on what the students saw as the most common behavioral habits among their peers, topping the list was smartphone checking while walking, followed by looking at the smartphone during meal time and holding the smartphone in the hands at all times.

The habit-inducing nature of the variety of features in the design of the smartphone and its apps is duly noted by the students. Many students explicitly pointed out that they are sensitive to all sorts of prompts and hints (e.g., tones, vibrations, flashing signals) from the phone, and have developed a compulsion to check it out, even if this is during class or late at night. Some students conceded to the irresistibility to upgrade at seeing the little red dot reminder that all brands of smartphone products have adopted indicating availability of newer versions of apps or latest system upgrades. Moreover, AI-operated apps to customize content to individual users are particularly powerful in getting users "hooked." One student expressed both her fascination and trepidation about Zhihu, a Quora type of peer-to-peer Question-and-Answer app this way:

> "At the start, I feel at total control. But the more I click on the app, the more I am trapped into it. In the blink of an eye, 20 min or more has flown by without me knowing it. I may feel it is a total waste of my time doing this. But next time I repeat doing the same thing [on the app]."

NOMOPHOBIA, FOMO, and Phubbing (RQ3)

An emerging line of research in recent years has ascertained the association of nomophobia with a number of negative outcomes pertinent to fear, stress, panic, and anxiety due to inability to access the smartphone (aka nomophobia) (Nie et al., 2020; Rodríguez-García et al., 2020). College students suffering from symptoms of nomophobia tend to struggle with concentrating in class (Lee et al., 2017) and perform poorly in academic achievement (Gutiérrez-Puertas et al., 2019). In order to contribute to this body of research, we asked questions of interviewees as regards the degree of pervasiveness of nomophobia and its varied symptomatic manifestations through a set of questions about their attitudes and personal experiences of dealing with situations absent of the smartphone. One question pertains to whether they think of their smartphones during class hours. Forty-three (or 61.4%) of the 70 students interviewed said they often or occasionally get distracted by thinking of their phones, with about 43% acknowledging occasionally engaging in quick phone checking during class. The reasons mentioned for the distraction are mostly one of the three (ranked in this order): the class gets uninspiring; there is an anticipation of time-sensitive information; and there is no specific reason other than the phone just pops up in the mind. Another question asked them if it is their habit to regularly check their smartphones while engaging in tasks such as academic homework, reading and exercising. While about half of the students said they can stay focused on these activities, 37.1% admitted to frequent phone checking while doing these things. It should be noted that the lattermost category involves not merely a quick thumbing through or transitory swipe of the smartphone; this rather entails extensive, concomitant use in parallel with other activities.

In response to the question how they feel when the phone is out of sight, approximately 18.6% (n = 13) said they would stay calm and cool-headed, vis-à-vis the rest of the 81.4% expressing varying levels of anxiety ranging from feeling insecure to panicking and agitation. As summarized in **Table 2**, the most common answers are feeling unsafe, disconnected, uneasy, anxious, a sense of loss, and agitated, whose level of severity steadily increases in accordance with the scale of smartphone dependency in the four user groups. Reversely, the percentage of calm-minded students while the phone is out of sight shows a counter trend – 50% for the below-average group, 22.2% for the average-use group, 14.3% for the heavy-use group, and 0% for the excessive-use group. The pattern along level of smartphone use versus frequency of phubbing and phone checking in the middle of the night (see **Table 2** for details).

Relatedly, we asked the students whether they had left their smartphones behind when going out for the day in the recent past, and if yes, what they had done. Twenty-seven students answered firmly that they had not left their phone back, and what is striking are the reasons they cited for *why this had not happened* – the consistent line therein is that the smartphone constitutes such an all-pervasive aspect of their everyday life that it is virtually impossible to go out without the phone. This sentiment is typified in these two remarks:

> "I won't forget my smartphone any day, because whenever I walk out of my dorm, the first thing I look at is my phone. I wouldn't walk further beyond a few steps on the stairs before I found out that the phone was not with me."

> "The smartphone is more than just a device of communication; it is a part of my body organs. The moment it's not with me, I will immediately notice. So I won't go out without my smartphone."

Of the 43 students who had experience of leaving their smartphones behind, the words that the students used to describe their feelings at that moment are (ranked in frequency): panicking, uneasy, distressful, restless, unsafe, scared, at a loss, detached from the world, bored, strange, and in despair. Interestingly, the key words mentioned by our interviewees bear substantial semblance to those used by undergraduate students in Furst and Evans's (2021) campus intercept interviews on students' reactions to temporary loss of possession of the smartphone. On the other end, only two students said they were "feelingless" (emotionless or unmoved). This response is quite typical:

> "I remember one time I did not have my smartphone with me. Without it, I didn't have any sense of safety, and felt very isolated, to the point of despair. The whole world felt strange to me, and I didn't know what to do."

As to what they would do next, 26 (60.5%) said adamantly that they must find a way to immediately go back and retrieve the phone, because otherwise they would not know how to make it through the day. Eleven said that they would wait a bit until they finished what was at hand and then find an opportune time to go back and fetch the phone. A common sentiment among these students during the time without the smartphone was that the time passed by unbearably slow, and they felt "strange" and "out of place" while seeing others were on their smartphones. Only six indicated that they could sustain the day without the smartphone, albeit not without any difficulty for everyone. Being away from the smartphone brought about some unanticipated jubilation for a few:

> "I initially panicked a bit [being away from the phone]. But after a while, I actually started to feel relieved at the thought of spending the way without the smartphone. It gave me a sense of comfort that this would be a day without the [virtual] crowd, free from messages and updates, a day when I could relax."

> "It felt weird at the beginning. But I got over that quickly, and gained a sense of elation [at not using the smartphone for the day]. I was able to focus my attention on other things and made a good day of it."

The haptic benefits, portability and personal nature of the smartphone may cultivate relationships beyond its practical and functional use, as users may "experience enhanced psychological comfort from engaging with their device, which allows it to serve as a palliative aid for owners during moments of stress" (Melumad and Pham, 2020, p. 251). Over 60% of the interviewees expressed a psychological sentiment of comfort and reassurance while physically holding the smartphone in their hands. The absence of the smartphone from their sight, or an extended period of time (which typically lasts a few minutes for most students) of not checking the phone creates a particular type of anxiety or distress triggered by FOMO among 68.6% of the students. Specific behavioral responses to mitigate FOMO cited by the students vary from constantly keeping an eye on the phone for cues (e.g., audio alert, vibrating notifications, customized prompts) to frequent phone checking to getting up at night hours for an quick updated skimming.

When asked if they would check the smartphone instead of paying attention to their companions during social conversations (phubbing), forty (constituting about 57%) out of the 70 students admitted doing this often or sometimes. The most-cited reasons for opting to do this are (ranked from high to low): to bypass boring conversations; to evade awkward moments with people they do not know well; not to miss important smartphone messages from friends; and others are looking at the smartphone. Close to 30% of the students mentioned phubbing as a social strategy during moments when they do not have anything to say or when they want to avoid speaking, especially in the company of others they do not perceive as intimate friends. Ten percent of the students alleged that they can manage to multitask between conversing with friends and checking the smartphone without affecting either in any negative manner. As a matter of fact, the prevalence of phubbing-related behavior in China in recent years has even led to the coinage of a new word in the Chinese language – *ditouzu*, or the "Heads-down Generation," to (derisively) refer to the tendency of people in late teens and early 20s to lower their heads in fixedly staring at the smartphone in social situations or while walking in public spaces.

Phubbing points to the increasing susceptibility of individuals to spend more and more time with their smartphones while less and less time engaging with each other, and may cause feelings of social exclusion, degrade interpersonal relationships, and impair personal well-being (David and Roberts, 2017). Responses to our question about the impact of the smartphone on interpersonal relationships are varied and can be thematically classified into four categories. About 45.7% (n = 32) of the informants answered in the affirmative (i.e., strengthening), because the smartphone has increased both the level of contact and the amount of content they exchange with their loved ones and friends. Many students stressed the affordance of the smartphone to enable constant engagement with their family even though they are separated from one another (living away from their families). On the opposing end, 30% of the interviewees felt that smartphone use has distanced them from their intimate circles, largely thanks to the reduction of face-to-face communications. An often-mentioned scenario is the decrease of conversations among family members while being together, and a few students admitted that the overreliance on the smartphone has impaired their competence to relate to their loved ones. About 12.9% (n = 9) of them said the smartphone has had no impact on their relationships with family and friends, while 11.4% reported mixed reactions (i.e., weaking some relationships but strengthening others).

Detox and Self-Regulation (RQ4)

With regard to our inquiries on whether the students made any efforts in cutting or controlling the amount of time they spend on the smartphone, thirty-six indicated they were not concerned about their smartphone time, nor had they tried to curtail its use. Eight said they made sporadic attempts to reduce smartphone use, although they were not concerned about the amount of time they spend on the smartphone. Twenty-six (37.1% of the total) students expressed concerns over the amount of time they spend on the smartphone, and adopted measures in monitoring and reducing their screen time.

Among the 34 students who took effort to monitor and limit smartphone use, the most common way of doing this, as reported by 30 students, is to resort to popular apps such as FocusToDo, Plantie, Screen Time, Tomato Timer, Forest, TODO for managing time and forcing users out after extended use. Rate of digital detox app adoption varies substantially across the four groups of users we identified in **Table 2**: excessive and below-average users are diametrically disposed to adopt detox apps (66.7% vs. 25%), with average and above-average users in between (50% vs. 42.9%). Excessive users, who face the highest risk of problematic use, have the highest rate of adoption, which reflect the perceived need of this group in resorting to detox app in cutting down use. Additionally, we were interested in the effect of such apps on those who were intent on curtailing smartphone use, and therefore only asked follow-up questions of the 26 interviewees who explicitly professed such goals. Nineteen of the 26 agreed that their measures were effective while seven answered otherwise.

Using app is not the only means to exert self-regulation over smartphone use. What seems at play in the process is individual goal setting and mental focus, a repeated theme we observed across the interviewees. Many students pointed out that the smartphone only becomes the centerpiece of free play and the locus to idle away time when they are unoccupied or unengaged with anything else, or at moments they feel bored. They have therefore devised various strategies to steer themselves away from the smartphone by engaging in these activities as mentioned in the interviews: doing physical exercises, going on outdoor excursions, reading, chatting in person with friends, turning off the phone, or placing the phone away for the time being. In the case that non-smartphone activities are not an option, five students indicated that sleeping it out works to keep them unhooked from the phone.

Finally, although not a specific focus of our research, the role of the smartphone in the college learning environment has come up repeatedly in our interview conversations with the students. In China, like most elsewhere, more and more college campuses embrace the flipped classroom pedagogical approach, which is a learning model that subverts the traditional teacher-centered class instruction into student-focused pre-class knowledge transfer via technology-mediated platforms including smartphone capabilities (Wei et al., 2020). As a result, the smartphone has become an important and pivotal tool in fostering learning through entertaining, mobile gaming, and other creative modalities (Krouska et al., 2020; Troussas et al., 2020). More than one-third of the students mentioned the various role of the smartphone in accomplishing academic and course-related tasks such as researching information, communicating about curricular activities, and reading class notes and course materials. To some extent, the smartphone has assumed some functions that used to be fulfilled by personal computers in the college learning environment, as acknowledged in our interviews. In this regard, the amount of smartphone time will be skewed significantly for those who are more dependent on the smartphone for learning purposes, and type of activities, rather than smartphone time, should be a more reliable indicator of problematic use.

DISCUSSION

Our research set out to interrogate the multifaceted dimensions of PSU among college students in China. Informed by extensive data we gathered from semi-structured in-depth interviews of 70 undergraduate students from seven college campuses, our findings contribute to the expanding body of academic literature related to this area of research in several ways. First of all, the smartphone has established a pervasive presence and has become a defining feature of the everyday lifestyle among college students. The amount of time the smartphone consumes the students is staggering, averaging close to 6 h during weekdays and nearly 8 h during weekend days. Our typology of time-based smartphone use yields four distinct types of users: hypo-connected antagonists, balanced majority, hyper-connected enthusiasts, and indulgent zealots.

In studying employees' experience with converged multi-functional mobile devices, Matusik and Mickel (2011) identified three types of users based on how they interpret and practice technology use: *enthusiastic reaction* puts a totally positive spin on the professional experience and perceives no cost; *balanced reaction* appreciates the benefits but also sees its downsides; and *trade-offs reaction* recognizes professional benefits but acknowledges significant personal costs with a common feeling of personal conflict and struggle in maintaining control. The smartphone use in our study differs from the previous context in that ours involves student users in a non-employment environment but the previous research includes mobile devices beyond the phone. Nonetheless, we found parallel as well as distinction between our groups and those by Matusik and Mickel. Our hyper-connected enthusiasts bear semblance to the technological enthusiasts as identified by Matusik and Mickel in that there is a noticeable craving for the smartphone among most of these students while discussing their smartphone use. The balanced majority revealed in our study share quite a bit with Matusik and Mickel's balanced reaction group. Their trade-offs group is divided into two groups on the opposite end in our research, with the hypo-connected antagonists casting a cautious eye on the downside of the smartphone while the indulgent zealots totally embracing the technology in the other direction.

With respect to the utility aspects of the smartphones, it is easy to note that WeChat has taken supremacy as the all-in-one platform for social networking among Chinese users. Since the advent of short message services (SMS), text messaging and voice call have been two of the most prodigiously used features in mobile services (Ling, 2004; Karnowski and Jandura, 2014). Our research findings, however, suggest signs of seismic transformations in the smartphone era. Conventional voice calls, albeit still used on a regular basis by all the students, have become secondary in terms of the amount of time expended by most of them in comparison with other affordances available on the smartphones – so much so that voice calling does not even make it to the top ten of the features in consuming everyday time of the students. Text messaging has been sidelined even further, with just a few interviewees mentioning engaging in that occasionally. This is not to suggest, nonetheless, that these students have stayed away from voice communications or text messaging. Rather, the indications are that students have uniformly expressed preferences in embracing the built-in text, voice and video chat features with WeChat. There is a clear displacement effect in which conventional text messaging and voice call functions are migrating to alternative smartphone-enabled venues.

In its over 100 years of research, habitual use of technology has been consistently found to be moderated by mechanisms that automatically trigger repetitive behaviors in response to recurring context cues with varying (intermittent) rewarding outcomes (Bayer and Larose, 2018). It is important to note that habit automaticity is a necessary but not determining condition causing compulsive or addictive behaviors, as many other factors play an essential role in shaping the path to pathology (Wood and Rünger, 2016). Smartphone technologies give primacy to haptics (i.e., making touch an analog of seeing and hearing) (Parisi and Archer, 2017), a feature that is particularly malleable to the design and implantation of habit-forming interfaces and apps (Stawarz et al., 2015). Our research findings have imparted numerous temporal, locale-based and context-derived behavioral tendencies of smartphone use among the students.

Contextual cues and situational factors play a pivotal role in the formation of behavioral habits. Through an online survey, Karnowski and Jandura (2014) deduced three main mobile usage patterns – "Mobile@home" (among known peers in familiar locations); "En route" (on the way among unknown people in unfamiliar surroundings); and "Hanging out with peers" (with peers in unknown locations. Habitual practices are associated the most frequently with the residence (the equivalent of their "home") by the informants in their interviews. Since all the students we interviewed are on-campus residents, the dorm is tantamount to the home of the employees investigated by Karnowski and Jandura, and their smartphone engagement bears some resemblance in that usage situations are the most dominant across interviewees. The "En route" moments for the students mostly comprise their in-transit time walking between the dorm, the cafeteria, classrooms and other venues on campus, while their "Hanging with peers" hours manifest profusely in the "empty" chunks of varying lengths such as intervals between classes and/or other obligated school activities, meal breaks and off-class hours. Our findings show that students' smartphone usage has displayed predictable patterns in connection to these various occasions in terms of both app checking and content browsing. One word of caution, however, we should highlight is that same habitual predisposition should not be construed as unidirectional in its consequence. A case in point is smartphone checking during late night hours, which may work toward pacifying some students but arousing others, thus producing very different impact on their sleep quality. While a common finding in quantitative research suggests an association between PSU and poor sleep quality among adolescent and youth populations (Hale et al., 2019; Mac Cárthaigh et al., 2020; Yang et al., 2020), results in our interview suggest the need for taking into consideration contextual clues and situational factors in order to develop a more nuanced understanding in disentangling causational attributions.

It is probably no surprise that our research has lent evidence to the undisputable presence of widespread nomophobia and FOMO among college youth. This finds testimonial in various manifestations, from thinking about the phone during class, to keeping the phone in sight and within reach, to holding in hand and never having left it behind in the memorable past, the smartphone has assumed a role beyond that of a technical gadget in sustaining students' emotional and functional stability. Results in our interviews indicate the level of smartphone dependency is positively related to the severity of disturbance while adversely related to the degree of self-imposture in a number of symptomatic manifestations under investigation.

Problematic smartphone use has emerged as an important public health issue in recent years, and both technical and non-technical interventions have been proposed as possible solutions to limit and control smartphone use (van Velthoven et al., 2018). The percentage of screen-time controlling app use in our cohort (42.9%) aligns up very nicely with Schmuck's (2020) study, which found that 41.7% of the surveyed 500 Australian adults adopted detox apps to limit and control smartphone time. In addition, Schmuck alleges her research evidence shows "for the first time that self-monitoring behavior using digital detox apps may prevent young adults to develop problematic or compulsive smartphone usage patterns due to using SNSs" based on multigroup analysis that "those young adults who used digital detox apps indicated lower levels of perceived PSU and higher levels of well-being in response to the use of SNSs" (Schmuck, 2020, p. 26). Findings in our study, however, paint a different and more nuanced picture. That excessive or problematic smartphone users are the most likely to resort to detox apps in exerting self-control cannot be construed as evidence to either refute or confirm the efficacy of these apps or such a mechanism; it is plausible that excessive smartphone dependency tends to lead to self-monitoring through detox apps. Whether it is accomplished through technology-based detox apps or through non-technological approaches, we found strong evidence that mental focus and individual goal setting play a central role in the success or the lack thereof in outcomes of moderating smartphone use. This accords cogently with the core premise that the exercise of free will is "a *causal primary*" to effect self-regulation (Binswanger, 1991), and it highlights the critical role of self-monitoring and self-reaction as conceived in the theory of self-control (Bandura, 1991).

Lastly, the results of our research are best understood in the context of its limitations. Due to the qualitative nature of our research design, the number of students we studied, although more than sufficient for in-depth interviews, is a small sample size compared with large-scale quantitative studies. Correspondingly, the perspectives and insight we generated from the data may not be generalizable to the large population of college students in China. The findings we presented in the paper call for corroboration and triangulation from large-scale datasets derived from cross-sectional or even longitudinal surveys. Moreover, differences in national settings are likely contributors to variations in usage patterns; it is therefore useful to make cross-national comparisons in deepening our understanding of PSU among global youth.

CONCLUSION

Problematic smartphone use is a pervasive phenomenon, and calls for attention from scholars with diverse backgrounds and contribution from multidisciplinary perspectives. Prevalence rate is particularly prominent among college-age population, as the smartphone has established itself as a hallmark of youth lifestyle. From its built-in technical features to the assortment of apps and the rich set of available content, the smartphone is conducive to repetitive, habit-forming patterns of usage. Students' engagement with the smartphone often displays predictable behavioral proclivities in response to specific temporal, locale-based and contextually driven cues and triggers. While informational use is universally found among all users, problematic use is typically associated with gaming, streaming, entertainment, and social networking gratifications. As smartphone further establishes itself as a viable tool in mediating college learning, time alone should not be used as a sole predictor of problematic use. Both activity type and level of engagement warrant consideration in evaluating PSU. Extensive interaction with the smartphone has led to a special type of attachment to the device that pertains to not just its utilitarian functionalities but also its affective bond, manifested in various symptoms of uneasiness, discomfort and anguish at moments of not being with or seeing the smartphone. While we found evidence of the efficacy of detox apps in curtailing use, mental focus and proactive goal setting seem to be the most productive in attaining self-regulatory goals. Perspectives from our qualitative data suggest the need for a more nuanced approach in taking into consideration contextual cues and situational factors in dissecting psychological and emotional outcomes of smartphone use and abuse.

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 Institute of Scientific Research at Minjiang University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CD, ZT, and SN were involved in the conception and design of the study, coordinated work to transcribe, and analyzed the data. ZT wrote the draft of the manuscript. CD and SN arranged and conducted the online interviews. All authors contributed to the article and approved the submitted version.

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Problematic Smartphone Use and Problematic Social Media Use: The Predictive Role of Self-Construal and the Mediating Effect of Fear Missing Out

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Problematic smartphone use (PSU) and problematic social media use (PSMU) are two interrelated constructs which have received significant research attention over the past decade. The present study investigated the relationship between self-construal (distinguished as independent and interdependent), PSU and PSMU with Fear of Missing Out (FoMO) as a mediating variable. The sample comprised 405 Italian students who completed standardized psychometric scales assessing the variables of the study. Bivariate correlations analysis showed that FoMO and independent self-construal was significantly and negatively associated. On the contrary, interdependent self-construal was significantly and positively associated with FoMO, PSU, and PSMU. Mediation analysis showed that FoMO mediated the relationship between self-construal and both PSMU and PSU, but at different levels. The results demonstrated that FoMO full mediated the relationships between interdependent self and PSU, whereas only partial mediation was found between interdependent self and PSMU. Therefore, taking these personality characteristics into account may help reduce dysfunctional behaviour associated with problematic technology use and promote psychological well-being among students. However, it is recommended that further studies replicate the proposed model by including other psychological constructs.

Keywords: self-construal, fear of missing out (FoMO), problematic smartphone use (PSU), problematic social media use (PSMU), interdependent self-construal, independent self-construal

INTRODUCTION

The powerful combination of internet and mobile technologies has increased the risk of new behavioral addictions. One of these potential behavioral addictions, namely problematic smartphone use (PSU), has emerged as a phenomenon of increased academic concern. PSU refers to excessive use of a smartphone with accompanying functional impairments in daily living, and symptoms resembling those found in more traditional psychoactive substance use disorders (1).

Additionally, it is important to investigate not only the consequences of excessive use but the predisposing factors and specific use motives, as well as cognitive and affective variables (e.g., expectancies, experienced gratification), leading to the problematic overuse of specific mobile applications (2).

Cross-sectional analysis has shown that PSU behavior has been associated with different negative consequences, such as depression (3), poor sleep quality [(4), for a review], poor academic achievement (5), and loss of control (6, 7). According to an international report, 97% of Italian individuals used their smartphone to access the internet and about 85.2% has been actively engaged with or contributed to social media in terms of communication among social groups (8). A recent meta-analysis identified specific predictive factors for PSU [(9), for a review]. Among these risk factors, it was found that individuals with a large social network may spend more time on smartphones than others to maintain relationships, increasing the risk of PSU over time.

A recent study conducted by Canale et al. (10), which used a Bayesian analyses approach, provided the first comprehensive test of the pathway model of PSU as posited by Billieux et al. (1). The results of the study indicated that each path (i.e., excessive reassurance, impulsive, and extraversion), was associated with distinct psychosocial and psychopathological variables. Therefore, several factors can influence the development of PSU. Among these factors, personality traits such as low self-control (7), Dark Triad traits (11, 12), and self-esteem (13, 14), as well as the contribution of metacognitions and smartphone use expectancies (15) have been identified as significant predictors of PSU. Moreover, personality is one of the most investigated variables since individual differences can shed light if specific personality traits predispose technology users to develop addictive behavior. The results of a recent meta-analysis indicated the presence of robust associations between PSU and high levels of neuroticism and lower levels of conscientiousness [(16), for a review].

Although PSU and problematic social media use (PSMU) are not included in the latest fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5), research concerning these new behavioral addictions should be addressed to understand the motivational factors and the clinical features, as well as the co-occurrence with other disorders rather than overemphasize specific technological aspects (i.e., stressing a dichotomy between predominantly mobile and predominantly non-mobile internet-use disorder) (17). PSMU can be described as an unhealthy excessive form of social media use, which is characterized by a lack of control over the behavior and continued behavior despite clinically impairing life consequences [see (18, 19), for a review]. Social media platforms (i.e., *Facebook, Instagram, Twitter*, etc.) are typically available over mobile devices with an internet connection. However, for a minority of individuals, the use of social media applications can become problematic or pathological, interfering with daily functioning, social relationships, and academic or work performance (20). Additionally, social media use is one of the most predominant activities engaged in on smartphones (21, 22), and use of social media is considered a vulnerability factor in developing PSU (23, 24). Smartphones with internet access provide constant availability to social media applications and provides immediate access for individuals to check their notifications, especially among those with lower self-control, which may result in PSU and PSMU [see (7, 24), for a review]. Consequently, it is important to explore possible psychological factors that may increase the risk of PSU and PSMU.

Markus and Kitayama (25) developed self-construal theory, which can be described as the "belief about the relationship between the self and others and, especially, the degree to which they see themselves as separate from others or as connected with others" (p. 226). Subsequently, Singelis (26) conceptualized self-construal "as a constellation of thoughts, feelings, and actions concerning one's relationship to others, and the self as distinct to others" (p. 581). More specifically, self-construal theory distinguishes between independent self and interdependent self. Individuals with independent self-construal evaluate themselves not in the context of others, such as family members, co-workers or colleagues, but are more self-contained and autonomous (27). In this view, the self is separate from the social context. More specifically, when individuals think about themselves, those with highly independent self-construal will have their abilities and attributes as a referent rather than referring to the thoughts or actions of others (28). This suggests they have a high level of self-esteem which allows them to validate their internal attributes. Conversely, individuals with interdependent self-construal feel more connected with others. Therefore, individuals are not separated from the social context and are more closed and less differentiated from others.

Individuals can develop both independent self and interdependent self simultaneously. Therefore, in everyone, these two aspects of self can coexist. For this reason, it is not correct to consider independent and interdependent self-construal as two extremes of the same dimension. They should be conceptualized as different aspects of the self-concept. Indeed, some individuals might have an independent self or an interdependent self that is more salient (25). This view avoids categorizing individuals as having either an independent self or interdependent self, rather individuals should be described as having a salient interdependent or independent self-construal (27, 29).

Previous findings on self-construal have demonstrated that it is an influential psychological variable that affects human technologies interaction as well as social media use (30). For example, a review of the literature suggested that individuals with an interdependent self are more prone to use social media (31). The results of another study showed that individuals with interdependent self-construal were more disposed to share personal information on online social media (32). Recently, the results of another study reported that females, compared to males, exhibited stronger prosocial motives for using SNSs, which was explained by their interdependent self-construal (33). Moreover, in their research on private university students in Lebanon, Hawi and Samaha (34) found that only independent self-construal was a significant and negative predictor of PSMU. However, as a personality trait, self-construal has been explored only with PSMU, but has not been widely considered in relation to its association with PSU (35). Therefore, investigating whether or not self-construal affects PSU is one of the objectives of the present paper.

Additionally, the present study investigated whether fear of missing out (FoMO) would significantly mediate the associations between self-construal, PSMU, and PSU. The concept of FoMO describes the individual's desire to keep up with what other individuals are doing online as well as the idea that other individuals experience more interesting events when the user is not online (36). Previous researchers have shown that FoMO can contribute to both PSMU (37) and PSU [see (37), for a review]. These findings are important to understand the association between the variables in the present study. A recent meta-analysis reported a significant positive relationship between FoMO and both social media use and PSMU (38). The apprehension that others might be having gratifying experiences from which an individual is absent seems to be one of the contributory factors in PSMU, driven by the need to get in touch with others, mainly when individuals use social media applications to socially interact. Therefore, FoMO appears to be a strong motivator underlying PSMU. It has been indicated that social media use and FoMO have a reciprocal relationship, and FoMO drives PSMU to fulfill individual psychological needs of belongingness, consequently reinforcing the risk of PSU because social media applications are mainly used by individuals on their smartphones (39, 40).

Moreover, prior studies have explored the mediating role of FoMO, supporting the proposed argument. For example, a recent study demonstrated that FoMO mediated the relationship between maximization (a personality trait that describes individual differences in the general tendency of striving to make the best choice) and PSU (13). Furthermore, the extant literature has demonstrated that FoMO can mediate psychological variables (i.e., depression, envy) and PSU (3, 41). A survey study also found that FoMO and relational (interdependent) self-construal had a moderated mediation effect on the relationship between smartphone addiction and interpersonal sensitivity (i.e., a personality tendency characterized by constantly worrying about negative social evaluation) (35). Although FoMO has been conceptualized in the framework of the self-determination theory (36), the relationship between self-construal and FoMO is still unclear. However, the findings of a recent study provided consistent and convergent findings that FoMO is positively associated with interdependent self-construal (30). Consequently, individuals with a salient interdependent self, compared to those with a salient independent self, may experience higher levels of FoMO. Indeed, individuals with salient interdependent self-construal evaluate other individuals around them as a part of their identities (42) and will be more worried about what other individuals around them are doing, especially when they are included in online social groups. Therefore, if individuals evaluate other people as a part of themselves, the likelihood of experiencing FoMO would be higher, especially for those who do not feel socially close to others in the offline world (43). Moreover, daily frustration to satisfy basic psychological needs may lead to high levels of FoMO, and in turn could motivate individuals to constantly engage with mobile social media applications subsequently increasing the risk of developing PSMU and PSU (44).

Individuals with a salient independent self, usually, feel less connected to others, since they do not expect to receive social approval (i.e., likes and positive remarks from their friends). Conversely, individuals with a salient interdependent self are more likely to fear that they could be missing out on things with their friends on social media platforms when temporarily leaving the social applications, which can lead to higher levels of FoMO. In other words, the independent self should be negatively related to FoMO. On the other hand, the salient interdependent self should be positively associated with FoMO. This view is supported by a previous study, which indicated that FoMO was significantly higher among individuals with low levels of self-esteem (13). However, no previous studies have explored how FoMO works in these relationships. Furthermore, a growing number of studies indicate that FoMO is positively and significantly associated with both PSMU and PSU (45–47). Additionally, a cross-sectional study indicated that FoMO is more important than other variables (e.g., avoidant attachment and anxiety) in predicting PSMU (48). Moreover, when controlling for FoMO, the effect between some personality traits (e.g., extraversion, and neuroticism), and PSMU no longer becomes significant because only FoMO predicts PSMU. Therefore, the associations between self-construal, PSMU, and PSU may be mediated by FoMO.

Relevant to the present study is the Interaction of Person-Affect-Cognition-Execution (I-PACE) model (49), which is a comprehensive model of factors influencing internet use/overuse. Personal factors, for example, include genetic and biological influences, psychopathology, personality, cognitions, and use motives. Responses to such personal factors comprise mechanisms that may be risk or resilience factors for internet use, including cognitive biases, coping style, etc. Such responses may lead to the decision to use a particular type of internet-enabled device (e.g., smartphone) or use a specific social media platform, which may lead to healthy gratification or excessive use (50). Additionally, according to Marengo et al. (16), the I-PACE model provides a theoretical framework to study internet-related disorders since there is an overlap between PSMU and PSU. Therefore, the present study investigated the relationships between self-construal, PSMU, and PSU, with FoMO as a mediating variable. As aforementioned, self-construal theory proposes self-independent and interdependent dimensions. In particular, the interdependent self is based on the individual's connection to others, demonstrating that the ability to fit into social groups represents an important basis of increasing self-esteem. At early stages, focusing on the person component of the I-PACE model (51), it has been found that personality traits, such as low conscientiousness, low self-esteem, and high neuroticism, are factors driving a heightened risk for internet-use disorders. Therefore, it is argued that individuals with interdependent self would be more concerned with what others are doing, which could result in high levels of FoMO. In the I-PACE model, FoMO would be categorized as a response style and involves negative mood in which individuals attempt to regulate by using technological devices such as smartphones or internet applications like social media allowing individuals to escape from daily stressful issues.

HYPOTHESES OF THE PRESENT STUDY

Given the diffusion of smartphones and the adverse influence on the self, it is important to explore the role of mediating mechanisms which can help in the development of prevention and intervention programs. Therefore, the primary objective of the present study is to examine why some individuals spend more time online on social media and use their smartphones so excessively that it results in symptoms of behavioral addiction (43). To address this research objective, it was hypothesized that individuals who view themselves as socially connected with others, missing any social event or discussion (interdependent self) will generate feelings of FoMO (H1), and in turn increase the risk of technological addiction (PSMU and PSU) (H2). However, if PSU is associated with different factors, such as cognition, personality, existing psychopathology, and motives for internet-related applications and smartphone use, as suggested by I-PACE model, dealing with these factors leads individuals to use social media platforms excessively could help individuals with PSU. Therefore, it was hypothesized that FoMO would mediate the predictive effect of self-construal on PSMU and PSU (H3). Finally, age and gender were entered as covariates of PSMU and PSU, since prior studies have reported younger age and female gender as significant predictors of PSMU (52) and PSU (53).

METHODS

Participants and Procedure

Participants were recruited on the university campus during regular teaching activities. After obtaining their informed consent, all participants were introduced to the study objectives, and they were invited to complete an anonymous and confidential paper-pen-pencil survey. All participants volunteered for the study and none of them received any kind of remuneration. Moreover, they were also allowed to withdraw their data from the study at any stage. Completing the questionnaire took ∼25 min. The language of the questionnaire was Italian. All the research material and procedures were designed according to the guidelines laid out by Ethics in Human Research and the Italian Association of Psychology. Approval for the study was provided by the Ethics Committee of the University of Calabria (Prot. n. 0043310).

The sample comprised 405 Italian students attending various university degrees courses (114 males [28.15%] and 288 females [71.11%]). Three students did not report their gender. The participants' ages ranged from 19 to 43 years (M = 22.11 years, SD = 3.80). Most participants were attending psychological and educational courses (60.48%). The remainder were enrolled on various courses such as economics (10.86%), engineering (5.18%), mathematics (8.39%), and computer science (11.85%). The remaining students (3.21%) did not indicate their degree courses.

Measures

Self-Construal

The 10-item Italian version of the Self-Construal Scale [(54), original version (26)] was used to assess two dimensions of the self: independent self-construal (e.g., *"I do my own thing, regardless of what others think"*), and interdependent self-construal (e.g., *"My happiness depends on the happiness of those around me"*). Participants report their level of agreement with each statement on a seven-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Scores range from 10 to 70 with higher total scores indicating higher levels of self-construal. The independent self-construal ($\alpha = 0.64$) and interdependent self-construal ($\alpha = 0.65$) subscales in the present study demonstrated lower than desired reliabilities (55).

Fear of Missing Out (FoMO)

The 10-item Italian version of the FoMO Scale [(56), original version (57)] was used to assess disposition toward FoMO. The scale items (e.g., *"I fear others have more rewarding experiences than me"*) are rated on a five-point scale from 1 (*not at all true of me*) to 5 (*extremely true of me*). Scores range from 10 to 50 with higher total scores indicating a higher level of FoMO. The reliability of the scale in the present study was good ($\alpha = 0.73$).

Problematic Social Media Use (PSMU)

The six-item Italian version of the Bergen Social Media Addiction Scale (BSMAS) [(58), original version (59)] was used to assess the risk of social media addiction over the past year. The six scale items (e.g., *"How often during the last year have you tried to cut down on the use of social media without success?"*) each reflect core addiction elements [i.e., salience, mood modification, tolerance, withdrawal, conflict, and relapse; (51)] and are rated on a five-point scale from 1 (*very rarely*) to 5 (*very often*). Scores range from 6 to 30 with higher scores indicating a greater risk of problematic social media use. The reliability of the scale in the present study was just below what would be ideally desired ($\alpha = 0.69$).

Problematic Smartphone Use (PSU)

The 10-item Italian short version of PSU Scale [(60), original version (57)] was used to assess problematic smartphone use. The items (e.g., *"I have used my smartphone longer than I had intended"*) are rated on a six-point scale from 1 (*strongly disagree*) to 6 (*strongly agree*). Scores range from 10 to 60 with higher scores indicating higher problematic smartphone use. The scale's reliability in the present study was very good ($\alpha = 0.80$).

Statistical Analyses

Preliminary statistical analyses were carried out with IBM SPSS Statistics v. 26 software. Descriptive analyses and bivariate correlations were computed. The mediating model was tested where FoMO was inserted as a mediator in the relationship between self-construal (predictor) and PSMU and PSU (outcomes). The mediational analysis was conducted *via* the use of the bootstrapping method with 95% bias-corrected confidence intervals and 10,000 bootstrap samples. The mediation model was estimated with Mplus 7.04 (61).

RESULTS

Preliminary Results

Descriptive statistics and bivariate correlations of the main variables are shown in **Table 1**. The results indicated that individuals with high interdependent self were more likely to have high levels of PSU. However, no significant association was found between independent self and PSU.

The mean of the self-construal scale indicated tendencies toward independent self rather than interdependent self in the present sample. Therefore, all the correlations values between the constructs were significant and satisfied the conditions for performing the mediation analysis.

Mediation Analysis

The results of the bootstrapping mediational analysis (**Figure 1**), controlled for gender and age, showed that the independent self was weakly negatively related to FoMO ($\beta = -0.160$, $SE = 0.050$, $t = -3.17$, $p < 0.01$, 95% CI [−0.26, −0.06]), while interdependent self was weakly positively related to FoMO ($\beta = 0.129$, $SE = 0.046$, $t = 2.82$, $p < 0.01$, 95% CI [0.04, 0.22]), and PSMU ($\beta = 0.110$, $SE = 0.049$, $t = 2.24$, $p < 0.05$, 95% CI [0.01, 0.21]). FoMO was positively associated with PSMU ($\beta = 0.322$, SE $= 0.049$, $t = 6.61$, $p < 0.001$, 95% CI [0.22, 0.42]) and PSU ($\beta = 0.335$, $SE = 0.048$, $t = 7.04$, $p < 0.001$, 95% CI [0.24, 0.42]), respectively. Additionally, there was no significant association between interdependent self and PSU ($\beta = 0.094$, $SE = 0.049$, $t = 1.91$, $p = 0.056$, 95% CI [−0.15, 0.04]). Age was negatively associated with FoMO ($\beta = -0.173$, $SE = 0.048$, $t = -3.60$, $p < 0.001$, 95% CI [−0.26, −0.07]) and PSMU ($\beta = -0.138$, $SE = 0.040$, $t = -3.49$, $p < 0.001$, 95% CI [-0.22,−0.06]), respectively. On the other hand, gender was only associated with PSMU ($\beta = 0.079$, $SE = 0.036$, $t = 2.15$, $p < 0.05$, 95% CI [0.00, 0.15]). Regarding the indirect effects (**Table 2**), FoMO partially mediated the relationship between interdependent self and PSMU. Finally, a full mediated effect of FoMO was found in the association between interdependent self and PSU.

Table 2 shows the results of the mediation analysis. The only significant effect was the relationship between interdependent self and PSMU, which was partially mediated by FoMO. FoMO fully mediated the relationship between self-construal and PSU. No other mediating effects emerged. Finally, the direct relationships between independent self on both PSMU and PSU were not significant.

TABLE 1 | Descriptive statistics and correlation coefficients between study variables.

	M	*SD*	Skewness	Kurtosis	1	2	3	4	5	6	7
Independent self	4.95	1.02	−0.19	−0.41	–						
Interdependent self	3.79	0.99	0.05	−0.17	0.06	–					
FoMO	2.17	0.59	0.61	0.32	−0.16**	0.12*	–				
PSMU	2.10	0.68	0.57	−0.03	−0.02	0.16**	0.35***	–			
PSU	2.68	0.85	0.35	−0.20	−0.05	0.14**	0.35***	0.58***	–		
Age	22.11	3.65	0.12	6.17	0.02	−0.02	−0.13**	−0.14**	−0.02	–	
Gender	–	–	–	–	0.03	−0.02	−0.06	0.14***	0.12*	−0.6	–

FoMO, fear of missing out; PSMU, problematic social media use; PSU, problematic smartphone use. Gender (0 = male, 1 = female) is point serial correlation (r_{pb}).
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

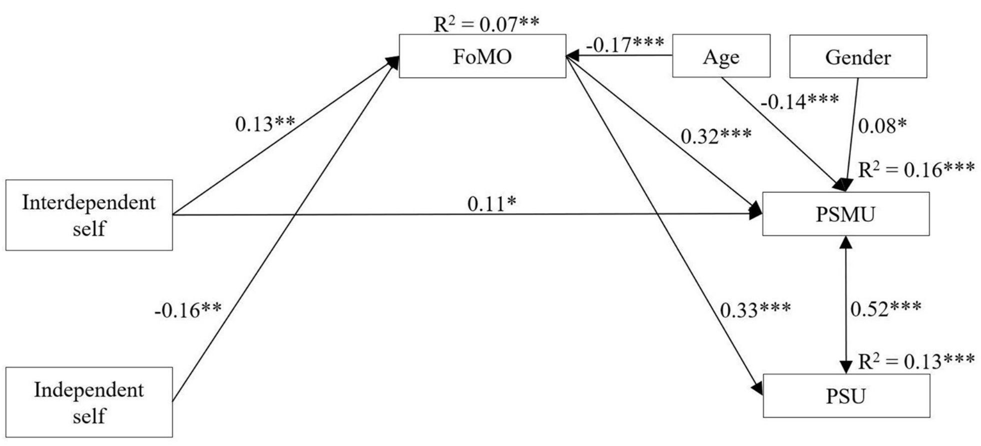

FIGURE 1 | Final estimated path model. For clarity, only the significant relationships are depicted in the figure. FoMO, fear of missing out; PSU, problematic smartphone use; PSMU, problematic social media use. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

TABLE 2 | Mediation and indirect effects with standardized estimates of FoMO for the relationship among self-construal (independent self and interdependent self), PSMU, and PSU.

Pathway	*Estimate*	*SE*	*Z*	*p*	95% [CI]
Independent self → PSMU					
Total	−0.03	0.05	−0.49	0.621	[−0.13, 0.08]
Indirect	−0.05	0.02	−2.89	0.004	[−0.09, −0.02]
Direct	−0.03	0.05	0.52	0.602	[−0.07, 0.12]
Independent self → PSU					
Total	−0.06	0.06	−1.14	0.256	[−0.17, 0.05]
Indirect	−0.05	0.02	−2.90	0.004	[−0.09, −0.02]
Direct	−0.01	0.05	−0.19	0.849	[−0.11, 0.10]
Interdependent self → PSMU					
Total	0.15	0.05	3.11	0.002	[0.05, 0.24]
Indirect	0.04	0.02	2.59	0.010	[0.01, 0.08]
Direct	0.11	0.05	2.27	0.025	[0.01, 0.21]
Interdependent self → PSU					
Total	0.14	0.05	2.72	0.007	[0.04, 0.23]
Indirect effect	0.04	0.02	2.58	0.010	[0.01, 0.08]
Direct	0.09	0.05	1.91	0.056	[−0.00, 0.18]

SE, standard error; PSMU, problematic social media use; PSU, problematic smartphone use.

DISCUSSION

The present study examined the mediating role of FoMO in understanding the relationship between self-construal (interdependent self and independent self), PSMU, and PSU both as to outcome variables. It was hypothesized that individuals with higher levels of interdependent self-construal would experience feelings of FoMO (H1), and in turn would be more at risk of PSMU and PSU (H2) both directly and indirectly through the mediating role of FoMO (H3). Overall, the present results suggest that interdependent self-construal was positively related to FoMO, which in turn was associated with greater PSMU and PSU (40). Consistent with the assumptions of the I-PACE model (49) FoMO, which can be considered a maladaptive psychological status, led to both PSMU and PSU. The results of the present paper contribute to the literature on FoMO by demonstrating that interdependent self is positively related to FoMO, and that independent self is negatively associated with FoMO, supporting the present authors' assumptions. Therefore, the present study contributes to the literature on behavioral addiction, particularly in relation to the mediating role of FoMO, by proposing a theoretical framework based on the self-construal theory (25). According to Dogan (30) when a person develops a self-concept of which other individuals are a part, a person will be more inclined to wonder about what others are doing. Individuals develop and shape themselves in connection with others, which represent a part of themselves, and then the desire to stay continually connected with what others are doing becomes inevitable (42, 43). Individuals with an interdependent self-construal are more likely to value connectedness (29). Consequently, they might experience FoMO due to the perceived disconnect with other individuals around them.

Moreover, FoMO could be one of the symptoms of individuals with an interdependent self who are struggling with problems of loneliness. These results are consistent with cross-sectional and experimental studies [e.g., (62)]. Compared to individuals with an independent self, those with a higher interdependent self would prefer social media over face-to-face relationships because this allows them to validate their internal attributes, and subsequently might lead to PSMU. Therefore, individuals with higher levels of interdependent self-construal are more worried about being negatively evaluated by others and are more afraid of missing the latest news concerning others, and are consequently more prone to use mobile social media applications excessively (31).

These results could explain why some types of individuals would be less concerned with active social media use, which in turn are more at risk in the use of smartphone applications. Individuals with a salient interdependent self may repeatedly experience FoMO. They may give less importance to their daily experiences, which represent an important opportunity to shape their sense of self, due to the inner desire to track others' everyday experiences using social media platforms. This allows them to regulate their levels of social appraisal and self-promotion with others. FoMO could work as an internal control mechanism for individuals with a salient interdependent self by offering the ability to protect their well-being aiming to seek reassurance and self-worth (30).

Viewed from the perspective of cultural factors, studies have shown that individuals living in a collectivistic culture tend to develop the interdependent self and report lower life satisfaction compared to individuals from individualistic cultures (30, 34). The present study reinforces these previous findings and underlines the importance of considering the role of FoMO in the relationship between the cultural aspects regarding self-construal theory and internet-related disorders in future cross-cultural psychology studies, especially because FoMO becomes a key factor when individuals in construing themselves give more importance to their connection to the community.

Consistent with the study's hypotheses, it was found that FoMO was a mediator in the relationship between self-construal and PSMU and PSU, but at different levels. The study found a fully-mediated relationship between interdependent self and PSU, and a partially-mediated association between interdependent self and PSMU. According to the results, the effects of FoMO leading to PSMU and PSU by considering the levels of self-construal were different. Interdependent self would reinforce FoMO, which in turn facilitates both PSMU and PSU among university students. Therefore, FoMO is not only an outcome that is affected by self-construal but also an internal motivation of PSMU and PSU behavior. These results fit with the I-PACE conceptualization of cognitive bias and coping style because of mechanisms in the relationship between predisposing factors and excessive internet-use disorders and related applications.

On the other hand, the negative association of independent self with FoMO indicates that people who perceive themselves as separate from others would be less concerned with active use of social applications for social purposes, and therefore they have less risk to develop addictive behavior to technologies (34). These differences in FoMO can also have implications in understanding the existence of indirect paths between self-construal on both PSMU and PSU. Additionally, the results of the present study underline that there are differences in the predictive and mediating variables of both PSMU and PSU. Therefore, these findings are important for designing intervention and prevention programs. Given the widespread use of both smartphones and social media applications, future preventive activities could be designed to promote the adoption of adaptive strategies to manage the experience of FoMO and consequently the risk of developing internet-related disorders. Intervention and prevention programs could focus on helping smartphone and social media users engage in more physical activities and develop offline social networks focusing on face-to-face interactions rather than through technology-mediated environments such as social media platforms (9).

Overall, the strategy that individuals adopt to develop their self-concept affects FoMO. When individuals use social media *via* smartphone applications to satisfy their psychological needs, FoMO will be more salient and the risk of developing an addiction to PSMU, and PSU is higher. Therefore, individuals should focus on personal autonomy to refrain from experiencing the FoMO, which should protect them from the negative consequences of the FoMO because it eases the awareness of the experience that the individual is missing out (30, 63). These results provide insight on the underlying mechanisms between self-construal, where the self is one of the core elements of an individual's identity, and internet-related disorders such as PSMU and PSU. Moreover, the results may also support the I-PACE model, which underlines that addictive behaviors (i.e., PSMU, PSU) result from interactions between a person's core characteristics and mediating/moderating variables (49), which may be dynamic and develop over time because of engagement in specific behaviors likely to be experienced as rewarding because it may help relieve stress.

The present study is not without limitations. First, although path analysis was used to test the study's hypotheses, the study was correlational. Therefore, no causal relationships can be inferred. Researchers should perform longitudinal studies to confirm the inferred causal relationships in the present study. Second, the data in the present study were all self-report. Therefore, future research could benefit by collecting data using mixed methods research approaches. Third, the present study only collected data from Italian university students with a bias toward females, therefore, the generalization of the findings is limited. Future research should use more diverse and representative samples to confirm these findings. Finally, the Cronbach alpha reliability values of the subscales in the Self-Construal Scale were below 0.7 which were less than ideal. Future studies should examine the proposed research model by considering the cultural-related and individual differences, for instance, between Asian and Western individuals. In a recent cross-cultural study the alpha coefficients for the independent and interdependent subscales of the Self-Construal Scale were different with low values for the Western group like those in the present study (62).

CONCLUSION

In summary, the present study contributes to the literature by testing a mediation model which offers an understanding of the relationships between self-construal, PSMU and PSU, *via* the mediating role of the FoMO. The results indicated that interdependent self-construal could work as a risk factor mainly for PSMU rather than PSU. Results also suggested that FoMO may account for the previously established relationship not only between self-construal and PSMU but mainly for PSU. However, future studies should analyse and replicate the proposed model with other psychological variables. For instance, social comparison can be evaluated as a mediator in this relationship. It is well-established that for individuals with higher interdependent self-construal, other people become a source of the definition of the self, and social comparison may be used primarily when self-improvements motives are strong. Furthermore, previous studies have indicated that social comparison is positively associated with social media use and PSU because they seek comparison information (64, 65).

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 University of Calabria. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

RS: conceived and designed the study, analyzed the data, and wrote the first draft of the paper. ZD, MG, and BK: reviewed and improved subsequent drafts of the paper. All authors have read and agreed to the published version of the manuscript.

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Examining the Interplay of Smartphone Use Disorder, Mental Health, and Physical Symptoms

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The current study examined antecedents and possible consequences of smartphone use disorder (SmUD). In particular, we aimed to increase the understanding of the interplay of SmUD, mental health, and physical symptoms. Studies found that SmUD is associated with diverse psychological and physical health impairments, ranging from depression and anxiety to headaches and sleep disturbances. Based on existing works, we assumed that mental problems mediate the relationship between SmUD and bodily problems. We conducted a cross-sectional random-quota online survey among 938 German smartphone owners aged 14 to 64 years. An instrument based on the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) was used to measure SmUD severity. The data was analyzed using structural equation modeling. We identified a rate of 4.0% potentially disordered users. Males and younger participants showed more signs of SmUD. As expected, SmUD severity was found to be associated with physical (more frequent headaches, sleep disturbances, gastrointestinal problems) as well as psychological (higher levels of loneliness, stress, depression/anxiety) health impairments. Investigating the interplay of these variables showed that depression and anxiety, and stress partially mediated the relationship between SmUD severity and physical symptoms. Taken together, our results confirm that increased SmUD severity is associated with mental problems as well as with somatic symptoms. We assume complex (and presumably circular) relationships, which future studies should examine in more detail. SmUD prevention and intervention programs should follow a broad approach that considers decreases in physical and mental health, possibly causing or resulting from SmUD.

Keywords: smartphone use, disorder, addiction, physical symptoms, depression, sleep disturbances, headaches, mental health

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INTRODUCTION

Smartphone use has rapidly increased in recent years. Currently, about 85% of the US population are smartphone owners (1). In European countries like Germany, rates even reached almost 90% (2). Empirical studies indicate that the increasing diffusion and intensified use of smartphones may be connected to several risks, such as decreases in academic performance [e.g., (3–5)] or a higher danger of being involved in accidents due to distraction [e.g., (6, 7)]. Furthermore, several studies have identified connections between excessive smartphone use and mental problems, such as depression, anxiety, or stress symptoms [e.g., (8–12)]. There is also evidence that excessive smartphone use is associated with physical health impairments, such as sleep disturbances (10–13).

More and more researchers have raised the question of whether smartphone use can take on addictive forms that require professional treatment. Using different terms like *smartphone addiction* [e.g., (14, 15)], *problematic smartphone use* [e.g., (8, 16)], or *smartphone dependence* [e.g., (17, 18)], scholars investigate the extent to which users show signs of a problematic overuse–such as a loss of control, tolerance, or withdrawal symptoms. In the context of computer and videogames, the World Health Organization (WHO) uses the term *Gaming Disorder* to describe such problematic forms of use. Consequently, scientists have started to use the terms *disorde*r or *disordered use* also in relation to other forms of addictive media technology use, like, for example, social media (use) disorder [e.g., (19, 20)]. Following Sha et al. (21) and others [e.g., (22, 23)] we will use the term *Smartphone Use Disorder* (SmUD) as a synonym for uncontrolled, addictive smartphone use in the following. As suggested by Montag et al. (24), we will abbreviate the term with SmUD because SUD could easily be misunderstood as an acronym for Substance Use Disorder.

Many existing studies on SmUD suffer from some methodological limitations. For example, it can be criticized that studies are often not comparable because of a lack of consistency in the diagnostic criteria that were applied. To date, no consensus about how to reliably measure disordered smartphone use has been achieved among scholars, resulting in a very high number of different scales [e.g., (15, 25, 26); for overviews, see (27, 28)]. Some of these instruments consisted of *ad-hoc* items, some adopted the substance abuse criteria from the 4th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-4) by the American Psychiatric Association (APA), and some adopted criteria from screening tools that were originally designed to measure pathological gambling, Internet addiction, or addictive shopping (27). Further, a majority of studies on SmUD is based on self-recruited and non-representative samples (27).

The current study draws data from a random-quota sample of German smartphone owners aged 14 to 64 years. To date, computer and video gaming disorder is the only form of addictive media technology use that has been defined in relevant manuals like the 11th revision of the International Classification of Diseases (ICD-11) by the WHO ("Gaming Disorder"), or the DSM-5 by the APA ("Internet Gaming Disorder"; IGD). However, there are good reasons to assume that SmUD and IGD are overlapping concepts (24). For example, Leung et al. (29) found that SmUD scores and IGD scores significantly correlated, which can be explained by the fact that many smartphone users play mobile games (24). Accordingly, several studies showed that game use positively predicted SmUD [e.g., (30, 31)]. Similarly, social media use disorder scores were found to correlate with SmUD scores (29), and social networking site use was identified a predictor of SmUD [e.g., (30, 32)]. Consequently, it has been argued that IGD and other types of Internet technology use disorders (like social media use disorder), "should [...] be defined by the same set of diagnostic criteria" [(33), p. 479]. In line with this argumentation, some recent studies have adopted the DSM-5 IGD criteria to measure disordered (addictive) smartphone use [e.g., (16, 34, 35)]. We follow this approach and use a DSM-5 based scale to measure SmUD.

The central aim of the current study was to deepen the understanding of the antecedents and possible consequences of SmUD. Based on theoretical considerations and previous findings, we constructed and tested a structural model that is presented in **Figure 1**. The different paths and hypotheses will be explained in detail in the following section.

Antecedents and Consequences of Smartphone Use Disorder

Existing studies have shown that age and gender play a role in the development of SmUD (11). Concerning age, research findings indicate that younger users constitute a particular at-risk group for SmUD [e.g., (14, 16, 36–38)]. Accordingly, we hypothesize that age is negatively related to SmUD severity (hypothesis **H1**). The relationship between gender and SmUD remained somewhat unclear with mixed results concerning the question of whether males or females are more at risk for the development of SmUD (14, 39, 40). Consequently, we ask how gender is related to SmUD (research question **RQ1**). Several studies have shown that higher smartphone usage times are associated with increased SmUD severity [e.g., (16, 36, 41, 42)]. We therefore hypothesize that smartphone minutes per week are positively related to SmUD severity (hypothesis **H2**).

A growing body of research focuses on examining psychosocial correlates of SmUD. Some studies considered variables such as stress, depression, anxiety, or loneliness as predictors of SmUD, while others argued that SmUD may lead to psychosocial problems (11). Both of these assumptions are plausible form a theoretical perspective and can be explained by the Interaction of Person-Affect-Cognition-Execution model [I-PACE; (43, 44)], one of the most established theoretical models to explain the development and maintenance of addictive behaviors. I-PACE considers psychopathology (e.g., depression and anxiety) as well as particular social cognitions (e.g., loneliness) as general predisposing variables that can increase the risk to develop addictive media use (43, 44). However, in the later stages of the "addiction process", excessive, disordered forms of use may also cause or further reinforce daily life problems, leading to social isolation and negative mental conditions [(43), p. 252]. In line with these assumptions, several cross-sectional studies have found loneliness, stress, anxiety, and depression were positively associated with SmUD [e.g., (8, 39, 45–49)]. Recent longitudinal studies have indicated that SmUD can lead to increases in loneliness and mental problems over time (50, 51). Against this background, we hypothesize that SmUD severity is positively related to higher levels of stress (hypothesis **H3**), depression and anxiety (hypothesis **H4**), and loneliness (hypothesis **H5**).

Physical health impairments possibly resulting from SmUD have much less often been examined than associations between SmUD and mental problems (11). However, there is some empirical evidence that SmUD is also related to somatic symptoms. For example, studies have reported a positive relationship between SmUD and sleep deprivation [e.g., (39, 46,

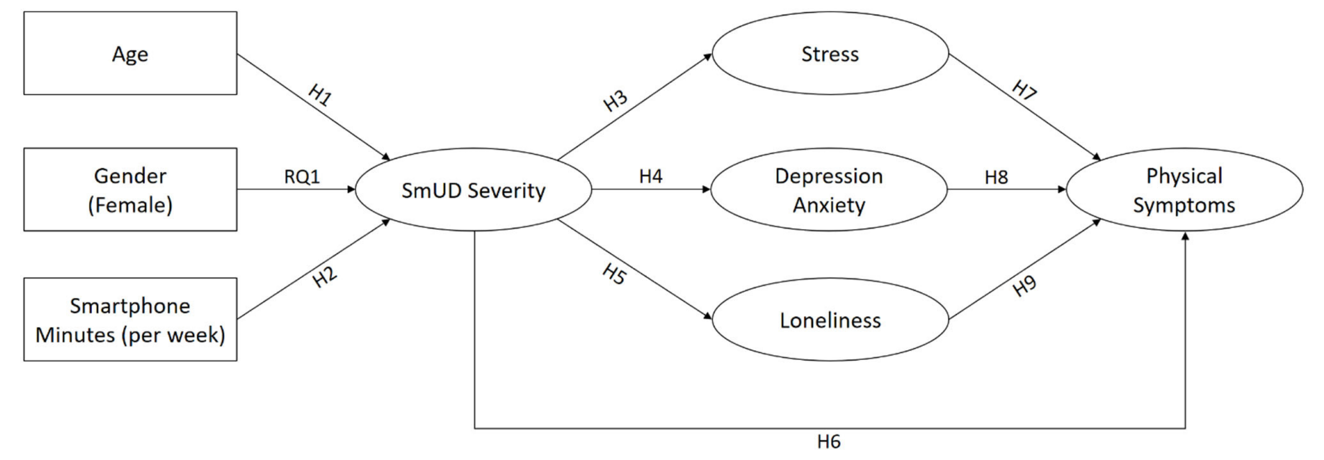

FIGURE 1 | Predicted structural model labeled with hypotheses and research questions. SmUD, smartphone use disorder.

52, 53)]. Fewer studies have investigated other bodily symptoms potentially resulting from SmUD, such as headaches or neck pain [e.g., (54, 55)]. In the current study, we consider three physical symptoms (sleep disturbances, headaches, and gastrointestinal problems) and predict positive associations with SmUD severity (hypothesis **H6**).

Research has shown that physical symptoms (like gastrointestinal problems, insomnia, and migraines) and mental problems (like depression and anxiety) often co-occur and can reinforce each other [e.g., (56–58)]. For example, a longitudinal study among UK residents showed that anxiety and depression at baseline increased the risk of suffering from insomnia 12 months later and vice versa (59). Further, there is empirical evidence that experiencing stress can trigger headaches (60), impair sleep (61), and may cause gastrointestinal problems (62). Also, loneliness was often considered a risk factor for health problems and has been shown to be positively related to sleep disturbances (63) and other somatic symptoms, such as headaches and nausea (64). Accordingly, we assume that higher levels of stress (hypothesis **H7**), depression and anxiety (hypothesis **H8**), and loneliness (hypothesis **H9**) are positively related to physical symptoms.

Notably, most existing studies investigated direct relationships between measurements of SmUD and selected different aspects of physical wellbeing [e.g., (46, 52, 54, 55)]. Yet, little is known about the interplay of mental problems and physical symptoms associated with SmUD. Demirci et al. (39) have shown that depression and anxiety acted as mediators in the relationship between SmUD and sleep disturbances. They argued that SmUD may lead to depression and anxiety, which, in turn, may cause sleep problems. Similarly, Liu et al. (65) found that rumination mediated the relationship between SmUD and sleep quality. In light of these results and against the background of the theoretical considerations and empirical findings discussed above, we argue that SmUD may increase mental problems and loneliness, which, in turn, could increase the risk to experience sleep disturbances, headaches and gastrointestinal problems. In other words, we hypothesize indirect (mediated) relationships between SmUD severity and physical symptoms via stress (hypothesis **H10**), depression and anxiety (hypothesis **H11**), and loneliness (hypothesis **H12**).

MATERIALS AND METHODS

Participants and Procedures

The current study was part of a larger online survey on media usage habits of German Internet users aged 14–64 years that was conducted in cooperation with a professional German survey research institute, adhering to the internationally recognized ICC/ESOMAR ethics code for social research and data analytics. The participants were informed about the general purpose of the study, consented in their participation, and had the right to opt out at any time. The participants were recruited via an online access panel and a random-quota procedure was applied to increase the representativeness of the data in terms of age, gender, education, and living region.

In total, 1,053 participants filled out the questionnaire. We screened the dataset for irregularities (i.e., straight-lining answers, very high numbers of missing values, obvious errors in answers to media use questions) and excluded 34 cases. Further, 81 non-smartphone owners were excluded, resulting in a final sample of $N = 938$ German smartphone owners aged 14–64 years. The mean age was 40.44 years ($SD = 13.73$). Gender was almost equally distributed with 455 female participants (48.5%) and 483 male participants (51.5%).

Measurements

Means, standard deviations, and Cronbach's alpha values for all measurements are reported in **Table 1**. Smartphone minutes per week, age, and gender were measured as self-reports.

Smartphone Use Disorder

Aiming to increase the validity and reliability of measuring SmUD, Hussain et al. (16) introduced the Problematic

TABLE 1 | Means, standard deviations, and Cronbach's alpha.

	M	*SD*	α
Smartphone minutes (per week)	765.58	935.44	–
SmUD severity	15.46	7.82	0.932
Depression/anxiety	3.47	3.10	0.890
Stress	5.42	2.08	0.772
Loneliness	6.91	2.44	0.829
Physical symptoms	7.03	2.76	0.725

SmUD, smartphone use disorder.

Smartphone Use Scale, which is an adaptation of the established IGDS9-SF by Pontes and Griffiths (66). The IGDS9-SF has been evaluated in numerous international studies [e.g., (67–70)] and is currently one of the most-often used instruments to measure IGD (71). It consists of nine items that were created based on the nine IGD criteria as defined by the APA in the DSM-5. Following the approach by Hussain et al. (16), we adapted a German version of the IGDS9-SF (72) to measure smartphone use instead of game use (e.g., "Do you use your smartphone in order to temporarily escape or relieve a negative mood (e.g., helplessness, guilt, anxiety)?"). The items were introduced by asking the participants about their smartphone usage over the past 12 months and each of the items had to be rated on a 5-point scale ranging from 1 = "never" to 5 = "very often".

According to Pontes and Griffiths (66), higher scores on the scale can be interpreted as a higher tendency toward disordered use. For research purposes, participants with scores of 36 to 45 points (i.e., all questions, on average, answered with "often" or "very often") can be considered potentially disordered game users (66). Hussain et al. (16) used the same criterion to assess the prevalence of SmUD.

Mental Problems

Depression and anxiety were measured with the German version (73) of the Patient Health Questionnaire (PHQ-4) by Kroenke et al. (74). The participants were asked to rate four items (e.g., "Feeling down, depressed, or hopeless.") to measure their mental condition ("Over the last two weeks, how often have you been bothered by the following problems?"; 0 = "not at all" to 3 = "nearly every day"). According to the developers of the instrument, the PHQ-4 can either be used to calculate separate depression and anxiety scores, or to calculate a composite depression and anxiety index based on all 4 items (74). In the current study, we opted for the single factor solution since depression and anxiety are closely related constructs (74) and we wanted to avoid multicollinearity in the structural model.

Loneliness was measured using the 3-item short version [(75); e.g., "How often do you feel that you lack companionship?"; 1 = "never" to 4 = "often"; German items: (76)] of the revised UCLA Loneliness Scale (77).

The participant's level of stress was measured with the 4-item short version of the Perceived Stress Scale (PSS-4) by Cohen et al. (78). For the current study, we used the translated German items by Stächele and Volz (79) that were rated on a 5-point scale ranging from 1 = "never" to 5 = "very often". Two positively worded items (e.g., "In the last month, how often have you felt confident about your ability to handle your personal problems?") were recoded before inspecting Cronbach's alpha. A value of $\alpha = 0.557$ indicated that the scale lacked reliability. Therefore, we decided to exclude the two recoded positive items, which increased Cronbach's alpha substantially to a satisfying level (see **Table 1**).

Physical Symptoms

Based on the Physical Health Questionnaire by Schat et al. (80), we created three items to measure how often the participants had experienced three widespread somatic symptoms. The participants were asked about their physical health conditions over the last month and had to indicate how often (1 = "never" to 5 = "very often") they suffered from (a) sleep disturbances, (b) headaches, and (c) gastrointestinal problems (e.g., nausea, abdominal pain, or diarrhea).

Statistical Analysis

Descriptive statistics were calculated using IBM SPSS Statistics. The predicted structural model (**Figure 1**) was computed using R and the lavaan package (81). We inspected skewness and kurtosis for each variable and conducted Mardia's test of multivariate skewness und kurtosis (82) using the psych package (83). Because the data was not normally distributed, the hypothesized model was calculated using the robust MLR estimator, which features maximum likelihood estimation with scaled test statistics and Huber-White corrected standard errors. FIML-imputation was used to handle missing data (66 missing patterns). For the indirect effects, 95% confidence intervals based on the Monte Carlo approach (84) were calculated using the semTools package (85). Model fit was evaluated based on the recommendations of Hu and Bentler (86): A Comparative Fit Index (CFI) and a Tucker-Lewis Index (TLI) close to 0.95, a Standardized Root Mean Square Residual (SRMR) below 0.08, and a Root Mean Square Error of Approximation (RMSEA) below 0.06.

RESULTS

To get an impression of the spread of SmUD in our sample, we calculated the prevalence of SmUD based on the cut-off point suggested by Pontes and Griffiths (66) and Hussain et al. (16). Thirty-five of the 874 participants that had completed all the questions of the screening tool reached SmUD scores of 36 points and above. This equals a rate of 4.0% potentially disordered smartphone users. Notably, we found that more males ($n = 28$, 6.2%) than females ($n = 7$, 1.7%) reached SmUD scores of 36 or above. This difference was significant, $\chi^2(1) = 11.68$, $p < 0.001$, Cramer's $V = 0.116$.

Structural Model

The estimated structural model is presented in **Figure 2**. SmUD severity, stress, depression/anxiety, loneliness, and physical symptoms were modeled as latent constructs based on manifest indicators (item scores), while age, gender (male = 0, female = 1) and smartphone minutes (per week) were added as observed variables. To control for the effects of age, gender, and

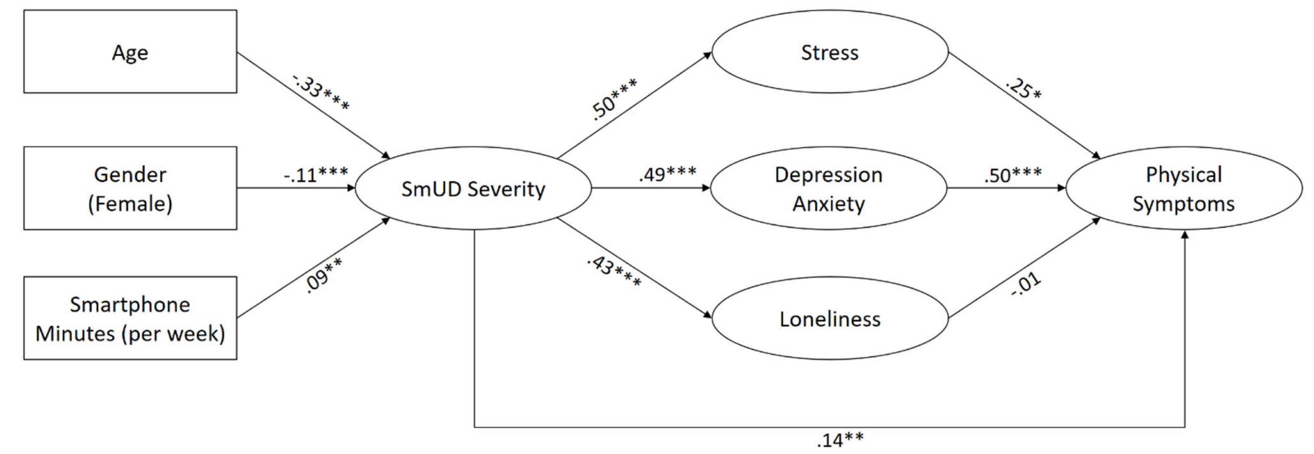

FIGURE 2 | Estimated structural model labeled with standardized regression coefficients. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Direct paths from age, gender, and smartphone minutes to indicators of mental problems, and physical symptoms were estimated but are not shown for a clearer illustration (see **Table 2** for a full matrix of all regression coefficients). SmUD, smartphone use disorder.

TABLE 2 | Complete matrix of model path weights.

	SmUD severity	Stress	Depression/anxiety	Loneliness	Physical symptoms
Age	−0.33***	−0.02	−0.04	−0.06	0.09*
Gender (female)	−0.11***	0.08*	0.05	0.01	0.14***
Smartphone minutes (per week)	0.09**	−0.03	−0.00	−0.02	−0.04
SmUD severity	–	0.50***	0.49***	0.43***	0.14**
Stress	–	–	–	–	0.25*
Depression/anxiety	–	–	–	–	0.50***
Loneliness	–	–	–	–	−0.01
R^2	0.15	0.25	0.26	0.21	0.61

Table shows standardized regression coefficients (β); n = 938.
****p < 0.001.*
***p < 0.01.*
**p < 0.05.*
SmUD, smartphone use disorder.

smartphone minutes, additional direct paths from these variables to mental problems and physical symptoms were calculated. For a clearer illustration of the hypothesized relationships, the coefficients of these additional paths are not included in **Figure 2**, but can be found in **Table 2**. The calculated fit indices indicated a good model fit: $\chi^2(227) = 707.48$, $p < 0.001$, CFI = 0.951, TLI = 0.941, RMSEA = 0.053, SRMR = 0.037.

Hypotheses **H1** and **H2** were confirmed: Age ($\beta = -0.33$, $p < 0.001$) and smartphone minutes per week ($\beta = 0.09$, $p < 0.01$) were both significantly related to SmUD severity in the expected directions. Concerning gender (**RQ1**), we found a small significant association indicating that males experienced higher levels of SmUD than females ($\beta = -0.11$, $p < 0.001$).

Affirming hypotheses **H3**, **H4**, and **H5**, we identified significant positive relationships between SmUD severity and stress ($\beta = 0.50$, $p < 0.001$), depression and anxiety ($\beta = 0.49$, $p < 0.001$), and loneliness ($\beta = 0.43$, $p < 0.001$). Further, SmUD severity was positively related to experiencing physical symptoms ($\beta = 0.14$, $p < 0.01$), thus supporting hypothesis **H6**.

In line with hypotheses **H7** and **H8**, we found that stress ($\beta = 0.25$, $p < 0.05$) as well as depression and anxiety ($\beta = 0.50$, p < 0.001) were positively related to physical symptoms. In contrast, hypothesis **H9** was not supported since loneliness was not significantly related to physical symptoms ($\beta = -0.01$, $p = 0.784$).

Finally, we tested the indirect (mediated) effects postulated in hypotheses **H10** to **H12**. **H10** and **H11** were both confirmed: SmUD showed a significant indirect relationship with physical symptoms via stress ($B = 0.09$ [LLCI = 0.02, ULCI = 0.17], $\beta = 0.12$, $p < 0.05$) and depression and anxiety ($B = 0.19$ [LLCI = 0.12, ULCI = 0.26], $\beta = 0.25$, $p < 0.001$). Hypothesis **H12** had to be rejected since loneliness did not mediate the relationship between SmUD and physical symptoms ($B = -0.00$ [LLCI = −0.04, ULCI = 0.03], $\beta = -0.01$, $p = 0.784$). The total effect (including direct and indirect paths) of SmUD on physical symptoms was $\beta = 0.50$ ($B = 0.39$ [LLCI = 0.31, ULCI = 0.46], $p < 0.001$).

DISCUSSION

While some previous studies have indicated prevalence rates of up to 30 to 40% of disordered (or at-risk) users in different populations [e.g., (7, 14, 32, 87)], our results indicate a relatively moderate rate of 4.0% potentially disordered users among German smartphone owners aged 14–64 years. This finding confirms the results of Hussain et al. (16), who used the same screening tool and also reported a relatively low rate of 2.7% disordered users in a (non-representative) sample of 13- to 69-year-old smartphone owners.

Using an adaptation of the IGDS9-SF [as one of the currently most-often used IGD scales; (71)] also makes it easier to compare our results with studies on other forms of media technology use disorders. For example, Reer et al. (72) used the same instrument and identified similar rates of disordered users among German gamers (2.4%) and social media users (2.7%). This raises the question of why IGD is defined in the manuals of the WHO and the APA, while SmUD or social media use disorder are not (even though they seem to be similarly prevalent). This is not an argument for or against the inclusion of these disorders in the relevant manuals, but it is certainly an observation of the unequal treatment of different forms of addictive media technology use.

The central aim of the current study was to examine antecedents (age, gender, smartphone minutes per week) and potential outcomes (mental problems, loneliness, physical symptoms) of SmUD severity.

Several studies have found that SmUD [e.g., (16, 36, 38)] and other forms of addictive media technology use [e.g., (88, 89)] are more prevalent among younger participants. Accordingly, we hypothesized a negative relationship between SmUD severity and age (**H1**), which was supported.

Concerning gender, studies have painted a heterogeneous picture, with some finding no significant differences [e.g., (40, 90)], some finding males [e.g., (14)], and some finding females [e.g., (39, 91)] to be more at risk of developing disordered forms of smartphone use. We asked the research question how SmUD is related to gender (**RQ1**) and identified a small significant negative relationship between female gender and SmUD, indicating that males scored higher on the screening tool. Furthermore, we identified a significantly higher proportion of male participants (6.2%) than female participants (1.7%) that reached scores above the cut-off point suggested by Pontes and Griffiths (66) and Hussain et al. (16).

We also examined how smartphone minutes per week were related to SmUD severity and hypothesized a positive association (**H2**). In line with previous studies [e.g., (16, 36, 41, 42)] and in support of our hypothesis, we found that those who use their smartphones more intensively showed more signs of SmUD. Notably, the strength of the association was smaller than one might have expected. This may be interpreted as a hint that intensified use of smartphones does not necessarily lead to SmUD. However, one should keep in mind that smartphone minutes per week were measured as self-reports. Thus, the small coefficient may also result from problems in objectively assessing screen time, an issue intensively discussed by researchers [e.g., (41, 42)].

Confirming previous findings [e.g., (8, 42, 45–48)] and our hypotheses (**H3-H5**), we found SmUD severity to be positively related to higher levels of stress, depression and anxiety, and loneliness. In our hypothesized model, we considered loneliness and mental problems consequences of SmUD. This assumption was based on recent longitudinal studies that indicated that SmUD can increase loneliness and mental problems over time (50, 51). However, we are aware that, because of the cross-sectional nature of our work, we cannot claim causality, that is, loneliness and mental problems could in general be causes or consequences of a higher SmUD tendency. Against the background of the I-PACE model (43, 44), both directions of effects are plausible. It can be argued that pre-existing psychosocial problems are predisposing factors for an unhealthy, escapist use of smartphones. However, in later phases of the addiction process, using smartphones in an excessive, disordered manner may also cause or further reinforce daily life problems, including emotional discomfort and loneliness (43). More longitudinal studies are necessary to further clarify the direction (or reciprocity) of these relationships.

The relationship between SmUD and physical health remained somewhat understudied so far (11). However, there is some empirical evidence that SmUD is associated with physical symptoms, such as sleep disturbances [e.g., (39, 46, 52, 53)]. Earlier studies have explained this relationship by possible direct effects of smartphone use on biological functioning [e.g., (92)]: Being permanently present, especially in the bedroom, smartphones may prevent users from sleeping, may disturb their biorhythms through screen light, and may induce a state of mental, emotional, and physiological arousal. Also, the effects of smartphone use on serum melatonin levels (which are responsible for sleep quality) have been discussed (93). In the current study, we considered three widespread physical symptoms (headaches, sleep disturbances, and gastrointestinal problems) and hypothesized a positive direct relationship with SmUD severity (**H6**), which was supported. This finding further underlines the assumption that SmUD may not only have a negative impact on psychosocial health, but could also lead to physical health impairments.

Based on studies that showed that loneliness, mental problems and physical symptoms often co-occur and can mutually affect each other [e.g., (56–64)], we hypothesized that stress (**H7**), depression and anxiety (**H8**), and loneliness (**H9**) were positively related to physical symptoms. Supporting hypotheses **H7** and **H8**, we found that stress and depression and anxiety positively predicted physical symptoms. These findings can be explained by previous works that argued that conditions such as depression, anxiety, and stress make sleep lighter and more discontinuous [e.g., (58, 61)]. Furthermore, psychological distress can increase the level of muscle tension, which in turn can affect physical symptoms, such as headaches (50). Also, gastrointestinal problems like nausea and diarrhea have previously been reported to be positively related to mental problems, such as stress, depression, and anxiety [e.g., (57, 62)]. However, hypothesis **H9** had to be rejected since loneliness showed no significant relationship with physical symptoms. This may (in parts) be explained by the results of a recent meta-analysis, showing that accounting for depression in multivariate analyses weakens the relationship between loneliness and sleep problems (63).

Further, we assumed that SmUD tendencies, physical symptoms, and psychosocial problems are not only directly related, but are also more complexly interwoven with each other. Research by Demirci et al. (39) and Liu et al. (65) indicated that SmUD can cause mental problems, which in turn can lead to sleep disturbances. Accordingly, we hypothesized that mental problems and loneliness mediate the relationship between SmUD tendencies and physical symptoms (**H10**-**H12**), which was confirmed for stress and depression/anxiety (but not for loneliness).

Taken together, the significant indirect associations we identified emphasize the necessity to not only consider direct relationships, but to also examine more complex models to further improve the understanding of SmUD and its potential outcomes. Notably, relationships between mental problems (e.g., depression and anxiety) and specific physical health impairments (e.g., migraine and sleep disturbances) were shown to be bidirectional [e.g., (52, 59, 94, 95)]. Thus, it may also be possible that physical symptoms resulting from SmUD contribute to the development or maintenance of negative mental states. An interesting task for future research could be to examine the interplay of SmUD, loneliness, mental problems, and physical symptoms based on a longitudinal study with several measurement points, allowing to also identify possible circular relationships.

Limitations

Our study is subject to some limitations. First, our results are based on cross-sectional data. The structural model was created against the background of existing studies and theoretical considerations. However, longitudinal studies are necessary to confirm our findings. Second, self-reported survey data (as used in the current study) always carries a certain risk of misjudgment of the own situation and behavior, and may be subject to social desirability. In general, we would like to emphasize the need to further improve the quality and validity of SmUD screening tools [also see (28)]. We think that Hussain et al.'s (16) approach to adapt an established scale that is based on the APA's IGD criteria is useful to improve the comparability between studies. However, it should be kept in mind that the IGD criteria were originally not designed to measure SmUD and that further evidence is needed to confirm their accuracy in measuring SmUD.

CONCLUSION

Our results confirm that increased SmUD severity is associated with several mental and physical health impairments. Further, the significant indirect paths we identified indicate that mental problems could play a crucial role in explaining the relationship between SmUD severity and physical symptoms (like sleep disturbances, gastrointestinal problems, and h eadaches). Against the background of the existing literature, we assume complex (and presumably circular) relationships between SmUD, mental health, and physical symptoms that should be further examined in future research. Unifying SmUD measurement criteria, improving the quality of screening tools, and conducting clinical studies, as well as more representative and longitudinal studies in different countries, are further important research tasks. From a practical perspective, our results underline the importance to follow a broad approach in prevention and intervention campaigns. To break the vicious cycle, such programs should not only focus on strategies to reduce screen time, but should also consider mental problems and physical symptoms that may have led to or may have resulted from SmUD.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because they are part of a larger representative survey study that covers several different topics and is subject to further analysis in other contexts. However, the raw data supporting the conclusions of this article are available to qualified researchers, upon reasonable request. Requests to access the datasets should be directed to FR, felix.reer@uni-muenster.de.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. 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

FR and TQ conceptualized the study. FR administrated the project, conducted the statistical analyses, and wrote the manuscript. L-OW and RJ contributed to the statistical analyses and the writing of the manuscript. TQ obtained the funding, provided feedback on the manuscript, and supervised the project. All authors contributed to the article and approved the submitted version.

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The Effect of Lockdown Due to the COVID-19 Pandemic on Digital Eye Strain Symptoms Among the General Population: A Cross-Sectional Survey

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Repetitive prolonged use of digital devices without regular breaks has detrimental effects on ocular health and quality of vision. Individuals with chronic eye problems and refractive errors are at higher risk of developing digital eye strain (DES). Correction of refractive errors, adopting healthy practices will reduce its risk. The survey examined the effect of prolonged lockdown on the development and increased severity of digital eye strain (DES) symptoms among the general population. An online survey was conducted in March 2020 on social media platforms in Jordan. Data from 1,460 responders were analyzed. About half of the respondents were between 30–49 years, 28.4% were retired, 21% had chronic systemic illness, and 23% reported chronic eye problems. A rise in the use of digital devices during lockdown was reported by 957 participants, with 33% of them used digital devices more than 4 h a day. The most common symptoms before and during lockdown were headache and neck / shoulder pain have the highest associations (X^2 = 280.0, 271.3, df = 4, $p < 0.001$ respectively). Female gender, existence of chronic eye problems and systemic diseases, and duration of using digital devices were found to be statistically significant factors associated with increasing severity of eye symptoms during lockdown. Not taking enough regular breaks from digital devices showed significant association with blurred vision at distance and near (X^2 = 13.03, 10.74, $df = 4$, P = 0.011, 0.03, respectively). People with chronic eye problems and increased time using devices during lockdown developed new eye complaints three times more than before the lockdown and males were two times more likely than females to have more severe eye symptoms.

Keywords: symptoms, digital eye strain, general population, COVID-19, neck pain

INTRODUCTION

Digital eye strain (DES), frequently referred to as computer vision syndrome (CVS) or visual tiredness, is a cluster of ocular, vision-related, and musculoskeletal symptoms caused by prolonged use of digital devices (also known as video display terminals [VDTs]). A "digital device" is any electronic hardware that is used on a daily basis and may include a variety of devices such as cell phones, smart wristwatches, desktop computers, tablets, virtual reality viewers, 3D displays, and e-readers. The most common symptoms of DES are eye pain, dry eyes, headaches, blurred vision, and neck and shoulder pain (1, 2). Due to the global shift in the usage of digital devices over the last few decades, DES has emerged into a very real and identifiable problem affecting millions of individuals and exposing individuals of all ages at risk (1, 2).

The repeated use of digital devices for more than two continuous hours is putting the user at a great risk of developing DES due to the excessive accommodative demands (1, 3). Refractive errors that are uncorrected, under-corrected, or over corrected can exaggerate the symptoms (4). Unlike printed pages, letters on digital displays are not sharply outlined, with weaker letters' contrast to the background, as well as the effect of glare and reflection, rendering viewing more difficult (5). Furthermore, given the various distances and angles of viewing, the eye movement and focusing demands are substantially higher than those needed when writing on or reading from paper. Muscle spasms and pain can occur as a result of poor posture when using digital screens, especially in the neck, shoulders, and back. This is particularly evident in people with refractive errors and substandard viewing glasses or contact lenses, which cause them to tilt their heads or lean on the screen in awkward ways in order to see more clearly (5). The majority of people develop DES when the visual demands of performing tasks overcome their visual capability to do so comfortably (6).

The DES conveys external symptoms similar to dry eye disease (DED), including ocular pain, foreign body sensation, tearing, burning, and heaviness of eyelids. Among other symptoms, extended use of digital devices exacerbates these symptoms. It is critical to distinguish DES from DED, despite the fact that they share similar symptoms and strongly associated (7). The DES presents symptoms that are both internal (e.g., blurred vision, headache, diplopia) and external in nature (e.g., neck and shoulder pain, foreign body sensation, burning sensation, photophobia) and are directly related to the excessive and repetitive use of VDTs (8). Adults are more prone to develop DED, which is caused by a variety of factors, as demonstrated by tear film instability induced by ocular conditions (9, 10).

Digital eye strain management is not simple. It requires the treatment of prior eye problems such as ocular surface disease and the optimal treatment of current eye symptoms by taking frequent breaks and adjusting the way video digital screens are presented by following healthy positions of posture (11–14). In addition, the correction of refractive errors, especially spherical hyperopia and astigmatism, is associated with better outcomes (4).

The spread of COVID-19 was rather troubling to health authorities and the public at large in early February 2020. Several countries agreed to suspend foreign and domestic travel and enforce curfews on their citizens for several weeks to slow the spread of the pandemic. As a result of this situation, people were forced to rely on the internet and digital devices as their primary means of communication. The authors found that prolonged use of digital devices, particularly by students and academics, appeared to be associated with an increase in eye symptoms, which inspired the concept for this survey. As a result, this survey aims to examine how lockdown has affected DES symptoms in the general population. An association was expected between occupation, age, gender, and the prevalence of chronic systemic and ocular disease, which would affect the emergence of new symptoms and increase the severity of DES symptoms (1, 3). We believe that the novelty of our study was in its objectives as it assessed the emergence of new symptoms due to the restrictive measures imposed on the general population.

Abbreviations: DES, digital eye strain; VDT, video display terminal.

METHODS

Between March 26 and April 29, 2020, an online, anonymous, cross-sectional, observational study was conducted. It consists of a self-administered web-based questionnaire conducted using social media platforms. Inclusion criteria were residency in Jordan, being 18 years of age or older, and a consent to participate. As a consequence, questions on age and desire to participate were included to the questionnaire at the beginning. The data collection started 7 days after the Jordanian lockdown began (March 19, 2020) and ended a few days before the lockdown ended to guarantee that digital eye strain symptoms are distinct from other stress-related symptoms such as headaches.

Ethical Considerations

Ethical approval was obtained from the Institutional Review Board of the Al-Balqa Applied University (BAU) abiding by the tenets of the declaration of Helsinki 1975 and its amendments in 2008 and later. The purpose of the study was clearly explained in the opening page of the survey and voluntary participation was encouraged. No personal information was obtained, and the confidentiality of the data was assured.

At the first part of the online survey, all participants were required to sign an electronic informed consent form that included extensive information on the study goals, objectives, methods, supervisor contact information, and IRB approval. Additionally, participants were instructed that participation was voluntary and that they might stop the survey at any stage. The data were kept confidential because all identifiable information was stripped and no identifier-related questions such as participant name, city of residence, or zip code were requested. Additionally, a study-specific unique identifier was generated for each participant, and this file was locked and password-protected with controlled access and authorizations for viewing, sharing, and using it reserved to the research team. All further analyses were conducted on this anonamyzed file. Participants did not receive any compensation or rewards for their participation in the study.

Jordan Population and Online Sampling Process

Non-probability sampling methods were used for the online survey, such as convenience sampling, volunteer opt-in panels, and snowball sampling. In general, a sample size of around 10% of the population, but not exceeding 1,000 participants, was considered appropriate. The total population of Jordan was estimated to be 10.5 million in 2020, with about 1.3 million Syrian refugees residing in the country. The authors computed a sample size using a prevalence of digital eye strain of 50% as the most judicious estimate with a margin of error of 2.5 % [95 percent confidence interval (CI): 47.5–52.5 percent]. Initially, the sample size (*n*) of 1,537 was calculated using the following formula: n = N x/[(N-1) E2+x]. Where N is the population size (10,500,000), E is the margin of error (2.5%), r is the frequency of digital eye strain (50%), and Z is the critical value for the confidence level (5%). After cleaning the dataset from incoherent and incomplete responses, the final sample size used was 1,460 (15).

To achieve a high response rate, demographic segmentation and social networks had been utilized to gather data from the respondents in universities, colleges, and social groups, as well as educators and university professors. To reach the target demographic, the survey link was posted on Facebook and other social media platforms favored by the participants, and they redistributed the survey via email, Messenger, and WhatsApp.

The Survey Instruments

The survey was online self-administered using Microsoft forms. The questionnaire instrument was developed based on literature review and frameworks similar studies (8, 16–19). It was originally written in English and then translated into Arabic, Jordan's official language. Afterwards, it was re-translated into English by two independent translators and compared by a third. Validity was tested in a pilot study with 30 randomly self-selected participants. The pilot study confirmed that the survey results were significant and could be administrated online.

The first introductory section emphasized the study's purpose and objectives, as well as a consent form. It was composed of three parts of closed-ended single- and multiple-choice questions; symptoms were graded using an adjectival scale. Part one of the survey covered screening questions to ensure that the expected target respondents were reached. This includes questions about age, cis-gender, and activity, as well as the existence of chronic systemic diseases such as diabetes mellitus, systemic hypertension, hyperlipidaemia, neurological disorders, and allergies. The second part examined how many hours per day were spent in front of screens, including television, phones, and computers, in the 2 weeks preceding the lockdown's start. The amount of hours spent watching digital gadgets was a multiple-choice question that ranged from 2 h to more than 10 h per day. The second part of the survey included additional exploratory questions about the presence of eye disorders before to the lockdown, including dry eye disease, allergic eye disease, cataract, glaucoma, age-related visual impairments, and retinal disorders. Finally, a three-point scale question was asked about the habit of taking regular breaks while using digital devices.

The final section of the survey investigated the influence of lockdown on the specific symptoms associated with digital eye strain. Following a brief introduction, a yes/no questions were presented to determine whether the subject experienced an emergence and increase in ocular symptoms during the lockdown. If the subject denied any development or increase in the symptoms severity, the survey was terminated. If the respondent indicates yes, he or she will be asked to rate their symptoms on a scale of absent to always present. The following diagram illustrated the survey conditional branching processes and participants numbers in each arm of the study (**Figure 1**).

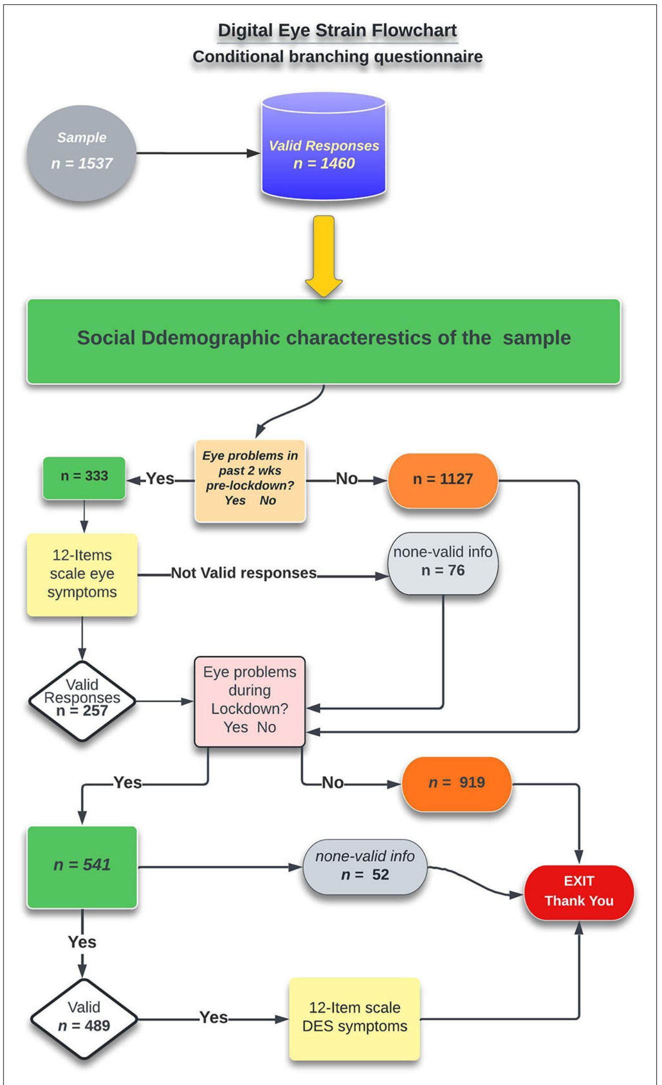

FIGURE 1 | Flowchart depicting the organization of the survey questions and their conditional branching.

A 12-item scale was used twice to assess the DES: the first time to determine the presence of those symptoms at the baseline (i.e., the weeks before the lockdown started) and the second time to determine the severity and the emergence of new symptoms. These included blurred vision at both distant and near distances, a burning sensation, redness, lacrimation, heaviness of the eyelids, eye discomfort (foreign body sensation), double vision, eye pain, headaches, photophobia, and neck / shoulder pain. To enable easier use by the public, the authors used a three-point adjectival scale (not present, occasionally present, and always present) rather than the standard five-point Likert scale. Finally, the authors examined how much time people spend on digital devices in two ways: how much time they spend on digital devices on a daily basis and and the amount of extra time they spend each day.

Data Management and Analysis

The data were collected using Microsoft® Forms and downloaded into Excel® for coding and de-identification before being imported into the Statistical Package for Social Science (IBM SPSS Statistics for Windows, version 25, IBM Corp., Armonk, N.Y., USA) for analysis.

Descriptive Statistics

A descriptive analysis was conducted to identify the statistical validity of all variables, and frequencies and percentages for the sample demographic characteristics and ocular and muscular symptoms were calculated. Cronbach's alpha (α) was used to determine the internal consistency reliability of the adjectival scales items. Several Cronbach's assumptions were examined and found to be consistent for each scale developed, including that the items on the scales were ordinal and the scales were unidimensional. The dependent variables in this study were the emergence of new eye complaints and the exacerbation of existing DES symptoms. A bivariate analysis was performed to evaluate the link between categorical variables (age groups, activity, and duration using digital devices). The logistic top-down step regression method was used to identify the relationship between sociodemographic health parameters and the occurrence of the two dependent variables; Odds Ratios (OR), also termed exp (B) in logistic regression output, 95% confidence intervals (95% CI) were reported where appropriate to indicate risk of developing ocular and/ or muscular symptoms. To investigate the existence of statistical correlations between demographic characteristics and ocular and muscular symptoms, a Chi-square test was used. For categorical variables, the chi-square test was used. Statistical significance was defined as a p-value of < 0.05.

RESULTS

Table 1 summarizes the sample's statistical distribution. The total sample size was 1,460 individuals, with a 5% rejection rate due to incomplete responses. Males comprised 59.5 % of interviewees. The majority the sample was between the ages of 30 and 49. Additionally, we found that the mean male age was 36.5 [±] 1.2 years, while the average female age was 39.4 [±] 1.5 years.

The majority of survey respondents were retired, constituting 28.4 percent of the total sample. According to the same table, 20.9 % of respondents had chronic diseases, while 22.9 % had chronic eye diseases. Prior to the lockdown, respondents reported spending an average of 5 [±] 2.6 h each day using digital devices. However, 957 respondents (65% of the total sample) reported that the lockdown increased their daily time spent on digital devices. The average daily increase in time was estimated to be 4 h (33 %).

Quality and Reliability of the Scale Used

The internal consistency of the adjectival scale for DES symptoms was tested using factor analysis, and the 12 items had a Cronbach's alpha of 0.812. Kaiser-Meyer-Olkin (KMO) sampling adequacy was 0.848 (It is recommended to pass the 0.7 level). Additionally, Bartlett's sphericity test result was 712.5 with a degree of freedom of 66 and < 0.001 indicating significance.

TABLE 1 | Descriptive statistics of the sample.

Variable	In % of total sample (n = 1,460)
Gender	
Male	59.5
Female	40.5
Age groups (years)	
17–5	2.7
18–29	29.2
30–49	47.9
50–99	20.2
Activity	
School student	3
University student	16.6
Technician	7.5
Health worker	13
Clerical service worker	19.7
Teachers	11.9
Retired	28.4
Chronic disease	
Yes	20.9
No	79.1
Chronic eye disease	
Yes	22.9
No	77.1
Baseline time using digital devices (hours/day)	
(1–2)	19.3
(3–5)	42.2
(6–8)	19.9
> 8	18.6
Increased time during lockdown (hours/day)	
= 0	35.5
<1	4.7
(1–2)	21.1
(3–4)	18
>4	21.8

Prevalence and Severity of DES Symptoms

The prevalence and severity of the 12 DES symptoms were evaluated using the survey instrument prior and during lockdown. The most common symptoms before lockdown were neck and shoulder pain, headaches, blurred vision at a distance, burning sensation, blurred vision of near objects, and photophobia. The most common symptoms reported during the lockdown were neck and shoulder pain, headaches, burning sensation, blurred vision at a distance, photophobia, blurred

TABLE 2 | Self-reported symptoms prior and during lockdown (value in % of total sample) with Chi-square test of independence.

Symptoms	Prior lockdown		During lockdown		X^{2a}	P-value
	Mild/Moderate *n* (%)	Severe *n* (%)	Mild/Moderate *n* (%)	Severe *n* (%)		
I. Accommodative symptoms						
Neck pain/Shoulder Pain	135 (9.2)	66 (4.5)	224 (15.3)	166 (11.4)	271.3	<0.001
Blurred vision at a distance	171 (11.7)	20 (1.4)	277 (19.0)	61 (4.2)	144.5	<0.001
Headache	146 (10.0)	44 (3.0)	249 (17.1)	109 (7.5)	280.0	<0.001
Blurred vision of near objects	131 (9.0)	55 (3.8)	193 (13.2)	123 (8.4)	202.4	<0.001
Eye strain	131 (9.0)	25 (1.7)	228 (15.6)	39 (2.7)	178.6	<0.001
Double vision	67 (4.6)	14 (1.0)	110 (7.5)	29 (2.0)	223.6	<0.001
II. Dry eye symptoms						
Burning sensation	163 (11.2)	24 (1.6)	302 (20.7)	55 (3.8)	151.1	<0.001
Photophobia	142 (9.7)	40 (2.7)	230 (15.8)	98 (6.7)	234.9	<0.001
Heaviness of eyelids	137 (9.4)	28 (1.9)	123 (8.4)	69 (4.7)	139.4	<0.001
Lacrimation	134 (9.2)	21 (1.4)	233 (16.0)	48 (3.3)	180.4	<0.001
FB sensation	106 (7.3)	15 (1.0)	181 (12.4)	36 (2.5)	225.8	<0.001
Eye redness	111 (7.6)	4 (0.3)	178 (12.2)	33 (2.3)	191.2	<0.001

[a], *Chi Square.*

vision of near objects, lacrimation, and eye strain as seen in **Table 2**.

The results of the logistic regression to study the factors associated with new eye complaints (model 1) and increased severity of current eye complaints (model 2) are reported in **Table 4**. Both models have a satisfactory goodness-of-fit according to the Chi-square test ($p < 0.0001$) and respectively $R^2 = 9$ and 14%.

The variables of chronic eye problems and increased time using digital devices during lockdown were found to be associated with the emergence of new eye complaints in model 1 in **Table 4**. The variable of chronic eye problems was significantly associated with having new eye complaints ($p < 0.002$). In comparing individuals with chronic eye problems to those who have not had chronic eye problems, the odds ratio shows that having new eye complaints after lockdown increased by around three times. The variable of increased time spent using digital devices during lockdown is significantly associated with the development of new eye complaints ($p < 0.001$). Furthermore, the odds ratio of 3.56 indicates that anyone who spent more time on digital devices had four times the risk of developing a new complaint as the person who did not spend time on them. In model 2, it was found that males developed severe eye symptoms two times more than females ($p < 0.001$). Odds ratios for the variables of chronic eye disease, increased time using digital devices during lockdown, and increased amount of time are higher than the odds ratios before lockdown, similar to model 1.

DISCUSSION

The government of Jordan imposed a strict lockdown and curfew hours for 6 weeks, beginning March 18, 2020 and ending April 29, 2020 to contain the COVID-19 pandemic. This study aimed to see how homebound lockdown affected the development and severity of baseline and new digital eye strain symptoms (DES).

The data revealed that young males responded to the online survey more than females, which was consistent with consumer behavior on social media platforms during the lockdown (20). This could have increased the prevalence of eye symptoms in male subjects, particularly the new onset of DES symptoms.

Females had more severe lockdown symptoms than males in this study, which were statistically significant for most symptoms such as neck/shoulder pain, photophobia, blurred vision at distance, eye redness, heavy eyelids, and difficulty focusing on near objects, as shown in **Table 3**.

Correlation between gender and musculoskeletal symptoms was explored. We found that females had more neck/shoulder pain during lockdown than prior to lockdown (**Table 2**). For instance, in addition to the time spent on social media; women are helping their children in online school learning. An effective policy is needed to rationalize and to impose regular breaks women use of social media and online learning platforms (21).

The majority of the survey respondents declare using digital devices more than an average of 5 h daily. In addition, this finding is consistent with the 65% ($n = 957$) persons that have reported an increase in their use of digital devices from which 21.8% of them reported 4 h or more during the lockdown period as depicted in **Table 1**. As people self-reported their time spent on digital devices, it could be expected that they underestimated their actual time spent on digital devices because they may not have counted internet, TV, mobile phones, or tablets. Recent studies have found a global trend toward spending more time with digital devices, particularly among younger generations (16, 17, 22). In 2016, Common Sense Media (CSM) reported that American parents of teenagers spend about 9 h per day

TABLE 3 | Sample characteristic factors associations with emergence of new DES symptoms and increased severity of existed symptoms.

Factor analyzed	Association of emergence of new eye symptom				Association of increased eye symptom severity			
	No *n* (%)	Yes *n* (%)	X^2	P-value	No *n* (%)	Yes *n* (%)	X^2	P-value
Gender								
Female	186 (12.7)	405 (27.7)	10.269	< 0.001*	102 (7.0)	190 (13.0)	5.374	0.02*
Male	341 (23.4)	528 (36.2)			151 (10.3)	84 (5.8)		
Age (in years)								
< 18	7 (0.5)	32 (2.2)	3.059	0.383	4 (0.3)	3 (0.2)	1.460	0.692
18–29	170 (12.0)	257 (17.6)			85 (5.8)	85 (5.8)		
30–49	247 (16.9)	452 (31.0)			112 (7.7)	135 (9.2)		
50 +	103 (7.1)	192 (13.2)			52 (3.6)	51 (3.5)		
Activity								
School student	9 (0.6)	35 (2.4)	16.908	0.01*	6 (4.1)	3 (0.2)	5.098	0.531
Univ. student	105 (7.2)	137 (9.4)			54 (3.7)	51 (3.5)		
Technician	46 (3.1)	63 (4.3)			25 (1.7)	21 (1.4)		
Health worker	60 (4.1)	130 (8.9)			26 (1.8)	34 (2.3)		
Clerical worker	83 (5.7)	204 (14.0)			43 (2.9)	40 (2.7)		
Teachers	63 (4.3)	63 (4.3)			26 (1.8)	37 (2.5)		
Retired	161 (11.0)	161 (11.0)			73 (5.0)	88 (6.0)		
Chronic systemic disease								
Yes	117 (8.0)	410 (28.1)	0.451	0.502	50 (3.4)	207 (14.1)	1.675	0.196
No	188 (12.9)	339 (23.2)			203 (13.9)	67 (4.6)		
Chronic eye disease								
Yes	182 (12.5)	158 (10.8)	18.42	< 0.001*	57 (4.0)	100 (6.8)	11.481	0.001*
No	741 (50.8)	376 (25.8)			196 (13.4)	174 (11.9)		
Time using digital devices before lockdown in hours/day								
1–2	190 (13.9)	95 (6.5)	4.824	0.185	47 (3.2)	47 (3.2)	5.354	0.148
3–5	399 (27.3)	218 (14.9)			93 (6.4)	123 (8.4)		
6–8	174 (11.9)	110 (7.5)			51 (3.5)	54 (3.7)		
>8	161 (11.0)	113 (7.7)						
Taking regularbreaks								
No	22 (1.5)	24 (1.6)	2.965	0.227	9 (0.6)	15 (1.0)	0.025	0.988
Sometimes	95 (6.5)	91 (6.2)			33 (2.3)	58 (4.0)		
Always	61 (4.2)	40 (2.7)			15 (1.0)	25 (1.7)		
Time increase using digital devices								
Yes	710 (48.6)	247 (16.9)	21.555	< 0.001*	253 (17.3)	27 (1.8)	429.26	0.001*
No	280 (19.2)	223 (15.3)			0.0 (0.0)	247 (16.9)		
Time using digital devices during lockdown (hours/day)								
= 0	503 (34.5)				503 (34.5)			
< 1	58 (4.0)	10 (0.7)	31.091	< 0.001*	58 (4.0)	10 (0.7)	30.833	0.001*
1–2	254 (17.4)	53 (3.6)			254 (17.4)	53 (3.6)		
3–4	191 (13.0)	72 (5.0)			191 (13.1)	72 (4.9)		
> 4	207 (14.2)	112 (7.7)			207 (14.2)	112 (7.7)		

**Indicates statistically significant values.*

on the internet (23). Similarly, a survey conducted by CMS in 2019 revealed that teenagers spend more than 7 h per day on media (24). According to Reddy et al. (18), using digital devices for more than 2 h per day has a significant impact on DES symptoms (18). Blatter et al. (19) also observed that increased computer use, with or without mouse use, was correlated with musculoskeletal pain and dysfunction. Moreover, they found positive associations with work-related upper limb disorders for both genders with computer use of more than 6 and 4 h per day, respectively (19).

In the current study, people who do not taking regular breaks were found to have strong association with blurred vision at a distance and difficulty focusing on near objects. However, this is not so for neck pain or dry eye symptoms, respectively. Logaraj

TABLE 4 | Factors associated with emergence of New Eye complaints and increased severity of current eye complaints by logistic regression.

Factor analyzed	Model 1: New complaint development		Model 2: Increased severity	
	OR (95% CI)	***p*–value**	**OR (95% CI)**	***p*–value**
Gender				
Female	1		1	
Male	1.30 (0.99–1.69)	0.051	1.78 (1.28–2.50)	0.001*
Age (in years)				
< 18	1		1	
18–29	3.23 (0.48–21.60)	0.226	0.54 (0.03–9.43)	0.676
30–49	3.33 (0.49–22.70)	0.219	0.58 (0.33–10.08)	0.706
50 +	2.99 (0.22–0.67)	0.269	0.43 (0.02–7.58)	0.561
Activity				
School student	1		1	
University student	1.47 (0.25–8.06)	0.695	4.73 (0.28–79.88)	0.281
Technician	1.42 (0.24–8.45)	0.579	5.60 (0.31–97.52)	0.238
Health worker	0.93 (0.16–5.34)	0.929	4.16 (0.24–70.70)	0.324
Clerical service worker	0.74 (0.13–4–27)	0.737	3.88 (0.23–65.91)	0.349
Teachers	1.06 (0.18–6.15)	0.951	4.52 (0.26–77.21)	0.297
Retired	0.96 (0.17–5.48)	0.962	6.09 (0.37–101.5)	0.369
Chronic systemic disease				
Yes	1.18 (0.87–1.59)	0.293	1.27 (0.88–1.85)	0.204
No	1		1	
Chronic eye disease				
Yes	2.64 (1.42–4.88)	0.002	2.63 (1.34–5.19)	0.005*
No	1		1	
Time using digital devices before lockdown in hours/day				
1–2	1		1	
3–5	0.71 (0.51–1.0)	0.054	1.29 (0.74–2.25)	0.364
6–8	0.78 (0.58–1.0)	0.092	1.71 (1.07–2.72)	0.023*
>8	0.90 (0.64–1.26)	0.545	1.37 (0.80–2.34)	0.253
Taking regular breaks				
No	1		1	
Sometimes	0.74 (0.38–1.45)	0.385	0.98 (0.47–2.05)	0.955
Always	0.49 (0.23–1.02)	0.058	0.79 (0.35–1.81)	0.582
Time increase using digital devices				
Yes	3.56 (1.87–5.24)	0.019	5.16 (3.73–7.92)	0.000*
No	1		1	
Time using digital devices during lockdown (hours/day)				
= 0				
< 1	1		1	
1–2	0.20 (0.14–0.29)	0.001*	3.43 (2.18–5.41)	0.001*
3–4	0.35 (0.25–0.48)	0.001*	6.23 (4.03–9.83)	0.001*
> 4	0.46 (0.34–0.62)	0.001*	9.06 (5.92–13.87)	0.001*

Indicates statistically significant values.

et al. (25) showed that students who took regular breaks were less likely to show symptoms of DES (25). Indeed, Lemma et al. (26) studied the effect of taking regular breaks on the development of DES when compared to those who did not take frequent breaks. It was found that secretaries who took regular breaks were 72.1 % less likely to experience digital eye strain (26).

Jordanian schools and universities rushed to adopt online education during the lockdown, resulting in a significant shift in the digital device usage habits of educators and students alike. Due to the compulsory online studies and high demand for internet, teachers, researchers and workers were among the most affected by new DES complaints during the lockdown (**Table 3**). This is in line with the findings of several studies conducted in Middle Eastern and Asian countries (17, 18, 22). Contrary to the hypothesis, technicians developed new symptoms of DES more than other activities (OR 1.42, 95 % C.I). The reason for this is that manual workers used digital devices for communication and online services more than they did previously. Interestingly, the lockdown resulted in an increase in the severity of symptoms reported by all respondents in the activity groups, with retired people having the highest odds ratio (OR 6.09, 95 % C.I.) followed by university students (OR 5.6, 95 % C.I.), which highlights the importance of public awareness and early management of DES in improving the education process and helping retired people improve their vision quality as seen in **Table 4**. Furthermore, retired people are at greater risk for DES because they are more likely to have chronic systemic and ocular diseases that were worsened by having to use digital devices for increased hours than they were when they first started (21).

This research showed that individuals with chronic eye problems are at a higher risk of developing new DES complaints and increasing the severity of their symptoms, even if they spend less time using digital. The results of Ranasinghe et al. (21) indicated that chronic eye diseases were the greatest risk factor for DES development among Sri Lankan computer workers (21). As well, both new and severe eye symptoms were associated with the presence of chronic systemic diseases such as hypertension, diabetes mellitus, dyslipidaemia, neurological disorders, and allergy, as shown in **Table 3**. The ocular symptoms of DES syndrome are classified into two groups, with the first being comprised of symptoms that are related to accommodation and that include blurred vision of near objects, blurry vision at a distance after using the computer, focusing difficulties between different distances, double vision, headaches, and neck and shoulder pain. The second is associated with dry eye and that included burning sensation, irritation, discomfort, sensitivity to bright light, eyestrain, and headaches (1). Eyestrain and headaches are linked to binocular visual stress and accommodation, in addition to their connection to dryness as in **Table 2** (16, 27).

The most common symptom was neck and/or upper shoulder pain, followed by symptoms of accommodative dysfunction and to a lesser extent dry eyes. Prior to the lockdown, approximately 201 participants reported neck and/or shoulder pain; however, during the lockdown, this number nearly doubled to 390. This is in line with similar studies that found neck pain to be a common symptom among computer users, ranging from 19% to 70% (11–13, 28, 29). Touch screen devices, according to Kargar et al., necessitate more hand and head movements, resulting in arm/neck pain (30). Another study found that 68% of participants experienced musculoskeletal pain as a result of using touch screens, with neck pain and upper shoulder pain reported at 84.6% and 65.4 %, respectively, due to unnatural sitting positions without adequate back support (31). Logaraj et al., who found that 60.7 % of medical students reported neck pain as the most common symptom of DES, reported similar findings (25). Workers who used computers for more than 6 h per day were more likely to report upper limb disorders, according to Blatter and Bongers (19). As an unexpected mechanism to explain musculoskeletal pain is the oculomotor accommodative, and vergences dysfunction due to DES; electromyography has shown that ciliary muscle contraction is associated with head and neck muscle activation. The stabilization of gaze by head and neck muscles during accommodation was studied by Richter et al. (32). They noticed increased trapezius muscle activity in a dose-dependent manner when subjects were given different lenses in front of their eyes to stimulate the ciliary body. More head and neck muscle activity was observed, as accommodation was activated (32). Research studies provide similar findings, but the symptoms occur in a different order that is reflective of sampling and geographical variations (17, 18, 33, 34).

As expected, blurred vision, both near and far, was the second most common symptom reported at baseline and during the lockdown (6, 25, 35, 36). Rosenfield et al. attributed it to an incorrect accommodative response, as well as a failure to relax the ciliary body after the visual demand was completed (3). The use of smart phones and handheld devices, according to Jaiswal et al. (36), cause symptoms that are similar to DES because they stimulate the accommodative facility, resulting in decreased amplitude when the eye is fatigued. Despite the fact that no definitive evidence has been found linking smartphones to accommodative facility dysfunction, additional research is required to uncover the actual impact of digital devices on long-term users (36).

Dry eye symptoms might not be a legitimate component of DES, as dry eye disease may aggravate accommodative symptoms, especially in elderly men and women, as well as those who have ocular surface disease. However, DES affects people under the age of 18 who use digital devices; this necessitates the need to develop a more specific and precise definition of DES (37). Many patients who use dry eye treatments and increase their rate of blinking did not notice an improvement in their digital eye strain symptoms. Rosenfield and Jaiswal examined various factors that affect dry eye disease and its relation to DES in their reviews (3, 36). They identified that various environmental factors, such as humidity, ambient lighting, fans, blinking rate, corneal exposure to air, gender, age, medications, systemic diseases, contact lenses, tear film volume, osmolality, and tear film composition, all affect the development of dry eye disease. Nonetheless, DES is still affecting normal people who are not at risk for dry eye disease (16, 22, 38, 39).

Limitations of the Study

The following limitations have been identified: To begin, the survey is based on a participant's self-report that has not been independently validated by clinical diagnostic testing. We avoided under- or over-estimating eye problems in our study by using an appropriate sample size and multivariate statistics. Second, the study did not include self-medication, medical, or environmental variables that may increase dry eye disease during lockdown. Third, an online survey has numerous limitations, including biased selection and the difficulty of measuring population changes over a single time period. However, the findings of this study established the lockdown effect on digital eye strain, particularly in Jordan.

CONCLUSIONS

The results of this online survey reveal the negative effect of COVID-19 on home confinement with eye problems due to the significant increase in usage time of digital devices, which is also indicative of a more sedentary lifestyle. The results concur with recent studies demonstrating that lockdown could dramatically increase digital eye strain that became a growing public health issue that affects people of all ages and occupational groups, posing a threat to their health and quality of life.

Indeed, individuals who spent more time on digital devices developed a new eye complaint four times more often than who did not. Females are at higher risk of having severe symptoms. As the first in Jordan, this study could explore the impact of lockdown on developing DES-related eye symptoms. The visual consequences of the COVID-19 outbreak, which placed a curfew on people all over the world, should attract more attention from researchers these days. Neglecting DES could cause the exacerbation of mild symptoms in people who had them before or the emergence of new complaints in people who never had them previously. The government of Jordan would develop public health interventions to mitigate the negative effects of internet use on eye problems that have manifested during the COVID-19 lockdown.

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 IRB Committee at Al-Balqa Applied University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MA, HJ, and HA: conceptualization, data curation, data analysis, writing—original draft preparation, and writing—reviewing and editing. MA and HJ: methodology. MA: supervision. All authors have agreed to the order of authorship and approved the submission of this version and are accountable for the content of this manuscript.

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