A profile analysis of problematic smartphone usage among college students during coronavirus disease 2019: Relations with the impact of news reports

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Abstract

The coronavirus disease 2019 (COVID-19) outbreak was the first pandemic to occur in a fully globalized society. The aims of the study were to explore the state of problematic smartphone use (PSU) and its risk factors during this incident. A total of 77,211 college students were surveyed online during the COVID-19 pandemic. Conducting latent profile analysis (LPA), we found the most support for a three-class model of subgroups: over-use group (17.3% of the sample), moderate-use group (54.8% of the sample), mild-use group (27.9% of the sample). The results of multinomial logistic regression show that college students who experienced an extreme negative impact from news reports were more likely to be included in the over-use group than in the mild-use group. These results providing insights that may help foster and develop appropriate and effective solutions to prevent PSU among college students during crises, such as reducing the coverage of negative news report.

Keywords Problematic smartphone usage · Latent profile analyses (LPA) · COVID-19 · News reports

Introduction

With the development of information technology and the increasing popularity of mobile networks and their applications, mobile phones are playing an increasingly important

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role in people's lives. According to a recent report by Bank-MyCell (2021), the number of smartphone users was approximately 6.37 billion in October 2021, which accounts for approximately 80.76% of the global population. China has the most active of smartphone users, and the penetration rate of smartphones has reached 63.8% in China (Newzoo, 2020). Although owners can use their smartphones to gather the latest news and stay well informed, there are potential health problems and risks caused by overuse of and problematic use of smartphones.

Screening studies estimate that problematic use of smartphones is a worldwide phenomenon and affects 9.3% to 48% of the population (Aljomaa et al., 2016; Yahyazadeh et al., 2017). College students are more vulnerable to problematic use of smartphones (Long et al., 2016). Notably, the focus of "problematic smartphone use" is "problematic use" rather than "smartphone". No scientific evidence showed that smartphone and other digital technology have harmful effects on the brain, emotions, and behavior (Bell et al., 2015). On the contrary, adolescents' use of social media had been found to enhance existing friendships and video game play was positively correlated with well-being (Johannes et al., 2021). But problematic use such as spending too much time might be accompanied by a diminished sense of

volitional control and induce persistent smartphone activity (Orben & Przybylski, 2020; Wang et al., 2015).

At this time, no mention has been made of smartphone addiction in either the Diagnostic and Statistical Manual of Mental Disorders: Fifth Edition (DSM-5) or in the International Classification of Diseases 11th Revision (ICD-11) draft. There is no consensus regarding the appropriate terms for describing the behavioural problems associated with problematic use of smartphones (i.e., addiction, disorder, or problematic use). The current study uses the term "problematic smartphone usage (PSU)", which implies that a person uses his or her phone in such a way that it leads to problematic outcomes but without making a clinical judgement as to whether this person has an addiction (Wang et al., 2015), to avoid potential controversies regarding the classification of behavioural addictions (Peters & Malesky, 2008) and to avoid overpathologizing behaviours that may be aspects of new normal.

Due to individual differences, PSUs, like other mental health problems, may have various manifestations. Uses and gratifications theory (UGT; Blumler, 1979) and compensatory internet use theory (CIUT; Kardefelt-Winther, 2014) assume that individual differences can drive technology use (including excessive use). However, little is known about the heterogeneity of PSU. Exploring its latent classes and its relations with other mental health diseases and risk factors is helpful for us to better understand this controversial mental health problem. Latent profile analyses (LPAs) are a type of mixture model for empirically uncovering heterogeneity among a sample of participants based on a set of cross-sectional continuous observed variables (McLachlan & Peel, 2000). Some studies have used mixture modelling (latent class analyses for categorical variables specifically) to explore smartphone usage patterns and further explore their relationship with PSU. Recently, only two papers have used mixture modelling (LPA, specifically) to directly explore the heterogeneity of PSU (Elhai et al., 2019; Méndez et al., 2020). Elhai and colleagues (2019) studied 302 U.S. university students and found three latent classes of PSU. Méndez et al. (2020) studied 1021 Murcia adolescents and similarly found three different types of PSU. However, these studies were conducted in America and Europe and used a relatively small sample.

Several studies have tried to identify predictive factors for PSU over the past decade. Background characteristics such as female gender and psychological constructs such as depression, anxiety, and negative affect have been supported in studies explaining increased PSU (Li et al., 2020; van Deursen et al., 2015). The COVID-19 outbreak was the first pandemic to occur in a fully globalized society (Ohme et al., 2020). Digital media devices such as smartphones might help people cope with the COVID-19 crisis, which would cause more serious problematic smartphone uses than

in regular times. Researchers have warned that a surge in smartphone use may lead to an increase in PSU during the COVID-19 pandemic (Elhai et al., 2020a, 2020b).

Smartphones are mainly used to obtain immediate access to information during COVID-19, especially around key events (Ohme et al., 2020). However, a crisis such as the COVID-19 outbreak can disrupt information routines. On the one hand, being informed may reduce fears and may make it easier for people to foresee developments and to react accordingly (Boyle et al., 2004). On the other hand, new sensational news reports may stimulate the subconscious perception of threat and induce fear, and fear has been shown to be associated with a considerable risk of the new-onset and recurrence of mental health disorders (Chen et al., 2021). Therefore, news reporting may be a "double-edged sword" that may have positive or/and negative emotional effects on people.

In summary, we conducted a nationwide survey to determine the classes and risk factors for PSU among college students during the COVID-19 pandemic and especially to explore the relationship between the impact of news reports and PSU. The reason for studying college students is that they are "digital natives" who grew up using smartphones and almost all college students in China have smartphones.

Meterial and Methods

Participants

A total of 100,310 people participated in the survey, of which 22,347 participants failed to complete smartphone addiction scale, and 752 participants had answers with a horizontal trend (filling in the same numbers) or a spiral trend (filling in the numbers in a regular and repeated manner, such as 1, 2, 3, and 4 in a continuous cycle). The final number of participants was 77,211. The demographic information is shown in Table 2. The mean age of the participants was 20.09 years ($SD = 1.37$), with a range from 16 to 27. A total of 31,826 (41.2%) participants were male.

Measures

Demographics

We asked about demographic characteristics such as sex, age, school and region.

Impact of news reports

Two items were used to assess the positive impact of news reports (e.g., To what extent have you been positively affected by news coverage of COVID-19?) and the negative

impact of news reports (e.g., To what extent have you been negatively affected by news coverage of COVID-19?) ranging from 1 (almost none) to 3 (extreme).

Smartphone Addiction Scale for College Students (SAS-C)

PSU was assessed with the Smartphone Addiction Scale for College Students (SAS-C), which was compiled by Shuang (2014). The SAS-C is composed of six factors: withdrawal behaviour, salience behaviour, social comfort, negative effects, use of applications (apps), and app renewal. A total of 22 items rated on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree) were used to assess smartphone use, with high scores representing high levels of addiction. In the current study, Cronbach's alpha for the scale was 0.920.

Center for Epidemiological Studies Depression Scale (CES-D-10)

Depression was assessed with the Center for Epidemiological Studies Depression Scale (CES-D-10), which was compiled by Andresen and colleagues (1994), translated into Chinese and revised by Yu et al. (2013). A total of 10 items rated on a 4-point scale ranging from 0 [rarely or none of the time (less than 1 day)] to 3 [most or all of the time (5–7 days)] were used to assess the frequency of symptoms in the past 2 weeks. The CES-D-10 includes 2 items on positive affect, with these 2 items being reverse scored. A cut-off score of 10 or higher indicates probable depressive symptoms (Andresen et al., 1994). In the current study, Cronbach's alpha for the scale was 0.752.

Generalized Anxiety Disorder Scale (GAD-7)

Anxiety was assessed with the Chinese version of the Generalized Anxiety Disorder Scale (GAD-7; He et al., 2010). A total of 7 items rated on a 4-point scale ranging from 0 (never) to 3 (almost every day) were used to assess the frequency of symptoms in the past 2 weeks. According to the established criteria, scores above 10 indicate probable anxiety symptoms (Lowe et al., 2008). In the current study, Cronbach's alpha for the scale was 0.920.

Procedure

The survey lasted from April 13 to 23, 2020, when the epidemic began to gradually improve in China and colleges and universities began to reopen. The survey was conducted in collaboration with the Chinese Psychological Association. The Chinese Psychological Association is an academic society affiliated with the Institute of Psychology, Chinese Academy of Sciences. Under the Psychological Crisis Intervention Committee of the Chinese Psychological Association, there is a National University Psychology Committee Collaborative Group, including 177 colleges and universities in China. Each class in each university was set up 1–2 psychological monitors responsible for contacting the whole class and concentrating the mental health states of students. Every university has aggregate hundreds or even thousands psychological monitors, who are led and trained by the National University Psychology Committee Collaborative Group. This questionnaire survey was sent by the National University Psychology Committee Collaborative Group to the psychological monitors, and then introduced to the students by the psychological monitors. College students were provided informed consent to participate in the survey after the beginning of school, and participation was voluntarily. College students who volunteered to participate in the survey could click a link to enter the online questionnaire system. The participants were notified that online and in-person psychological counselling services were available if needed after the survey.

Statistical analysis, and Ethics

Data were analysed with SPSS 26.0 and *R* 4.0.4 for Mac. First, the R package tidyLPA (Rosenberg et al., 2018) was used to determine the optimal number of latent profiles to fit the data. One to 6 class solutions of LPA models were evaluated and compared based on fit indices, parsimony, and interpretability. We assessed comparative model fit using the following indices: Akaike's information criterion (AIC), Bayesian information criterion (BIC), and sample-size-adjusted Bayesian information criterion (SABIC), with lower values indicating better model fit; (2) entropy, with values between 0 and 1 and higher values indicating higher classification accuracy; and (3) significant bootstrap likelihood ratio test (BLRT), indicating that the k-profiles model was a significantly better fit to the data than the k-1 profiles model. In addition, we also considered the interpretability of the profiles and whether each profile consisted of at least 5% of the sample (Nylund et al., 2007).

Second, the chi-square test and one-way ANOVA were used to examine differences in each variable in each profile. Third, multinomial logistic regression analyses were used to identify the risk factors for profile membership.

The study design and procedures were approved by the ethics review committee of the Institute of Psychology, Chinese Academy of Science (Protocol name: Evaluation and intervention of mental health of people affected by COVID-19). All subjects were informed about the study and all provided informed consent.

Results

Descriptive statistics

Depression total scores averaged 7.56 ($SD = 5.27$). Anxiety total scores averaged 2.50 ($SD = 3.56$). PSU summed scores averaged 57.23 ($SD = 14.18$). Using a cut-off score of 10, 24,736 (32.0% of the sample) college students had probable depression, and 3674 (4.8% of the sample) college students had probable anxiety.

Latent profile analyses results

The fit indices for 1 to 6 class solutions for problematic smartphones are shown in Table 1. The model showed that the BLRT was significant for the 1 to 6 class solutions. The AIC, BIC and SABIC values decreased rapidly in 1- to 3-class solutions and slowly in 4- to 6-class solutions. All entropy values were close to 0.9, and the difference was small. The PSU scores of each item for 1 to 6 class solutions are shown in Fig. S1, in which the PSU score is only high or low, regardless of the classification. Considering

all the above conditions, the 3-class model was chosen as the final solution.

As shown in Fig. 1, those in profile 1 (17.3% of the sample) were classified into the over-use group because they had the higher levels than the other two profiles of PSU. Those in profile 2 (54.8% of the sample) were classified into the moderate-use group because they had medium levels of PSU. Those in profile 3 (27.9% of the sample) were classified into the mild-use group because they had the lowest levels of PSU. Furthermore, the mean score of the item *I had to open the same app more than three times on the same day* was higher than that of the other items. The mean score of the item *My smartphone is an important part of my life* was higher than those of the other items for the over-use group; the mean score of the item *I open the apps on my smartphone when I have nothing to say to my friends* was higher than those of the other items for the moderate-use group; the mean score of the item *Classmates and friends often say that I spend too much time on my smartphone* was higher than those of the other items for the mild-use group. However, the mean score of the item *I care about the latest apps and download them to my phone* was lower than those of the other items for the over-use group; the mean scores of

Table 1 Goodness-of-fit statistics for each class solution ($n = 77,211$)

	AIC	BIC	SABIC	Entropy	*p*-BLRT	min-proportions
1 class	4,980,701	4,981,109	4,980,969	1	< 0.01	1
2 classes	4,625,056	4,625,676	4,625,464	0.89	< 0.01	0.47
3 classes	4,514,407	4,515,240	4,514,954	0.88	< 0.01	0.17
4 classes	4,450,781	4,451,826	4,451,467	0.90	< 0.01	0.09
5 classes	4,401,477	4,402,736	4,402,304	0.88	< 0.01	0.08
6 classes	4,372,134	4,373,605	4,337,100	0.87	< 0.01	0.06

Fig. 1 The 3 latent profiles using the PSU item scores. Note. Horizontal ordinate SASC07, 11, 13, 14, 15, 19, 21 are the corresponding items of withdrawal behaviour, SASC01, 02, 04 are the corresponding items of salience behaviour; SASC05, 06, 16 are the corresponding items of social comfort, SASC03, 09, 10, 17 are the corresponding items of negative effects, SASC08, 18, 22 are the corresponding items of use of apps, and SASC12, 20 are the corresponding items of app renewal. See Table S1 for the items of the scale
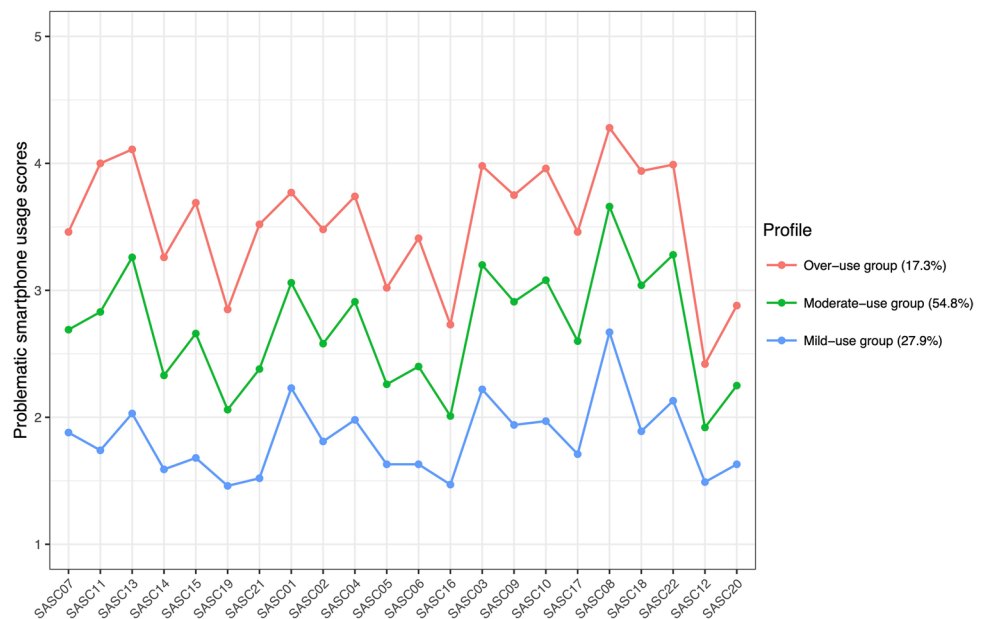
the items *I care about the latest apps and download them to my phone*, *I monitor the online situation of my friends with my smartphones to the extent of insomnia* and *I often have the illusion that my smartphone is ringing or shakes* were lower than those of the other items for the moderate- and mild- use groups.

Using a cut-off score of 10, the prevalences of depression in college students in the mild, moderate and over use groups were 15.3%, 31.3%, and 61.2%, respectively. The prevalence of anxiety in college students in the mild, moderate and over use groups were 1.4%, 3.4%, and 14.3%, respectively.

Predictors of group membership

The chi-square test and one-way ANOVA examining the differences in sex, age, the impact of news reports, depression and anxiety in the three profiles are shown in Table 2. We included the variables that reached significance in the logistic regression analysis.

Multinomial logistic regression analysis was used to determine which predictors were still associated with the profile groups when controlling for the shared variance between the predictor variables. We compared each pair of groups and calculated the odds ratios (ORs) for the strengths of these associations (see Table 3). We focus on the OR larger than 2.0 especially, that is, compare to those in the mild-use group, the college students in the over-use group experience an extreme negative impact from news reports rather than almost no negative impact from news reports (OR = 2.65, 95% CI = 2.43 ~ 2.88). Other ORs are small means slight trends: compared to those in the mild-use group, 1) the college students in the over-use group were more likely to be female (OR = 1.57, 95% CI = 1.50 ~ 1.65), be younger (OR = 0.91, 95% CI = 0.89 ~ 0.92), experience an extreme positive impact from news reports rather than little positive impact from news reports (OR = 1.12, 95% CI = 1.05 ~ 1.20), experience a general positive impact from news reports rather than almost no positive impact of news reports (OR = 1.12, 95% CI = 1.05 ~ 1.20), experience a general negative impact from news reports rather than almost no negative impact of news reports (OR = 1.75, 95% CI = 1.65 ~ 1.85), report higher scores of depression (OR = 1.20, 95% CI = 1.19 ~ 1.21), and report higher scores of anxiety (OR = 1.20, 95% CI = 1.18 ~ 1.21); and 2) college students in the moderate-use group were more likely to be female (OR = 1.42, 95% CI = 1.37 ~ 1.47), be younger (OR = 0.95, 95% CI = 0.94 ~ 0.96), experience an extreme positive impact from news reports rather than almost no positive impact from news reports (OR = 1.09, 95% CI = 1.04 ~ 1.14), experience a general positive impact from news reports rather than almost no positive impact from news reports (OR = 1.18, 95% CI = 1.13 ~ 1.24), experience an extreme negative impact from news reports rather than almost no negative impact from news reports (OR = 1.64, 95% CI = 1.53 ~ 1.76), experience a general negative impact from news reports rather than almost no negative impact of news reports (OR = 1.45, 95% CI = 1.39 ~ 1.51), report higher scores of depression (OR = 1.10, 95% CI = 1.10 ~ 1.11), and report higher scores of anxiety (OR = 1.10, 95% CI = 1.10 ~ 1.12). Compared to those in the moderate-use group, the college students in the over-use group were more likely to be female (OR = 1.11, 95% CI = 1.06 ~ 1.16), be younger (OR = 0.96, 95% CI = 0.94 ~ 0.97), experience an extreme negative impact

Table 2 Variable characteristics and difference test results for each latent group

	n (%)/M (SD)	Mild-use ($n=21{,}503$) n (%)/M (SD)	Moderate-use ($n=42{,}338$) n (%)/M (SD)	Over-use ($n=13{,}370$) n (%)/M (SD)	$\mathcal{X}^2$/ F	*p*-value	d
Sex					555.09	<0.001	0.17
Male	31,826 (41.2)	10,290 (47.9)	16,551 (39.1)	4985 (37.3)			
Female	45,385 (58.8)	11,213 (52.1)	25,787 (60.9)	8385 (62.7)			
Age, years	20.90 (1.37)	20.95 (1.39)	20.88 (1.36)	20.86 (1.36)	22.93	<0.001	0.001
Positive impact of news reports					216.22	<0.001	0.11
Extreme	24,754 (32.1)	7402 (34.4)	13,209 (31.2)	4143 (31.0)			
General	34,384 (44.5)	8762 (40.7)	19,716 (46.6)	5906 (44.2)			
Almost None	18,073 (23.4)	5339 (25.1)	9413 (22.2)	3321 (24.8)			
Negative impact of news reports					3335.00	<0.001	0.42
Extreme	8082 (10.5)	1196 (5.6)	4278 (10.1)	2608 (19.5)			
General	28,193 (36.5)	5909 (27.5)	16,610 (39.2)	5674 (42.4)			
Almost none	40,936 (53.0)	14,398 (66.9)	21,450 (50.7)	5088 (38.0)			
Depression	7.56 (5.27)	5.00 (4.36)	7.59 (4.72)	11.54 (5.71)	7599.05	<0.001	0.16
Anxiety	2.50 (3.56)	1.02 (2.40)	2.41 (3.21)	5.16 (4.57)	6525.39	<0.001	0.15

Table 3 Multinomial logistic regression predicting profile membership

		B	SE	OR	95% CI	*p*-value
Over-use vs. Mild-use [a]	Sex					
	Female	0.45	0.02	1.57	[1.50, 1.65]	<0.001
	Male	0	-	1	-	-
	Age, years	-0.10	0.01	0.91	[0.89, 0.92]	<0.001
	Positive impact of news reports					
	Extreme	0.12	0.03	1.12	[1.05, 1.20]	0.001
	General	0.11	0.03	1.12	[1.05, 1.20]	0.001
	Almost none	0	-	1	-	-
	Negative impact of news reports					
	Extreme	0.97	0.04	2.65	[2.43, 2.88]	<0.001
	General	0.56	0.03	1.75	[1.65, 1.85]	<0.001
	Almost none	0	-	1	-	-
	Depression	0.18	0.004	1.20	[1.19, 1.21]	<0.001
	Anxiety	0.18	0.01	1.20	[1.18, 1.21]	<0.001
Moderate-use vs. Mild-use [a]	Sex					
	Female	0.35	0.02	1.42	[1.37, 1.47]	<0.001
	Male	0	-	1	-	-
	Age, years	-0.05	0.01	0.95	[0.94, 0.96]	<0.001
	Positive impact of news reports					
	Extreme	0.09	0.02	1.09	[1.04, 1.14]	<0.001
	General	0.17	0.02	1.18	[1.13, 1.24]	<0.001
	Almost none	0	-	1	-	-
	Negative impact of news reports					
	Extreme	0.50	0.04	1.64	[1.53, 1.76]	<0.001
	General	0.37	0.02	1.45	[1.39, 1.51]	<0.001
	Almost none	0	-	1	-	-
	Depression	0.10	0.003	1.10	[1.10, 1.11]	<0.001
	Anxiety	0.10	0.01	1.11	[1.10, 1.12]	<0.001
Over-use vs. Moderate-use [a]	Sex					
	Female	0.10	0.02	1.11	[1.06, 1.16]	<0.001
	Male	0	-	1	-	-
	Age, years	-0.05	0.01	0.96	[0.94, 0.97]	<0.001
	Positive impact of news reports					
	Extreme	0.03	0.03	1.03	[0.98, 1.09]	0.278
	General	-0.06	0.03	0.95	[0.90, 1.00]	0.053
	Almost none	0	-	1	-	-
	Negative impact of news reports					
	Extreme	0.48	0.03	1.62	[1.52, 1.72]	<0.001
	General	0.19	0.02	1.21	[1.15, 1.27]	<0.001
	Almost none	0	-	1	-	-
	Depression	0.09	0.003	1.09	[1.09, 1.10]	<0.001
	Anxiety	0.08	0.004	1.08	[1.07, 1.09]	<0.001

B = Beta. SE = Standard Error. OR = Odds Ratio. CI = Confidence Interval

[a] indicates the reference profile

from news reports rather than almost no negative impact from news reports (OR = 1.62, 95% CI = 1.52 ~ 1.72), experience a general negative impact from news reports rather than almost no negative impact of news reports (OR = 1.21, 95% CI = 1.15 ~ 1.27), and report higher scores of depression (OR = 1.09, 95% CI = 1.09 ~ 1.10), and report higher scores of anxiety (OR = 1.08, 95% CI = 1.07 ~ 1.09).

In summary, college students who experienced an extreme negative impact from news reports were more likely to be included in the over-use group. College students who

were female, were younger, experienced a positive or negative impact from news reports, and reported higher depression or anxiety were likely to be included in the moderate-use or over-use group.

Discussion

Our aim was to evaluate the possible latent subgroups of PSU and its risk factors. We were also interested in exploring the relationships between the responses to news reports and PSU latent class membership during the COVID-19 pandemic. We found that three latent classes of individuals emerge based on the PSU item responses, including over-use group (17.3% of the sample), moderate-use group (54.8% of the sample), mild-use group (27.9% of the sample). College students who experienced an extreme negative impact from news reports were more likely to be included in the over-use group. There are also some slight correlations: college students who were female, were younger, experienced a positive or negative response to news reports, and reported higher depression or anxiety scores were likely to be included in the moderate-use or over-use groups.

Three classes of PSU were found among the college students during COVID-19. Our results support those from Elhai et al. (2019) and Méndez et al. (2020), who also found three classes, sampling a tiny fraction of U.S. college students or adolescents. We found that the scoring trend of the three classes of PSUs for each item was consistent; that is, the categories had different item scores but no item preference. This finding is consistent with the research results of Elhai et al. (2019) for college students but inconsistent with the results of Méndez et al. (2020) for adolescents, who found higher levels of conflict related to mobile phone abuse in the PSU group. The possible reason is that PSU among children and adolescents is more complex. Children and adolescents are usually mentally immature and have less self-regulatory ability (Li et al., 2018). Thus, a greater variation in behavioural preference of latent classes may be expected.

News updates are published immediately as a result of accelerated information cycles in journalism enabled by growing digitalization (Stroud et al., 2019). The relationship between the impact of news reports and PSU deserves attention, especially during a major global public health event in which people make seek information to a degree previously unconsidered. The current research found that college students who experienced negative impact from news reports were more likely to be included in the moderate-use or over-use groups than in the mild-use group. Negative effects of news reports play a major role in stronger problematic smartphone use because negative reinforcement may prompt automatic motivation to engage in behaviours (Elhai et al., 2017). The information in today's society is volatile, especially

during a global crisis, thus, negative emotions become increasingly more common during the constant search for news (Chen et al., 2021; Elhai et al., 2020a, 2020b). Another possible reason is that individuals who experience negative emotions alleviate those emotions by playing games, watching videos and chatting on their smartphones, making them more prone to addiction. Unfortunately, we did not measure what they were doing with their smartphones. This needs further research.

College students who were female, were younger, and reported higher depression or anxiety scores were likely to be included in the moderate-use and over-use groups than in the mild-use group. These findings fit with UGT based on individual differences and CIUT based on psychopathology. It is consistent with previous conclusions about the relationships among gender, depression, anxiety and PSU (Li et al., 2020; van Deursen et al., 2015). Since PSU was not included in the DSM-5 or ICD-11, there are no official or uniform diagnostic criteria to date. We can boldly speculate that PSU is associated with transdiagnostic constructs relevant to the development and maintenance of depression and anxiety. Therefore, the causal relationships between anxiety, depression and PSU and the correlation between symptoms need to be further studied.

Several limitations should be considered when interpreting the findings of the present study. First, due to its cross-sectional nature, we interpreted the results at the correlational level. Subsequent studies are encouraged to use longitudinal or experimental designs based on our current findings to track changes over time. Second, we measured PSU with a self-report scale, which may limit the validity of responses, as objective measures of smartphone use are more valid (Rozgonjuk et al., 2018). Finally, we did not collect the type of content and the amount of time the participants consumed on their smartphone, which may correlate to PSU.

Despite these limitations, the current study offers insights into subgroups with symptom presentations based on PSU ratings, as well as further exploration of transdiagnostic psychopathology constructs in connection with PSU. Additionally, the study demonstrates relations between PSU severity and the impact of news reports.

Conclusions

The present study found that three latent classes of individuals emerged based on PSU item responses. College students who experienced an extreme negative impact from news reports were more likely to be included in the over-use group. Also, college student who were female, were younger, experienced a positive impact from news reports, and reported higher depression or anxiety scores were likely to be included in the moderate-use or over-use groups than

in the mild-use group. These findings provide insights that may help foster and develop appropriate and effective solutions to prevent PSU among college students (young adults), such as paying more attention to girls and individuals with high levels of anxiety and depression in crisis events and reducing the coverage of negative news during crises.

Declarations

Conflict of interest There is no conflict of interest.

References

Aljomaa, S. S., Qudah, M. F., Albursan, I. S., Bakhiet, S. F., & Abduljabbar, A. S. (2016). Smartphone addiction among university students in the light of some variables. *Computers in Human Behavior, 61*, 155–164. https://doi.org/10.1016/j.chb.2016.03.041

Andresen, E. M., Malmgren, J. A., Carter, W. B., & Patrick, D. L. (1994). Screening for depression in well older adults: Evaluation of a short form of the CES-D (Center for Epidemiologic Studies Depression Scale). *American Journal of Preventive Medicine, 10*(2), 77–84. https://doi.org/10.1016/S0749-3797(18)30622-6

BankMyCell. (2021). How many smartphones are in the world? Source: https://www.bankmycell.com/blog/how-many-phones-are-in-the-world. Accessed on October 15th, 2021.

Bell, V., Bishop, D. V. M., & Przybylski, A. K. (2015). The debate over digital technology and young people. BMJ, h3064. https://doi.org/10.1136/bmj.h3064.

Blumler, J. G. (1979). The role of theory in uses and gratifications studies. *Communication Research, 6*, 9–36. https://doi.org/10.1177/009365027900600102

Boyle, M. P., Schmierbach, M., Armstrong, C. L., McLeod, D. M., Shah, D. V., & Pan, Z. (2004). Information seeking and emotional reactions to the September 11 terrorist attacks. *Journalism & Mass Communication Quarterly, 81*(1), 155–167. https://doi.org/10.1177/107769900408100111

Chen, Y., Huang, X., Zhang, C., An, Y., Liang, Y., Yang, Y., & Liu, Z. (2021). Prevalence and predictors of posttraumatic stress disorder, depression and anxiety among hospitalized patients with coronavirus disease 2019 in China. *BMC Psychiatry, 21*(1). https://doi.org/10.1186/s12888-021-03076-7.

Deursen, A. J., Bolle, C. L., Hegner, S. M., & Kommers, P. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior, 45*, 411–420. https://doi.org/10.1016/J.CHB.2014.12.039

Elhai, J. D., Levine, J. C., Dvorak, R. D., Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders,* 207. https://doi.org/10.1016/j.jad.2016.08.030

Elhai, J. D., McKay, D., Yang, H., Minaya, C., Montag, C., Asmundson, G. (2020a). Health anxiety related to problematic smartphone use and gaming disorder severity during COVID-19: Fear of missing out as a mediator. *Human Behavior and Emerging Technologies.* https://doi.org/10.1002/hbe2.227

Elhai, J. D., Rozgonjuk, D., Yildirim, C., Alghraibeh, A. M., & Alafnan, A. A. (2019). Worry and anger are associated with latent classes of problematic smartphone use severity among college students. *Journal of Affective Disorders, 246*, 209–216. https://doi.org/10.1016/j.jad.2018.12.047

Elhai, J. D., Yang, H., McKay, D., & Asmundson, G. (2020b). COVID-19 anxiety symptoms associated with problematic smartphone use severity in Chinese adults. *Journal of Affective Disorders, 274*, 576–582. https://doi.org/10.1016/j.jad.2020.05.080

He, X., Li, C., Qian, J., Cui, H., & Wu, W. (2010). Reliability and validity of a generalized anxiety scale in general hospital outpatients. *Shanghai Archives of Psychiatry, 22*(4), 200–203. https://doi.org/10.3969/j.issn.1002-0829.2010.04.002

Johannes, N., Vuorre, M., & Przybylski, A. K. (2021). Video game play is positively correlated with well-being. *Royal Society Open Science,* (2). https://doi.org/10.1098/RSOS.202049.

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior, 31*, 351–354. https://doi.org/10.1016/j.chb.2013.10.059

Li, L., Xu, D., Chai, J., Wang, D., Li, L., Zhang, L., Lu, L., Ng, C. H., Ungvari, G. S., Mei, S., & Xiang, Y. (2018). Prevalence of Internet addiction disorder in Chinese university students: A comprehensive meta-analysis of observational studies. *Journal of Behavioral Addictions, 7*(3), 610–623. https://doi.org/10.1556/2006.7.2018.53

Li, Y., Li, G., Liu, L., & Wu, H. (2020). Correlations between mobile phone addiction and anxiety, depression, impulsivity, and poor sleep quality among college students: A systematic review and meta-analysis. *Journal of Behavioral Addictions, 9*(3), 551–571. https://doi.org/10.1556/2006.2020.00057

Long, J., Liu, T. Q., Liao, Y. H., Qi, C., He, H. Y., Chen, S. B., et al. (2016). Prevalence and correlates of problematic smartphone use in a large random sample of Chinese undergraduates. *BMC Psychiatry, 16*(1), 408. https://doi.org/10.1186/s12888-016-1083-3

Löwe, B., Decker, O., Müller, S. V., Brähler, E., Schellberg, D., Herzog, W., & Herzberg, P. Y. (2008). Validation and standardization of the generalized anxiety disorder screener (GAD-7) in the general population. *Medical Care, 46*, 266–274. https://doi.org/10.1097/MLR.0b013e318160d093

McLachlan, G. J., Peel, D. (2000). *Finite mixture models Wiley series in probability and statistics.* https://doi.org/10.1002/0471721182

Méndez, I., Jorquera Hernández, A. B., & Ruiz-Esteban, C. (2020). Profiles of mobile phone problem use in bullying and cyberbullying among adolescents. *Frontiers in Psychology, 11*, 596961. https://doi.org/10.3389/fpsyg.2020.596961

Newzoo. (2020). Top countries by smartphone users. Source: https://newzoo.com/insights/rankings/top-countries-by-smartphone-penetration-and-users/. Accessed 15 Oct 2021

Nylund, K. L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Ohme, J., Vanden Abeele, M. M., Van Gaeveren, K., Durnez, W., & De Marez, L. (2020). Staying informed and bridging "social distance": Smartphone news use and mobile messaging behaviors of Flemish adults during the first weeks of the COVID-19 pandemic. *Socius, 6*(6780). https://doi.org/10.1177/2378023120950190

Orben, A., & Przybylski, A. K. (2020). Teenage sleep and technology engagement across the week. *PeerJ, 8*, e8427. https://doi.org/10.7717/peerj.8427

Peters, C. S., & Malesky, L. A. (2008). Problematic usage among highly-engaged players of massively multiplayer online role playing games. *Cyberpsychology & Behavior : The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society, 11*(4), 481–484. https://doi.org/10.1089/cpb.2007.0140

Robinson, T. E., & Berridge, K. C. (1993). The neural basis of drug craving: An incentive-sensitization theory of addiction. *Brain Research Reviews, 18*, 247–291. https://doi.org/10.1016/0165-0173(93)90013-P

Robinson, T. E., & Berridge, K. C. (2003). Addiction. *Annual Review of Psychology, 54*(1), 25–53. https://doi.org/10.1146/annurev.psych.54.101601.145237

Rosenberg, J. M., Beymer, P. N., Anderson, D. J., & Schmidt, J. A. (2018). tidyLPA: An R package to easily carry out latent profile analysis (LPA) using open-source or commercial software. *Journal of Open Source Software, 3*(30), 978. https://doi.org/10.21105/joss.00978

Rozgonjuk, D., Levine, J. C., Hall, B. J., & Elhai, J. D. (2018). The association between problematic smartphone use, depression and anxiety symptom severity, and objectively measured smartphone use over one week. *Computers in Human Behavior, 87*, 10–17. https://doi.org/10.1016/j.chb.2018.05.019

Shuang, S. (2014). Development of the smartphone addiction scale for college students. *Chinese Mental Health Journal, 28*(5), 392–397. https://doi.org/10.3969/j.issn.1000-6729.2014.05.013

Stroud, N. J., Peacock, C., & Curry, A. L. (2019). The effects of mobile push notifications on news consumption and learning. *Digital Journalism, 8*(1), 32–48. https://doi.org/10.1080/21670811.2019.1655462

Tao, J., Luo, C., Huang, J., & Liang, L. (2018). Meta-analysis of the current situation of mobile phone dependence among college students in China (in Chinese). *Chinese Journal of School Health, 39(9)*, 1391–1394. https://doi.org/10.16835/j.cnki.1000-9817.2018.09.032

Wang, J. L., Wang, H. Z., Gaskin, J., & Wang, L. H. (2015). The role of stress and motivation in problematic smartphone use among college students. *Computers in Human Behavior, 53*, 181–188. https://doi.org/10.1016/j.chb.2015.07.005

Yahyazadeh, S., Fallahi-khoshknab, M., Norouzi, K., & Dalvandi, A. (2017). The prevalence of smart phone addiction among students in medical sciences universities in Tehran 2016. *Advances in Nursing & Midwifery, 26*, 1–10. https://doi.org/10.22037/ANM.V26I94.15723

Yu, S. C., Lin, Y. H., & Hsu, W. H. (2013). Applying structural equation modeling to report psychometric properties of Chinese version 10-item CES-D depression scale. *Quality & Quantity, 47*(3), 1511–1518. https://doi.org/10.1007/S11135-011-9604-0