The impact of social media, gaming, and smartphone usage on mental health

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The impact of social media, gaming, and smartphone usage on mental health

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Editorial: The impact of social media, gaming, and smartphone usage on mental health

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digital wellbeing, cyberpsychology, addiction, gaming, social media

Editorial on the Research Topic
The impact of social media, gaming, and smartphone usage on mental health

In 2019, the World Health Organization ratified the inclusion of "gaming disorder" in its official diagnostic system, the 11th revision of the International Classification of Disease (1). That year also saw a raft of new legislation proposed to the US Senate, such as the SMART, Detour, and Filter Bubble Transparency Acts. These proposed laws aimed to regulate social media platforms in the interests of public mental health. Around the same time, the Chinese government enacted laws targeting video game play. One of the initiatives was a curfew prohibiting minors from playing video games between 10 pm and 8 am, with the responsibility for implementation primarily placed on the gaming industry (2). All these legislative and nosological moves reflect a growing global concern about the potential adverse impacts of digital technology on our physical, mental and social health.

Research, however, has not kept pace with our concerns or, indeed, with the advent and proliferation of new digital technologies. The paucity of conclusive evidence concerning the psychological harms (or safety) of digital technologies has frequently led to premature conclusions, with tentative speculation often distorted and broadly amplified by media hyperbole. One such notion is that screen time (time spent on digital technology), especially social media, is unequivocally associated with, and perhaps even causative of, poorer psychological well-being. While several studies report such associations (3, 4), others don't, and some even find positive links in specific contexts (5, 6). Further research, with greater nuance and methodological sophistication, is required.

A significant challenge for empirical research exploring the mental health implications of digital technologies (tech) is that these electronic tools, services, and platforms evolve rapidly. Progress in the tech world is frequently characterized by radical - disruptive - impacts. Conversely, methodologically robust research moves much slower, typically inching forward incrementally. Furthermore, digital technologies, such as the internet, are global in their reach. At the same time, much of the research to date has focused on populations within individual countries, typically the high-income nations of the global north. However, patterns of usage and associations observed in the global north may not be applicable across cultures or other world regions. For instance, rates of gaming disorder symptomatology vary significantly by nation and world region (7), as do rates of problematic social media use.

Cognizant of these current challenges, this Research Topic explores the use of digital technology and its potential impact on mental health from diverse perspectives across numerous world regions. Several of the articles in this Research Topic explore the socio-demographic correlates of problematic technology use among citizens of lower-and middle-income nations. Al-Mamun et al., for example, examine problematic technology use among university students in Bangladesh, while Thomas et al. perform a similar epidemiological exploration across 30 nations with broad representation from countries outside of Europe and North America.

Beyond the multinational focus, the Research Topic also focuses on relatively neglected populations. For example, Guo et al. explore internet use and depression among older adults. Considering current demographic transitions (e.g., increased longevity and falling birth rates) and global population ageing, this is a knowledge gap that requires addressing,

Several of the studies in this Research Topic also aim to explore the impact of the COVID-19 pandemic on technology use. An obvious consequence of the pandemic is that more people than ever before are now working remotely, with a greater deal of their working lives being spent online via digital technology (8). A previous review (9) exploring the mental and physical health effects of remote working reported a broad array of associated problems, including stress, depression, fatigue and reduced quality of life. Exploring technology use during the COVID-19 pandemic offers us potential insights into the mental health implications of our increasingly digitized lifestyles.

We are entangled in a web of digital technologies, from occupation functioning to recreational pursuits. This Research Topic contributes to a broad and evolving evidence base concerning the links between technology use and our mental health. We hope this Research Topic encourages further research at this critical human-computer interface.

Author contributions

JT: Writing – original draft, Writing – review & editing. FA-B: Writing – original draft, Writing – review & editing. CG: Writing – original draft, Writing – review & editing.

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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References

1. World Health Organization. (2018). International classification of diseases for mortality and morbidity statistics (11th Revision). World Health Organization.

2. Goh B. *Three hours a week: Play time's over for China's young video gamers, in Reuters*. China: Reuters (2021).

3. Twenge JM, Joiner TE, Rogers ML, Martin GN. Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clin Psychol Sci* (2018) 6(1):3–17. doi: 10.1177/2167702617723376

4. Madhav KC, Sherchand SP, Sherchan S. Association between screen time and depression among US adults. *Prev Med Rep* (2017) 8:67–71. doi: 10.1016/j.pmedr.2017.08.005

5. Boer M, van den Eijnden RJJM, Boniel-Nissim M, Wong S-L, Inchley JC, Badura P, et al. Adolescents' Intense and problematic social media use and their well-being in 29 countries. *J Adolesc Health* (2020) 66(6, Supplement):S89–99. doi: 10.1016/j.jadohealth.2020.02.014

6. Johannes N, Vuorre M, Przybylski AK. Video game play is positively correlated with well-being. *R Soc Open Sci* (2021) 8(2):202049. doi: 10.1098/rsos.202049

7. Thomas J, Gaspar C, Al-Beyahi F, Al-Bassam B, Aljedawi Y. International comparison of gaming disorder symptomatology: analysis of ithra's 30-nation digital wellbeing survey. *Computers in Human Behaviour* (In Review). doi: 10.2139/ssrn.4489171

8. McKinsey. *The future of work after COVID-19*. London (2021).

9. Oakman J, Kinsman N, Stuckey R, Graham M, Weale V. A rapid review of mental and physical health effects of working at home: how do we optimise health? *BMC Public Health* (2020) 20(1):1825. doi: 10.1186/s12889-020-09875-z

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The Role of Problematic Smartphone Uses and Psychological Distress in the Relationship Between Sleep Quality and Disordered Eating Behaviors Among Chinese College Students

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Background: Sleep problems and eating disorders (EDs) are both serious public health concerns often seen in young adults. Yet, the underlying mechanisms for such associations are largely unknown. This study aims to examine potential serial multiple mediation effects of problematic smartphone use (PSU) and psychological distress (i.e., depressive and anxiety symptoms) in the relationship between sleep quality and disordered eating behaviors/attitudes (DEBs).

Methods: A total of 4,325 students from two Tibet universities in China (2,657 females and 1,668 males) completed an online survey that included the following measurements: Eating Attitude Test-26 for disordered eating behaviors/attitudes, the Chinese Version of Pittsburgh Sleep Quality Index (CPSQI), Smartphone Addiction Scale—Short Version (SAS-SV) for problematic smartphone use, Patient Health Questionnaire-9 (PHQ-9) and Generalized Anxiety Disorder-7 (GAD-7) for psychological distress.

Results: While the direct path linking sleep quality and DEBs was not found to be significant (Standardized $\beta = 0.006$, 95% CI = −0.0667∼0.0970), both PSU (Standardized $\beta = 0.016$, 95% CI = 0.0256∼0.0591) and anxiety symptoms (Standardized $\beta = 0.014$, 95% CI = 0.0203∼0.0526) may mediate a link between sleep quality and DEBs; serial multiple mediation analysis revealed that a serial indirect pathway of "sleep quality -> PSU -> anxiety symptoms -> DEBs" existed(Standardized $\beta = 0.001$, 95% CI = 0.0002∼0.0012). Similarly, while the direct path linking sleep quality and DEBs was not found to be significant (Standardized $\beta = 0.006$, 95% CI = −0.0667∼0.0970), both PSU (Standardized $\beta = 0.020$, 95% CI = 0.0337∼0.0692) and depressive symptoms (Standardized $\beta = 0.015$, 95% CI = 0.0139∼0.0652) may mediate a link between sleep quality and DEBs; serial multiple mediation analysis revealed that a serial indirect pathway of “sleep quality -> PSU -> depressive symptoms -> DEBs” existed (Standardized $\beta = 0.001$, 95% CI = 0.0006~0.0038).

Conclusions: Psychological and behavioral factors may comprehensively work together, leading to flow-on effects from sleep problems to disordered eating behaviors among university students. Appropriate interventions that target problematic smartphone use could thus potentially reduce anxiety and depression levels, which in turn will provide a buffer against the negative impact of poor sleep quality on eating disorder symptoms.

Keywords: disordered eating behaviors, sleep quality, problematic smartphone use, anxiety symptoms, depressive symptoms

INTRODUCTION

Eating disorders (EDs) are serious psychiatric disorders with core features such as disturbance in body image, extreme eating behaviors, and weight control (1, 2). The lifetime prevalence rate of EDs is 2–8% in the US (3), and 20–20.6% of the college students were at risk of an eating disorder in some South-East Asian countries (4). Recent studies show that the prevalence of EDs in China is increasing (5). Tong et al., found a comparable prevalence of EDs in female university students (3.53% for binge-eating disorder, 2.98% for bulimia nervosa, and 1.05% for anorexia nervosa) to that of their western counterparts (6, 7). EDs are associated with a variety of adverse outcomes, which seriously affect people’s quality of life (8–12). However, research on eating disorders in China has not attracted enough attention.

Many factors may be related to increased risks of EDs, and several are especially prevalent for students in the stage of emerging adulthood (18–26 years old). Sleep abnormality may have an effect through impacting physical and mental well-being (13–16), along with fluctuations of several hormones such as cortisol, leptin, melanocortin (1, 17–19). In addition, problematic smartphone use (PSU) and psychological distress such as depression may also affect both sleep quality and EDs. The interconnectedness and bidirectional relationships of these physiological, psychological, and behavioral pathways have not been fully understood, thus the goal of this current study was to clarify the pathways that mediate these factors.

PSU has been reported to have a strong correlation with sleep quality where students’ sleep quality worsens with increasing mobile phone addiction levels, and this relationship may be bidirectional (20–23). PSU is also related to EDs (24–27). Taken together, PSU could play a mediating role between sleep quality and eating disorders. Similarly, psychological distress including anxiety and depression has also been reported to be associated with sleep disorders (28–31) and EDs (12, 32–37) independently. And, the proposed mediating roles of anxiety/depression between sleep disorders and ED symptomology have been repeatedly shown in previous studies involving different samples (e.g., Inpatient, children, college women, and community adults) (9, 15, 36, 37).

There were also links reported between PSU and psychological distress (38, 39), where Sangmin Jun et al. found that the relationship between mobile phone addiction and depressive symptoms may present a vicious circle using a longitudinal data (38). Moreover, smartphone addiction was found to mediate the relationship between negative affect and sleep quality among Chinese university students (23).

Given the correlations stated above are established based on studies conducted across a wide range of countries mostly focusing on western cultures, the current study aims to extend upon these researches to provide valuable data on students in Tibet that possesses unique culture and diet. The association between sleep quality and disordered eating was investigated by examining serial multiple mediations linking sleep quality to EDs through PSU and psychological distress (i.e., depressive and anxiety) in Chinese Tibetan college students. Given that EDs require clinical diagnosis, disordered eating behaviors/attitudes (DEBs) were used, which refer to behaviors that deviate from normal but have not yet met the diagnostic criteria for eating disorder (40). We hypothesize that sleep quality would be related to DEBs and that PSU and depressive/anxiety would independently and in series mediate the association between sleep quality and DEBs (**Figure 1**). Through clarifying a pathway, our results may help inform the development of effective intervention and prevention strategies targeting young adults’ DEBs.

METHODS

Participants

A cross-sectional study was conducted from June 2021 to July 2021 by cluster convenience sampling from two universities in Tibet of China. The survey was completed on the online platform (Wenjuanxing) (41). About 15 student cadres from different colleges are recruited and trained as research assistants. Each research assistant sends a pre-made link containing the questionnaire content to the class’s WeChat group or QQ group. Each IP was set to accept only one response. Participants were informed in advance of the purpose of the survey and were voluntarily enrolled. All information provided by participants was confidential and anonymous. A total of 4,885 respondents completed and submitted the survey. Based on the method recommended by Greszki et al. 507 individuals whose response times were very short were eliminated (42). In addition, 53 cases with incomplete information or were answered identically for each question were also deleted. Overall, 4,325 subjects were included in the analysis with an effective response rate of 88.5%.

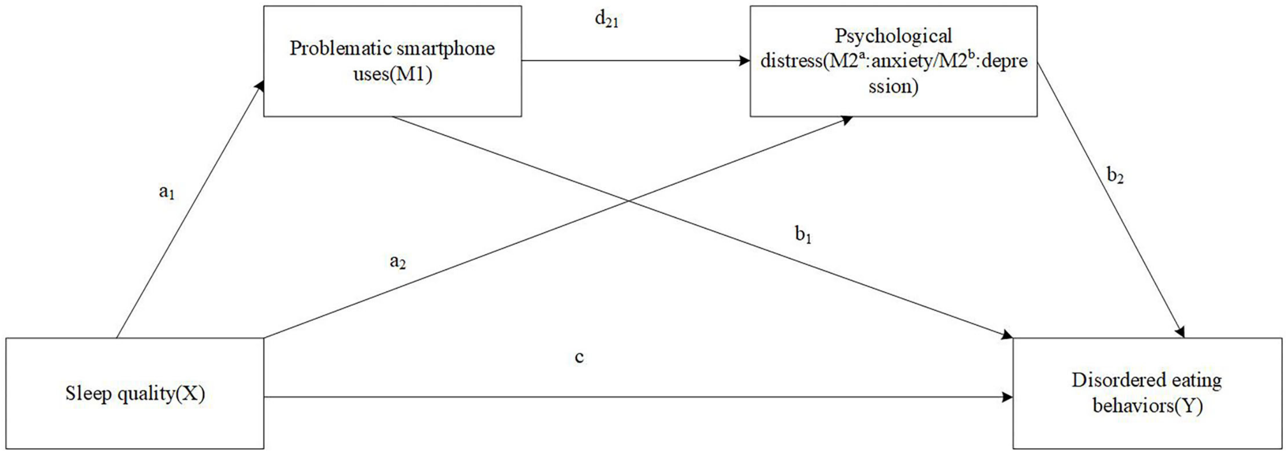

FIGURE 1 | The proposed serial multiple mediation of problematic smartphone uses and psychological distress between sleep quality and disordered eating behaviors.

Measures

Demographic and Clinical Characteristics

The demographic and clinical characteristics included sex (males = 1, females =2), age, ethnicity (Han =1, Tibetan = 2, others = 3), household socioeconomic status (HSS), smoking, drinking and body mass index (BMI) were collected. HSS was measured by asking students' perceptions of their current family economic situation (Response categories: excellent or very good = 1, good =2, and fair or poor =3). BMI was calculated based on students' self-reported height and weight. Based on the BMI standards for Chinese adults (43), the subjects were classified as underweight (BMI < 18.5 kg/m^2), normal weight (18.5–23.9), overweight (24–27.9) and obese (>28). Students that smoked or drank alcohol at least once in the past 30 days were classified as current smokers or drinkers, respectively (44, 45).

Disordered Eating Behaviors/Attitudes

Eating Attitude Test-26 (EAT-26) is a self-administrated questionnaire that evaluates disordered eating behaviors/attitudes (46). The questionnaire consists of 26 items, which mainly involve diet-related attitudes, beliefs and behaviors, and appearance perception. Each item of EAT-26 is scored on a 6-point Likert scale ranging from 0 (never) to 5 (always). The EAT-26 consists of three sub scales: diet, bulimia and food preoccupation, and oral control. After converting the 6-point Likert score into a 4-point format, the total score (ranges from 0 to 78) is calculated by summarizing all items. A higher EAT-26 total score indicates more eating disorder symptoms. The Chinese version of the EAT-26 demonstrated good internal consistency, test-retest reliability and convergent validity (47). The Cronbach's α of the EAT-26 in the present study was 0.855.

Sleep Quality

Sleep quality over the past month was measured by the self-reported Chinese Version of the Pittsburgh Sleep Quality Index (CPSQI) (48). It contains questions regarding 7 sleep components (each scored on a 0–3 scale): subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbance, use of sleep medications, and daytime dysfunction. The global score, which is the cumulative score of seven components, can range from 0 to 21. A higher score indicates poorer sleep quality. The CPSQI has good reliability and validity (48).

Problematic Smartphone Use

Problematic smartphone use severity was assessed by the Smartphone Addiction Scale-short Version (SAS-SV) (49), which is the shortened version of the original SAS (50). The SAS-SV consists of 10 items with response options from "Strongly disagree = 0" to "Strongly agree = 6." The total score of the SAS-SV ranged from 10 to 60, with a higher score representing higher risk of PSU. The Chinese scale version of SAS-SV has a good internal consistency (49). Cronbach's coefficient in our sample was 0.912tba1.

Psychological Distress

Depressive symptoms were measured by Patient Health Questionnaire-9 (PHQ-9), which is a self-report questionnaire consisting of nine items matching the Diagnostic and Statistics Manual of Mental Disorders-Fifth Edition criteria of major depression (51). Each item is used to evaluate feelings in the past 2 weeks. Response options ranged from "not at all = 0" to "nearly every day = 3." The total sum of PHQ-9 scores ranges from zero to 27. The Cronbach's alpha coefficient in this study was 0.920.

Symptoms of anxiety were assessed by using the Generalized Anxiety Disorder-7 (GAD-7) (52). The seven items reflect the frequency of the seven core symptoms in the past 2 weeks, using a 4-point Likert rating scale for duration assessment "not at all = 0" to "almost every day = 3." The total score of GAD-7 ranged from 0 to 21. Higher scores represent higher severity for anxiety. In this study, Cronbach's coefficient of the GAD-7 was 0.937.

Statistical Analysis

Data analyses were carried out in SPSS version 23.0 for Windows (IBM Corp., Armonk, New York, USA). First, descriptive analyses were used to describe the sample characteristics across sex; *t*-tests or chi-square tests were used to compare between groups. Second, the bivariate relationships of the studied variables were examined using Pearson's bivariate correlations. Third, the serial multiple mediating models were tested using the SPSS PROCESS macro version 3.3 developed by Preacher and Hayes, with model 6 and 10,000 bootstrapping samples (53). A significant effect was inferred statistically if the 95% bootstrap confidence interval (CI) did not include 0. Two serial multiple mediation models of a and b were analyzed to examine PSU(M1) and psychological distress ($M2^a$ as anxiety and $M2^b$ as depression, respectively) as serial mediators in the relationship between sleep quality (X) and DEBs (Y) (as shown in **Figure 1**). The total indirect effect of each model included three specific indirect effects as follows: (1) through PSU (a_1b_1), through psychological distress (a_2b_2), and through PSU and psychological distress in serial ($a_1d_{21}b_2$). All the models controlled for sex, age, ethnicity, HSS, BMI, smoking, and drinking. Model (a) controlled for depression in particular, and model (b) controlled for anxiety. Missing data of relevant variables was <2% and eliminated in the serial multiple mediating analyses. *P*-value < 0.05 was considered statistically significant (2-sided tests).

TABLE 1 | Participant characteristics stratified by sex.

Variable	Male, *n* (%)	Female, *n* (%)	Total, *n* (%)	*p*-value[#]
Total	1,668 (38.6)	2,657 (61.4)	4,325 (100)	
Age (year)	20.1 (1.6)	19.8 (1.1)	19.9 (1.3)	<0.001
Ethnicity				
Han	773 (46.3)	970 (36.5)	1,743 (40.3)	<0.001
Tibetan	849 (50.9)	1,621 (61.0)	2,470 (57.1)	
Others	46 (2.8)	66 (2.5)	112 (2.6)	
HSS				
Good	267 (16.0)	423 (15.9)	690 (16.0)	<0.001
Average	799 (47.9)	1,497 (56.3)	2,296 (53.0)	
Poor	602 (36.1)	737 (27.7)	1,339 (31.0)	
BMI				
Underweight	189 (11.4)	520 (19.6)	709 (16.4)	<0.001
Normal weight	1,092 (65.6)	1,793 (67.6)	2,885 (66.8)	
Overweight	258 (15.5)	248 (9.3)	506 (11.7)	
Obese	125 (7.5)	92 (3.5)	217 (5.0)	
Smoking				
No	911 (54.6)	2,524 (95.0)	3,435 (79.4)	<0.001
Yes	757 (45.4)	133 (5.0)	890 (20.6)	
Drinking				
No	502 (30.1)	1,515 (57.0)	2,017 (46.6)	<0.001
Yes	1,166 (69.9)	1,142 (43.0)	2,308 (53.4)	
CPSQI score	5.4 (2.9)	5.6 (2.7)	5.5 (2.8)	0.013
SAS-ST score	33.4 (10.1)	35.6 (9.1)	34.8 (9.6)	<0.001
GAD-7 score	10.9 (4.3)	11.7 (4.4)	11.4 (4.4)	<0.001
PHQ-9 score	13.8 (4.9)	14.5 (4.9)	14.2 (4.9)	<0.001
EAT-26 score	5.7 (6.4)	7.5 (7.3)	6.8 (6.9)	<0.001

HSS, household socioeconomic status; BMI, body mass index; CPSQI, Chinese Version of the Pittsburgh Sleep Quality Index; SAS-ST, smartphone addiction scale-short version; GAD-7, Generalized Anxiety Disorder-7; PHQ-9, Patient Health Questionnaire-9; EAT-26, Eating Attitude Test-26.

[#]The chi-square test was used for categorical variables, and the t test was used for age, CPSQI, SAS-ST, GAD-7, PHQ-9 and EAT-26 scores.

RESULTS

Demographics and Anterior Analyses

The data on the distribution of basic demographic information and some variables of participants according to sex are shown in **Table 1**. Of the enrolled students, 38.6% (1,668) were males, 61.4% (2,657) were females, with an overall mean age of 19.9 (SD: ± 1.3) years. The proportions of Tibetan and Han students were 57.1% (2,470) and 40.3% (1,742), respectively. 69.0% (3,786) of students reported good and average household socioeconomic status. Underweight, overweight, and obese were 16.4% (709), 11.7 (506), and 5.0% (217), respectively. Approximately 20.6% (890) students admitted to smoking, and 53.4% (2,308) reported drinking. The mean scores of CPSQI, SAS-ST, GAD-7, PHQ-9, EAT-26 were significantly higher in female than male students ($p < 0.001$).

TABLE 2 | Intercorrelations among study variables.

Variable	1	2	3	4	5
1. **Sleep quality**	1				
2. **PSU**	0.248***	1			
3. **Depression**	0.537***	0.319***	1		
4. **Anxiety**	0.497***	0.296***	0.806***	1	
5. **DEBs**	0.187***	0.250***	0.293***	0.304***	1

****p < 0.001.*

Correlational Analysis

Sleep quality were positively associated with PSU ($r = 0.248$, $p < 0.001$), anxiety ($r = 0.497$, $p < 0.001$), depression ($r = 0.537$, $p < 0.001$), and DEBs ($r = 0.187$, $p < 0.001$). PSU were positively associated with anxiety ($r = 0.296$, $p < 0.001$), depression ($r = 0.319$, $p < 0.001$), and DEBs ($r = 0.250$, $p < 0.001$). Depression was positively associated with anxiety ($r = 0.806$, $p < 0.001$) and DEBs ($r = 0.293$, $p < 0.001$). Anxiety was positively associated with DEBs ($r = 0.304$, $p < 0.001$) (as shown in **Table 2**).

Serial Multiple Mediating Analysis

Results of the serial multiple mediation model (a) including sleep quality, PSU, anxiety, and DEBs are displayed in **Figure 2** and **Table 3**. The association between poor sleep quality and DEBs was statistically significant (total effect c: Standardized $\beta = 0.037$, 95% CI = 0.0104∼0.1751), and a total of 15.7% of the variance was explained by the combined contribution of sleep quality and covariates. The specific indirect effect through PSU was significant (a_1b_1: Standardized $\beta = 0.016$, 95% CI = 0.0256∼0.0591). The specific indirect effect through anxiety was significant (a_2b_2: Standardized $\beta = 0.014$, 95% CI = 0.0203∼0.0526). Finally, the significant indirect effect of

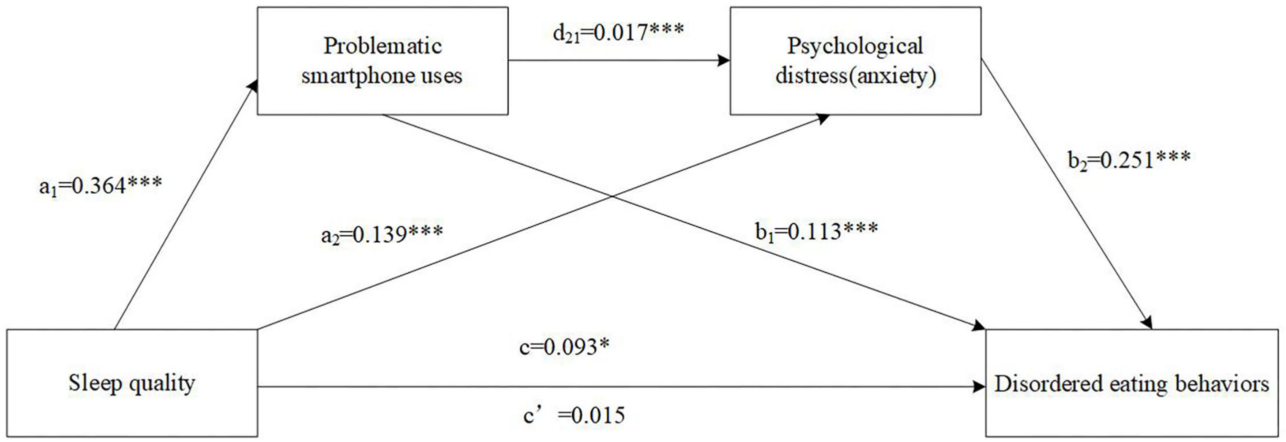

FIGURE 2 | The serial multiple mediation of problematic smartphone uses and anxiety between sleep quality and disordered eating behaviors. Path coefficients are shown in unstandardized regression coefficient, c = total effect, c′ = direct effect. The covariates were sex, age, ethnicity, HSS, BMI, smoking, drinking and depression. ***p < 0.001, *p < 0.05.

TABLE 3 | Results of the serial mediation models of PSU and psychological distress (i.e., depression and anxiety symptoms) on the relationship between sleep quality and DEBs.

Path	*B*	*β*	SE	95%CI	
				Lower	Upper
Model[a]					
Total effect	0.093	0.037	0.042	0.0104	0.1751
Direct effect	0.015	0.006	0.042	0.0667	0.0970
Total indirect effect	0.078	0.031	0.013	0.0549	0.1053
Sleep quality -> PSU -> DEBs:	0.041	0.016	0.009	0.0256	0.0591
Sleep quality -> Anxiety -> DEBs:	0.035	0.014	0.008	0.0203	0.0526
Sleep quality -> PSU -> Anxiety -> DEBs:	0.002	0.001	0.001	0.0006	0.0030
Model[b]					
Total effect	0.106	0.042	0.041	0.0264	0.1864
Direct effect	0.015	0.006	0.042	0.0667	0.0970
Total indirect effect	0.091	0.036	0.016	0.0613	0.1221
Sleep quality -> PSU -> DEBs:	0.051	0.021	0.009	0.0337	0.0692
Sleep quality -> Depression -> DEBs:	0.039	0.015	0.013	0.0139	0.0652
Sleep quality -> PSU -> Depression -> DEBs:	0.002	0.001	0.001	0.0006	0.0038

B, non-standardized regression coefficient; β, standardized regression coefficient; SE, standard error; CI, confidence interval.
All models controlled for sex, age, ethnicity, HSS, BMI, smoking and drinking, with model [a] controlled depression and model [b] anxiety additionally.

sleep quality on DEBs through both PSU and anxiety ($a_1d_{21}b_2$: Standardized $\beta = 0.001$, 95% CI = 0.0002~0.0012) was tested. However, the direct effect of poor sleep quality on DEBs was not statistically significant (direct effect c': Standardized $\beta = 0.006$, 95% CI = −0.0667~0.0970).

Results of the serial multiple mediation model (b) including sleep quality, PSU, depression, and DEBs are displayed in **Figure 3** and **Table 3**. The association between poor sleep quality and DEBs was statistically significant (total effect c: Standardized $\beta = 0.042$, 95% CI = 0.0264~0.1864), and a total of 13.9% of the variance was explained by the combined contribution of sleep quality and covariates. The specific indirect effect through PSU was significant (a_1b_1: Standardized $\beta = 0.020$, 95% CI = 0.0337~0.0692). The specific indirect effect through depression was significant (a_2b_2: Standardized $\beta = 0.015$, 95% CI = 0.0139~0.0652). Finally, the significant indirect effect of sleep quality on DEBs through both PSU and depression ($a_1d_{21}b_2$: Standardized $\beta = 0.001$, 95% CI = 0.0006~0.0038) was tested. However, the direct effect of poor sleep quality on DEBs was not statistically significant (direct effect c': Standardized $\beta = 0.006$, 95% CI = −0.0667~0.0970).

DISCUSSION

The present study investigated the relationships among sleep quality, PSU, psychological distress and DEBs based on the

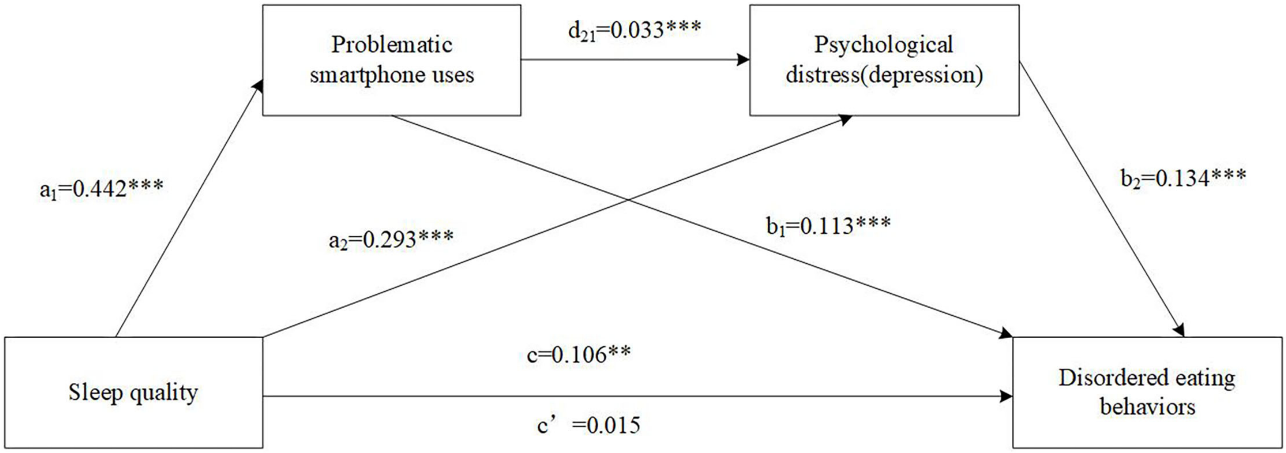

FIGURE 3 | The serial multiple mediation of problematic smartphone uses and depression between sleep quality and disordered eating behaviors. Path coefficients are shown in unstandardized regression coefficient, c = total effect, c′ = direct effect. The covariates were sex, age, ethnicity, HSS, BMI, smoking, drinking and anxiety. ***$p < 0.001$, **$p < 0.01$.

demographic of Chinese Tibet university students. Poor sleep quality was found to be positively associated with DEBs. Results of serial multiple mediation analyses indicated that PSU and psychological distress (i.e., anxiety and depression) could fully mediate the relationship between sleep quality and DEBs. Multiple indirect pathways from sleep quality to eating disorder symptoms were revealed. First, PSU mediate the relationship between sleep quality and DEBs. Second, psychological distress (i.e., anxiety and depression) mediated the relationship between sleep quality and DEBs. Third, PSU and psychological distress (i.e., anxiety and depression) jointly played a serial mediating role in the relationship between sleep quality and DEBs.

Previously, despite the individual links established between sleep problems, problematic mobile phone use, and disordered eating, there were no comprehensive investigations that explored their relationships. Our analysis suggested that mobile phone addiction contributes to the relationship between sleep and eating disorders. Previous studies have established that PSU is aggravated by daytime sleepiness, poor sleep quality and insomnia, which are in turn associated with impulsivity and poor self-regulation leading to higher risks of addiction (54, 55). PSU could be related to eating disorders in several ways. Distractions from excessive mobile phone use may impact satiety registration due to effects on the inferior frontal gyrus under distractive environments, leading to subconscious increased food intake (56). Bombardment of unrealistic body images, thin ideas and diet may incites stress and frustration in young adults (57). The compelling drive to adhere to the thin ideal also triggers body dissatisfaction, exacerbating risks of disordered eating (58, 59). Unbalanced time-allocation toward phone use and meals is another explanation that may result in meal skips, thus promoting unhealthy snacks (26) and ultimately eating problems.

In line with previous studies, psychological distress such as anxiety and depression symptoms significantly mediated the effect of sleep quality on disordered eating in the current study. Therese E. et al., found that depression and anxiety mediated the association between insomnia symptom severity and binge eating frequency (15). Selena et al., found that the relationship between sleep onset latency and emotional eating was mediated by trait anxiety but not depressive symptomatology in minority children (37). In a longitudinal study of clinical patients, depression was found to significantly mediates the relationship between poor sleep at admission (T0) and eating disorder symptoms after 6 months of standard treatment (T1) (36). In addition, the relationship between insomnia and eating psychopathology can be explained by both depression and anxiety in college women (9). This is the first time the roles of depression/anxiety in the relationship between sleep quality and disordered eating was explored for China Tibet college students including Tibetan, Han and other ethnic groups. In view of the complexity and multidimensional nature of sleep problems (60) and disordered eating (1), it is necessary to conduct further research into the mechanisms of psychological distress in the relationship between different sleep components and eating disorder subtypes.

We were able to confirm the direct effects of PSU on depression and anxiety that are consistent with previous reports (38, 61, 62). The serial mediation role we identified for PSU and psychological distress in the relationship between sleep quality and DEBs was "sleep quality -> PSU -> psychological distress -> DEBs." Young adults who reported poor sleep quality tended to have higher levels of PSU and depression/anxiety symptoms, which in turn would lead to high levels of DEBs. This complex mediation pathway builds upon previous research (9, 15, 23, 36, 37), showing that psychology and behavior factors together contribute to the mechanism in the relationship between poor sleep and disordered eating.

These findings have important theoretical implications for understanding the development and prevention of DEBs. In theory, based on the sleep-health framework conceptualized by Buysee (60), sleep as a biological drive is bidirectionally related to physical, mental, and neurobehavioral health. This study extends the previous research by including a potential behavioral addiction and psychological distress (depression and anxiety symptoms) as intermediary variables to comprehensively explore their mechanism underlying how sleep quality exerts an effect on DEBs (14). On the other hand, from the perspective of practical implications, our model shows that it could be postulated that reducing levels of mobile phone addiction, anxiety and depression by improving sleep quality may be beneficial to students' disordered eating behaviors. Sleep hygiene, mobile phone and internet use hygiene, mental health education courses, professional psychological counseling and other interventions should be considered and implemented.

The current study has several interpretive caveats. First, the current study proposes a preliminary exploration for the associations, where longitudinal studies are greatly needed to further assess the causal relationship. Second, the data was collected by self-reported measures, so reporting bias may be introduced. Nonetheless, self-reported questionnaires were proven to be valid and applied worldwide. Third, although a number of potential confounders were included, there are some unmeasured confounders (e.g., parenting styles, substance use and other variables) that may contribute to these associations (63, 64). Forth, the current study only includes college students who are currently on campus and did not account for those absent. Despite its limitations, this study uses a relatively large sample to explore how mediations are related using multiple series mediation models, which expands the psychological and behavioral mechanisms of sleep problems affecting eating disorders.

CONCLUSION

To conclude, this study comprehensively tested psychological and behavioral mechanisms underlying the association between sleep quality and disordered eating behaviors among university students from Tibet, China. Other than the direct effect of sleep quality on disordered eating behaviors, indirect pathways were clarified where sleep quality effects disordered eating behaviors through problematic smartphone use and psychological distress (i.e., depression/anxiety). Our research indicated that appropriated interventions that target problematic smartphone use could potentially reduce anxiety and depression level, which will in turn provide a buffer against the negative impact of poor sleep quality on eating disorder symptoms.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article are available through the Sun Yat-sen University. Contact Ciyong Lu for access approval.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Sun Yat-sen University, School of Public Health Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

RW: conceptualized and designed the present study, carried out the initial analyses, and drafted the manuscript. LG and CL: concept, design, and revising the manuscript. HR, JS, WL, MZ, and YH: design, formal analysis, and interpretation of the data and revising the article. WW and CL: project administration, supervising the project, and revising the manuscript. All authors have read and agreed to the published version of the manuscript.

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REFERENCES

1. Allison KC, Spaeth A, Hopkins CM. Sleep and eating disorders. *Curr Psychiatry Rep.* (2016) 18:92. doi: 10.1007/s11920-016-0728-8
2. Wade TD, Keski-Rahkonen A, Hudson JI. Epidemiology of eating disorders. In: *Textbook of Psychiatric Epidemiology*. Chichester, UK: John Wiley & Sons, Ltd. (2011). p. 343–60. doi: 10.1002/9780470976739.ch20
3. Nagata JM, Garber AK, Tabler JL, Murray SB, Bibbins-Domingo K. Prevalence and correlates of disordered eating behaviors among young adults with overweight or obesity. *J Gen Intern Med.* (2018) 33:1337–43. doi: 10.1007/s11606-018-4465-z
4. Pengpid S, Peltzer K. Risk of disordered eating attitudes and its relation to mental health among university students in ASEAN. *Eat Weight Disord.* (2018) 23:349–55. doi: 10.1007/s40519-018-0507-0
5. Yao S, Zhang R, Thornton LM, Peat CM, Qi B, Du S, et al. Screen-detected disordered eating and related traits in a large population sample of females in mainland China: China Health and Nutrition Survey. *Int J Eat Disord.* (2021) 54:24–35. doi: 10.1002/eat.23409
6. Tong J, Miao S, Wang J, Yang F, Lai H, Zhang C, et al. A two-stage epidemiologic study on prevalence of eating disorders in female university students in Wuhan, China. *Soc Psychiatry Psychiatr Epidemiol.* (2014) 49:499–505. doi: 10.1007/s00127-013-0694-y
7. Hudson JI, Hiripi E, Pope HG, Kessler RC. The prevalence and correlates of eating disorders in the National Comorbidity Survey Replication. *Biol Psychiatry.* (2007) 61:348–58. doi: 10.1016/j.biopsych.2006.03.040
8. Striegel-Moore RH, Bulik CM. Risk factors for eating disorders. *Am Psychol.* (2007) 62:181–98. doi: 10.1037/0003-066X.62.3.181
9. Goel NJ, Sadeh-Sharvit S, Trockel M, Flatt RE, Fitzsimmons-Craft EE, Balantekin KN, et al. Depression and anxiety mediate the relationship between

insomnia and eating disorders in college women. *J Am Coll Health.* (2020) 1–6. doi: 10.1080/07448481.2019.1710152
10. Tromp MD, Donners AA, Garssen J, Verster JC. Sleep, eating disorder symptoms, and daytime functioning. *Nat Sci Sleep.* (2016) 8:35–40. doi: 10.2147/NSS.S97574
11. Neumark-Sztainer D, Wall M, Larson NI, Eisenberg ME, Loth K. Dieting and disordered eating behaviors from adolescence to young adulthood: findings from a 10-year longitudinal study. *J Am Dietetic Assoc.* (2011) 111:1004–11. doi: 10.1016/j.jada.2011.04.012
12. Schaumberg K, Zerwas S, Goodman E, Yilmaz Z, Bulik CM, Micali N. Anxiety disorder symptoms at age 10 predict eating disorder symptoms and diagnoses in adolescence. *J Child Psychol Psychiatry.* (2019) 60:686–96. doi: 10.1111/jcpp.12984
13. Liang H, Beydoun HA, Hossain S, Maldonado A, Zonderman AB, Fanelli-Kuczmarski MT, et al. Dietary Approaches to Stop Hypertension (DASH) score and its association with sleep quality in a national survey of middle-aged and older men and women. *Nutrients.* (2020) 12:1510. doi: 10.3390/nu12051510
14. Cooper AR, Loeb KL, McGlinchey EL. Sleep and eating disorders: current research and future directions. *Curr Opin Psychol.* (2020) 34:89–94. doi: 10.1016/j.copsyc.2019.11.005
15. Kenny TE, Wijk MV, Singleton C, Carter JC. An examination of the relationship between binge eating disorder and insomnia symptoms. *Eur Eating Disord Rev.* (2018) 26:186–96. doi: 10.1002/erv.2587
16. Martínez-de-Quel Ó, Suárez-Iglesias D, López-Flores M, Pérez CA. Physical activity, dietary habits and sleep quality before and during COVID-19 lockdown: a longitudinal study. *Appetite.* (2021) 158:105019. doi: 10.1016/j.appet.2020.105019
17. Micioni Di Bonaventura E, Botticelli L, Tomassoni D, Tayebati SK, Micioni Di Bonaventura MV, et al. The melanocortin system behind the dysfunctional eating behaviors. *Nutrients.* (2020) 12:3502. doi: 10.3390/nu12113502
18. Rosenberg N, Bloch M, Ben Avi I, Rouach V, Schreiber S, Stern N, et al. Cortisol response and desire to binge following psychological stress: comparison between obese subjects with and without binge eating disorder. *Psychiatry Res.* (2013) 208:156–61. doi: 10.1016/j.psychres.2012.09.050
19. Coutinho WF, Moreira RO, Spagnol C, Appolinario JC. Does binge eating disorder alter cortisol secretion in obese women. *Eat Behav.* (2007) 8:59–64. doi: 10.1016/j.eatbeh.2006.01.002
20. Demirci K, Akgönül M, Akpinar A. Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *J Behav Addict.* (2015) 4:85–92. doi: 10.1556/2006.4.2015.010
21. Sahin S, Ozdemir K, Unsal A, Temiz N. Evaluation of mobile phone addiction level and sleep quality in university students. *Pak J Med Sci.* (2013) 29:913. doi: 10.12669/pjms.294.3686
22. Lee JE, Jang S-I, Ju YJ, Kim W, Lee HJ, Park E-C. Relationship between mobile phone addiction and the incidence of poor and short sleep among Korean adolescents: a longitudinal study of the Korean children & youth panel survey. *J Korean Med Sci.* (2017) 32:1166–72. doi: 10.3346/jkms.2017.32.7.1166
23. Li L, Griffiths MD, Mei S, Niu Z. Fear of missing out and smartphone addiction mediates the relationship between positive and negative affect and sleep quality among Chinese university students. *Front Psychiatry.* (2020) 11:877. doi: 10.3389/fpsyt.2020.00877
24. Tao Z. The relationship between Internet addiction and bulimia in a sample of Chinese college students: depression as partial mediator between Internet addiction and bulimia. *Eat Weight Disord.* (2013) 18:233–43. doi: 10.1007/s40519-013-0025-z
25. Tao ZL, Liu Y. Is there a relationship between Internet dependence and eating disorders? A comparison study of Internet dependents and non-Internet dependents. *Eat Weight Disord.* (2009) 14:e77–83. doi: 10.1007/BF03327803
26. Tayhan Kartal F, Yabanci Ayhan N. Relationship between eating disorders and internet and smartphone addiction in college students. *Eat Weight Disord.* (2020) 26:1853–62. doi: 10.1007/s40519-020-01027-x
27. Fang L, Xu X, Lin X, Chen Y, Zheng F, Bei Y, et al. [Association of mobile phone overuse with sleep disorder and unhealthy eating behaviors in college students of a medical university in Guangzhou]. *Nan Fang Yi Ke Da Xue Xue Bao.* (2019) 39:1500–5. doi: 10.12122/j.issn.1673-4254.2019.12.16
28. Wells RD, Day RC, Carney RM, Freedland KE, Duntley SP. Depression predicts self-reported sleep quality in patients with obstructive sleep apnea. *Psychosom Med.* (2004) 66:692–7. doi: 10.1097/01.psy.0000140002.84288.e1
29. Wakefield JRH, Bowe M, Kellezi B, Butcher A, Groeger JA. Longitudinal associations between family identification, loneliness, depression, and sleep quality. *Br J Health Psychol.* (2020) 25:1–16. doi: 10.1111/bjhp.12391
30. Lovato N, Gradisar M. A meta-analysis and model of the relationship between sleep and depression in adolescents: recommendations for future research and clinical practice. *Sleep Med Rev.* (2014) 18:521–9. doi: 10.1016/j.smrv.2014.03.006
31. Wang W, Du X, Guo Y, Li W, Teopiz KM, Shi J, et al. The associations between sleep situations and mental health among Chinese adolescents: a longitudinal study. *Sleep Med.* (2021) 82:71–7. doi: 10.1016/j.sleep.2021.03.009
32. Puccio F, Fuller-Tyszkiewicz M, Youssef G, Mitchell S, Byrne M, Allen N, et al. Longitudinal bi-directional effects of disordered eating, depression and anxiety. *Eur Eat Disord Rev.* (2017) 25:351–8. doi: 10.1002/erv.2525
33. Puccio F, Fuller-Tyszkiewicz M, Ong D, Krug I. A systematic review and meta-analysis on the longitudinal relationship between eating pathology and depression. *Int J Eat Disord.* (2016) 49:439–54. doi: 10.1002/eat.22506
34. Dellava JE, Kendler KS, Neale MC. Generalized anxiety disorder and anorexia nervosa: evidence of shared genetic variation. *Depress Anxiety.* (2011) 28:728–33. doi: 10.1002/da.20834
35. Schwarze NJ, Oliver JM, Handal PJ. Binge eating as related to negative self-awareness, depression, and avoidance coping in undergraduates. *J Coll Student Dev.* (2003) 44:644–52. doi: 10.1353/csd.2003.0058
36. Lombardo C, Battagliese G, Venezia C, Salvemini V. Persistence of poor sleep predicts the severity of the clinical condition after 6 months of standard treatment in patients with eating disorders. *Eat Behav.* (2015) 18:16–9. doi: 10.1016/j.eatbeh.2015.03.003
37. Nguyen-Rodriguez ST, McClain AD, Spruijt-Metz D. Anxiety mediates the relationship between sleep onset latency and emotional eating in minority children. *Eat Behav.* (2010) 11:297–300. doi: 10.1016/j.eatbeh.2010.07.003
38. Jun S. The reciprocal longitudinal relationships between mobile phone addiction and depressive symptoms among Korean adolescents. *Comp Hum Behav.* (2016) 58:179–86. doi: 10.1016/j.chb.2015.12.061
39. Liu S, Wing YK, Hao Y, Li W, Zhang J, Zhang B. The associations of long-time mobile phone use with sleep disturbances and mental distress in technical college students: a prospective cohort study. *Sleep.* (2019) 42:zsy213. doi: 10.1093/sleep/zsy213
40. Leme ACB, Haines J, Tang L, Dunker KLL, Philippi ST, Fisberg M, et al. Impact of strategies for preventing obesity and risk factors for eating disorders among adolescents: a systematic review. *Nutrients.* (2020) 12:3134. doi: 10.3390/nu12103134
41. Wenjuanxing. Available online at: https://www.wjx.cn/ (accessed September 24, 2021).
42. Greszki R, Meyer M, Schoen H. Exploring the effects of removing "Too Fast" responses and respondents from web surveys. *Public Opin Quart.* (2015) 79:471–503. doi: 10.1093/poq/nfu058
43. Zhou B-F, Cooperative Meta-Analysis Group of the Working Group on Obesity in China. Predictive values of body mass index and waist circumference for risk factors of certain related diseases in Chinese adults–study on optimal cut-off points of body mass index and waist circumference in Chinese adults. *Biomed Environ Sci.* (2002) 15:83–96.
44. Acierno R, Kilpatrick DG, Resnick H, Saunders B, De Arellano M, Best C. Assault, PTSD, family substance use, and depression as risk factors for cigarette use in youth: findings from the national survey of adolescents. *J Trauma Stress.* (2000) 13:381–. doi: 10.1023/A:1007772905696
45. Huang R, Ho SY, Wang MP, Lo WS, Lam TH. Sociodemographic risk factors of alcohol drinking in Hong Kong adolescents. *J Epidemiol Community Health.* (2016) 70:374–9. doi: 10.1136/jech-2015-206418
46. Garner DM, Olmsted MP, Bohr Y, Garfinkel PE. The Eating Attitudes Test: psychometric features and clinical correlates. *Psychol Med.* (1982) 12:871–8. doi: 10.1017/S0033291700049163
47. Kang Q, Chan RCK, Li X, Arcelus J, Yue L, Huang J, et al. Psychometric properties of the Chinese version of the eating attitudes test in young female patients with eating disorders in mainland China. *Eur Eat Disord Rev.* (2017) 25:613–7. doi: 10.1002/erv.2560

48. Tsai P-S, Wang S-Y, Wang M-Y, Su C-T, Yang T-T, Huang C-J, et al. Psychometric evaluation of the Chinese version of the Pittsburgh Sleep Quality Index (CPSQI) in primary insomnia and control subjects. *Qual Life Res.* (2005) 14:1943–52. doi: 10.1007/s11136-005-4346-x
49. Luk TT, Wang MP, Shen C, Wan A, Chau PH, Oliffe J, et al. Short version of the Smartphone Addiction Scale in Chinese adults: psychometric properties, sociodemographic, and health behavioral correlates. *J Behav Addict.* (2018) 7:1157–65. doi: 10.1556/2006.7.2018.105
50. Kwon M, Kim D-J, Cho H, Yang S. The smartphone addiction scale: development and validation of a short version for adolescents. *PLoS ONE.* (2013) 8:e83558. doi: 10.1371/journal.pone.0083558
51. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med.* (2001) 16:606–13. doi: 10.1046/j.1525-1497.2001.016009606.x
52. Spitzer R, Kroenke K, Williams J, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch Intern Med.* (2006) 166:1092–7. doi: 10.1001/archinte.166.10.1092
53. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach*. New York, NY: Guilford Publications (2017).
54. Kang Y, Liu S, Yang L, Xu B, Lin L, Xie L, et al. Testing the bidirectional associations of mobile phone addiction behaviors with mental distress, sleep disturbances, and sleep patterns: a one-year prospective study among Chinese college students. *Front Psychiatry.* (2020) 11:634. doi: 10.3389/fpsyt.2020.00634
55. Logan RW, Hasler BP, Forbes EE, Franzen PL, Torregrossa MM, Huang YH, et al. Impact of sleep and circadian rhythms on addiction vulnerability in adolescents. *Biol Psychiatry.* (2018) 83:987–96. doi: 10.1016/j.biopsych.2017.11.035
56. Duif I, Wegman J, Graaf K de, Smeets PAM, Aarts E. Distraction attenuates goal-directed neural responses for food rewards. *bioRXiv*. (2020). doi: 10.1101/2020.01.13.904532
57. Derenne J, Beresin E. Body Image, media, and eating disorders—a 10-year update. *Acad Psychiatry.* (2018) 42:129–34. doi: 10.1007/s40596-017-0832-z
58. Huang Q, Peng W, Ahn S. When media become the mirror: a meta-analysis on media and body image. *Media Psychol.* (2021) 24:437–89. doi: 10.1080/15213269.2020.1737545
59. Stewart S-J, Ogden J. The impact of body diversity vs thin-idealistic media messaging on health outcomes: an experimental study. *Psychol Health Med.* (2021) 26:631–43. doi: 10.1080/13548506.2020.1859565
60. Buysse DJ. Sleep health: can we define it? Does it matter? *Sleep.* (2014) 37:9–17. doi: 10.5665/sleep.3298
61. Winkler A, Jeromin F, Doering BK, Barke A. Problematic smartphone use has detrimental effects on mental health and somatic symptoms in a heterogeneous sample of German adults. *Comput Hum Behav.* (2020) 113:106500. doi: 10.1016/j.chb.2020.106500
62. Sohn SY, Rees P, Wildridge B, Kalk NJ, Carter B. Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: a systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry.* (2019) 19:356. doi: 10.1186/s12888-019-2350-x
63. Peleg O, Tzischinsky O, Spivak-Lavi Z. Depression and social anxiety mediate the relationship between parenting styles and risk of eating disorders: a study among Arab adolescents. *Int J Psychol.* (2021) 56:853–64. doi: 10.1002/ijop.12787
64. Bahji A, Mazhar MN, Hudson CC, Nadkarni P, MacNeil BA, Hawken E. Prevalence of substance use disorder comorbidity among individuals with eating disorders: a systematic review and meta-analysis. *Psychiatry Res.* (2019) 273:58–66. doi: 10.1016/j.psychres.2019.01.007

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Global Adversities, the Media, and Mental Health

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Global communities are currently confronted with a number of complex problems and threats, the reality of which is amplified by the media. These environmental and socio-political stressors have been accompanied by the spread of problematic psychological and behavioural tendencies, such as the growing polarisation of opinions and values, online radicalisation and extremism, deepening xenophobia and nationalism, the proliferation of irrational beliefs and conspiracy theories, and resistance to rational public policy measures. Here we argue that although they fall outside the scope of psychopathology, they nevertheless currently constitute a major challenge for psychiatry as a research domain and a clinical practise. To substantiate this claim, we outline the mechanisms by which media-transmitted stressors impact mental well-being and possibly psychopathology. The common denominator of these global problems and the media's construction of reality is the increase in uncertainty, unpredictability, and uncontrollability, which prompts defensive responding and, in predisposed individuals, functions as a potent source of chronic stress. These contribute to cognitive inflexibility, a strong predisposing factor for the development of rigid beliefs and attitudes, which to varying degrees underlie the adverse psychological and behavioural tendencies mentioned above. We suggest that the tightening of beliefs and ideas that is the result of cognitive rigidity may correspond to the clinical characteristics of induced delusional disorder. This can be seen as a (ultimately maladaptive) defensive strategy for coping with a high degree of uncertainty and unpredictability. We conclude by briefly outlining the possible ways in which psychiatry can face this challenge.

Keywords: adversity, uncertainty, media news, stress, inflexibility

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Anyone who risks deeper immersion in the news media might be excused for harbouring a pessimistic outlook on the state of the world. Global communities are currently confronted with a plethora of complex problems and threats: advancing and potentially catastrophic climate change, accelerating economic inequality, renewed hostility among superpowers and a mounting arms race, widespread displacement and migration, the resurgence of authoritarian political tendencies in many parts of the world, and the global COVID-19 pandemic—to name only the most obvious ones. Every day, millions of people are affected by upheavals, political conflicts, and natural disasters. These problems have been accompanied and amplified by the spread of problematic psychological and behavioural tendencies, such as a steep increase in the polarisation of opinions and values, radicalisation and extremism, deepening xenophobia and nationalism, the proliferation of irrational beliefs and conspiracy theories, resistance to rational public policy measures, and the viral diffusion of negative emotions in the public space and on social media. People's mental states are being massively manipulated with the use of new media, on a scale unprecedented since

WW II. Opinion-makers and scientists have repeatedly drawn links between the complicated state of the world and people's psychological well-being and there are widespread concerns that these phenomena constitute a threat to social health and are undermining democratic principles. Indeed, the humanistic concerns about the collective sanity of society that were raised by some thinkers in the (mid-) twentieth century resonate powerfully in the world today (1).

The above-mentioned adverse behavioural phenomena have been addressed by novel research in social psychology, cognitive science and neuroscience. In contrast to these efforts, psychiatry has so far been rather reticent in responding to them, despite the fact that it must certainly deal with their consequences. One exception is the growing literature on the relationship between mass violence and mental health (2–4) and assesments of acts of extremist violence in forensic psychiatry (5–7). But overall, psychiatry has not yet sufficiently reacted to the spread of negative collective mental states, that are the result of the real or perceived threats confronting global communities and the ways they impact individual mental well-being. Here, we argue that the mental and behavioural problems that are part and parcel of the current complicated state of the world and the individual responses to it, currently constitute a major challenge for psychiatry as a research domain and a clinical practise. To substantiate this claim, we will here briefly outline the mechanisms by which media-transmitted stressors impact mental well-being.

AN ETHICAL AND A POLITICAL CHALLENGE

A consistent line of thinking that spans both extreme critical positions and more mainstream views has long insisted on the need to demarcate mental illness from other forms of mental distress that are caused by social problems (8, 9). This position is explicitly embraced in current diagnostic schemes, where suffering and maladaptive behaviour that are the result of social circumstances are distinguished from mental disorders. According to DSM-5, mental suffering, socially deviant behaviour, and conflicts that exists primarily between the individual and society "... are not mental disorders unless the deviance or conflict results from a dysfunction in the individual. . . " [(10), p.20]. Even the socially most destructive phenomena, such as terrorism and mass violence, presuppose cognitive distortions (11) but cannot simply be accounted for in terms of mental pathology. It could thus be argued that psychiatry's reticence about the above-mentioned negative stereotypes, beliefs, and behaviours is in fact justified: while they are to various degrees morally repulsive and socially destructive—and indeed pathological in social sense—their links to psychopathology are tenuous. But while there is an obvious imperative to resist the psychiatrisation of new and pressing social pathologies, to assert that psychiatry should stay clear of these murky waters is no less problematic—and in our view untenable—for at least two principal reasons.

The first reason becomes apparent if we accept that the social mandate of psychiatry is not just the treatment of mental disorders but includes also the preservation of mental health. Under the well-established dual-factor or two-continua models of mental health and illness (12) and the dimensional model of psychopathology (13), mental health presupposes not just the absence of mental illness, but also high degree of subjective well-being (12, 14). Clearly, the above mentioned adverse psychological and behavioural tendencies manifest as maladaptive, individually and socially harmful behaviours that affect the mental well-being of individual subjects, before impacting society at large. Thus, even if they are not in a categorical sense mental disorders, psychiatrists are still unwittingly faced with their individual and social consequences.

Second, as recent research has amply demonstrated, the cognitive and neural mechanisms that underly these phenomena—such as the intolerance of uncertainty, emotional dysregulation, cognitive biases, impulsivity, the dysregulation of valuation and decision-making—are the very same mechanisms that have been discovered to be causally implicated in the pathogenesis of a variety of mental disorders. They exist on a continuum with a range of mental disorders, as will be discussed below.

These points are perhaps best illustrated with a short vignette: Martin is a 40-year-old technician who recently lost his job and lives alone in a small town in an economically depressed area. His social relationships mainly take the form of interacting with online communities of like-minded individuals. He spends most of his time devouring alternative online media outlets, and contributing to online forums and blogs, which includes spreading fake-news and conspiracy theories. Although his personal experience with ethnic minorities is limited to contact with two gypsy families in his neighbourhood and the Vietnamese greengrocer in a shop that he frequents, he readily admits to feelings of suspicion and hatred towards Jews, Arabs, and—above all—refugees, who, he believes, are infiltrating the country with the aim of destroying it. Since the beginning of the COVID pandemic, he has steadfastly refused to follow public health measures, believing the pandemic is a hoax. Prone to constant feelings of anger and anxiety, his problems have worsened since he lost his job several months ago: he experiences bouts of anger, anxiety, and a feeling of helplessness almost every day. He alleviates these feelings with daily doses of cheap alcohol and recently also with benzodiazepines obtained from an online dealer. Having repeatedly posted online material celebrating the killing of Muslims and gypsies, he has been targeted by the police's cyber-crime unit and is currently facing criminal prosecution.

Whether his condition is best characterised as "problems in living" (15), as "harmful mental dysfunction" (16), or perhaps as "clinical psychological problems" (17), a condition that requires interventive treatment, is a moot point. He may never receive any psychiatric diagnosis, and a forensic psychiatric evaluation (should it come to that) would most likely rule out a mental disorder as the cause of his criminal behaviour. Yet, his is clearly a state of compromised mental health, involving both subjective mental suffering and personally disastrous as well as socially harmful behavioural choices, which affect other people and as a consequence increase the toxicity of the social environment. What is critical to Martin's condition is how his predicament is unfolding as he attempts to make sense of and cope both with his real personal lived experiences (such as his precarious existence) and with the reality of the outside world, as constructed by the various media to which he willingly exposes himself.

MEDIA, UNCERTAINTY, AND STRESS

A major consequence of the above-mentioned global problems and the social construction of reality by the media is a massive increase in the uncertainty, unpredictability, and uncontrollability that characterises the world at large and, consequently, individual lives as well. It is well-known that the media is dominated by negative information and people display a negativity bias towards the news (18, 19). Across a number of studies, the media news have been consistently identified as a source of chronic stress and decreased mental well-being (20–22). This is even worse in the case of content disseminated by alternative outlets and weaponised artificial intelligence propaganda, whose very purpose is to increase people's uncertainty about the state of the world and each individual's prospects within it. This impacts mental well-being—and potentially psychopathology—principally in two interlinked ways.

First, it is well established that humans display sustained vigilance and defensive responding under conditions of uncertainty (23, 24). Recent evidence suggests that an intolerance of uncertainty is a critical transdiagnostic component of internalising psychopathology across a range of mental disorders (25, 26). Computations of subjective estimates of uncertainty predict acute stress response in humans (27) as well as depressive symptoms (28). While space constraints preclude more extensive discussion, it should be noted that the negative effects of uncertainty and unpredictability to a large extent depend on the individual subject's mental construction of the future. The key cognitive mechanisms include an episodic and semantic simulation of future events (29), whose links to psychopathology have recently been extensively examined (30, 31). Since imagining aversive events has emotionally negative consequences, internal simulations themselves incur some of the same costs as real-world experience (32). The aversive reaction is then the result of both the perceived threat to one's motivations and goals and to a decreasing ability to make meaningful sense of a changing and volatile social environment. People experiencing uncertainty and the aversive feelings that attend it will engage in actions to reduce it by initiating processes of compensatory control in an effort to imbue the world with order and predictability (33, 34).

Second, the uncontrollability and inescapability of both real and future imagined states of the world—and one's personal prospects in it—acts in predisposed individuals as a potent source of chronic stress. Indeed, in current theorising, stress itself is regarded as a form of uncertainty (35). If, following a recently proposed model, chronic stress is conceptualised as arising from a generalised perception of unsafety (36), the effect of the media can be seen as constructing the world as unsafe by default. Chronic stressors, characterised by uncontrollability and inescapability, have long been recognised as a major aetiological factor in depressed affect (37–39). This no longer pertains just to stressors at the proximal level of existence (such as health problems, interpersonal relations, financial difficulties and job insecurity etc.), but includes the distal and more abstract contextual level as well.

Furthermore, chronic stress has been found to disrupt neuroplasticity (40–42), a consequence of which is a decrease in psychological and cognitive flexibility. Psychological and cognitive inflexibility is a transdiagnostically relevant aethiological factor that is correlated and co-occurs with a number of cognitive and behavioural processes that underlie and maintain psychopathology (43, 44). Rigid cognitions are connected with a tendency towards negative appraisals of stressful situations (45, 46). Cognitive inflexibility predisposes for ruminative thought patterns in depression, anxiety disorders, and obsessive-compulsive disorder, and subjects with high cognitive inflexibility typically struggle to switch their attention away from internally-focused negative rumination (47, 48).

COGNITIVE INFLEXIBILITY AND DELUSION-LIKE BELIEFS

Cognitive inflexibility in itself, along with accompanying cognitive deficits, is a strong predisposing factor for the development of rigid beliefs and attitudes, which are what to varying degrees underlie almost all the problematic psychological and behavioural tendencies that were mentioned at the beginning of this article. Psychological models, such as the uncertainty-identity theory (49) and compensatory control theory (50, 51), have elaborated on how ideological inflexibility and extremism stems from a defensive need to alleviate uncertainty. Meanwhile, growing empirical evidence on the cognitive underpinnings of political ideologies confirms that cognitive rigidity is indeed linked to ideological extremism, partisanship, and dogmatism (52).

Furthermore, there has long been observed an association between belief inflexibility and delusions (53, 54). In some instances, rigidly held beliefs and attitudes acquire a delusional quality and can best be accounted for as instances of over-valued ideas (55, 56), or shared delusion-like beliefs (6, 7). In the realm of conspiratorial thinking, these rigid ideations may correspond to the clinical characteristics of an induced delusional disorder (or "*folie à deux*")—a rare psychiatric condition in which an "inducer" (primary patient) transmits his or her delusional beliefs to another subject; both then share the same delusional ideation. As proposed by Dewhurst and Todd: (i) the persons involved should be closely associated, (ii) the content of the delusions should be identical or very similar, and (iii) the persons involved should accept, share, and support each other's delusions (57–59). The situation of the proximity of the inducer and followers and the simultaneous separation from other people who could offer an alternative, corrective point of view is now, because of the contemporary media echo chambers, even more extreme and beyond the scope imagined by the authors of the original definition.

Delusion-like beliefs are frequently found in the general population, spanning the continuum between mental illness and normalcy (60). While a variety of "tightened beliefs under uncertainty" (61), which extend into delusion-like beliefs, are in principle correctly positioned outside the sphere of psychiatric nosology, their underlying mechanisms at the systems and neural level provide a definite link to mental illness. One critical component of this link is what recent computational psychiatry call the "strong priors" model of hallucinations and delusions (62, 63). Tightened beliefs result in a limited number of rigid interpretation schemes [that is, priors at high levels of abstraction in a hierarchically structured environment (64)], which are typically observed among people with delusional and compulsive thoughts. Such high-level conceptual and belief priors about the world become strong and resistant to updating (65). As noted, people who are experiencing uncertainty will engage in actions to reduce it and the aversive feelings it generates by initiating processes of compensatory control. However, individuals cannot always resolve uncertainty by reconstructing their internal model of the world. A tightening of beliefs and ideas that is the result of a cognitive rigidity instantiated by strong priors can then be understood as an (ultimately maladaptive) defensive strategy for coping: to conserve energy and to avoid any further aversive emotional reactions brought about by the untolerable uncertainty. It can be seen as a shortcut in the process of active inference, the process of trying to make sense of an increasingly complex and uncontrollable state of affairs (the world) and one's own position in it.

COGNITIVE INFEXIBILITY AND RIGID BELIEFS AT THE SOCIETY-WIDE LEVEL

A fundamental challenge for psychiatry is that aversive emotional reactions and a tightening of beliefs under the conditions of massive uncertainty and uncontrollability that media representations of social reality produce no longer concern just lonely violent extremists or fringe conspiratorial movements that subsist on fake news, as these reactions and beliefs are now being observed on a mass scale. This shift is being driven by the information infrastructure with rapid diffusion of media content that provide competing and incompatible constructions of social reality (66–68). As reactions to the COVID-19 pandemic have dramatically shown, it is increasingly being observed to also affect people who to now have not been drawn to fake news or inclined towards conspirational thinking or delusion-like beliefs, but who are nonetheless finding it difficult to adjust to and cope with the multiple burdens of global threats which impinge on their lives directly.

Importantly, a tightening of beliefs under conditions of chronic stress and uncertainty does not automatically translate into maladaptive or deviant social behaviour. Such behaviours, in any case, can take a range of forms, from the relatively innocuous (sharing fake news via e-mail) to the more consequential, such as refusing to adhere to public policy measures (wearing face masks during a pandemic) and offensive, deviant, and ultimately even violent acts. Cumulatively, such acts and behaviours threaten the stability of society as such, and by creating an increasingly toxic social environment they have downstream consequences for the clinical practise of psychiatry. However, for such behaviours to arise, further factors, such as the dysregulation of decision-making and cognitive control systems—e.g., the inhibition of habitual or impulsive responses, the inhibition of flexible updating and switching of behavioural dispositions, the dysfunctional emotional regulation and others (69–71)– must also be present. One of the topmost priorities for research is to identify the mechanisms and situational triggers through which rigid beliefs may turn to maladaptive and deviant behaviour.

FACING THE CHALLENGE

How can psychiatric research and practise respond to this challenge? On a conceptual level, psychiatry needs to embrace (the not so new) position that mental states have a collective dimension (72, 73) and devote substantially more attention to the problem of how individual mental health is dynamically constrained and affected by interactions between individual minds and brains in a social space. It also requires psychiatric research to be increasingly interlinked with relevant research domains in the social sciences and in media and communication studies. From a public-health and policy perspective, the main issue is to build resilience against the adverse consequences of media-transmitted stressors. Here psychiatry should much more actively engage in efforts to mitigate the amplifying effects of the media in spreading stress and uncertainty and to address the downstream adverse mental and behavioural consequences of this. It needs to be more involved in areas such as media education and proactive policies targeting the spread of disinformation.

Even greater potential for action may arise at the level of fostering individual protective factors and resilience against media-induced adversity. Given the identified mechanisms contributing to the development of maladaptive responses, these preventive and well-being supporting strategies should be primarily based on the promotion of psychological and structural and functional neural plasticity, which could help to acquire and foster neural resilience in people and could thereby have a beneficial effect on socioemotional well-being (74, 75). Remediation strategies should be aimed at the relaxation of pathologically over-weighted "priors" or habits of mind and behaviour (76).

It would be naïve to expect that global environmental and socio-political stressors will have a less stressful impact on communities and individuals in the decades to come. The adverse psychological and behavioural tendencies discussed above that have arisen largely in response to these stressors are thus unlikely to recede. Unless psychiatric research and practise accept the major role they need to play in responding to these negative phenomena, clinicians will increasingly be overwhelmed by their mental health sequelae.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

LK drafted the article. JH contributed to writing. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Fromm E. *The Sane Society*. London: Routledge & Kegan Paul Ltd. (1955).
2. Bhui K, James A, Wessely S. Mental illness and terrorism. *Br Med J*. (2016) 54:i4869. doi: 10.1136/bmj.i4869
3. Dom G, Schouler-Ocak M, Bhui K, Demunter H, Kuey L, Raballo A, et al. Mass violence, radicalization and terrorism: a role for psychiatric profession? *Eur Psychiatry*. (2018) 49:78–80. doi: 10.1016/j.eurpsy.2018.01.001
4. Misiak B, Samochowiec J, Bhui K, Schouler-Ocak M, Demunter H, Kuey L, et al. A systematic review on the relationship between mental health, radicalization and mass violence. *Eur Psychiatry*. (2019) 56:51–9. doi: 10.1016/j.eurpsy.2018.11.005
5. Cunningham MD. Differentiating delusional disorder from the radicalization of extreme beliefs: a 17-factor model. *J. Threat Assess. Manag.* (2018) 5:137–54. doi: 10.1037/tam0000106
6. Pierre J. Integrating non-psychiatric models of delusion-like beliefs into forensic psychiatric assessment. *J Am Acad Psychiatry Law*. (2019) 47:171–79. doi: 10.29158/JAAPL.003833-19
7. Pierre JM. Forensic psychiatry versus the varieties of delusion-like belief. *J Am Acad Psychiatry Law*. (2020) 48:327–34. doi: 10.29158/JAAPL.200013-20
8. Scheff. *Being Mentally ill: A Sociology Theory*. Chicago: Aldine (1966).
9. Verhaeghe P. *What About me*? *The Struggle for Identity in a Market-Based Society*. London: Scribe (2014).
10. *Diagnostic and Statistical Manual of Mental Disorders*, *5th Edn*. American Psychiatric Association (2013).
11. Kruglanski AW, Bélanger JJ, Gunaratna R. Three *Pillars of Radicalization: Needs, Narratives, and Networks*. Oxford: Oxford University Press (2020).
12. Keyes C. The mental health continuum: from languishing to flourishing in life. *J Health Soc Behav*. (2002) 43:207–22. doi: 10.2307/3090197
13. Widiger T, Gore W. Dimensional versus categorical models of psychopathology. In: *Encyclopedia of Clinical Psychology*. John Wiley & Sons, Inc. (2015).
14. Westerhof G, Keyes C. Mental illness and mental health: the two continua model across the lifespan. *J Adult Dev*. (2010) 17:110–19. doi: 10.1007/s10804-009-9082-y
15. Szasz TS. The myth of mental illness. *Am Psychol*. (1960) 15:113–8. doi: 10.1037/h0046535
16. Wakefield JC. The concept of mental disorder: on the boundary between biological facts and social values. *Am Psychol*. (1992) 47:373–88. doi: 10.1037/0003-066X.47.3.373
17. Bakker G. A new conception and subsequent taxonomy of clinical psychological problems. *BMC Psychol*. (2019) 10:7:46. doi: 10.1186/s40359-019-0318-8
18. Soroka S, Fournier P, Nir L. Cross-national evidence of a negativity bias in psychophysiological reactions to news. *Proc Natl Acad Sci USA*. (2019) 116:18888–92. doi: 10.1073/pnas.1908369116
19. Soroka S, McAdams S. News, politics, and negativity. *Political Commun*. (2015) 32:1–22. doi: 10.1080/10584609.2014.881942
20. McNaughton-Cassill M. The news media and psychological distress. *Anxiety Stress Coping*. (2001) 14:193–211. doi: 10.1080/10615800108248354
21. Boukes M, Vliegenthart R. News consumption and its unpleasant side effect: studying the effect of hard and soft news exposure on mental well-being over time. *J Media Psychol*. (2017) 29:137–47. doi: 10.1027/1864-1105/a000224
22. Thompson R, Jones N, Holman E, Silver R. Media exposure to mass violence events can fuel a cycle of distress. *Sci Adv*. (2019) 5:eaav3502. doi: 10.1126/sciadv.aav3502
23. Grupe DW, Nitschke JB. Uncertainty and anticipation in anxiety: an integrated neurobiological and psychological perspective. *Nat. Rev. Neurosci.* (2013) 14:488–501. doi: 10.1038/nrn3524
24. Carleton RN. Into the unknown: a review and synthesis of contemporary models involving uncertainty. *J Anxiety Disor*. (2016) 39:30–43. doi: 10.1016/j.janxdis.2016.02.007
25. McEvoy P, Mahoney A. To be sure, to be sure: intolerance of uncertainty mediates symptoms of various anxiety disorders and depression. *Behav Ther*. (2012) 43:533–45. doi: 10.1016/j.beth.2011.02.007
26. Rosser BA. Intolerance of uncertainty as a transdiagnostic mechanism of psychological difficulties: a systematic review of evidence pertaining to causality and temporal precedence. *Cognit Ther Res*. (2019) 43:438–63. doi: 10.1007/s10608-018-9964-z
27. de Berker AO, Rutledge RB, Mathys C, Marshall L, Cross G, Dolan RJ, et al. Computations of uncertainty mediate acute stress responses in humans. *Nat Commun*. (2016) 7:10996. doi: 10.1038/ncomms10996
28. Yao N, Qian M, Jiang Y, Elhai J. The influence of intolerance of uncertainty on anxiety and depression symptoms in chinese-speaking samples: structure and validity of the chinese translation of the intolerance of uncertainty scale. *J Pers Assess*. (2021) 103:406–15. doi: 10.1080/00223891.2020.1739058
29. Szpunar KK, Spreng RN, Schacter DL. A taxonomy of prospection: introducing an organizational framework for future-oriented cognition. *Proc Natl Acad Sci USA*. (2014) 111:18414–21. doi: 10.1073/pnas.1417144111
30. Miloyan B, Pachana NA, Suddendorf T. The future is here: a review of foresight systems in anxiety and depression. *Cogn Emot*. (2014) 28:1–16. doi: 10.1080/02699931.2013.863179
31. MacLeod A. Prospection, well-being and memory. *Mem Stud*. (2016) 9:266–74. doi: 10.1177/1750698016645233
32. Adams RA, Huys QJM, Roiser JP. Computational psychiatry: towards a mathematically defined understanding of mental illness. *J Neurol Neurosurg Psych*. (2016) 87:53–63. doi: 10.1136/jnnp-2015-310737
33. Lerner M. *The Belief in a Just World: A Fundamental Delusion*. New York, NY: Plenum (1980).
34. Landau MJ, Kay AC, Whitson JA. Compensatory control and the appeal of a structured world. *Psychol Bull*. (2015) 141:694–722. doi: 10.1037/a0038703
35. Peters A, McEwen BS, Friston K. Uncertainty and stress: why it causes diseases and how it is mastered by the brain. *Prog Neurobiol*. (2017) 156:164–88. doi: 10.1016/j.pneurobio.2017.05.004
36. Brosschot JF, Verkuil B, Thayer J. Exposed to events that never happen: generalized unsafety, the default stress response, and prolonged autonomic activity. *Neurosci Biobehav Rev*. (2017) 74(Pt B):287–96. doi: 10.1016/j.neubiorev.2016.07.019
37. Abramson L, Seligman M, Teasdale J. Learned helplessness in humans: critique and reformulation. *J Abnorm Psychol*. (1978) 87:49–74. doi: 10.1037/0021-843X.87.1.49
38. Kendler KS, Hettema JM, Butera F, Gardner CO, Prescott CA. Life event dimensions of loss, humiliation, entrapment and danger in the prediction of onsets of major depression and generalized anxiety. *Arch Gen Psychiatry*. (2003) 60:789–96. doi: 10.1001/archpsyc.60.8.789

39. Pizzagalli DA. Depression, stress, and anhedonia: toward a synthesis and integrated model. *Annu Rev Clin Psychol.* (2014) 10:393–423. doi: 10.1146/annurev-clinpsy-050212-185606
40. Kolassa I, Elbert T. Structural and functional neuroplasticity in relation to traumatic stress. *Curr Dir Psychol Sci.* (2007) 16:321–25. doi: 10.1111/j.1467-8721.2007.00529.x
41. Pittenger C, Duman R. Stress, depression, and neuroplasticity: a convergence of mechanisms. *Neuropsychopharmacology.* (2008) 33:88. doi: 10.1038/sj.npp.1301574
42. McEwen BS, Bowles NP, Gray JD, Hill MN, Hunter RG, Karatsoreos IN, et al. Mechanisms of stress in the brain. *Nat Neurosci.* (2015) 18:1353–63. doi: 10.1038/nn.4086
43. Morris L, Mansell W. A systematic review of the relationship between rigidity/flexibility and transdiagnostic cognitive and behavioral processes that maintain psychopathology. *J Exp Psychopathol.* (2018) 9:431. doi: 10.1177/2043808718779431
44. Uddin L. Cognitive and behavioural flexibility: neural mechanisms and clinical considerations. *Nat Rev Neurosci.* (2021) 22:167–79. doi: 10.1038/s41583-021-00428-w
45. Olinger LJ, Kuiper NA, Shaw BF. Dysfunctional attitudes and stressful life events: an interactive model of depression. *Cognit Ther Res.* (1987) 11:25–40. doi: 10.1007/BF01183130
46. Malouff JM, Schutte NS, McClelland T. Examination of the relationship between irrational beliefs and state anxiety. *Pers Individ Dif.* (1992) 13:451–6. doi: 10.1016/0191-8869(92)90074-Y
47. Davis RN, Nolen-Hoeksema S. Cognitive inflexibility among ruminators and nonruminators. *Cognit Ther Res.* (2000) 24:699–711. doi: 10.1023/A:1005591412406
48. Meiran N, Diamond G, Toder D, Nemets B. Cognitive rigidity in unipolar depression and obsessive compulsive disorder: examination of task switching, stroop, working memory updating and post-conflict adaptation. *Psychiatry Res.* (2011) 185:149–56. doi: 10.1016/j.psychres.2010.04.044
49. Hogg MA. From uncertainty to extremism: social categorization and identity processes. *Curr Dir Psychol Sci.* (2014) 23:338–42. doi: 10.1177/0963721414540168
50. Kay AC, Eibach RP. Compensatory control and its implications for ideological extremism. *J Soc Issues.* (2013) 69:564–85. doi: 10.1111/josi.12029
51. Whitson JA, Galinsky AD, Kay A. The emotional roots of conspiratorial perceptions, system justification, and belief in the paranormal. *J Exp Soc Psychol.* (2015) 56:89–95. doi: 10.1016/j.jesp.2014.09.002
52. Zmigrod L. The role of cognitive rigidity in political ideologies: theory, evidence, future directions. *Curr Opin Behav Sci.* (2020) 34:34–9. doi: 10.1016/j.cobeha.2019.10.016
53. Freeman D, Garety PA, Fowler D, Kuipers E, Bebbington PE, Dunn G. Why do people with delusions fail to choose more realistic explanations for their experiences? An empirical investigation. *J Consult Clin Psychol.* (2004) 72:671–80. doi: 10.1037/0022-006X.72.4.671
54. Garety PA, Freeman D, Jolley S, Dunn G, Bebbington PE, Fowler DG, et al. Reasoning, emotions, and delusional conviction in psychosis. *J Abnorm Psychol.* (2005) 114:373–84. doi: 10.1037/0021-843X.114.3.373
55. Veale D. Over-valued ideas: a conceptual analysis. *Behav Res Ther.* (2002) 40:383–400. doi: 10.1016/S0005-7967(01)00016-X
56. Rahman T, Meloy JR, Bauer R. Extreme overvalued belief and the legacy of Carl Wernicke. *J Am Acad Psychiatry Law.* (2019) 47:180–7. doi: 10.29158/JAAPL.003847-19
57. Dewhurst WG, Todd J. The psychosis of association – folie à deux. *J Nerv Ment Dis.* (1956) 124:451–9. doi: 10.1097/00005053-195611000-00003
58. Wehmeier P, Barth N, Remschmidt H. Induced delusional disorder: a review of the concept and an unususal case of folie à famille. *Psychopathology.* (2003) 36:37–45. doi: 10.1159/000069657
59. Reif A, Pfuhlmann B. Folie à deux versus genetically driven delusional disorder: case reports and nosological considerations. *Compr Psychiatry.* (2004) 45:155–60. doi: 10.1016/j.comppsych.2003.09.004
60. Pechey R, Haligan P. The prevalence of delusion-like beliefs relative to sociocultural beliefs in the general population. *Psychopathology.* (2011) 44:106–15. doi: 10.1159/000319788
61. Carhart-Harris R. How do psychedelics work. *Curr Opin Psychiatry.* (2019) 32:16–21. doi: 10.1097/YCO.0000000000000467
62. Corlett PR, Horga G, Fletcher PC, Alderson-Day B, Schmack K, Powers AR. Hallucinations and strong priors. *Trends Cogn Sci.* (2018) 23:114–27. doi: 10.1016/j.tics.2018.12.001
63. Sterzer P, Adams RA, Fletcher P, Frith C, Lawrie SM, Muckli L, et al. The predictive coding account of psychosis. *Biol Psychiatry.* (2018) 84:63443. doi: 10.1016/j.biopsych.2018.05.015
64. Huys QJ, Maia TV, Frank MJ. Computational psychiatry as a bridge from neuroscience to clinical applications. *Nat Neurosci.* (2016) 19:404–13. doi: 10.1038/nn.4238
65. Kube, T, Rozenkrantz L. When beliefs face reality: an integrative review of belief updating in mental health and illness. *Perspect Psychol Sci.* (2020) 16:247–74. doi: 10.31234/osf.io/cy64r
66. Del Vicario M, Bessi A, Zollo F, Petroni F, Scala A, Caldarelli G, et al. The spreading of misinformation online. *Proc Natl Acad Sci USA.* (2016) 113:554–9. doi: 10.1073/pnas.1517441113
67. Seifert CM. The distributed influence of misinformation. *J Appl Res Mem Cogn.* (2017) 6:397–400. doi: 10.1016/j.jarmac.2017.09.003
68. Vosoughi S, Roy D, Aral S. The spread of true and false news online. *Science.* (2018) 359:1146–51. doi: 10.1126/science.aap9559
69. Goschke T. Dysfunctions of decision-making and cognitive control as transdiganostic mechanisms of mental disorders: advancers, gaps, and needs in current research. *Int J Methods Psychiatr Res.* (2014) 23(Suppl 1):41–57. doi: 10.1002/mpr.1410
70. Frijda NH, Ridderinkhof KR, Rietveld E. Impulsive action: emotional impulses and their control. *Front Psychol.* (2014) 5:518. doi: 10.3389/fpsyg.2014.00518
71. Heatherton TF, Wagner DD. Cognitive neuroscience of self-regulation failure. *Trends Cog Sci.* (2011) 15:132–39. doi: 10.1016/j.tics.2010.12.005
72. Bostock WW, Bostock ECS. Disorders of the collective mental state. *J Psychol Psychotherapy.* (2017) 7:6. doi: 10.4172/2161-0487.1000331
73. Kesner L. Mental Ill-Health and the Epidemiology of Representations. *Front Psychiatry.* (2018) 9:289. doi: 10.3389/fpsyt.2018.00289
74. Holz NE, Tost H, Meyer-Lindenberg A. Resilience and the brain: a key role for regulatory circuits linked to social stress and support. *Mol Psychiatry.* (2019) 25:379–96. doi: 10.1038/s41380-019-0551-9
75. Davidson RJ, McEwen BS. Social influences on neuroplasticity: stress and interventions to promote well-being. *Nat Neurosci.* (2012) 15:689–95. doi: 10.1038/nn.3093
76. Kočárová R, Horáček J, Carhart-Harris R. Does psychedelic therapy have a transdiagnostic action and prophylactic potential? *Front. Psychiatry.* (2021) 12:661233. doi: 10.3389/fpsyt.2021.661233

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Characteristics of High Suicide Risk Messages From Users of a Social Network—Sina Weibo "Tree Hole"

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Background: People with suicidal ideation post suicide-related information on social media, and some may choose collective suicide. Sina Weibo is one of the most popular social media platforms in China, and "Zoufan" is one of the largest depression "Tree Holes." To collect suicide warning information and prevent suicide behaviors, researchers conducted real-time network monitoring of messages in the "Zoufan" tree hole via artificial intelligence robots.

Objective: To explore characteristics of time, content and suicidal behaviors by analyzing high suicide risk comments in the "Zoufan" tree hole.

Methods: Knowledge graph technology was used to screen high suicide risk comments in the "Zoufan" tree hole. Users' level of activity was analyzed by calculating the number of messages per hour. Words in messages were segmented by a Jieba tool. Keywords and a keywords co-occurrence matrix were extracted using a TF-IDF algorithm. Gephi software was used to conduct keywords co-occurrence network analysis.

Results: Among 5,766 high suicide risk comments, 73.27% were level 7 (suicide method was determined but not the suicide date). Females and users from economically developed cities are more likely to express suicide ideation on social media. High suicide risk users were more active during nighttime, and they expressed strong negative emotions and willingness to end their life. Jumping off buildings, wrist slashing, burning charcoal, hanging and sleeping pills were the most frequently mentioned suicide methods. About 17.55% of comments included suicide invitations. Negative cognition and emotions are the most common suicide reason.

Conclusion: Users sending high risk suicide messages on social media expressed strong suicidal ideation. Females and users from economically developed cities were more likely to leave high suicide risk comments on social media. Nighttime was the most active period for users. Characteristics of high suicide risk messages help to improve the automatic suicide monitoring system. More advanced technologies are needed to perform critical analysis to obtain accurate characteristics of the users and messages on social media. It is necessary to improve the 24-h crisis warning and intervention system for social media and create a good online social environment.

Keywords: suicide, tree hole of Weibo, artificial intelligence, social media, content analysis

INTRODUCTION

Suicide is an important social issue and has become the second leading cause of death among 15–29 years old globally (1). In China, the suicide rate is 0.0097% (2). Early identification of people with suicide risk is crucial for suicide prevention. However, these people usually do not actively seek help, so traditional methods such as self-reported ratings and structured interviews are ineffective in identifying suicide risk in time. Nowadays, because of the large number of Internet users and the anonymity of the Internet, people tend to express their negative emotions, even suicidal thoughts and plans through social media. Posting suicide or self-harm information on social media is regarded as a signal of suicidal ideation, and it may increase the contagious effect of suicidality since suicidal behaviors may be learned from others (3–5). Therefore, the association between suicide and social media has become a public health concern (6).

The words people used on social media are important cues to their mental health status. Due to a large number of posts and comments on social media, it is hard to identify and analyze suicide-related texts manually. In recent years, many machine learning methods were used for text sentiment analysis. A review showed that natural language processing and information retrieval methods were frequently used to extract language characteristics and predict future incidents of suicide or suicide attempts (7). In China, studies analyzing suicide-related text on social media were mainly based on Sina Weibo, the most popular microblog with a 42.3% utilization rate in China (8). A study used deep learning methods to build a text classifier to identify users on Sina Weibo with depression and negative emotions, and it found users with depression were more active than general users, and they expressed hopelessness or sadness, discussed depression treatment, suicide or self-injury (9). Another study showed that the Simplified Chinese-Linguistic Inquiry and Word Count (SC-LIWC) dictionary and machine learning method were useful to automatically identify language markers of suicide risk or emotional distress of users on Sina Weibo (10), and a higher usage of pronouns, prepend words (mainly preposition), multifunction words and a lower frequency of verb usage in messages, and a greater total word count were associated with a higher suicide possibility (10). Sina Weibo users who ended his or her life interacted less with others, had a higher level of self-concern, and used more negative expressions, more religious and death-related words, and less work-related words (11).

Huang developed the "Tree Hole Intelligent Agent" by using Knowledge Graph technology to automatically identify users with different levels of suicide risk in the "Zoufan" tree hole (12). "Zoufan" is one of the biggest "Tree Holes" on Sina Weibo. On March 17, 2012, a Sina Weibo user named "Zoufan" posted her last tweet: "I suffer from depression, so I just choose to die, for no important reason. Don't worry about my death." After her death, her last post attracted many people to express their negative emotions and became a "Tree Hole." To date, there are more than 2 million messages from 350,000 users commented under her last post which share suicidal thoughts and plans. Some users even sent suicide invitations to implement collective suicide. The analysis of general comments in the "Zoufan" tree hole showed that 52% of comments tended to be negative; emotional expression, relationships and social support, sleep and death were high-frequency keywords mentioned in messages (13). Huang's "Tree Hole Intelligent Agent" classifies the suicide risk of "Tree Holes" users according to the certainty of suicide methods and the urgency of time mentioned in their comments. High suicide risk messages refer to those including suicide plans or indicating users may commit suicide soon. High suicide risk users are people who send high suicide risk messages. The "Tree Hole Action" started by Huang provides proactive suicide crisis intervention for high suicide risk users, and it has temporarily prevented 3,629 potential suicides from 2018 to 2020 (14).

High suicide risk users on social media should be the focus of suicide prevention because they are most likely to commit suicide and need timely crisis intervention. However, current studies are not enough to provide a clear portrait of high suicide risk users on social media. In addition, most studies analyzed posts on users' home pages rather than their comments under others' posts. The latter is more difficult to be found by familiar people, so it may provide a better understanding of the inner world of users with suicide risk. The comments section is also interactive because users not only express themselves but also discuss with others.

Therefore, this study analyzed the high suicide risk comments under the last post of the "Zoufan" tree hole to explore the characteristics of users and high suicide risk messages. The findings can provide insights into the portrait of high suicide risk users on social media, help to improve the performance of "Tree Hole Intelligent Agent," and facilitate the development of early suicide monitoring and proactive crisis intervention such as "Tree Hole Action" intervention through artificial intelligence technology. The findings also provide evidence for developing targeted long-term support programs on social media for high suicide risk users.

METHODS

Data Collection

"Tree Hole" AI robots were used to crawl users' messages in the "Zoufan" tree hole from November 6, 2018 to May 5, 2020. According to the certainty of suicide manner and the urgency of the time, a suicide risk rating was established by using Knowledge Graph technology (12). The Knowledge Graph is a graph-based knowledge representation and organization method, which can represent systematic, structured, and integrated domain-specific knowledge based on semantic technology (12, 15). The suicide risk classification standards are as follows (12): level 10 (suicide may be in progress), level 9 (suicide method has been determined and may occur soon), level 8 (suicide has been planned, and the suicide date is generally determined), level 7 (suicide method has been determined, and the suicide date is unknown), level 6 (suicide has been planned, and the suicide date is unknown), level 5 (expression of strong desire to commit suicide, and the suicide method is unknown), level 4 (suicidal desire has been expressed, and the specific method and plan are unknown), level 3 (intense survival pain, and no suicidal wishes expressed), level 2 (survival pain has been clearly expressed, and no suicidal wishes expressed), level 1 (survival pain is partially expressed, and no suicidal wishes expressed), and level 0 (no expression of survival pain noted). Messages were graded automatically by AI robots, and levels from 6 to 10 were marked as high suicide risk messages. The accuracy of the identification of suicide risk has reached 82% (12).

Data Analysis

The age, gender and region of Sina Weibo users were described by frequency and percentage. The users' level of activity was analyzed by calculating the number of messages per hour.

Words in the messages were segmented by a Jieba tool. The keywords and a keywords co-occurrence matrix were extracted using a TF-IDF algorithm. Jieba tool is a method suitable for Chinese word segmentation, which can divide continuous word sequences into word sequences. TF-IDF (Term Frequency-Inverse Document Frequency) algorithm is a statistical method used to evaluate the importance of words in the text, and a weighted technology in information retrieval and data mining (16). Researchers divided high-frequency keywords into four classifications (suicide-related words, emotion expression words, role-relevant words and time and place relevant words) manually according to the contents. Keywords co-occurrence network analysis was constructed by Gephi 0.9.2 software. Each node represented a keyword; "degree" represented the frequency of the paired keywords that appeared together in each message; "edge" meant the connection between the paired keywords. The weight of the edge referred to the closeness of the paired keywords. The greater the weight of the edge, the closer the relationship between the two nodes.

To explore the suicide characteristics, researchers reviewed each message, manually annotated the suicide reasons, and identified if the users sent suicide invitations.

Ethical Approval

This study received approval from the Ethics Committee of Wuhan University School of Medicine (code: 2020YF0075).

RESULTS

General and Time Characteristics

In this study, there were totally 5,760 high suicide risk messages: 1,190 (20.66%) were level 6, 4,222 (73.30%) were level 7, 48 (0.83%) were level 8, and 300 (5.21%) were level 9.

According to users' registration information, 2,105 (64.79%) were female users, 762 (23.45%) were male users and 382 (11.76%) had no gender identified. Many users (1,818) reported a geographic location, including outside of China (249, 13.70%), Guangdong (236, 12.98%), Beijing (142, 7.81%), Jiangsu (115, 6.33%), and Sichuan (102, 5.61%), etc. (see **Figure 1**).

About 19.08% of messages were posted between 23:00 and 01:00, while the fewest messages (264, 4.58%) were posted between 05:00 and 07:00 (see **Figure 2**). The horizontal axis represents the time of the message posting and the vertical axis represents message volume per hour.

Content Characteristics

The keywords extracted by the TF-IDF algorithm were sorted by weight. The weight is a statistical measure calculated by TF-IDF to evaluate the importance of a word in a text or corpus (17). The top 20 keywords with great weight are shown in **Table 1**. The top 50 keywords are shown in the **Appendix**.

The high-frequency keywords were divided into four classifications, including suicide-related words, emotion expression words, role-relevant words and time and place-relevant words (see **Table 2**). Suicide-related words and emotion expression words were the most mentioned classifications. Jumping off buildings, wrist slashing, burning charcoal, hanging and sleeping pills were the most mentioned suicide methods.

The keywords co-occurrence network analysis showed that "world-leave," "jump off buildings-really," "jump off buildings-slash wrist," "jump off buildings-hang," and "suicide-burn charcoal" were the top five co-occurrence relationships. The top five related keywords with "pain" were "jump off buildings," "burn charcoal," "slash wrist," "hang," and "really." The top five related keywords with "happy" were "jump off buildings," "really," "jump down," "alive," and "burn charcoal" (see **Table 3**).

Both of the keywords and the keywords co-occurrence network analysis showed that high suicide risk users had a strong willingness to end his or her life, and they were concerned about suicide methods and expressed great negative emotions. It is consistent with many original posts. For example, "I searched many methods, jumping into a river, burning charcoal, taking medicine, jumping off the building. The highest success rate should be to jump off the building......"

Suicidal Characteristics

Among all high suicide-risk messages, 1,011 (17.55%) included suicide invitations and 327 (5.68%) were automatically rated as high suicide risk by AI roots but didn't express definite suicide ideation, such as "No, friends. The world may not be worth living, but there are also some things in the world that you will cherish."

There were different reasons for sending suicide invitations to others. Some users want to suicide with others because they have no courage or they want to have a companion: "It's lonely to die alone, is there anyone die with me?" "I thought that if two people died together, maybe I'll have more courage."

Negative cognition and emotions such as sadness, desperation and meaninglessness, mental disorders and specific problems in life such as family issues were common suicide reasons in

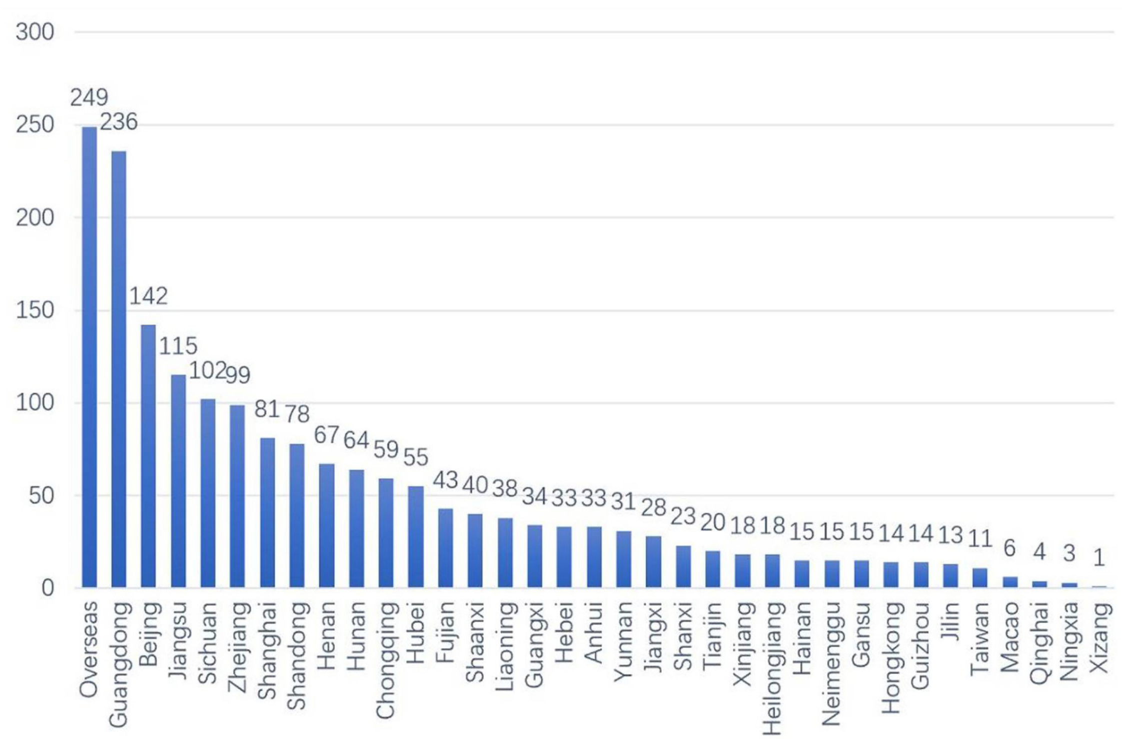

FIGURE 1 | The geographic location of users.

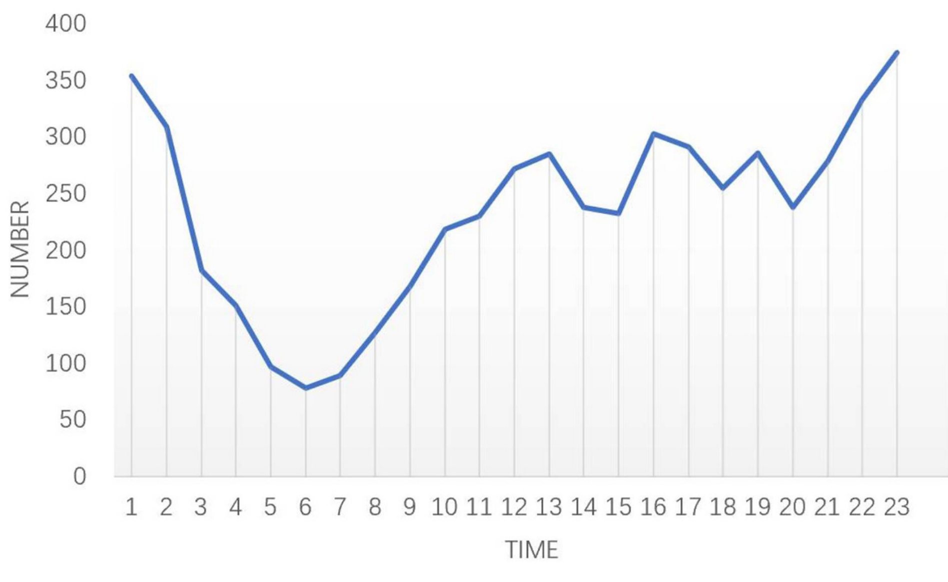

FIGURE 2 | Characteristics of high suicide risk messages.

high suicide risk messages. Some users were not willing to seek help, for example, "I know I have been ill for a long time, but I am reluctant to spend money to see a doctor..." Some users expressed suicidal ideation but did not implement it because they were worried about their family: "I want to jump off the building, but I worried my parents will be sad, I have no courage."

DISCUSSION

This study analyzed the characteristics of users with high suicide risk and their comments under the last post of "Zoufan" tree hole— one of the biggest "Tree Holes" in Sina Weibo. The study showed that females and users from economically developed cities are more likely to express suicide ideation on social media. High suicide risk users were more active during nighttime, and they expressed strong negative emotions and willingness to end their life. Jumping off buildings, wrist slashing, burning charcoal, hanging and sleeping pills were the most frequently mentioned suicide methods. The most common suicide reasons were negative cognition and emotions. About 17.55% of comments included suicide invitations. Some users did not commit suicide because they did not want their families to suffer because of their death.

What This Study Adds to Current Literature

First, previous studies mainly analyzed the content characteristics of posts on users' home pages, but this study included the comments with high suicide risk that were publicly available under the last post of a girl who killed herself named "Zoufan." Because the "Zoufan" tree hole is one of the biggest "Tree Holes" in Sina Weibo, these comments can help to provide a better understanding regarding the inner world of users with high suicide risk. Second, our previous study about the general comments under the last post of "Zoufan" showed that 52% of comments expressed negative emotion. By comparing the characteristics of general comments with high suicide risk comments, relationship-related keywords (e.g., "I love you," "boyfriend," "break up") and sleep-related keywords (e.g., "can't fall asleep," "insomnia") were frequently mentioned in general comments (13), but these were not high-frequency keywords in high suicide risk comments. In contrast, time and place relevant words (e.g., "school," "hospital," "roof") were high-frequency keywords in high suicide risk comments but not in

TABLE 1 | Characteristics of keywords (Top 20).

Keyword	Weight (frequency)	Keyword	Weight (frequency)
Jump off buildings	0.6644 (1662)	Leave	0.0646 (356)
Slash wrist	0.4353 (977)	World	0.0564 (380)
Burn charcoal	0.3406 (888)	Don't want	0.0559 (268)
Hang	0.1546 (385)	Have or not	0.0559 (224)
Really	0.1218 (592)	Alive	0.0463 (171)
Jump into a river	0.1178 (253)	Feel	0.0427 (200)
Jump down	0.1005 (286)	Uncomfortable	0.0378 (131)
Suicide	0.0920 (366)	Taking pills	0.0345 (109)
Pain	0.0840 (328)	Afraid of pain	0.0321 (69)
Sleeping pills	0.0729 (189)	Sad	0.0316 (121)

TABLE 3 | Co-occurrence relationships of keywords (Top 10).

Partial keywords	Co-occurrence keywords (frequency)
Pain	Jump off buildings (228), burn charcoal (214), slash wrist (162), hang (128), really (124), very painful (108), not painful (80), alive (70), world (64), leave (54)
Uncomfortable	World (34), very painful (16), mama (16), can't stand (14), very tired (12), wake up (8), useless (8), afraid of pain (6), death method (6), parents (4)
Happy	Jump off buildings (78), really (40), jump down (22), alive (20), burn charcoal (18), sad (18), hope (16), world (16), like (14), feel (14)
Alive	Really (90), world (64), very tired (38), hang (36), want to die (36), burn charcoal (34), well (30), pass away (30), go to die (30), parents (26)
Suicide	Burn charcoal (254), jump off buildings (236), slash wrist (172), really (128), don't want to (80), depression (76), want to die (76), pain (64), world (56), sleep pills (52)

TABLE 2 | Classification of high-frequency keywords (unit: frequency).

Suicide-related words		Emotion expression words		Role-relevant words		Time and place relevant words	
Jump off buildings	1,662	Pain	328	Parents	125	School	54
Slash wrist	977	Uncomfortable	252	Mama	107	Hospital	49
Burn charcoal	888	Happy	121	Family	68	Roof	29
Hang	385	Dare not	120	Wardmate	50	Window	28
Suicide	366	Afraid	107	Kids	44	Balcony	21
Leave	356	Like	94	Girls	34	Early morning	21
Jump into a river/sea	293	Sorry	71	Classmate	27	Just now	77
Jump down	286	Afraid of pain	69	Doctor	24	A few days	62
Sleeping pills	189	Hahaha	69	Elderly sister	19	Recently	61
Death	86	Desperate	54	Daughter	18	Before	47
Relieve	73	Broken down	45	Boyfriend	17	Tonight	35
Self-harm	49	Regret	41			Last night	27
Posthumous papers	43	Dislike	39			Future	20
Hang to die	29	Very tired	31			Daytime	16
Pesticide	23	Sad	31			Afternoon	16

general comments (13). Suicide-related words such as jump off buildings, slash wrist, burn charcoal were high-frequency keywords in both but were mentioned more frequently in high suicide risk comments than general comments (13). These linguistic features help to form the portrait of high suicide risk users on social media, which is crucial for suicide monitoring and intervention.

Implications for Automatically Suicide Monitoring and Identification

The findings of this study provide evidence to improve the performance of the "Tree Hole Intelligent Agent," which is developed based on knowledge graph technology (12). Ontology can be regarded as a specific type of knowledge graph (12). Now the "Tree Hole Ontology" has four parts: suicide ontology, time ontology, space ontology and desire ontology. This study showed that besides suicide-related words, time and place related words, emotion expression words and role-related words were also high-frequency words mentioned by high suicide risk users. Therefore, emotion ontology and relationship ontology can be added to improve the performance of "Tree Hole Intelligent Agent." The results of content analysis in this study also contribute to the complement of "suicide dictionary" which can be used in suicide tendency analysis. The co-occurrence words help to enrich and expand the logical rules of knowledge-based methods (18), as domain knowledge to build deep learning based sentiment analysis algorithms (19).

Implications for Mental Health Promotion Projects and Social Media Suicide Intervention Systems

The suicide crisis interventions require close collaboration among the government, society, social media platforms, healthcare professionals and the family. Government and the society should publicize mental health education and life education, help people to enhance positive coping skills, destigmatize mental illness and emphasize the importance of seeking help when necessary. Since expressing emotions is a protective factor of suicide (20), it is important to create a friendly and supportive environment for people to express their emotions. People with suicidal thoughts are more willing to seek help from mental health hotlines and the internet due to the convenience and anonymity (21), so the government, social media platforms and healthcare institutions could work together to set up mental health hotlines and online forums to provide professional consultations and interventions.

When building mental health service systems, the government and healthcare institutions should pay more attention to high-risk regions, actively publicize ways to cope with work and life pressure and focus on improving social support networks. Because high risk suicide users are more active at night, when healthcare providers deliver mental health education through social media, sending posts at night may be more effective (22). Due to the reduced availability of healthcare workers at night, it is necessary to develop automatic identification technology to enhance monitoring during the nighttime. Artificial intelligence technology could monitor the messages continuously and identify high suicide risk messages automatically. Since time is vital for suicide intervention, it is necessary to develop crisis intervention guidelines for suicide risk users on social media. Social media platforms can also introduce relevant policies like forbidding users to post messages including suicide invitations.

Family support is a crucial protective factor of suicide, and good family relationships can be a protective factor in preventing suicide (23). Therefore, the family needs to focus on the emotional status of their family members, notice early signs of suicide and seek professional interventions when necessary (24). Healthcare professionals should also incorporate family support and education into crisis interventions.

Implications for Future Research

Because Sina Weibo has a 140-character limit for each comment, future studies could analyze users' comments in "Tree Holes" and posts on their home page together to get more comprehensive user portraits. The cross-cultural research of characteristics of suicide messages may also be implemented. Apart from the "Zoufan" tree hole, there are many other "Tree Holes" on Sina Weibo, so the automatic suicide monitoring model and intervention system developed for the "Zoufan" tree hole can be extended to other "Tree Holes."

Limitations

Firstly, messages in "Tree Holes" are fragmented and can't completely reflect the user's overall state. Secondly, because of the anonymity of online social media, the authenticity of messages and users' information can't be completely assured. Thirdly, using a software program to do the text analysis based on an identified algorithm may not accurately depict the characteristics of users' messages. For instance, sometimes software wrongly identifies the message advising others not to jump off buildings as a high suicide risk message. Future technology development can make up for this limitation, and software is expected to automatically identify and classify the cause of suicide to help researchers work more efficiently. In addition, classifications of keywords were based on keywords rather than deep semantics analysis of the complete text. More mature text semantic analysis technology can solve this problem in the future.

CONCLUSION

Users sending high risk suicide messages on social media expressed strong suicidal ideation. Females and users from economically developed cities were more likely to leave high suicide risk comments on social media. Nighttime was the most active period for users. Characteristics of high suicide risk messages help to improve the automatic suicide monitoring system. More advanced technologies are needed to perform critical analysis to obtain accurate characteristics of the users and messages on social media. Future research should more pay attention to the mental health of social media users, improve the 24-h crisis warning and intervention system for social media and create a good online social environment.

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 received approval from the Ethics Committee of Wuhan University School of Medicine (code: 2020YF0075).

AUTHOR CONTRIBUTIONS

BXY, PC, QL, JZ, and LW designed the study and wrote the research protocol. PC, XYL, BXY, QL, FY, JZ, LW, ZH, GF, DL, XQW, and WL did the literature review, managed the field survey, quality control, and statistical analysis and prepared the manuscript draft. QL, XYL, BXY, and FY contributed to the revisions in depth for the manuscript. BXY, QL, JZ, and LW supervised the survey and checked the data. All authors contributed to and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2022.789504/full#supplementary-material

REFERENCES

1. WHO. *Suicide.* Geneva: World Health Organization (2019). Available online at: https://www.who.int/news-room/fact-sheets/detail/suicide (accessed February 02, 2021).
2. WHO. *World Health Statistics Geneva: World Health Organization*. (2018). Available online at: https://www.who.int/data/gho/data/themes/topics/topic-details/GHO/world-health-statistics
3. Cheng Q, Kwok CL, Zhu T, Guan L, Yip PS. Suicide communication on social media and its psychological mechanisms: an examination of chinese microblog users. *Int J Environ Res Public Health.* (2015) 12:11506–27. doi: 10.3390/ijerph120911506
4. Wang Z, Yu G, Tian X. Exploring behavior of people with suicidal ideation in a chinese online suicidal community. *Int J Environ Res Public Health.* (2018) 16:54. doi: 10.3390/ijerph16010054
5. Tang J, Yu G, Yao X. A comparative study of online depression communities in China. *Int J Environ Res Public Health.* (2020) 17:5023. doi: 10.3390/ijerph17145023
6. Li A, Huang X, Jiao D, O'Dea B, Zhu T, Christensen H. An analysis of stigma and suicide literacy in responses to suicides broadcast on social media. *Asia-Pac Psychiat.* (2018) 10:12314. doi: 10.1111/appy.12314
7. Cheng Q, Lui CSM. Applying text mining methods to suicide research. *Suicide Life Threat Behav.* (2021) 51:137–47. doi: 10.1111/sltb.12680
8. Times G. AI helps to prevent suicides during COVID-19 epidemic (2021). Available online at: https://www.globaltimes.cn/page/202101/1214074.shtml (accessed February 02, 2021).
9. Yao X, Yu G, Tian X, Tang J. Patterns and longitudinal changes in negative emotions of people with depression on sina weibo. *Telemed e-health.* (2020) 26:734–43. doi: 10.1089/tmj.2019.0108
10. Cheng Q, Li TM, Kwok C-L, Zhu T, Yip PS. Assessing suicide risk and emotional distress in Chinese social media: a text mining and machine learning study. *J Med Internet Res.* (2017) 19:e243. doi: 10.2196/jmir.7276
11. Li G, Bibo H, Tianli L, Qijin C, Fai YPS, Tingshao Z. A pilot study of differences in behavioral and linguistic characteristics between Sina suicide microblog users and Sina microblog users without suicide idea. *Chin J Epidemiol.* (2015) 36:421–5. doi: 10.3760/cma.j.issn.0254-6450.2015.05.003
12. Huang ZS, Hu Q, Gu GJ, Yang J, Feng Y, Wang G. Web-based intelligent agents for suicide monitoring and early warning. *Chin Digital Med.* (2019) 14:3–6. doi: 10.3969/j.issn.1673-7571.2019.03.001
13. Chen P, Qian YX, Huang ZS, Zhao C, Liu ZC, Yang BX, et al. Negative emotional characteristics of Weibo "Tree Hole" users. *Chin Mental Health J.* (2020) 34:437–44. doi: 10.3969/j.issn.1000-6729.2020.5.009
14. Yang BX, Xia L, Liu L, Nie W, Liu Q, Li XY, et al. A suicide monitoring and crisis intervention strategy based on knowledge graph technology for "tree hole" microblog users in China. *Front Psychol.* (2021) 12:674481. doi: 10.3389/fpsyg.2021.674481
15. Li L, Wang P, Yan J, Wang Y, Li S, Jiang J, et al. Real-world data medical knowledge graph: construction and applications. *Artif Intell Med.* (2020) 103:101817. doi: 10.1016/j.artmed.2020.101817
16. Zhang W, Yoshida T, Tang X. A comparative study of TF*IDF, LSI and multi-words for text classification. *Expert Syst App.* (2011) 38:2758–65. doi: 10.1016/j.eswa.2010.08.066
17. Wu HC, Luk RWP, Wong KF, Kwok KL. Interpreting TF-IDF term weights as making relevance decisions. *Transact Inform Syst*. (2008) 26:55–9. doi: 10.1145/1361684.1361686
18. Yu H, Li H, Mao D, Cai Q. A relationship extraction method for domain knowledge graph construction. *World Wide Web.* (2020) 23:765. doi: 10.1007/s11280-019-00765-y
19. Schouten K, Weijde O, Frasincar F, Dekker R. Supervised and unsupervised aspect category detection for sentiment analysis with co-occurrence data. *IEEE Transactions Cybernetics.* (2017) 2017:1–13. doi: 10.1109/TCYB.2017.2688801
20. Xue MX. *Research on Postgraduate Freshmen Suicide Risk Assessment and Intervention from the Perspective of Family Ecology [Master]*: East China Jiaotong University (2020).
21. Zhang L, Feng YY, Zhou HB, Du CC. Analysis on help-seeking behavior and its influencing factors among community residents with suicidal intention. *Chin J Health Educ.* (2020) 36:475–7+81. doi: 10.16168/j.cnki.issn.1002-9982.2020.05.020
22. Tian X, Batterham P, Song S, Yao X, Yu G. Characterizing depression issues on Sina Weibo. *Int J Environ Res Public Health.* (2018) 15:764. doi: 10.3390/ijerph15040764
23. Cong AC, Wu Y, Cai YY, Chen HY, Xu YF. Association of suicidal ideation with family environment and psychological resilience in adolescents. *Chin J Contem Pediatr.* (2019) 21:479–84. doi: 10.7499/j.issn.1008-8830.2019.05.016
24. Junus A, Yip PSF. Suicide risk profile and the social convoy: Population-level patterns of the young generation's help-seeking behavior and

implications for suicide prevention. *J Affect Disord.* (2021) 297:559–69. doi: 10.1016/j.jad.2021.10.106

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Socio-Demographic and Attitudinal Correlates of Problematic Social Media Use: Analysis of Ithra's 30-Nation Digital Wellbeing Survey

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Time spent on social media continues to rise globally. For some individuals, social media use can become maladaptive and associated with clinically significant social and occupational impairments. This problematic social media use (PSMU) is also linked with poorer health and wellbeing. Much of our existing PSMU knowledge comes from single nation studies, heavily focused on adolescent and college-age samples. This study uses data from Ithra's 2021 global digital wellbeing survey to explore rates of PSMU and identify socio-demographic and attitudinal correlates. Participants ($N = 15{,}000$) were representative adult samples ($N = 500$) drawn from 30 nations. All participants provided socio-demographic data and completed a measure of PSMU, along with questions assessing attitudes toward social media and general usage patterns. PSMU prevalence was 6.82%, varying from 1.7 to 18.4% between nations. Multivariate logistical regression identified several correlates, including national culture, age, parenthood and frequency of use. These findings can help inform public policy and public health initiatives to reduce PSMU prevalence.

Keywords: social media use, social media disorder, internet addiction, international, national culture

> *"…new technology does not add or subtract, it changes everything. In the year 1500, 50 years after the printing press was invented, we did not have the old Europe plus the printing press—we had a different Europe"* (1).

INTRODUCTION

One of the most widespread and rapidly embraced information age technologies is social media. In the 25 years since the first primitive platforms emerged, the number of active users has grown exponentially, reaching around 4.48 billion in July 2021 (2). While the definition of "active use" varies, it generally denotes individuals who log in and perform actions that facilitate direct exchanges with other users, for example, sharing messages, posting images, and commenting on peer-content (3). Social media use among US adolescents increased markedly between 2010 and 2015 (4). International industry data extend and confirm this trend, with social media users averaging 145 min per day in 2020, up from 90 min per day in 2012 (5).

Beyond the usage norms, however, there are also concerns that social media use can become maladaptive, resembling a behavioral addiction or an impulse control disorder (6–10). This evolving concept of a pathological form of social media use is typically traced to the work of Griffiths (11, 12). Building on the work of Brown (13), Griffiths proposed a "components" model of addiction, arguing for a common set of symptoms (salience, mood modification, tolerance, withdrawal, conflict and relapse) shared by all addictions, including behavioral addictions. For Griffiths, this could be extended to video games (14), internet use (15) and more. Further pioneering work in online addictions drew on the DSM-IV (16) conceptualization of pathological gambling (9). Young proposed a set of diagnostic criteria for internet addiction disorder (preoccupation, tolerance, withdrawal, relapse/persistence, mood modification/escape, deception, displacement, and conflict) that have subsequently influenced the conceptualization and measurement of gaming (17) and social media (18) disorder (19). Young's internet addiction concept is broad, comprising five subtypes, including cybersexual addiction, gaming addiction, internet compulsions (online gambling/shopping), compulsive information seeking, and cyberrelationship addiction (10). This last subtype–cyberrelationship addiction-comes closest to our contemporary ideas about maladaptive social media use.

The current nomenclature attached to compulsive and dysfunctional social media use includes social media disorder, social media addiction, or compulsive social media use. However, perhaps due to the lack of conceptual clarity and consensus, the term "problematic social media use" (PSMU) has also gained traction in recent years. For example, between July 2020 and July 2021, PubMed included 26 articles with the phrase "problematic social media use" in the title; for "social media addiction", there were 17, and for "social media disorder", just 4. Despite these concerns over social media use, contemporary psychiatric nosology in the form of the ICD-11 (20) and DSM-5 (21) have yet to include social media addiction/PSMU as an official diagnostic entity. Gaming disorder was included in the ICD-11 in 2019 as a behavioral addiction.

Because currently PSMU is not listed in DSM-5 or in ICD-11 as a preliminary or formal diagnostic entity, there is some controversy in conceptualization and in distinguishing between normal and maladaptive use of social media. On one hand, PSMU can be seen as part of Internet addictions in general. For example, aligned with the DSM-IV (16) criteria for pathological gambling, Young (9) proposed a set of diagnostic criteria for Internet addiction disorder, variously listed as: preoccupation, tolerance, withdrawal, persistence, mood modification, deception, displacement, and conflict. Young's et al. (10) concept of Internet addiction is overarching, comprising at least five subtypes: cybersexual addiction, gaming addiction, Internet compulsions (online gambling/shopping), compulsive information seeking, and cyberrelationship (social media) addiction. From this perspective, PSMU can be seen as part of Internet addiction and may well co-occur with other its known subtypes. And while some of the subtypes of the Internet addiction are becoming recognized as a potential independent diagnosis, to date, however, there remains a lack of conceptual clarity and nosological consensus concerning maladaptive social media use. Several definitions of problematic social media use can be found in the literature. For example, social network site addiction is a commonly used term in research in this field (22, 23), and it emphasizes the same aspects of addiction that are seen in substance and behavioral addictions, namely salience, tolerance, mood modification, conflict, withdrawal, problems, and relapse (23). Some researchers have taken on an approach of applying the diagnostic criteria of the Internet gaming disorder to the maladaptive and compulsive use of social media and referred to it as social media disorder (18). Other researchers (24) use a term problematic social networking site use (PSNSU), while pointing out that terms as diverse as: Facebook addiction, addictive use of social networking sites, Internet-communication disorder, smartphone use disorder, smartphone addiction, and Internet communication/social networks use disorder have also been used in the field (24). The latter term (Internet communication/social networks use) was suggested to be used as a part of Internet use disorders distinguishing between mobile and non-mobile Internet use disorders (25), however this taxonomy remains work in progress as the field still requires clarity on what criteria can be used to classify an online behavior as disorder besides the over-use as such (24).

Considering the controversies with conceptualizing the maladaptive use of social media, and considering it is not currently outlined as a formal disorder, we follow the common approach in this field of research when referring to this maladaptive online behavior, and use a broader term in our study, namely-problematic social media use (PSMU). And while no common definition of PSMU exists to date, it is commonly interpreted as a maladaptive form of social media use that is characterized by loss of control, compulsiveness and experiencing negative consequences from the excessive use of social media such as negative impact on daily life, performance at work or school, social activities, interpersonal relations and on the overall health and sense of wellbeing (22, 26). Problematic social media use, however, remains a condition for further study.

Much of this further study has investigated the prevalence of PSMU, associated morbidities and its implications for health and wellbeing. There are now several meta-analytic reviews reporting epidemiological data for PSMU. Notably, Cheng et al. (27) combined data from 62 independent studies, including 34,798 participants from 32 nations. The pooled prevalence for PSMU in their analysis was 5%. This figure was arrived at using the most stringent screening criteria, counting only those individuals classified as experiencing "very severe symptoms". When relaxed criteria were used, the pooled prevalence rose to 13%, with a high degree of international variability. Cheng et al. also grouped nations by national cultural values, specifically, the degree to which each society emphasized individualist (independence) vs. collectivist (interdependence) values (28). Rates of PSMU were significantly higher among collectivist (e.g., Japan, India, Taiwan) populations (31%) compared to their individualist (e.g., USA, UK, Australia) counterparts (14%). The influence of cultural values on PSMU remains an area for future research (27).

Another meta-analysis explored gender-related differences in PSMU and gaming disorder (29). This analysis included 53 independent studies, including 82,440 participants from 21 nations/regions. Across the whole sample, there were relatively higher levels of PSMU among women (small effect size), while men were more likely to meet the screening criteria for gaming disorder (moderate effect size). Again, however, these findings demonstrated significant international variability. For example, India's pattern showed larger gaming disorder effects in females and PSMU in males (29). Similarly, for PSMU, gender-related differences in effect sizes were larger in Asian nations than their European and North American counterparts. These findings, again, highlight the need for studies to get beyond single nation data and explore PSMU internationally and cross-culturally.

Beyond meta-analytic studies, extensive multinational primary research studies of PSMU are scarce. However, Boer et al. (30) explored data from the 2017/2018 Health Behaviors in School-aged Children (HBSC) survey. This multinational survey assessed PSMU and wellbeing (life satisfaction, school satisfaction, family and peer-support) among 154, 981 adolescents across 29, primarily, European countries (30). The average PSMU prevalence across territories was 7.38%, ranging from 14.17% for Spain to a low of 3.22% for the Netherlands. PSMU was, without exception, negatively associated with poorer scores across all the wellbeing domains. This study also looked at "intense social media use", defined as high-frequency use, without behavioral addiction symptomatology. Across all nations, 34.03% of adolescents were categorized as intense users. Unlike PSMU, however, intense use was not unequivocally associated with poorer wellbeing. In those nations where intense social media use was a norm (high prevalence of intense users), it was even associated with higher levels of wellbeing. This study highlights the critical distinction between frequent/intense and problematic use, where frequent use is not necessarily problematic and may even be associated with better wellbeing in specific contexts. Rather than frequency/intensity of use, features such as loss of control and preoccupation are more likely to underpin PSMU's observed association with poorer wellbeing (30).

While shedding important light on PSMU, these studies have several limitations. First, the individual studies included in the meta-analyses were undertaken in different years, at different times of the year. These temporal differences may impact findings, especially when attempting to compare nations, regions, or cultures. Furthermore, the current conceptual ambiguity surrounding PSMU means that the pooled studies frequently rely on different screening tools to identify cases. This may introduce variations due to methods used. Furthermore, most of the individual studies in the pooled meta-analyses focus on young people (school and college-age students), disproportionately from Europe and North America (29). This Western focus is also true of the one large multinational study we were able to identify.

The present study aims to address some of these previous limitations. Using multivariate logistic regression, it also aims to identify and clearly communicate the socio-demographic and attitudinal correlates of PSMU across a diverse multinational sample of adults aged 18 to 91. In addition, our study examines PSMU data from a multi-regional (Americas, Middle East, Africa, Asia) digital wellbeing survey administered to a sample of 15,000 adults across 30 territories within a 1-month data collection window. These multinational data provide an opportunity to identify and describe regional differences while exploring socio-demographic and attitudinal variables associated with PSMU. Based on previous research, we formulated the following research hypotheses about the PSMU and age of the participants as well as regarding the PSMU and national culture. Our first hypothesis is in line with Cheng et al. (27) where we hypothesize that, after adjusting for other socio-demographic variables, collectivist nations will report higher rates of PSMU than their individualist counterparts. Similarly, in line with earlier research (31), we predict higher rates of PSMU among participants from the younger age group. However, we make no specific directional predictions regarding PSMU's association with the study's other variables.

METHODS

Participants

The 30-nation digital wellbeing survey (DWS) was commissioned by King Abdulaziz Center for World Culture (Ithra). Data collection was managed by PSB Insights, a global analytics consultancy with a 40-year track record in offering research and polling services across more than 100 countries. PBS routinely conduct extensive multinational surveys, a notable example being the annual Arab Youth Survey, currently in its 13th year. For the DWS, all materials were translated and back-translated from English into the majority language of each of the 30 participating territories. The samples in each nation were probability-based representative draws of 500 individuals. Participants were drawn at random from the pre-existing panels. Depending on the nation, panel sizes varied from 10s of thousands to millions. In each country, a representative sample of the adult population (18 years old and older) was ensured by applying demographic quotas (stratification), including age, gender, region, and nationality (in some countries). Potential participants were excluded if they were under 18 or not literate in the major language of the territory they reside in. Thus, the final survey was administered online to nationally representative samples of 500 internet-using adults within each participating territory. Respondents were drawn from existing participant banks (panels) with participation incentives offered following local practices. The final anonymized sample totaled 15,000 individuals, with all data collected between June 12th and July

TABLE 1 | Sample characteristics: frequency counts and percentages for the study's main demographic variables.

Variable	Frequency (%) Whole sample	Frequency (%) Social media user
Gender		
Female	7,201 (48.0%)	5,254 (49.5%)
Male	7,799 (52.0%)	5,364 (50.5%)
Age group		
Over 35 yrs.	7,662 (51.1%)	5,227 (49.2%)
35 yrs. and under	7,338 (49.9%)	5,391 (50.8%)
Completed College		
No	6,950 (46.3%)	4,731 (44.6%)
Yes	8,050 (53.7%)	5,887 (55.4%)
National culture		
Individualist	4,500 (30.0%)	3,080 (29.0%)
Collectivist	10,500 (70.0%)	7,538 (70.9%)
Household income		
High (above national median)	6,918 (46.1%)	4,993 (47.0%)
Low (national median or less)	8,082 (53.9%)	5,625 (53.0%)
Number of children under 18 yrs.		
None	7,757 (51.7%)	5,230 (49.3%)
One	3,374 (22.5%)	2,543 (23.9%)
Two	2,555 (17.0%)	1,940 (18.3%)
Three-Five	1,207 (8.0%)	849 (8.0%)
More than 5	107 (0.7%)	56 (0.5%)

11th, 2021. Ithra's internal review board granted the ethical approval for the study (IRS 202171). Because the samples from each nation were drawn using probability-based random sampling method, and they were drawn from the representative existing panels of the data collection agency, it allows for the generalization of the findings to larger populations from which the national samples were drawn.

Sample Characteristics

The median age of participants across the whole sample was 36 years (age range 27–50 years), 10,618 (70.8%) reported using social media. Social media users were slightly younger, Mdn = 35 (age range 27–48 years), than their non-using counterparts. **Table 1** above displays additional sample characteristics.

Measures

The DWS is an extensive battery, including over 300 items spanning a broad range of demographics and digital wellbeing related topics. However, the present analysis focuses specifically on items related to social media use.

Problematic Social Media Use

The DWS contained eight items explicitly assessing problematic social media use. This content was based on simplifying items from the Bergen Social Media Addiction Scale (32) and the Social Media Disorder Scale (18). This simplification was deemed essential to facilitate content translation across multiple different languages. In line with Young's (9) work on internet addiction, the unequivocal endorsement of at least five items/symptoms ("strongly agree") was used as a cut-off for the assignment of problematic use status. This cut-off is also aligned with existing DSM-5 criteria for diagnosing pathological gambling (33). The eight items included on the DWS are listed in **Table 2** in descending endorsement order.

Demographic Items

Individual-level demographic items included nationality (30 nations), gender, age, education level, number of children under 18 years of age, household income. Except for age, responses to these demographic items were nominal or ordinal data. For the present analysis, however, responses to most variables were dichotomized. This dichotomization gave us high (above the national median) vs. low household income (median or below), children vs. no children, completed college vs. never completed college and two age groups based on a median split: over 35 vs. 35 and under. Additionally, we included national culture data for each participant based on the Hofstede Insights scores for each nation (28). Specifically, we included scores on the individualism dimension (0 to 100), which allowed us to categorize participants as belonging to either an individualist (individualism score > 50) or a collectivist society. Based on Hofstede's quantitative model of national culture (28), *individualist* societies are generally characterized by their emphasis on the "personal". In individualist societies, personal freedoms, and individual achievements are particularly important. People are expected to be independent, to take care of themselves and their immediate family, making their own choices. The opposite end of this dimension is referred to as *collectivism*. In contradistinction to individualist societies, collectivist societies are viewed as emphasizing group harmony over and above individual achievements. Interdependence rather than independence is valued, and the cohesion and wellbeing of the broader social group is given precedence over and above personal interest and individual gain. Some hallmarks of collectivist societies within this framework include living in larger extended families, and higher rates of consanguineous (cousin) marriage (34). The dichotomization/categorization of continuous variables is commonly used in health research to stratify participants according to putative risk/resilience factors, thereby facilitating the development of easily communicated models of greatest need/highest risk (35). However, for bivariate correlational analyses, we also retained and used the continuous values for individualism (scores range 13 to 91) and age (age range 18 to 91 years).

Attitudinal and Behavioral Items

In addition to demographics, the survey also captured information about self-reported social media use and attitudes toward this technology. The survey asked about daily usage patterns: time spent (per day) on social media. The response options ranged from "<10 min per day" to "4 h or more per day". The survey also asked participants what impact social media had on their quality of life. Quality of life was not assessed as a

TABLE 2 | PSMU Items listed in descending order of endorsement.

Item	Symptom	*M*	*SD*
I normally use social media for longer than I initially intended	Persistence	2.72	1.030
I sometimes find it difficult to disconnect from social media	Persistence	2.46	1.059
I spend less time than I should doing other day to day activities (such as household chores), because of the time I spend on social media	Displacement	2.39	1.041
I have fewer other interests (such as hobbies and other entertainment activities) because of using social media	Displacement	2.38	1.044
I need to spend increasing amounts of time engaged on social media to enjoy it	Tolerance	2.22	1.010
I feel irritability, anxiety or sadness when I stop using social media or can't use it	Withdrawal	2.05	1.029
I have misled friends, family members, or others about the amount of time I spend using social media.	Deception	1.94	1.016
Using social media has caused problems between me and my family/friends.	Conflict	1.93	1.001

The internal reliability for the PSMU measure in the present study was good, Chronbach's $\alpha = 0.878$.

separate variable. The respondents were asked to report whether they felt that social media impacted their quality of life by either improving or reducing it. The response options to this item were: "it generally improves my quality of life" or "it generally reduces my quality of life". Finally, participants were also asked if they had ever successfully undertaken an intentional period of abstinence (detox) from social media. For the present analysis, all responses to these variables were again dichotomized. This categorization gave us intense/frequent users (2 h or more per day) vs. infrequent users (<2 h per day), those who felt social media improved their quality of life (QoL) vs. reduced their QoL, and those who had and had not successfully abstained from social media for at least 1 week.

Analysis

Descriptive and inferential analyses were conducted to examine the hypotheses and to reach the objectives of the study. First, means along with the standard deviations, and where appropriate, medians with interquartile range were calculated for all the continuous variables. The proportion scores were calculated for the categorical variables. Independent sample *T*-test along with the Cohen's d effect size estimates were used to examine the group differences (gender, national culture) for PSMU scores. Inferential analyses allowed us to examine the relationships between potential predictors and PSMU. Pearson's bivariate correlation coefficients were calculated to test the associations between continuous variables. Bivariate and multivariate logistic regressions were conducted to examine the predictors of PSMU across individual sets of associations followed by adjusted analyses in which the associations were adjusted for covariates. Bivariate and multivariate logistic regressions were conducted with R (R Core Team, 2020), using generalized linear models in the base package.

RESULTS

Descriptive Analysis

PSMU scores were normally distributed ($M = 17.98$, $SD = 6.00$), while age was slightly left-skewed due to a larger number of relatively young people in the sample ($Mdn = 35.0$, IQR = 21.0). The mean number of PSMU symptoms strongly endorsed was 1.16 ($SD = 1.75$). The percentage of participants scoring above the PSMU cut-off (strong endorsement of 5 or more of the eight symptoms) was 6.82%. Mean PSMU scores by nation are detailed in **Table 3**. A further breakdown of PSMU percentages by socio-demographic and attitudinal variables are detailed in **Table 4**.

Gender-Related Differences, National Culture, and Age

An exploration of gender-related differences for PSMU scores found that men ($M = 18.08$, $SD = 5.99$) and women ($M = 17.89$, $SD = 6.01$) experienced similar levels of PSMU. An independent samples *t*-test confirmed that these marginal differences in PSMU scores were not statistically significant. There were, however, minimal but statistically significant gender-related differences at the item/symptom level, with males reporting higher scores than their female counterparts for specific PSMU items relating to (2) tolerance, (4) conflict and (5) deception. Conversely, females reported higher scores than males for (6) persistence. Details of items showing gender-related differences are reported in **Table 5**.

Exploring PSMU scores and national culture (collectivist vs. individualist) revealed that participants in collectivist nations ($M = 19.05$, $SD = 5.61$) generally scored higher than their individualist counterparts ($M = 15.39$, $SD = 6.14$). An independent samples *T*-test demonstrated that these group differences were statistically significant, t (10,616) $= -29.65$, $p < 0.001$, $d = -0.63$. This finding was also replicated at the PSMU item level, with the collectivist group scoring higher than their individualist counterparts on all items, $p < 0.001$ in all instances, with effect sizes ranging from Cohen's $d = 0.3$ to 0.6. We also conducted a Pearson's bivariate correlation between the continuous values for individualism, PSMU scores and age. As hypothesized, individualism scores were negatively correlated with PSMU, r (10,616) $= -0.275$, $p < 0.001$. Similarly, PSMU scores were negatively correlated with age, r (10,616) $= -0.332$, $p < 0.001$, Finally, age was positively correlated with individualism r (10,616) $= 0.384$, $p < 0.001$. While adjusting for covariates, we undertook bivariate and multivariate logistic regression to explore these data further. This analysis also allows us to communicate an easily comprehended statistical risk model (35).

Regression Analysis

Bivariate and multivariate logistic regressions were conducted with R (R Core Team, 2020), using generalized linear models in the base package. A binary logistic regression model was

TABLE 3 | Mean PSMU by nation in descending order of percentage above the cut-off.

Nation	*N*	*M*	*SD*	*% PSMU*
India	369	21.631	6.406	18.4
Pakistan	330	20.555	5.580	13.6
Indonesia	341	19.023	5.686	11.7
Ghana	416	19.762	5.462	10.8
Kuwait	320	20.153	5.150	10
UAE	323	20.087	5.226	9.9
Egypt	380	21.045	4.553	9.7
South Africa	423	18.478	5.900	9.2
Kenya	435	19.32	5.335	9.2
Mexico	399	17.278	6.121	8.5
Saudi Arabia	316	20.737	4.955	7.9
Nigeria	430	19.193	5.127	7.7
Algeria	329	19.283	5.159	7.3
Turkey	385	19.906	4.769	7.3
Brazil	391	17.829	5.548	6.4
China	341	21.150	4.886	6.2
Germany	287	14.387	6.594	5.6
France	310	15.168	6.100	5.5
US	330	15.476	6.615	4.7
Colombia	376	16.689	5.387	4
Russia	360	17.211	5.735	3.9
Japan	255	16.898	5.389	3.9
Singapore	364	19.184	5.189	3.3
Sweden	346	14.269	5.796	3.2
Argentina	385	15.956	5.312	3.1
Australia	355	15.397	5.981	3.1
Canada	327	14.945	5.869	2.4
Italy	351	14.752	5.681	2.3
UK	351	14.761	5.705	2
South Korea	293	17.038	5.643	1.7

used to predict PSMU status (strong endorsement of 5 or more PSMU symptoms), computing bivariate odds ratios (OR) and multivariate adjusted odds ratios (AOR) for all predictor variables. The predictor variables were age group, gender, national culture, household income bracket, education, parent status (having children under 18 years old), social media use-time status, history of successful abstention attempts and perceived impact of social media on the quality of life (QoL). The specifics of this analysis are detailed in **Table 4**.

DISCUSSION

This work explored problematic social media use (PSMU) across 30 nations. Beyond describing international variation in prevalence, the study also sought to identify several socio-demographic and attitudinal correlates of PSMU in adult population. Such an analysis contributes to our understanding of this emerging phenomenon that has implications for psychological wellbeing (9, 10, 12, 15).

In line with previous multinational studies (27, 30), rates of PSMU varied greatly between nations. In the present study, PSMU rates varied from a high of 18.4% for India to a low of 1.7% for South Korea. Some of this variation may be explicable in terms of population age. For example, according to UN data, the median age in India, as of 2020, is 28.4, while South Korea's median age is 43.7. This difference is reflected in our sample, with the mean age for Indian respondents being 35.2, while the South Koreans were significantly older, 44.4. However, regardless of individual age, living in a nation with a relatively youthful or relatively aging population may impact the frequency or style of social media use. For example, social media use may become more broadly normalized across all age groups in a more youthful national population.

Another possible explanation for the international variability in PSMU prevalence is the differing internet penetration rates, that is, the number of internet connections per head of population. Boer et al. (30) suspected that national internet penetration rates might influence the prevalence of PSMU. However, they found no such association across 29 nations. Furthermore, South Korea has one of the highest internet penetration rates in the world. It is also worth noting that over the past decade, the South Korean government have been aggressively responsive to the issue of internet addiction, viewing it as a serious social and public health problem (36). The South Korean government was an innovator and early adopter of public policy aimed at curbing problematic internet use, with measures such as "Internet Shutdown" and "Cooling Off" aimed at limiting adolescents' nocturnal online activities (37). Perhaps the lower rates of PSMU observed for South Korea in the present study are partly due to this proactive approach to the issue.

Beyond the median age of the population and internet-related public policy, there are likely to be other within-country factors responsible for the international variability in prevalence. National culture is one such candidate variable. To test our hypothesis about the cultural differences between the nations, we examined the scores of PSMU across the 30 nations that took part in this survey. Being from a collectivist society was predictive of PSMU. Looking at the nations with the highest rates of PSMU, the top 50% are all categorized as having collectivist national cultures (28). Furthermore, four of the five nations with the lowest rates of PSMU are individualist. This pattern of findings aligns with Cheng et al. (27), where data from a large multinational meta-analysis demonstrated a similar pattern of heightened PSMU among participants from relatively collectivist nations. It might be that the values and obligations associated with collectivism such as, compliance to social norms (fitting-in) and maintaining close kinship connections (38), drives a more compulsive style of social media use in such societies, leading to higher rates of PSMU. These ideas are certainly an area for future research.

Looking at the whole sample, we could also identify six robust predictors (in the statistical sense) of PSMU across nations. Foremost among these was time spent on social media. After adjusting for all other variables in the model, those who reported spending 2 hours (intense users) or more per day on social media were more than twice as likely to score above the PSMU cut-off. Several earlier studies also report this association (6, 18, 39).

TABLE 4 | Bivariate and multivariate logistic regression predicting PSMU scores above cut-off.

	N	PSMU *N (%)*	Odds ratio	Adjusted odds ratio
Over 35				
Yes	5,199	245 (4.7%)	–	–
No	5,386	477 (8.9%)	1.965 (1.676–2.303)***	1.246 (1.032–1.505)*
Gender				
Male	5,355	361 (6.7%)	–	–
Female	5,230	361 (6.9%)	1.026 (0.882–1.193)	1.029 (0.866–1.222)
National culture				
Individualist	3,047	125 (4.1%)	–	–
Collectivist	7,222	527 (7.9%)	2.011 (1.649–2.452)***	1.537 (1.190–1.985)***
Household income				
High	4,975	312 (6.3%)	–	–
Low	5,610	410 (7.3%)	1.123 (1.012–1.371)*	1.082 (0.906–1.291)
Completed college				
No	4,717	323 (6.8%)	–	–
Yes	5,868	399 (6.8%)	1.008 (0.865–1.172)	1.123 (0.938–1.344)
Children under 18				
No	5,202	257 (4.9%)	–	–
Yes	5,383	465 (8.6%)	1.819 (1.554–2.129)***	1.535 (1.273–1.850)***
Daily use-time				
Low (<2 h)	3,027	84 (2.8.%)	–	–
High (>=2 h)	7,558	638 (8.4%)	3.230 (2.563–4.072)***	2.403 (1.819–3.176)***
Abstention attempts				
Yes	2,281	142 (6.2%)	–	–
No	8,304	580 (7.0%)	2.167 (1.835–2.560)***	1.321 (1.101–1.584)**
Impact on QoL				
Improved	7,783	467 (6.0%)	–	–
Reduced	2,802	255 (9.1%)	1.567 (1.336–1.838)***	1.818 (1.517–2.183)***

Adjusted Odds Rartio model included all variables listed above, Ns ranged from 10,585 to 10,618 due to occasional missing data.
*** <0.001.
** <0.01.
* <0.05.

TABLE 5 | PSMU items with statistically significant gender-related differences.

Item	Content	*t*	*p*	*Cohen's d*
2	I need to spend increasing amount of time engaged on social media in order to enjoy it	4.209	<0.001	0.082
4	Using social media has caused problems between me and my friends and family	2.973	0.003	0.058
5	I have misled friends, family members, or others about the amount of time I spend using social media	3.277	0.001	0.064
6	I normally use social media for longer than I initially intended	–2.638	0.008	–0.051

However, within the present study design, it is not possible to distinguish cause from consequence. Time spent on social media may result from having developed problematic usage patterns. It might equally be a precondition or precursor to the development of PSMU among the vulnerable. The vast majority of intense users did not score above the PSMU cut-off, and previous research has even reported a positive association between intense social media use and wellbeing in specific contexts where intense use is relatively normative (30). Similarly, in the present analysis, although uncommon, some of the infrequent users also reported PSMU. What constitutes intense use is likely to vary across time and place and between individuals. For some people, 30 min of social media use may be highly ego-dystonic, likely to cause distress for themselves and significant others.

Other attitudinal and behavioral predictors included viewing social media as detrimental to one's quality of life and having never successfully attempted to abstain (detox) from social media. Like "time-spent on social media", the inability or unwillingness to complete a period of abstinence can be viewed as a consequence of PSMU. Conversely, it might also be argued that consciously imposing periods of abstinence (prolonged breaks) on oneself offer some protection against social media use becoming problematic. In contrast, the association between perceptions of social media as negatively impacting one's quality of life is most simply explained as a possible consequence of PSMU.

We have also tested the hypothesis that PSMU is associated with younger age. Our findings showed that amongst the influential socio-demographic predictors of PSMU were younger age group, national culture and parenthood (being a parent to a minor). The association with younger age (adolescence) has been widely reported (31) and perhaps reflects generational differences in early exposure and early adoption of such emerging technologies. Although statistically significant, the age group difference in the present study had the lowest of all the adjusted odds ratios (1.2). As earlier generations increasingly adopt social media in existing users age, these age-related differences for PSMU may well fade.

The fact that parenthood was predictive of PSMU is interesting. Unfortunately, we cannot identify any previous studies that have included this as a variable, perhaps due to the pervasive focus on adolescents. In explaining the present finding, we propose that the stress associated with parenting may lead to PSMU as a form of mood-modification or escape strategy.

There is a growing body of evidence detailing lower levels of subjective wellbeing and higher stress levels among parents compared to nonparents (40). These higher stress levels are variously attributed to the time/role demands, financial burden and sleep deprivation associated with parenthood (40).

Finally, being from a collectivist society was predictive of PSMU. As discussed above, this is a finding that merits further research, and it might be that collectivist family structures and communication patterns increase the risk of PSMU.

While this study sheds new multinational cross-generational light on our understanding of PSMU, it also has several significant limitations. Firstly, the cross-sectional and correlational design means that any discussion about causation is, at best, tentative/speculative. The measure of time spent online in our study was a self-reported estimate that may potentially carry some bias. Future studies should seek opportunities to utilize objective measures of online behavior, such as using the specialized monitoring software. Using an adapted/original 8-item PSMU measure limits meaningful cross-study comparisons. Although the PSMU measure used had good face validity, and the items were drawn from well-validated existing tools, the percentage of PSMU are not directly interpretable in the context of earlier research. However, the primary aim of the present study was to look at variation between nations and identify potentially helpful correlates as a preliminary step toward informing public policy and health initiatives aimed at reducing PSMU incidence and prevalence. In our study, we did not have a variable measuring such important sociodemographic characteristic as the place of residence. Therefore, we recommend that future studies examining the cultural differences in the context of PSMU should include such a variable in their analysis to allow a thorough examination of cultural differences.

Based on our findings and the mentioned above limitations, we propose the following directions for future studies. Further studies could explore the role of culture in PSMU and perhaps examine the role of culture also in the context of other online behaviors such as internet gaming. This will allow to ascertain the observed differences and to better understand the mechanisms behind the differing risks in people from individualist vs. collectivist societies. Another area of exploration that warrants further research is related to our finding of the role of parenthood (being a parent of a minor) in PSMU. Future studies could examine what aspects of parenthood appear to drive the possible risks of PSMU associated with parenting or examine whether PSMU is a manifestation of maladaptive parenting practices or perhaps a result of other factors, such as parental psychological wellbeing.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because the ethical approval for the study requires that only anonymized data may be shared on request with verified researchers. Requests to access the datasets should be directed to Prof. Justin Thomas, Justin.Thomas@zu.ac.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ithra's Internal Review Board (IRS 202171). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

JT contributed to conception of the project, analysis, and drafting of the manuscript. MV contributed to submission and review process. FA, BA, and YA contributed to the data collection and drafting of the manuscript. All authors contributed to the article and approved the submitted version.

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REFERENCES

1. Postman N. *Technopoly: The Surrender of Culture to Technology*. New York, NY: Vintage (1993). p. 8.
2. Datareportal. *Global Social Media Stats*. Datareportal (2021).
3. Verduyn P, Lee DS, Park J, Shablack H, Orvell A, Bayer J, et al. Passive Facebook usage undermines affective wellbeing: experimental and longitudinal evidence. *J Exp Psychol Gen*. (2015) 144:480–8. doi: 10.1037/xge0000057
4. Twenge JM, Joiner TE, Rogers ML, Martin GN. Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clin Psychol Sci*. (2018) 6:3–17. doi: 10.1177/2167702617723376
5. Statistica. *Daily Time Spent on Social Networking by Internet Users Worldwide from 2012 to 2020*. Statistica (2021).
6. Boer M, Stevens GWJM, Finkenauer C, de Looze ME, van den Eijnden RJJM. Social media use intensity, social media use problems, and mental health among adolescents: investigating directionality and mediating processes. *Comput Hum Behav*. (2021) 116:106645. doi: 10.1016/j.chb.2020.106645
7. Casale S. Problematic social media use: conceptualization, assessment and trends in scientific literature. *Addict Behav Rep*. (2020) 12:100281. doi: 10.1016/j.abrep.2020.100281
8. Chegeni M, Shahrbabaki PM, Shahrbabaki ME, Nakhaee N, Haghdoost A. Why people are becoming addicted to social media: a qualitative study. *J Educ Health Promot*. (2021) 10:175. doi: 10.4103/jehp.jehp_1109_20
9. Young KS. Internet addiction: the emergence of a new clinical disorder. *Cyberpsychology Behav Soc Netw*. (1998) 1:237–44. doi: 10.1089/cpb.1998.1.237
10. Young KS. Internet addiction: evaluation and treatment. *BMJ*. (1999) 319(Suppl S4):9910351. doi: 10.1136/sbmj.9910351
11. Griffiths MD. Nicotine, tobacco and addiction. *Nature*. (1996) 384:18. doi: 10.1038/384018a0
12. Griffiths M. A "components" model of addiction within a biopsychosocial framework. *J Subst Use*. (2005) 10:191–7. doi: 10.1080/14659890500114359
13. Brown RIF. Some contributions of the study of gambling to the study of other addictions. In: Eadington WR, Cornelius J, editors. *Gambling Behavior and Problem Gambling*. Reno, NV: University of Nevada Press (1993). p. 241–72.
14. Griffiths MD. *Gambling and Gaming Addictions in Adolescence*. Leicester: British Psychological Society/Blackwell. (2002).
15. Griffiths M. Internet addiction-time to be taken seriously? *Addict Res*. (2000) 8:413–8. doi: 10.3109/16066350009005587
16. American Psychiatric Association. *Diagnostic and statistical manual of mental disorders: DSM-IV*. Washington, DC: American Psychiatric Association (1994).
17. Pontes HM, Griffiths MD. Measuring DSM-5 internet gaming disorder: development and validation of a short psychometric scale. *Comput Hum Behav*. (2015) 45:137–43. doi: 10.1016/j.chb.2014.12.006
18. van den Eijnden RJJM, Lemmens JS, Valkenburg PM. The social media disorder scale. *Comput Hum Behav*. (2016) 61:478–87. doi: 10.1016/j.chb.2016.03.038
19. Petry NM, Rehbein F, Gentile DA, Lemmens JS, Rumpf HJ, Mößle T, et al. An international consensus for assessing internet gaming disorder using the new DSM-5 approach. *Addiction*. (2014) 109:1399–406. doi: 10.1111/add.12457
20. World Health Organization. *International Classification of Diseases for Mortality and Morbidity Statistics (11th Revision)*. WHO (2018).
21. American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders: DSM-5*. Association AP, editor. Arlington, VA: American Psychiatric Association (2013).
22. Andreassen CS, Pallesen S. Social network site addiction-an overview. *Curr Pharm Des*. (2014) 20:4053–61. doi: 10.2174/13816128113199990616
23. Andreassen CS. Online social network site addiction: a comprehensive review. *Curr Addict Rep*. (2015) 2:175–84. doi: 10.1007/s40429-015-0056-9
24. Hussain Z, Starcevic V. Problematic social networking site use: a brief review of recent research methods and the way forward. *Curr Opin psychol*. (2020) 36:89–95. doi: 10.1016/j.copsyc.2020.05.007
25. Montag C, Wegmann E, Sariyska R, Demetrovics Z, Brand M. How to overcome taxonomical problems in the study of Internet use disorders and what to do with "smartphone addiction?" *J Behav Addict*. (2021) 9:908–14. doi: 10.1556/2006.8.2019.59
26. Andreassen CS, Pallesen S, Griffiths MD. The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addict Behav*. (2017) 64:287–93. doi: 10.1016/j.addbeh.2016.03.006
27. Cheng C, Lau Y-C, Chan L, Luk JW. Prevalence of social media addiction across 32 nations: meta-analysis with subgroup analysis of classification schemes and cultural values. *Addict Behav*. (2021) 117:106845. doi: 10.1016/j.addbeh.2021.106845
28. Hofstede G. *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations*. 2nd ed. London: Sage Publications (2001).
29. Su W, Han X, Yu H, Wu Y, Potenza MN. Do men become addicted to internet gaming and women to social media? A meta-analysis examining gender-related differences in specific internet addiction. *Comput Hum Behav*. (2020) 113:106480. doi: 10.1016/j.chb.2020.106480
30. Boer M, van den Eijnden RJJM, Boniel-Nissim M, Wong S-L, Inchley JC, Badura P, et al. Adolescents' intense and problematic social media use and their wellbeing in 29 countries. *J Adolesc Health*. (2020) 66(6, Supplement):S89–99. doi: 10.1016/j.jadohealth.2020.02.014
31. Nakayama H, Mihara S, Higuchi S. Treatment and risk factors of Internet use disorders. *Psychiatry Clin Neurosci*. (2017) 71:492–505. doi: 10.1111/pcn.12493
32. Schou Andreassen C, Billieux J, Griffiths MD, Kuss DJ, Demetrovics Z, Mazzoni E, et al. The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: a large-scale cross-sectional study. *Psychol Addict Behav*. (2016) 30:252–62. doi: 10.1037/adb0000160
33. van Rooij AJ, Prause N. A critical review of "Internet addiction" criteria with suggestions for the future. *J Behav Addict*. (2014) 3:203–13. doi: 10.1556/JBA.3.2014.4.1
34. Woodley MA, Bell E. Consanguinity as a major predictor of levels of democracy: a study of 70 nations. *J Cross Cult Psychol*. (2013) 44:263–80. doi: 10.1177/0022022112443855
35. Nelson SLP, Ramakrishnan V, Nietert PJ, Kamen DL, Ramos PS, Wolf BJ. An evaluation of common methods for dichotomization of continuous variables to discriminate disease status. *Commun Stat Theory Methods*. (2017) 46:10823–34. doi: 10.1080/03610926.2016.1248783
36. Heo J, Oh J, Subramanian SV, Kim Y, Kawachi I. Addictive internet use among Korean adolescents: a national survey. *PloS One*. (2014) 9:e87819. doi: 10.1371/journal.pone.0087819
37. Hawkins M. *South Korea Introduces Yet Another Law to Curb Gaming's Ills: NBC News*. (2012). Retrieved from: https://www.nbcnews.com/tech/tech-news/south-korea-introduces-yet-another-law-curb-gamings-ills-flna158168 (accessed December 25, 2021).
38. Heinrichs N, Rapee R, Alden L, Bögels S, Hofmann SG, Oh KJ, et al. Cultural differences in perceived social norms and social anxiety. *Behav Res Ther*. (2006) 44:1187–97. doi: 10.1016/j.brat.2005.09.006
39. Boer M, Stevens G, Finkenauer C, van den Eijnden R. Attention deficit hyperactivity disorder-symptoms, social media use intensity, and social media use problems in adolescents: investigating directionality. *Child Dev*. (2020) 91:e853–65. doi: 10.1111/cdev.13334
40. Glass J, Simon RW, Andersson MA. Parenthood and happiness: effects of work-family reconciliation policies in

22 OECD countries. *AJS*. (2016) 122:886–929. doi: 10.1086/688892

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Facebook use and its predictive factors among students: Evidence from a lower- and middle-income country, Bangladesh

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Background: Facebook is a popular social networking site in the modern world. It has an adverse effect such as impairing daily health and psychological health and also interpersonal relationships when the use becomes problematic.

Aims: To examine problematic Facebook use (PFU) and its predictors among Bangladeshi students during the COVID-19 pandemic.

Method: A cross-sectional online survey was conducted among 601 Bangladeshi students and collected data related to socio-demographic information, behavioral health, internet use behavior, depression, anxiety and problematic Facebook use [assessed using the Bergen Facebook Addiction Scale (BFAS)]. The data were analyzed using descriptive (frequencies and percentages) and inferential statistics (independent sample *t*-tests, one-way ANOVAs, correlations, and multivariable linear regression).

Results: The results indicated that 29.1% of participants were problematic Facebook users (using cutoff $\geq$18 out of 30). Medical college students had higher mean score on PFU than other students ($p < 0.001$). In addition, the mean score of PFU was significantly higher among the students who were in a relationship ($p = 0.001$), did not engage in physical activity ($p < 0.001$), used the internet more than 5 h per day ($p < 0.001$), used social media ($p < 0.001$), and had depression or anxiety symptoms ($p < 0.001$). PFU was significantly associated with depression and anxiety among the whole sample. Predictive factors for PFU included relationship status, daily internet use time, gaming, social media use, depression, and anxiety. The model predicted almost 33.2% variance for PFU.

Conclusions: Findings suggest interventions should be implemented for students with a special focus on medical students who had higher score of PFU than other types of students.

KEYWORDS

COVID-19, problematic Facebook use, Facebook addiction, online behavior, students

Introduction

Millions of individuals worldwide have been affected by the disruptive consequences of the COVID-19 pandemic. To combat the pandemic, governments implemented preventive actions to minimize the spread of the virus such as national and local lockdowns, closing all educational institutions and introducing online teaching, shutting down non-essential businesses, and enforcing spatial distancing. Such measures were also introduced in Bangladesh (where the present study was carried out) (1, 2). Such measures have led to a situation of increased social media use to stay connected with work colleagues, to engage in education activities, and to interact socially with friends and acquaintances (3, 4).

Facebook is widely considered as one of the most popular social networking sites globally, and it has had a significant impact on interpersonal communication (5). However, problematic Facebook use (PFU) occurs when the engagement becomes uncontrollably excessive and has a negative impact and clinically impairs daily activities, interpersonal relationships, and psychological well-being (6, 7). Moreover, a recent study reported that students who were problematic Facebook users scored significantly higher than non-problematic Facebook users on the meaninglessness of effortfulness, belief in fate, and belief in an unjust world (8). During the COVID-19 pandemic, problematic social media use appears to have increased because individuals' use of technologies has increased as a result of home confinement and/or staying at home for quarantining purposes (9, 10) and technology-associated risky behaviors have been reported (11).

Dhaka, the capital of Bangladesh, had the second highest Facebook use among all cities globally in 2018 (12) and suggests PFU might be a growing issue (13). In March, 2020, it was reported that there were more than 37 million Facebook users in Bangladesh, which increased to more than 44 million by the end of the year (14). One-quarter of the Bangladeshi population are currently active users of Facebook, and young adults (aged 18–24 years) are the largest group of users (14). The number of adult users using social networking sites has increased during the COVID-19 pandemic because of switching to online learning and fewer opportunities to meet socially (10). For instance, an online survey among Italian adults during the COVID-19 pandemic lockdown reported social networking use had increased significantly (10), as has been found in other studies [e.g., (15, 16)].

Excessive Facebook use has the potential to interrupt learning processes and can result in a negative impact on academic performance (17). Moreover, problematic Facebook use can be deleterious to physical and psychological wellbeing among a minority of individuals. For instance, PFU has been associated with depression, anxiety, stress, low self-esteem, personality disorder, and (in extreme cases) suicidality (18–20). One study conducted during the pandemic in Bangladesh related to social media use (as opposed to PFU) by Hossain et al. (9), reported that increased social media exposure over 4 h per day led individuals to be more anxious than individuals who used it for <2 h daily.

Despite increasing concern, there have been few studies assessing PFU in Bangladesh during COVID-19 although two studies were conducted prior to the pandemic. Mamun and Griffiths (13) surveyed 300 Bangladeshi university students and reported a PFU prevalence rate of 39.7%. This study reported that PFU was associated with being single, having less involvement in physical activities, sleep disturbance (when individuals sleep more or <6–7 h of sleep nightly), time spent on Facebook (≥5 h per day), and depression symptoms. Another study by Sayeed et al. (21) surveyed 404 university students and reported a similar PFU prevalence rate of 36.9%. In this study, PFU was associated with having relationship break-ups, having history of domestic violence, having stressful life events, suffering from sleep disturbance (i.e., more than 8 h sleep status compared to 6–8 h normal status), spending more than 5 h daily time on Facebook, and having symptoms of depression (21).

Internet use appears to have increased during the pandemic because the time spent indoors has greatly increased due to self-isolation, lockdowns and quarantines. Moreover, there appears to be far more research on Facebook addiction in high-income countries than in lower- and middle-income (LMIC) countries probably because internet use is more widespread than high-income countries. Therefore, the present study was carried out in a LMIC country. Additionally, PFU has not been examined in Bangladesh during the pandemic. Given the lack of research, the present study investigated PFU among Bangladeshi students to (i) examine the prevalence of problematic Facebook use during the COVID-19 pandemic, and (ii) identify the correlates and predictive factors of PFU. As the study was exploratory, there were no specific hypotheses.

Methods

Study procedure and participants

A web-based survey was carried out among the Bangladeshi students between October 7 and November 2, 2020 through the use of *Google Forms*. The Checklist for Reporting Results of Internet E-Surveys was utilized in conducting the survey. A structured questionnaire was used for this study recruiting participants from social media such as Facebook, WhatsApp, etc. in Bangladesh where students interact with each other. A convenience sampling technique was utilized to collect data and the study inclusion criteria were being a Bangladeshi student, studying at high school, college or university, having access to the internet, and wanting to voluntarily participate in the study. A total of 617 individuals completed the survey but after removing the incomplete responses, 601 survey responses were considered for final analysis. The survey included questions concerning socio-demographics, behavioral health, and internet use behaviors, along with psychometric scales assessing depression, anxiety, and problematic Facebook use.

Ethical considerations

Informed consent was outlined in the description of the study purpose. No incentives (e.g., monetary rewards, prizes, or non-monetary incentives) were offered to participate in the survey. The respondents were only able to participate in the survey after they agreed to the online consent (that adhered to the guidelines of the Helsinki Declaration, 1975). Participants were assured about the anonymity and confidentiality of the data and they had the full right to withdraw their responses at any time during the survey time. Formal ethics permission was also provided by the ethical review committee of Institute of Allergy and Clinical Immunology of Bangladesh, Dhaka, Bangladesh. A copy of the English translation of the survey is available from the corresponding author on request.

Measures

Sociodemographic factors

Sociodemographic information was collected regarding gender, educational status (e.g., university, medical college, high school), present residence (e.g., urban or rural), relationship status (i.e., single, in a relationship, married), monthly family income (e.g., lower-class = <15,000 BDT, middle class = 15,001–30,000 BDT, upper class = more than 30,000 BDT) and type of family (e.g., nuclear or extended family). Additionally, their current living condition with family was also assessed.

Behavioral health-related measures

Behavioral health related information was collected based on participants smoking status, sleep status, and physical exercise. For assessing sleeping patterns, the study followed prior Bangladeshi studies comprising three categories [e.g., normal sleeping status = 6–7 h (22)]. Physical exercise in the form of walking, cycling, swimming, or other activities for at least 30 min daily was considered. Perceived health status was assessed by asking participants whether they suffered from chronic diseases or not (e.g., asthma, diabetes, heart problems, kidney problems, etc.) (13, 23).

Online use behaviors

Several online use behaviors were assessed in the present study. Considering the prior Bangladeshi studies, the duration of online use was assessed utilizing categories (e.g., <2 h, 2–3 h, 4–5 h, and more than 5 h). The online activities included educational activities, chatting/texting, online gaming, watching/streaming videos/films, social media browsing, watching sexual materials/pornography, and online shopping (13, 23).

Depression

The two-item Patient Health Questionnaire (PHQ-2) was used for assessing the presence of depression. Participants are asked how often they experienced the two core criteria for depressive disorders over the past 2 weeks (i.e., "Little interest or pleasure in doing things", and "Feeling down, depressed, or hopeless"), which are responded to on a 4-point Likert scale (0 = not at all, 1 = several days, 2 = more than half the days, 3 = nearly every day) (24, 25). The total score ranges from 0 to 6, where ≥ 3 was considered as the cutoff point indicating the presence of depression (25). In the present study, the Cronbach's alpha was 0.73.

Anxiety

The two-item Generalized Anxiety Disorder (GAD-2) scale was used for assessing the presence of anxiety. Participants are asked how often they experienced the two core criteria for anxiety disorders over the past 2 weeks (i.e., "Feeling nervous, anxious or on edge", and "Not being able to stop or control worrying"), which are responded to on a 4-point Likert scale (0 = not at all, 1 = several days, 2 = more than half the days, 3 = nearly every day) (25, 26). The total score ranges from 0 to 6, where ≥ 3 was considered as the cutoff point indicating the presence of anxiety (25). In the present study, the Cronbach's alpha was 0.73.

Problematic Facebook use

The Bergen Facebook Addiction Scale was used for assessing problematic Facebook Use (27). The scale comprises six items (e.g., "How often in the last year have you spent a lot of time thinking about Facebook or planned use of Facebook?"), which are responded to on a 5-point Likert scale from 1 (very rarely) to 5 (very often). A score of $\geq$18 (out of 30) was used as cutoff score to operationally define problematic Facebook users (27) as has been used in previous studies in Bangladesh [e.g., (13, 21)]. In the present study, the Cronbach's alpha was 0.73.

Statistical analysis

IBM SPSS Statistics for Windows (Version 25.0. Armonk, NY: IBM Corp.) and Microsoft Excel 2019 were used for statistical analysis. Descriptive statistics (such as frequency, and percentages, mean, and standard deviation), and inferential statistics were applied in the present study. The data distribution was normal and multi collinearity-related issues were absent. Therefore, parametric tests such as analysis of variance (ANOVA) test, and independent sample t-test were used considering the variables category to assess mean differences among the studied variables using Bonferroni correction, with $p = 0.002$ as the significance level. The Pearson correlation was used to establish the linear association between continuous variables and problematic Facebook use. A multivariable linear regression model was utilized to identify the predictive factors influencing problematic Facebook use with a 95% confidence interval.

Results

Characteristics of the participants

More than half of the participants were male (57.2%) and used the internet daily for more than 5 h (53.2%). Nearly two-thirds were university students (65.6%), more than one-quarter were medical college students (29.6%), and the remainder were high school students aged 18–19 years (4.8%). Approximately three-quarters came from an urban area (75.2%) and nuclear family (78%), and 44.6% had more than 30,000 (BDT) monthly income. Four-fifths of participants were single (79.5%). Approximately half of the participants (49.1%) took part in physical exercise and more than 90% used the internet for messaging, watching videos, and browsing social media. Additionally, 43.3% and 32.6% of the participants reported depression and anxiety symptomology, respectively (Table 1).

Mean differences of studied variables with problematic Facebook use

The mean BFAS score was 16 out of 30 (SD ± 5.72) and slightly more than one-quarter (29.1%) were classified as problematic Facebook users (cutoff: ≥18). Table 1 showed no significant gender differences among the participants in terms of PFU. Medical students reported significantly higher PFU score than the other cohorts ($F = 10.923$, $p < 0.001$) whereas those in a relationship had significantly higher PFU score than single and married participants ($F = 7.550$, $p = 0.001$). PFU levels were significantly higher among participants who did not engage in physical exercise ($t = 4.188$, $p < 0.001$) and used the internet for more than 5 h daily ($F = 21.561$, $p < 0.001$). In relation to specific types of internet use, messaging ($p = 0.024$) and social media browsing ($p < 0.001$) were significantly associated with PFU. In addition, depression and anxiety symptomology were both significantly associated with PFU ($p < 0.001$).

Correlation coefficient between continuous variables and problematic Facebook use

The result showed that PFU had a significant linear relationship with depression and anxiety. The relationship of PFU with depression ($r = 0.411$, $p < 0.001$) and anxiety ($r = 0.460$, $p < 0.001$) was moderately strong while depression and anxiety was strongly related ($r = 0.630$, $p < 0.001$) (Table 2).

Predictive models for problematic Facebook use

Table 3 presents predictive models for PFU using multivariable linear regression. The model predicted that increasing in daily internet use time ($B = 1.293$, $p < 0.001$), social media use ($B = 5.297$, $p < 0.001$), depression ($B = 0.671$, $p < 0.001$), and anxiety ($B = 1.119$, $p < 0.001$) can positively increase the PFU. Additionally, relationship status ($B = -0.741$, $p = 0.020$), and gaming ($B = -0.982$, $p = 0.046$) negatively impacted PFU. The overall model explained 33.2% variance for predicting PFU [$F (18, 582) = 16.085$, $p < 0.001$, $R^2 = 0.332$].

Discussion

Using a cutoff score of ≥18 out of 30 on the Bergen Facebook Addiction Scale, 29.1% of the sample were operationally defined as problematic Facebook users. This prevalence rate of PFU is lower than the two previous Bangladeshi studies among Bangladeshi university students utilizing the same instrument [39.7% in (13), 36.9% in (21)]. No previous study has investigated PFU during the pandemic in Bangladesh. It was expected that students would be at higher risk of PFU given the higher exposure to the internet during the pandemic.

The lower prevalence of PFU in the present study may have been because students spent more time on other internet-related activities (such as online learning and teaching). Studies conducted outside of Bangladesh have also reported higher rate of problematic Facebook use among students than in the present study including Malaysia [47% of the university students ($n = 441$) (28)], and Thailand [41.8%; of the high school students ($n = 972$) (29)]. The prevalence rate of PFU in a study among postgraduate university students ($n = 100$) in India was 26% (30). The differences in prevalence rates may simply have been due to methodological factors such as the different samples, setting, and sample size.

Results showed no significant gender differences among the participants in respect to PFU. This concurs with the findings of the two previous Bangladeshi studies (13, 21). Relationship status was not significantly associated with PFU in previous Bangladeshi studies (13, 21), but a two-fold higher risk of PFU

TABLE 1 Distribution of the studied variables with problematic Facebook use.

Variables	Total sample		F/*t*-test value	*p*-value
	n (%)	Mean ± SD (BFAS score)		
Socio-demographic variables				
Gender				
Male	344 (57.2)	15.86 ± 5.63	−0.719	0.473
Female	257 (42.8)	16.20 ± 5.82		
Educational status				
University	394 (65.6)	15.68 ± 5.41	10.923	**<0.001**
Medical college	178 (29.6)	17.29 ± 5.86		
High school	29 (4.8)	12.51 ± 6.80		
Current residence				
Rural	149 (24.8)	15.99 ± 5.43	−0.037	0.971
Urban	452 (75.2)	16.01 ± 5.81		
Monthly family income (BDT)				
<15,000	106 (17.6)	15.85 ± 5.64	1.212	0.298
15,000–3,000	227 (37.8)	16.46 ± 5.42		
>30,000	268 (44.6)	15.67 ± 5.97		
Family type				
Joint	132 (22.0)	15.99 ± 5.14	−0.036	0.971
Nuclear	469 (78.0)	16.01 ± 5.87		
Relationship status				
Single	478 (79.5)	16.19 ± 5.62	7.550	**0.001**
In a relationship	67 (11.1)	16.92 ± 5.63		
Married	56 (9.3)	13.30 ± 5.92		
Currently living with family				
No	78 (13.0)	15.56 ± 5.98	−0.735	0.462
Yes	523 (87.0)	16.07 ± 5.67		
Behavioral health-related questions				
Number of daily sleeping hours				
<6 h	69 (11.5)	15.47 ± 5.62	0.601	0.549
6–7 h	324 (53.9)	15.93 ± 5.48		
More than 7 h	208 (34.6)	16.30 ± 6.09		
Physical exercise				
No	306 (50.9)	16.95 ± 5.69	4.188	**<0.001**
Yes	295 (49.1)	15.02 ± 5.58		
Smoking status				
No	550 (91.5)	16.09 ± 5.62	1.163	0.245
Yes	51 (8.5)	15.11 ± 6.65		
Perceived health related problem				
No	536 (89.2)	15.92 ± 5.58	−0.865	0.390
Yes	65 (10.2)	16.67 ± 6.70		
Online use behaviors				
Daily internet use time				
<2 h	23 (3.8)	11.21 ± 3.94	21.561	**<0.001**
2–3 h	114 (19.0)	14.06 ± 5.06		
4–5 h	144 (24.0)	14.86 ± 4.87		
More than 5 h	320 (53.2)	17.55 ± 5.88		

(Continued)

TABLE 1 Continued

Variables	Total sample		F/t test value	*p*-value
	n (%)	Mean ± SD (BFAS score)		
Purpose of online use (Yes vs. No)				
Educational	506 (84.2)	15.89 ± 5.62 vs. 16.58 ± 6.17	1.080	0.281
Messaging	581 (96.7)	16.14 ± 5.61 vs. 12.15 ± 7.22	−2.444	**0.024**
Gaming	148 (24.6)	15.97 ± 5.80 vs. 16.01 ± 5.69	0.070	0.944
Watching video	556 (92.5)	16.09 ± 5.65 vs. 14.97 ± 6.42	−1.258	0.209
Social media use	574 (95.5)	16.29 ± 5.59 vs. 9.85 ± 4.80	−5.884	**<0.001**
Shopping	128 (21.3)	16.00 ± 5.82 vs. 16.01 ± 5.69	0.019	0.985
News	379 (63.1)	15.87 ± 5.61 vs. 16.23 ± 5.89	0.756	0.450
Others	405 (67.4)	16.20 ± 5.71 vs. 15.61 ± 5.90	−1.182	0.238
Psychopathological factors				
Depression (Cutoff point: ≥3 out of 6)				
Probable depression	260 (43.3)	18.10 ± 5.67	−8.259	**<0.001**
Normal	341 (56.7)	14.41 ± 5.21		
Anxiety (Cutoff point: ≥3 out of 6)				
Probable anxiety	196 (32.6)	19.09 ± 5.66	−9.588	**<0.001**
Normal	405 (67.4)	14.51 ± 5.11		

The bold values referred to significant results.

TABLE 2 Correlation coefficients between continuous variables and problematic Facebook use.

Variables	Mean ± SD	Problematic Facebook use	Depression	Anxiety
Problematic Facebook use	16.0 ± 5.71	1		
Depression	2.37 ± 1.42	0.411**	1	
Anxiety	2.07 ± 1.57	0.460**	0.630**	1

**Correlation is significant at the 0.01 level (2-tailed).

was found among students who had failed to initiate a romantic relationship (21). The present study found a significantly higher risk of PFU among participants currently in a relationship compared to those who were married or single. In-person interaction may have been restricted between such participants during the long-enforced lockdown. Therefore, they may have spent more time on Facebook maintaining communication with each other, which contributed to PFU.

The present study also found that medical students had a higher level of PFU than university or high school students which has not been explored in any previous studies. Facebook generally attracts students with its various features (e.g., communication, entertainment, and information exchange) particularly in the home-confined situation that occurred during the COVID-19 pandemic. In general, medical students have more stressful academic study than other students (31) which may result in students using Facebook primarily to relieve stressful academic pressures. Furthermore, in order to connect with friends or family members, Facebook use may result in students spending increasingly more time on the site, leading to problematic or addictive behavior for some. The present study also suggested that high school students reported less PFU. This may be because they are restricted in using their smartphones by their parents in Bangladeshi culture.

Predictably, and as with previous Bangladeshi studies (13, 21) spending more time on internet was associated with PFU in the present study. Given that individuals are spending more time on Facebook, it is likely that they are using the platform for various online purposes (e.g., messaging friends, watching videos, reading news, etc.,). The online use of messaging and social media browsing was predictably associated with problematic Facebook use given that Facebook use comprises both these online activities, but educational use of the internet was not associated with PFU in the present study. It is evident that PFU can adversely affect a user's mental health and has been regarded as a global public health concern among a minority of social media users (18, 20). As expected, depression and anxiety symptomology had

TABLE 3 Predictive models for problematic Facebook use.

Variables	Model Fit: F (18, 582) = 16.085, $p < 0.001$, $R^2 = 0.332$				
	B	Std. Error	β	95% CI (LB, UB) for B	p
Constant	4.711	2.129		0.529, 8.893	0.027
Relationship status	−0.741	0.317	−0.082	−1.363, −0.118	0.020
Daily internet use time	1.293	0.228	0.203	0.845, 1.740	<0.001
Gaming	−0.982	0.492	−0.074	−1.948, −0.015	0.046
Social media use	5.297	1.021	0.192	3.291, 7.303	<0.001
Depression	0.671	0.179	0.167	0.319, 1.023	<0.001
Anxiety	1.119	0.162	0.308	0.801, 1.437	<0.001

Only significant variables have been shown in the table. B = Unstandardized coefficient; β = Standardized coefficient; LB = Lower bound; UB = Upper bound.

the strongest associations with PFU. Previous studies have indicated that PFU is associated with depression (32–34). Prior Bangladeshi studies have reported that depressed students are approximately at two to three times greater risk of PFU (13, 21). Similarly, other studies have reported anxiety as a predictor of PFU (35–37). Studies have also shown that trait anxiety is a positive predictor for PFU in the US (36), Pakistan (37), and other countries (18).

The present study findings also concur with previous research that depression and anxiety (as assessed using the PHQ-2 and GAD-2 scales) were significantly associated with PFU during COVID-19 pandemic, indicating that students with depression and anxiety who uses Facebook are at increased risk of developing PFU. However, the study did not directly ask students if their depression and anxiety symptoms had worsened during the pandemic. As a result, future research should determine whether an increase in PFU is associated with an increase in reported depression or anxiety symptoms.

The present study has some limitations. As the study was conducted online, used convenience sampling, and had a modestly sized sample, various selection biases may have arisen. Moreover, the study was non-representative in nature as only participants from a few higher educational establishments were recruited, some types of students were not represented (e.g., there were no engineering students and specific study disciplines were not asked in the survey), all participants were recruited online, and the data were self-report, all of which have well-known methods biases. Finally, it should also be noted that although the BFAS has been used in Bangladesh in a few previous studies it has not been officially validated into Bangla.

Conclusion

The study found that 29.1% students were problematic Facebook users. Medical college students had higher score on PFU than others, whereas relationship status, daily internet use time, social media use, and psychological symptoms were the predictive factors for PFU. Although this study reported lower prevalence rate of PFU than the prior Bangladeshi studies, the proportion of students at risk of PFU was still arguably of concern. Educational institutes should implement interventions to reduce PFU among students. Additionally, therapeutic interventions can be developed for healthy and safe Facebook use with a focus on student mental health given its association with PFU.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the corresponding author upon reasonable request.

Ethics statement

The studies involving human participants were reviewed and approved by Institute of Allergy and Clinical Immunology of Bangladesh, Dhaka, Bangladesh (Reference: IRBIACIB/CEC/03202030). The patients/participants provided their written informed consent to participate in this study.

Author contributions

FA-M and MM conceptualized the study and wrote the first draft, whereas all author contributed to revise the manuscript. FA-M, IH, and MM partook in study implementation, data collection, and data analysis. MG and MM supervised the project. 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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References

1. Akter T, Zeba Z, Hosen I, Al-Mamun F, Mamun MA. Impact of the COVID-19 pandemic on BMI: its changes in relation to socio-demographic and physical activity patterns based on a short period. *PLoS ONE.* (2022) 17:e0266024. doi: 10.1371/journal.pone.0266024

2. Raquib A, Raquib R, Jamil S, Hossain A, Al-Mamun F, Mamun MA. Knowledge, Attitudes, and Practices toward the prevention of COVID-19 in Bangladesh: a systematic review and meta-analysis. *Front Med.* (2022) 9:856156. doi: 10.3389/fmed.2022.856156

3. Hosen I, Al Mamun F, Sikder MT, Abbasi AZ, Zou L, Guo T, et al. Prevalence and associated factors of problematic smartphone use during the COVID-19 pandemic: A Bangladeshi study. *Risk Manag Healthc Policy.* (2021) 14:3797–805. doi: 10.2147/RMHP.S325126

4. Islam MS, Sujan MSH, Tasnim R, Mohona RA, Ferdous MZ, Kamruzzaman S, et al. Problematic smartphone and social media use among bangladeshi college and university students amid COVID-19: the role of psychological well-being and pandemic related factors. *Front Psychiatry.* (2021) 12:647386. doi: 10.3389/fpsyt.2021.647386

5. Pang PC-I, Cai Q, Jiang W, Chan KS. Engagement of government social media on Facebook during the COVID-19 pandemic in Macao. *Int J Environ Res Public Health.* (2021) 18:3508. doi: 10.3390/ijerph18073508

6. Marino C, Gini G, Vieno A, Spada MM. A comprehensive meta-analysis on problematic Facebook use. *Comput Hum Behav.* (2018) 83:262–77. doi: 10.1016/j.chb.2018.02.009

7. Schou Andreassen C, Pallesen S. Social network site addiction-an overview. *Curr Pharm Des.* (2014) 20:4053–61. doi: 10.2174/13816128113199990616

8. Salik Sengul Y, Kahraman T, Ozcan Kahraman B. Problematic Facebook use behavior and locus of control in physiotherapy students. *Bulletin Faculty Phys Ther.* (2021) 26:13. doi: 10.1186/s43161-021-00031-1

9. Hossain MT, Ahammed B, Chanda SK, Jahan N, Ela MZ, Islam MN. Social and electronic media exposure and generalized anxiety disorder among people during COVID-19 outbreak in Bangladesh: a preliminary observation. *PLoS ONE.* (2020) 15:e0238974. doi: 10.1371/journal.pone.0238974

10. Gioia F, Fioravanti G, Casale S, Boursier V. The effects of the fear of missing out on people's social networking sites use during the COVID-19 pandemic: The mediating role of online relational closeness and individuals' online communication attitude. *Front Psychiatr.* (2021) 12:620442. doi: 10.3389/fpsyt.2021.620442

11. Jahan I, Hosen I, Al Mamun F, Kaggwa MM, Griffiths MD, Mamun MA. How has the COVID-19 pandemic impacted internet use behaviors and facilitated problematic internet use? A bangladeshi study. *Psychol Res Behav Manage.* (2021) 14:1127–38. doi: 10.2147/PRBM.S323570

12. Kemp S. *Digital in 2018: World's Internet Users Pass the 4 Billion Mark - We are Social.* (2018)

13. Mamun MA, Griffiths MD. The association between Facebook addiction and depression: A pilot survey study among Bangladeshi students. *Psychiatry Res.* (2019) 271:628–33. doi: 10.1016/j.psychres.2018.12.039

14. Napoleon Cat. *Facebook users in Bangladesh*. (2020). Available online at: https://napoleoncat.com/stats/facebook-users-in-bangladesh/2020/01/ (accessed July 4, 2022).

15. Ahmad AR, Murad HR. The impact of social media on panic during the COVID-19 pandemic in Iraqi Kurdistan: online questionnaire study. *J Med Internet Res.* (2020) 22:e19556. doi: 10.2196/19556

16. Kaya T. The changes in the effects of social media use of Cypriots due to COVID-19 pandemic. *Technol Soc.* (2020) 63:101380. doi: 10.1016/j.techsoc.2020.101380

17. Karpinski AC, Kirschner PA, Ozer I, Mellott JA, Ochwo P. An exploration of social networking site use, multitasking, and academic performance among United States and European university students. *Comput Human Behav.* (2013) 29:1182–92. doi: 10.1016/j.chb.2012.10.011

18. Hussain Z, Griffiths MD. Problematic social networking site use and comorbid psychiatric disorders: A systematic review of recent large-scale studies. *Front Psychiatry.* (2018) 9:686. doi: 10.3389/fpsyt.2018.00686

19. Kircaburun K, Alhabash S, Tosuntaş SB, Griffiths MD. Uses and gratifications of problematic social media use among university students: a simultaneous examination of the Big Five of personality traits, social media platforms, and social media use motives. *Int J Ment Health Addict.* (2020) 18:525–47. doi: 10.1007/s11469-018-9940-6

20. Kuss DJ, Griffiths MD. Excessive online social networking: can adolescents become addicted to Facebook? *Edu Health.* (2011) 29:63–6.

21. Sayeed A, Hassan MN, Rahman MH, El Hayek S, Al Banna MH, Mallick T, et al. Facebook addiction associated with internet activity, depression and behavioral factors among university students of Bangladesh: A cross-sectional study. *Child Youth Serv Rev.* (2020) 118:105424. doi: 10.1016/j.childyouth.2020.105424

22. Mamun MA, Hossain MS, Moonajilin MS, Masud MT, Misti JM, Griffiths MD. Does loneliness, self-esteem and psychological distress correlate with problematic internet use? A Bangladeshi survey study. *Asia Pac Psychiatry.* (2020) 12:e12386. doi: 10.1111/appy.12386

23. Mamun MA, Hossain MS, Siddique AB, Sikder MT, Kuss DJ, Griffiths MD. Problematic internet use in Bangladeshi students: the role of socio-demographic factors, depression, anxiety, and stress. *Asian J Psychiatr.* (2019) 44:48–54. doi: 10.1016/j.ajp.2019.07.005

24. Kroenke K, Spitzer RL, Williams JBW. The Patient Health Questionnaire-2: validity of a two-item depression screener. *Med Care.* (2003) 41:1284–92. doi: 10.1097/01.MLR.0000093487.78664.3C

25. Löwe B, Wahl I, Rose M, Spitzer C, Glaesmer H, Wingenfeld K, et al. A 4-item measure of depression and anxiety: validation and standardization of the Patient Health Questionnaire-4 (PHQ-4) in the general population. *J Affect Disord.* (2010) 122:86–95. doi: 10.1016/j.jad.2009.06.019

26. Kroenke K, Spitzer RL, Williams JBW, Monahan PO, Löwe B. Anxiety disorders in primary care: prevalence, impairment, comorbidity, and detection. *Ann Intern Med.* (2007) 146:317–25. doi: 10.7326/0003-4819-146-5-200703060-00004

27. Andreassen CS, Torsheim T, Brunborg GS, Pallesen S. Development of a Facebook addiction scale. *Psychol Rep.* (2012) 110:501–17. doi: 10.2466/02.09.18.PR0.110.2.501-517

28. Jafarkarimi H, Sim ATH, Saadatdoost R, Hee JM. Facebook addiction among Malaysian students. *Int J Inform Edu Technol.* (2016) 6:465. doi: 10.7763/IJIET.2016.V6.733

29. Khumsri J, Yingyeun R, Manwong M, Hanprathet N, Phanasathit M. Prevalence of Facebook addiction and related factors among thai high school students. *J Med Assoc Thai.* (2015) 98:S51–60.

30. Shettar M, Karkal R, Kakunje A, Mendonsa RD, Chandran VVM. Facebook addiction and loneliness in the post-graduate students of a university in southern India. *Int J Soc Psychiatr.* (2017) 63:325–9. doi: 10.1177/0020764017705895

31. Gazzaz ZJ, Baig M, Al Alhendi BSM, Al Suliman MMO, Al Alhendi AS, Al-Grad MSH, et al. Perceived stress, reasons for and sources of stress among medical students at Rabigh Medical College, King Abdulaziz University, Jeddah, Saudi Arabia. *BMC Med Educ.* (2018) 18:29. doi: 10.1186/s12909-018-1133-2

32. Bányai F, Zsila Á, Király O, Maraz A, Elekes Z, Griffiths MD, et al. Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLoS ONE.* (2017) 12:e0169839. doi: 10.1371/journal.pone.0169839

33. Malaeb D, Salameh P, Barbar S, Awad E, Haddad C, Hallit R, et al. Problematic social media use and mental health (depression, anxiety, and insomnia) among Lebanese adults: any mediating effect of stress? *Perspect Psychiatr Care.* (2020) 57:539–49. doi: 10.1111/ppc.12576

34. Shensa A, Escobar-Viera CG, Sidani JE, Bowman ND, Marshal MP, Primack BA. Problematic social media use and depressive symptoms among US young adults: a nationally-representative study. *Soc Sci Med.* (2017) 182:150–7. doi: 10.1016/j.socscimed.2017.03.061

35. Koc M, Gulyagci S. Facebook addiction among Turkish college students: the role of psychological health, demographic, and usage characteristics. *Cyberpsychol Behav Soc Network.* (2013) 16:279–84. doi: 10.1089/cyber.2012.0249

36. Xie W, Karan K. Predicting Facebook addiction and state anxiety without Facebook by gender, trait anxiety, Facebook intensity, and different Facebook activities. *J Behav Addict.* (2019) 8:79–87. doi: 10.1556/2006.8.2019.09

37. Zaffar M, Mahmood S, Saleem M, Zakaria E. Facebook addiction: Relation with depression, anxiety, loneliness and academic performance of Pakistani students. *Sci Int.* (2015) 27:2469–75.

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Increased digital media use is associated with sleep problems among university students: A study during the COVID-19 pandemic in Japan

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This retrospective cohort study investigates the association between the incidence of sleep problems and changes in digital media use among university students during the COVID-19 pandemic. It used data from annual health check-ups performed at a Japanese university in 2019 and 2020. Students undergoing these check-ups were identified to respond to questions about sleep problems, digital media use, breakfast and exercise habits, and stress. In total, 3,869 students were included in the analysis. The association between the incidence of sleep problems in 2020 and the changes in digital media use between 2019 and 2020 was assessed using logistic regression models. The rate of long digital media use ($\geq$ 2 hours) in 2019 was 42.6%, while in 2020 it was 53.6%. Incidence of sleep problems was observed in 244 students (6.3%) in 2020. There were 786 students (20.3%) who used digital media for $\leq$ 2 h in 2019 and $\geq$ 2 h in 2020. From the sample, 66 students (8.4%) reported incidence of sleep problems in 2020. Additionally, those respondents who specifically reported increased digital media use between 2019 and 2020 (increased use) where at greater risk (OR: 1.76; 95% CI: 1.21, 2.55) of reporting sleep problems in 2020, even after controlling for other study variables. Thus, this study provides evidence that the incidence of sleep problems has had a significant association with an increase in digital media use among university students throughout the COVID-19 pandemic. These findings highlight the importance of ensuring appropriate digital media use among students for improved quality of sleep.

KEYWORDS
digital media use, university students, COVID-19, retrospective study, sleep problems

Introduction

Since 2020, the world has been witnessing the spread of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which has resulted in the COVID-19 pandemic. In Japan, the first case of COVID-19 infection was reported on 15 January 2020, and the Japanese government declared a state of emergency on 7 April 2020. To prevent the spread of infection, educational institutions were required to discontinue in-person teaching, and to conduct classes and share learning material online. Most students had to stay home and study by themselves, without face-to-face communication with teachers and friends. Such isolation resulted in severe psychological stress among university students (1, 2).

Studies have reported that increased levels of psychological distress during the COVID-19 pandemic were associated with sleep problems (3). The unusual conditions associated with the pandemic affected students' lifestyles, including sleep habits. A recent study in China revealed increased screen and sleep time, and decreased physical activity, among adolescents (4). Studies in Italy revealed delayed sleep rhythms and poor sleep quality during the COVID-19 lockdown (5, 6). In Spain, nursing students spent more time in bed during the lockdown but displayed an adverse quality of sleep (7).

Reports have indicated that insomnia may be associated with stressful environments (8, 9). A study from China revealed that the prevalence of insomnia symptoms in college students during the COVID-19 pandemic was 25.7% (10). This figure exceeds the 23.6% prevalence reported for Chinese university students during the pre-COVID-19 period (11).

Extensive social media use among students is associated with poorer sleep patterns, delayed onset of sleep, delayed waking up time on school days, and difficulty falling asleep after waking up (12). During the pandemic, many university students in home quarantine were exposed to stressful COVID-19-related information through social media (13); thus, an increased fear of COVID-19 might have partially affected the rise in sleep problems (14). Another cross-sectional study reported that addiction to social media during the COVID-19 pandemic was positively associated with poor sleep, anxiety, and depression in Bangladeshi college and university students (15).

Previous research has described several possible mechanisms for how digital media use might impact sleep. First, time spent using digital media might directly replace sleep time or other habits related to better sleep. Second, emotional stimulation caused by digital media might cause sleep problems *via* physiological reactions (16, 17). Third, exposure to blue light might affect physiological functions, including circadian rhythms (18). Light-emitting diodes, which are used in computers and smartphones, have the strongest intensity in blue wavelengths (400–490 nm) of the visible light range (18). Chang and colleagues (19) established that the use of light-emitting electronic devices before bedtime inhibits melatonin secretion and disrupts circadian rhythms. Melatonin is a hormone produced in the corpus at night and plays an important role in sleep and mood management synchronizing circadian rhythms (20). The abovementioned reports indicate that exposure to blue light from electronic devices can negatively affect sleep patterns by inhibiting the melatonin pathway.

This study investigates the association between the incidence of sleep problems in 2020 and changes in digital media use from 2019 to 2020 among university students in Japan. To the best of our knowledge, no cohort study has reported an association between the frequency of sleep problems and increased digital media use among university students during the COVID-19 pandemic. We believe that the findings of this retrospective cohort study will encourage university students to be more cautious about their digital media use and improve their sleep quality.

Materials and methods

Study participants and procedure

Of the 14,940 students who attended Osaka University in 2019 and 2020, 4,510 students who underwent annual health check-ups in April were eligible for this study (response rate: 30.2%). The students accessed the website for annual health check-ups operated by Osaka University and answered an online questionnaire about sleep problems, digital media use, stress, and their habits at the time of response. The questionnaire was answered in April of each fiscal year. We excluded the following individuals: (1) students who reported having sleep problems in 2019 (n = 243; 5.4%); and (2) international students (n = 398; 8.8%). The final sample included 3,869 students (85.8% of those initially selected; see Figure 1). This study used an opt-out approach for informed consent, according to the Japanese Ethical Guidelines for Medical and Health Research Involving Human Subjects. According to the Osaka University and government regulations, all students were required to undergo annual health check-ups. Students were informed in the privacy policy that the collected data would be anonymized and used for future research and operational improvements. The protocol for this study was approved by the Ethics Committee of the Health and Counseling Center, Osaka University (number 14, 2022) and the Ethics Committee of the Osaka University Hospital (number 18352-2, 2022). The details of the study were presented on the university's website, and a contact point was set up to ensure that participants could opt out of the use of existing data. All data was retrieved from the electronic database of the Health and Counseling Center, Osaka University. All procedures in this study involving human participants were performed in accordance with the ethical standards of the institutional and national research committee and with the 1964

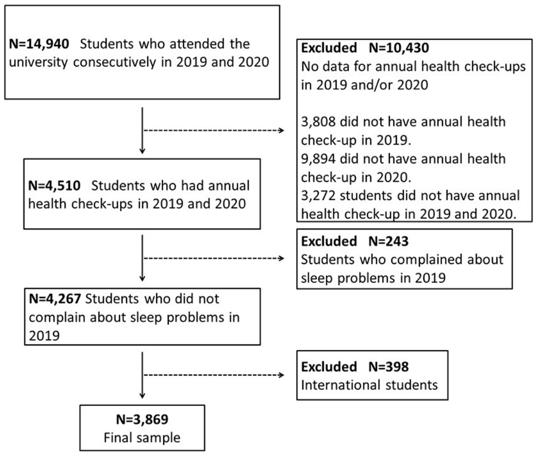

FIGURE 1
Flow diagram of participant selection.

Helsinki Declaration and its later amendments or comparable ethical standards.

Measures

The students were required to answer questions at each health check-up in 2019 and 2020, as described below:

Sleep problems

Sleep problems were assessed based on the following question: "Do you have difficulty in sleeping?" Two response options were provided: "yes" and "no".

Digital media use

Digital media use was determined by the following question: "How many hours a day do you spend using a social networking service and email, surfing the Internet, or playing games?" It was accompanied by five response options: "30 min or less," "30–60 min," "1–2 h," "2–3 h," and "3 h or more." In this study, short digital media use was defined as $\leq$ 2 h and long digital media use as $\geq$ 2 h based on the study by Wu et al. (21). We set the cut-off point at 2 h; the students using digital media for $\geq$ 2 h were assumed to be at high risk of sleep problems. To assess changes in digital media use, the students were divided into four groups: Short-Short, Short-Long, Long-Short, and Long-Long, based on how much time they spent using digital media in 2019 and 2020. For example, the "Short-Long" group included students who used digital media for $\leq$ 2 h in 2019 and $\geq$ 2 h in 2020.

Stress

To assess how often they felt stressed, students were asked, "Do you feel stressed?" and instructed to respond by choosing one of the following options: "almost never," "sometimes," "often," and "always".

Breakfast habits

To assess students' eating habits, the question, "Do you eat breakfast?" was posed and accompanied by four response options, namely: "almost always," "usually," "sometimes," and "almost never".

Exercise habits

To assess students' exercise habits, students were asked, "How many days a week do you perform exercises?" and offered five response choices: "0 days," "1 day," "2 days," "3 or 4 days," and "5 or more days".

Statistical analyses

Digital media use was used to classify students' demographic characteristics. The chi-square test and one-way ANOVA were used to assess differences in characteristics among the four groups classified by digital media use.

Univariable and multivariable logistic regression models using the incidence of sleep problems in 2020 as a dependent variable were used to calculate unadjusted and adjusted odds ratios (OR) with 95% confidence intervals (CI) of age, sex, exercise and breakfast habits in 2020, and the change in digital media use.

Continuous variables were expressed as mean $\pm$ standard deviation (SD) and categorical variables were expressed as numbers and proportions. Statistical significance was set at $P <$ 0.05. All statistical analyses were performed using SPSS version 26 (SPSS Inc., Chicago, IL, USA).

Results

Characteristics of the participants in 2020 by changes in digital media use from 2019 to 2020

Table 1 shows the characteristics of the 3,869 students according to the changes in digital media use from 2019 to 2020. The sample comprised 2,484 male (64.2%) and 1,385 female (35.8%) students, with a mean age of 22.7 years (SD = 4.0). The group that reported short digital media use in both 2019 and 2020 (Short-Short group) included 1,435 students (37.1%), whereas 786 students (20.3%) reported using digital media for

TABLE 1 Students' characteristics in 2020 according to changes in digital media use from 2019 to 2020.

		Total $n = 3{,}869$		Short-Short $n = 1{,}435$		Short-Long $n = 786$		Long-Short $n = 361$		Long-Long $n = 1{,}287$		*p-value*
Age, years[a]		22.7 ± 4.0		23.8 ± 5.5		22.2 ± 2.5		22.3± 3.0		22.0 ± 2.5		<0.001
Male, *n* (%)		2,484	(64.2%)	912	(63.6%)	501	(63.7%)	210	(58.2%)	861	(66.9%)	0.018
Female, *n* (%)		1,385	(35.8%)	523	(36.4%)	285	(36.3%)	151	(41.8%)	426	(33.1%)	
Incidence of sleep problems, *n* (%)		244	(6.3%)	61	(4.3%)	66	(8.4%)	26	(7.2%)	91	(7.1%)	<0.001
Stress, *n* (%)	Almost never	1,299	(33.6%)	521	(36.3%)	247	(31.4%)	118	(32.7%)	413	(32.1%)	0.214
	Sometimes	1,981	(51.2%)	716	(49.9%)	417	(53.1%)	189	(52.4%)	659	(51.2%)	
	Often	495	(12.8%)	168	(11.7%)	102	(13.0%)	42	(11.6%)	183	(14.2%)	
	Always	94	(2.4%)	30	(2.1%)	20	(2.5%)	12	(3.3%)	32	(2.5%)	
Breakfast, *n* (%)	Almost always	2,298	(59.4%)	929	(64.7%)	445	(56.6%)	228	(63.2%)	696	(54.1%)	<0.001
	Usually	720	(18.6%)	265	(18.5%)	147	(18.7%)	63	(17.5%)	245	(19.0%)	
	Sometimes	513	(13.3%)	138	(9.6%)	124	(15.8%)	36	(10.0%)	215	(16.7%)	
	Almost never	338	(8.7%)	103	(7.2%)	70	(8.9%)	34	(9.4%)	131	(10.2%)	
Exercise, *n* (%)	0 days per week	1,791	(46.3%)	626	(43.6%)	351	(44.7%)	162	(44.9%)	652	(50.7%)	0.046
	1 day per week	760	(19.6%)	301	(21.0%)	152	(19.3%)	69	(19.1%)	238	(18.5%)	
	2 days per week	580	(15.0%)	237	(16.5%)	116	(14.8%)	52	(14.4%)	175	(13.6%)	
	3 to 4 days per week	514	(13.3%)	184	(12.8%)	122	(15.5%)	55	(15.2%)	153	(11.9%)	
	5 or more days per week	224	(5.8%)	87	(6.1%)	45	(5.7%)	23	(6.4%)	69	(5.4%)	

[a]Mean ± standard deviation.

more prolonged durations in 2020 than in 2019 (Short-Long group). A total of 1,287 students (33.3%) reported long durations of digital media use in both 2019 and 2020. The rate of long digital media use in 2019 was 42.6%, while in 2020 it was 53.6%. Incidence of sleep problems was observed in 244 students (6.3%) in 2020. In the Short-Long group, 66 students (8.4%) reported incidence of sleep problems, which was higher than that in all the other groups. Regarding the degree of stress, almost half of the students in each group reported feeling stressed "sometimes." Regarding the habit of eating breakfast, more than half of the students in each group responded with "almost always." Moreover, over 40% of the students reported no exercise habits.

The association between the incidence of sleep problems and changes in digital media use from 2019 to 2020

As shown in Table 2, the Short-Long group in digital media use was significantly associated with the incidence of sleep problems in the unadjusted model (OR: 2.07; 95% CI: 1.44, 2.96), and even after adjusting for all other factors (adjusted OR: 1.76; 95% CI: 1.21, 2.55). Frequency of stress was significantly associated with the incidence of sleep problems, and students with higher stress tended to show higher odds of sleep problems. As for breakfast, "Usually" and "Sometimes" were significantly associated with the incidence of sleep problems. However, no significant association was found between frequency of exercise and the incidence of sleep problems.

Discussion

This study investigated the association between the incidence of sleep problems and changes in digital media use from 2019 to 2020 among university students during the COVID-19 pandemic. Incidence of sleep problems was observed in 244 students (6.3%) in 2020. We assessed additional factors that may affect students' sleep patterns. Both breakfast and exercise habits are considered important lifestyle factors that affect sleep (22, 23). During the COVID-19 pandemic, a lack of exercise habits was reported as a risk factor for sleep disorders in China (24). Therefore, in addition to digital media use, these habits were assessed. Furthermore, the degree of stress, which is considered to be a significant risk factor for sleep problems experienced by students, was assessed. Even after adjusting for the abovementioned factors, an increase in digital media use from 2019 to 2020 was significantly associated with the incidence of sleep problems in 2020.

In the adjusted model for other risk factors of sleep problems, the Short-Long group had a change in digital media exposure to $\geq$ 2 h, which may have caused sleep problems through some physiological responses. In contrast, the Long-Short group did not show a significant risk of sleep problems caused by digital media use. These results imply that digital media use of $\leq$ 2 h might not increase the risk of sleep problems

TABLE 2 The association between the incidence of sleep problems and changes in digital media use from 2019 to 2020.

		Unadjusted model		Adjusted model	
		OR [95%CI]	*p-value*	OR [95%CI]	*p-value*
Age, per 1 year		0.95 [0.91, 1.00]	0.026	0.93 [0.88, 0.98]	0.006
Female (vs. Male)		0.94 [0.71, 1.23]	0.644	0.85 [0.64, 1.14]	0.274
Stress	Almost never	0.52 [0.36, 0.74]	<0.001	0.51 [0.35, 0.73]	<0.001
	Sometimes	1.00 [reference]		1.00 [reference]	
	Often	2.06 [1.47, 2,87]	<0.001	2.13 [1.52, 2.99]	<0.001
	Always	6.70 [4.15, 10.82]	<0.001	7.66 [4.63, 12.66]	<0.001
Digital media use	Short-Short	1.00 [reference]		1.00 [reference]	
	Short-Long	2.07 [1.44, 2.96]	<0.001	1.76 [1.21, 2.55]	0.003
	Long-Short	1.75 [1.09, 2.81]	0.021	1.53 [0.94, 2.50]	0.088
	Long-Long	1.71 [1.23, 2.39]	0.002	1.40 [0.99, 1.98]	0.057
Breakfast	Almost always	1.00 [reference]		1.00 [reference]	
	Usually	1.53 [1.09, 2.13]	0.013	1.44 [1.02, 2.03]	0.037
	Sometimes	1.90 [1.33, 2.70]	<0.001	1.66 [1.14, 2.41]	0.008
	Almost never	1.63 [1.06, 2.52]	0.027	1.44 [0.91, 2.27]	0.119
Exercise	0 days per week	1.00 [reference]		1.00 [reference]	
	1 day per week	0.74 [0.51, 1.08]	0.115	0.88 [0.60, 1.30]	0.519
	2 days per week	1.13 [0.78, 1.62]	0.523	1.34 [0.92, 1.95]	0.126
	3 to 4 days per week	0.93 [0.62, 1.40]	0.735	1.05 [0.69, 1.60]	0.806
	5 or more days per week	0.80 [0.43, 1.47]	0.462	0.88 [0.47, 1.66]	0.695

OR, odds ratio; CI, confidence interval.

compared to that of $\geq$ 2 h. The Long-Long group showed lower odds of sleep problems than the Short-Long group. That could possibly be because students who use digital media of $\geq$ 2 h already had sleep problems in 2019 and might have been excluded during participant selection. With respect to the Long-Long group, no statistically significant association was found, but there was a tendency toward increased risk with a p-value of 0.057. Thus, it is considered that this does not rule out an association between digital media use of $\geq$ 2 h over a long period and the risk of sleep problems.

A recent systematic review and meta-analysis showed that the prevalence of insomnia among populations affected by COVID-19 was 23.9% (25). To our knowledge, no study has longitudinally investigated the incidence of sleep problems among university students during the COVID-19 pandemic. However, Carter and colleagues revealed that bedtime media device use was strongly associated with poor sleep quality and daytime sleepiness (26). In particular, the COVID-19 pandemic has resulted in an increased reliance on various electronic devices to connect to the Internet, leading to increased screen time (27). Furthermore, a cross-sectional study in Bangladesh found that addiction to social media was positively associated with poor sleep among college and university students (15). In this study, the incidence of sleep problems was significantly associated with an increase in digital media use from $\leq$ 2 h to $\geq$ 2 h. Wu et al. (21) showed that high screen time, categorized as >2 h per day, was significantly positively correlated with poor sleep quality among Chinese college students. The results of this study are consistent with the abovementioned finding.

This study has some limitations. First, the participants were all students of the same university. The effects of the COVID-19 pandemic might vary depending on where the students live. It has been reported that living in cities is a risk factor for insomnia symptoms, compared with living in rural areas (10). In addition, the lower the level of knowledge about COVID-19, the higher the prevalence of insomnia symptoms among students (10). This result implies that providing relevant and accurate COVID-19-related information might protect university students from sleep problems. Therefore, it is necessary to verify whether the present results are reproducible in future studies in other universities. Second, this study was based on students' subjective reports during annual health check-ups. In particular, "sleep problems" were not based on a clinical diagnosis as represented by the DSM-5. During the check-ups, sleep problems were assessed by one yes-or-no question rather than the degree of sleep problems. Therefore, this study could not assess changes in sleep problem severity. Thus, future studies using a structured measurement tool, such as the Pittsburgh Sleep Quality Index, are required to assess sleep problems and their components in detail. Further research is also needed to objectively measure sleep parameters using other methods, such as actigraphy. Third, the degree of stress was defined by only one question for the reasons mentioned above. The use of a comprehensive stress-assessment questionnaire is warranted in further studies to examine the impact of stress on our results in more detail. Fourth, timeframes were not set for each question at the health check-ups. The students reported their sleep problems, digital media use, stress, and habits at the time of response. The effect of independent factors on the incidence of sleep problems might vary depending on the duration of exposure to each factor. Fifth, breakfast and exercise habits were assessed by a question about frequency. In this study, no stepwise association in breakfast habits was found such that students who ate breakfast less frequently were related with incidence of sleep problems. Regarding exercise, there was no significant association between the frequency of exercise and incidence of sleep problems. In addition to frequency of breakfast or exercise, contents might influence the incidence of sleep problems (23, 28), however, this study could not assess these aspects in detail. Sixth, the sample in this study included students who had undergone annual health check-ups in two consecutive years (2019 and 2020), as described in the participant selection flow diagram. Of the 14,940 students, 3,808 (dropout rate: 25.5%) did not have a health check-up in 2019 and 9,894 (dropout rate: 66.2%) did not have one in 2020. The dropout rate in 2020 was very high, which might be due to limitations on receiving health check-ups during the COVID-19 pandemic. Such a high exclusion rate in the target population could be considered a selection bias in the study sample. Finally, this study could not assess the sleep problems of international students. International students were excluded during participant selection because they tend to contact their family and friends in their home country while adjusting to different time zones, which might make differences in the time using digital media. Additionally, international students who went home for spring vacation and could not return to Japan due to the COVID-19 pandemic might answer the questionnaire at health check-ups from their home country in 2020. International students were considered unsuitable for the purpose of this study because of differences in their lifestyles and surroundings.

Conclusions

This study assessed the relationship between the incidence of sleep problems and changes in digital media use among university students during the COVID-19 pandemic. The results showed that incidence of sleep problems was significantly associated with an increase in digital media use, even after adjusting for the effects of related and underlying factors. This is the first study that investigated the relationship between incidence of sleep problems and changes in digital media use during the COVID-19 pandemic among university students in Japan. The results provide a warning to university students regarding long digital media use, and highlight the need to ensure appropriate digital media use to maintain sleep quality, particularly during situations that can result in abrupt lifestyle changes.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The datasets generated during the current study are not publicly available because of privacy considerations regarding the participants. Requests to access these datasets should be directed to HA, hadachi@psy.med.osaka-u.ac.jp.

Ethics statement

The studies involving human participants were reviewed and approved by the Ethics Committee of the Health and Counseling Center, Osaka University (number 14, 2022) and Ethics Committee of the Osaka University Hospital (number 18352-2, 2022). The Ethics Committee waived the requirement of written informed consent for participation.

Author contributions

Conceptualization and formal analysis: KW and HA. Methodology: KW, HA, and RY. Investigation and writing—original draft draft preparation: KW. Data curation: RY. writing—review and editing: HA, RY, RF, DI, DK, YS, SA, NM, YM, MM, NN, TK, and MI. All authors contributed to writing the final manuscript and approved the final 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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References

1. Sahu P. Closure of universities due to coronavirus disease 2019 (COVID-19): impact on education and mental health of students and academic staff. *Cureus.* (2020) 12:e7541. doi: 10.7759/cureus.7541

2. Arima M, Takamiya Y, Furuta A, Siriratsivawong K, Tsuchiya S, Izumi M. Factors associated with the mental health status of medical students during the COVID-19 pandemic: a cross-sectional study in Japan. *BMJ.* (2020) 10:e043728. doi: 10.1136/bmjopen-2020-043728

3. Alimoradi Z, Brostrom A, Tsang HWH, Griffiths MD, Haghayegh S, Ohayon MM, et al. Sleep problems during COVID-19 pandemic and its association to psychological distress: a systematic review and meta-analysis. *E Clin Med.* (2021) 36:e100916. doi: 10.1016/j.eclinm.2021.100916

4. Yang S, Guo B, Ao L, Yang C, Zhang L, Zhou J, et al. Obesity and activity patterns before and during COVID-19 lockdown among youths in China. *Clin Obes.* (2020) 10:e12416. doi: 10.1111/cob.12416

5. Cellini N, Canale N, Mioni G, Costa S. Changes in sleep pattern, sense of time and digital media use during COVID-19 lockdown in Italy. *J Sleep Res.* (2020) 29:e13074. doi: 10.1111/jsr.13074

6. Marelli S, Castelnuovo A, Somma A, Castronovo V, Mombelli S, Bottoni D, et al. Impact of COVID-19 lockdown on sleep quality in university students and administration staff. *J Neurol.* (2021) 268:8–15. doi: 10.1007/s00415-020-10056-6

7. Romero-Blanco C, Rodríguez-Almagro J, Onieva-Zafra MD, Parra-Fernandez ML, Prado-Laguna MDL, Hernandez-Martinez A. Sleep pattern changes in nursing students during the COVID-19 lockdown. *Int J Environ Res Public Health.* (2020) 17:5222. doi: 10.3390/ijerph17145222

8. Nunn CL, Samson DR, Krystal AD. Shining evolutionary light on human sleep and sleep disorders. *Evol Med Public Health.* (2016) 2016:227–43. doi: 10.1093/emph/eow018

9. Kalmbach DA, Anderson JR, Drake CL. The impact of stress on sleep: pathogenic sleep reactivity as a vulnerability to insomnia and circadian disorders. *J Sleep Res.* (2018) 27:e12710. doi: 10.1111/jsr.12710

10. Zhou S-J, Wang L-L, Yang R, Zhang L-G, Guo Z-C, Chen J-C, et al. Sleep problems among Chinese adolescents and young adults during the coronavirus-2019 pandemic. *Sleep Med.* (2020) 74:39–47. doi: 10.1016/j.sleep.2020.06.001

11. Li L, Wang YY, Wang S-B, Zhang L, Li L, Xu D-D, et al. Prevalence of sleep disturbances in Chinese university students: a comprehensive meta-analysis. *J Sleep Res.* (2018) 27:e12648. doi: 10.1111/jsr.12648

12. Scott H, Biello SM, Woods HC. Social media use and adolescent sleep patterns: cross-sectional findings from the UK millennium cohort study. *BMJ.* (2019) 9:e031161. doi: 10.1136/bmjopen-2019-031161

13. Tang W, Hu T, Hu B, Jin C, Wang G, Xie C, et al. Prevalence and correlates of PTSD and depressive symptoms one month after the outbreak of the COVID-19 epidemic in a sample of home-quarantined Chinese university students. *J Affect Disord.* (2020) 274:1–7. doi: 10.1016/j.jad.2020.05.009

14. Lin C-Y, Broström A, Griffiths MD, Pakpour AH. Investigating mediated effects of fear of COVID-19 and COVID-19 misunderstanding in the association between problematic social media use, psychological distress, and insomnia. *Internet Interv.* (2020) 21:100345. doi: 10.1016/j.invent.2020.100345

15. Islam S, Sujan SH, Tasnim R, Mohona RA, Ferdous MZ, Kamruzzaman S, et al. Problematic smartphone and social media use among Bangladeshi college and university students amid COVID-19: the role of psychological well-being and pandemic related factors. *Front Psychiatry.* (2021) 12:e647386. doi: 10.3389/fpsyt.2021.647386

16. Gregory AM, Sadeh A. Annual Research Review: sleep problems in childhood psychiatric disorders – a review of the latest science. *J Child Psychol Psychiatry.* (2016) 57:296–317. doi: 10.1111/jcpp.12469

17. Cain N, Gradisar M. Electronic media use and sleep in school-aged children and adolescents: a review. *Sleep Med.* (2010) 11:735–42. doi: 10.1016/j.sleep.2010.02.006

18. Tosini G, Ferguson I, Tsubota K. Effects of blue light on the circadian system and eye physiology. *Mol Vis.* (2016) 22:61–72.

19. Chang A-M, Aeschbach D, Duffy JF, Czeisler CA. Evening use of light-emitting eReaders negatively affects sleep, circadian timing, and next-morning alertness. *Proc Natl Acad Sci U S A.* (2015) 112:1232–7. doi: 10.1073/pnas.1418490112

20. Rondanelli M, Faliva MA, Perna S, Antoniello N. Update on the role of melatonin in the prevention of cancer tumorigenesis and in the management of cancer correlates, such as sleep-wake and mood disturbances: review and remarks. *Aging Clin Exp Res.* (2013) 25:499–510. doi: 10.1007/s40520-013-0118-6

21. Wu X, Tao S, Zhang Y, Zhang S, Tao F. Low physical activity and high screen time can increase the risks of mental health problems and poor sleep quality among Chinese college students. *PLoS ONE.* (2015) 10:e0119607. doi: 10.1371/journal.pone.0119607

22. St-Onge M-P, Mikic A, Pietrolungo CE. Effects of diet on sleep quality. *Adv Nutr.* (2016) 7:938–49. doi: 10.3945/an.116.012336

23. Kredlow MA, Capozzoli MC, Hearon BA, Calkins AW, Otto MW. The effects of physical activity on sleep: a meta-analytic review. *J Behav Med.* (2015) 38:427–49. doi: 10.1007/s10865-015-9617-6

24. Fu W, Wang C, Zou L, Guo Y, Lu Z, Yan S, et al. Psychological health, sleep quality, and coping styles to stress facing the COVID-19 in Wuhan, China. *Transl Psychiatry.* (2020) 10:225. doi: 10.1038/s41398-020-00913-3

25. Cénat JM, Blais-Rochette C, Kokou-Kpolou CK, Noorishad P-G, Mukunzi JN, Mclntee S-E, et al. Prevalence of symptoms of depression, anxiety, insomnia, posttraumatic stress disorder, and psychological distress among populations affected by the COVID-19 pandemic: a systematic review and meta-analysis. *Psychiatry Res.* (2021) 295:113599. doi: 10.1016/j.psychres.2020.113599

26. Carter B, Rees P, Hale L, Bhattacharjee D, Paradkar MS. Association between portable screen-based media device access or use and sleep outcomes: a systematic review and meta-analysis. *JAMA Pediatr.* (2016) 170:1202–8. doi: 10.1001/jamapediatrics.2016.2341

27. Majumdar P, Biswas A, Sahu S. COVID-19 pandemic and lockdown: cause of sleep disruption, depression, somatic pain, and increased screen exposure of office workers and students of India. *Chronobiol Int.* (2020) 37:1191–200. doi: 10.1080/07420528.2020.1786107

28. Tanaka E, Yatsuya H, Uemura M, Murata C, Otsuka R, Toyoshima H, et al. Associations of protein, fat, and carbohydrate intakes with insomnia symptoms among middle-aged Japanese workers. *J Epidemiol.* (2013) 23:132–8. doi: 10.2188/jea.JE20120101

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Mobile phone addiction and depressive symptoms among Chinese University students: The mediating role of sleep disturbances and the moderating role of gender

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Background: With the continuous updating of mobile phone functions, the phenomenon of mobile phone addiction among University students is becoming more and more serious. It is important to identify the potential risk factors for mobile phone addiction. The aim of the study was to examine whether there is a relationship between mobile phone addiction and depression symptoms in University students, and to investigate whether sleep disturbances play a mediating role between mobile phone addiction and depression symptoms, as well as the moderating role of gender.

Methods: A cross-sectional study, carried out between September to December 2021, recruited 973 students (478 males) from seven comprehensive universities in western China. The Mobile Phone Addiction Index (MPAI), the Patient Health Questionnaire-9 (PHQ9), and the Pittsburgh Sleep Quality Index (PSQI) were used to complete measures of mobile phone addiction, depressive symptoms, and sleep disturbances. For statistical analyses, descriptive statistics, correlation, regression, mediation and moderated mediation analyses were used. Furthermore, we tested the mediation model and moderated mediation model using the SPSS macro PROCESS.

Results: In this study, it was found that there were positive correlations between mobile phone addiction and depressive symptoms among Chinese University students. Mediation analyses revealed that this relationship was partially mediated by sleep disturbances, but the mediating role was not moderated by gender.

Conclusion: Sleep disturbances have a partial mediating role in the relationship between mobile phone addiction and depressive symptoms. Our results highlight the critical role of prevention and early identification of mobile phone addiction among University students, especially those with sleep disturbances.

KEYWORDS

mobile phone addiction, depressive symptoms, sleep disturbances, University student, gender

Introduction

As an excellent carrier of mobile Internet development, mobile phones have opened up new interactions and experiences in the fields of social communication, access to information, m-commerce, m-learning, and the healthcare system (1–4). However, the versatility of mobile phones has led to an increasing number of people overusing them, especially among University students (5). Overuse of mobile phones is now often associated with potentially harmful and/or destructive behaviors, and this problematic mobile phone use has generally been conceptualized as a behavioral addiction (6, 7). Mobile phone addiction can be regarded as an impulse control disorder, which refers to behavioral and emotional problems caused by uncontrolled, inappropriate or excessive use of mobile phones, and a compulsive state in which an individual's physiological, psychological, and/or social functions are impaired (8–10).

Mobile phone addiction could lead to negative health outcomes. Studies have indirectly shown that there may be biological and psychological links among mobile phone addiction, sleep disturbances, and depressive symptoms. Mobile phone addiction is a risk factor for sleep disturbances, prolonged mobile phones use is significantly linked to insomnia and shortened sleep duration (11–14). Moreover, constant exposure to blue light suppresses melatonin production, causing circadian disruption, sleep disturbances, and mental overload, which might be an important factor in developing psychopathological symptoms, such as depression (15, 16). Mobile phone addicts are more likely to adopt unhealthy lifestyles, which could also be considered as predisposing factors for depression (17). Therefore, mobile phone addiction could lead to serious psychological problems such as depression symptoms, anxiety, and serious health problems, such as sleep disturbances (18, 19).

Despite the extensive research on the relationship between mobile phone addiction, depression symptoms, and sleep disturbances, previous findings are inconsistent or comprehensive, and more research is needed to confirm these findings in different social and cultural contexts. To fill these research gaps, we conducted the study in a sample of Chinese University students. In the present study, we aimed to determine whether prevention and reduction of mobile phone addiction could help alleviate depressive symptoms among Chinese University students. To further understand whether sleep disturbances can be improved by reducing mobile phone addiction, and depressive symptoms could be alleviated by improving sleep disturbances.

Abbreviations: SD, Standard Deviation; MPAI, Mobile Phone Addiction Index; PHQ9, Patient Health Questionnaire-9; PSQI, Pittsburgh Sleep Quality Index; CI, Confidence Interval; β, Standardized Regression Coefficient; S.E., Standard Error; LLCI, Lower Level Confidence Interval; ULCI, Upper Level Confidence Interval.

Literature review and research hypotheses

In recent years, studies have reported the association between mobile phone addiction and depression among University students in different countries. Specifically, a series of cross-sectional research revealed that mobile phone addiction is positively associated with depressive symptoms among college students in Turkey, Japan, South Korea, Austrian, and Lebanon (20–25). A prospective cohort study found that a bidirectional longitudinal relationship between duration of mobile phone use and severity of depression (26). A meta-analysis of 40 studies provided solid evidence that mobile phone addiction was positively correlated with depressive symptoms and sleep disturbances among University students (27). A study using a sample of 188 University students in South Korea found that there was a significant relationship exists between mobile phone addiction and depressive symptoms, but there was no strong correlation between sleep disturbances and mobile phone addiction (23). However, a study conducted among students at Surat University, India showed that there was a moderate correlation between mobile phone addiction and depression, as well as between mobile phone addiction and sleep quality (28). Apart from this, conclusions from a systematic review and meta-analysis of included studies published between 2010 and 2019 showed that mobile phone addiction was significantly associated with increased risk of sleep disturbances and depressive symptoms among University students, and that sleep quality was influenced by multiple factors, including gender (29). The effects of mobile phone addiction on one's emotions are likely to be mediated by other variables, rather than a direct effect (27). Therefore, the association between mobile phone addiction and depression symptoms needs to be examined in more diverse samples to further explore the underlying mechanism involved in the process. The study demonstrated that problematic mobile phone use was associated with mental health among University students, and sleep quality played a mediating role in this relationship (30). However, a study conducted among Turkish University students reported that depressive symptoms as a mediator between mobile phone overuse and sleep disturbances (20). The following subsections detail the specific arguments regarding these relationships in this study and present the underlying rationale.

Mobile phone addiction and depressive symptoms

Depression, as a negative emotion, refers to a cluster of repetitive and significant internalized problems, with low mood, poor initiative, low self-esteem, feelings of uselessness loss of interest in activities once enjoyed, etc., that have persisted for some time and caused distress to the individual (31, 32). The concept of reciprocal determinism in Bandura's (1986) social cognition theory (33) points out that there is an interplay between individuals' behavior and emotion is reciprocal, and individuals' behavior not only reacts to emotion but also affects their emotion (34). That is to say, individuals' use of mobile phones may produce depressive symptoms, while individual depression caused by excessive use of mobile phones may also have an impact on individual mood. At present, there are multiple literatures discussing the negative emotions represented by depression leading to problematic mobile phone use (35, 36). Compensatory Internet use theory, for example, suggests that people with depressive symptoms may tend to use the Internet to avoid current negative feelings, which increases motivation to go online (37). As a portable surfing tool, mobile phones are convenient for people to surf the Internet, which may aggravate problematic mobile phone use and develop into mobile phone addiction. Therefore, our study focuses on the first half of the pathway of the concept of reciprocal determinism.

In recent years, empirical evidence linking mobile phone addiction levels to depressive symptoms has rapidly accumulated. Although studies have been carried out among University students in China, the relationship between mobile phone addiction and depressive symptoms has rarely been examined in a sample of students from comprehensive universities in western China. Therefore, University students in western China were selected as samples for this study. We put forward the following hypothesis:

Hypothesis 1: Mobile phone addiction would positively predict depressive symptoms among Chinese University students.

The mediating role of sleep disturbances

One of the central factors of mobile phone addiction was personal dependence, and its consequences include stress, mental overload, role conflicts, sleep disturbances, feelings of guilt due to inability to achieve set goals, and so on, which are major sources of depressive symptoms (16). Brand et al. (38) proposed an updated version of the Interaction of Person-Affect-Cognition-Execution (I-PACE) model. This model is a theoretical approach to describe the process of addictive behaviors by combining the individual psychological and neuroscientific theories of substance use disorder and behavioral addiction. It explains a series of addictive behaviors, including mobile phone addiction. The model proposes that the disorders caused by addictive behaviors are the consequence of the interaction between a person's core characteristics and several moderating and mediating variables. The model also points out that these variables may not be static but dynamic, developing over time as a result of engaging in specific behaviors. In this study, we identified sleep disturbances as a disorder due to mobile phone addictive behaviors. Here, the second hypothesis was raised:

Hypothesis 2: Sleep disturbances would play a mediating role between mobile phone addiction and depressive symptoms.

Hypothesis 2a: Mobile phone addiction would positively predict sleep disturbances among Chinese University students.

Hypothesis 2b: Sleep disturbances would positively predict depressive symptoms among Chinese University students.

The moderating role of gender

According to our hypothesis, mobile phone addiction may predict depressive symptoms through the effect of sleep disturbances, while the intensity of this mediation effect is unlikely to be identical for all the University students. Although a theme of interest to many researchers is related to gender differences in mobile phone addiction, the role of gender as an individual characteristic in the formation of mobile phone addiction is far from clear. Previous studies have shown that there were differences between male and female in sleep quality and mobile phone use preference among young adults. Females have better sleep quality than males, they had shorter sleep onset latency, better sleep efficiency (39). Males were more likely to play online games, watch mobile videos and listen to music, while females were more likely to use social networking services and mobile phone communication functions (40). In other words, females answer phone calls and text messages more often. While young adult females reported better sleep quality, spending an amount of time answering phone calls and texts after sleep onset could be an emotional component or sleep hygiene issues that lead to sleep disturbances (41).

Studies demonstrated that mobile phone addiction was associated with sleep disturbances for the male (42). However, other studies have found that the moderating effect of gender on mobile phone use is inconclusive (43). Based on the I-PACE model, we argue that gender may play a role in this process. To be specific, this study will test whether the association between mobile phone addiction and sleep disturbances in University students would be moderated by their gender. Here we put forward the third hypothesis:

Hypothesis 3: Gender would moderate the relationship between sleep disturbances and depressive symptoms. Specifically, mobile phone addiction would result in more depressive symptoms for female University students.

The present study

Based on the literature review mentioned above, the present study constructed a moderating effect model to examine the mediating role of sleep disturbances between mobile phone addiction and depressive symptoms among Chinese University students. In addition, we tested whether the indirect path between mobile phone addiction and sleep disturbances would be moderated by their gender.

Methods

Study design and participants

Multi-stage stratified random sampling method was conducted to randomly select students from seven comprehensive universities, which are Shaanxi Normal University, Tianshui Normal College, Xi'an University of Electronic Science and Technology, Xi'an University of Technology, Xi'an Jiaotong University, Xi'an University of Technology, and Xi'an University of Science and Technology (including many disciplines and majors, such as humanities and social sciences, medicine, science and technology) in western China for questionnaire survey. Our questionnaire was issued from September 13 to December 12 in 2021. Firstly, we randomly selected different classes from each University. After that, paper questionnaires were distributed to each participant, who was guided by well-trained investigators to complete the written questionnaire within 20 min, so as to ensure the validity of the questionnaire. It should be noted that the investigators' guidance has not been involved the discussion of the questionnaire contents, but only for the filling in the instructions, such as explaining the reserved time and indicating where to fill in the answers. The inclusion criteria were full-time students without jobs. One Thousand and forty-four students were recruited. Of all participants, 71 students had to be excluded for missing or unreliable data on some vital study variables. After excluding the invalid data, the valid sample size was 973 University students (478 of them were male).

Procedure

The study protocol was approved by the Biomedical Ethics Committee of Xi'an Jiaotong University. Verbal informed consent was obtained from participants before the data collection. Participants were told that their participation was entirely voluntary and that they could terminate at any time. They were also told that all the data collected were anonymous and that their responses would be kept confidential. Written informed consent to participation was not required for this study in accordance with the national legislation and the institutional requirements.

Measures

Sociodemographic characteristics

Demographic data of participants included gender, age, residence (1 = rural; 2 = urban), and self-rated health. Participants ranged in age from 17 to 25 years old (M = 19 years old, SD = 1.04). More than half of the participants came from urban areas (55.9%). Most of participants' self-rated as being in good health (44.3%). In the full sample, the mean score of the Mobile Phone Addiction Index (MPAI) was 36.03 (SD = 12.66). The mean score of the Patient Health Questionnaire-9 (PHQ9) was 4.34 (SD = 4.15), and the mean score of the Pittsburgh Sleep Quality Index (PSQI) was 5.46 (SD = 2.71). The role of gender was one of the main concerns in our study, the descriptive information about variables in the male and female groups showed that the average scores of females were higher than that of males in the three scales. The current sample reported moderate sleep disturbances. Among the seven dimensions of sleep disturbances, except for the two dimensions of sleep duration and habitual sleep efficiency, which reported slightly higher scores for males, while the other five dimensions reported higher average scores for females (see Table 1).

Mobile phone addiction

Mobile phone addiction was assessed using the Chinese version of the Mobile Phone Addiction Index (MPAI) (9), which was compiled based on the twenty-seven-item Mobile Phone Problem Use Scale (MPPUS) (44). This is a self-report questionnaire that involves rating 17 items and representative items were "Your friends and family have complained about you using your mobile phone.", "You try to spend less time on your phone, but you can't.", "You find yourself addicted to mobile phone when there are other things you need to do, and that can cause you some trouble.". The four factorial components of the scale were inability to control craving, feeling anxious and lost, withdrawal or escape, and productivity loss. The measurement was based on a Likert 5-point scale ranges from "1 = Not at all" to "5 = Always", with higher scores indicating higher levels of mobile phone addiction. For the current study, Cronbach's alpha for this scale was 0.913, demonstrating good internal consistency.

Depression symptoms (PHQ-9)

Patient Health Questionnaire-9 (PHQ-9) (45) is a 9-item self-reported questionnaire that assesses the major symptoms of depression outlined in Diagnostic and Statistics Manual of Mental Disorders- Fourth Edition (DSM-IV) (46) (e.g., "Having

TABLE 1 Participant characteristics for the entire sample and by gender ($n = 973$).

Variables	Full sample			Male ($N = 478$)		Female ($N = 495$)		*P*-value
	N (%)	Mean (SD)	Range	*N* (%)	Mean (SD)	*N* (%)	Mean (SD)	
Age	973 (100.0)	19 (1.04)	17-25	478 (100.0)	19.15 (1.70)	495 (100.0)	19.47 (1.92)	0.003
Residence	970 (99.7)			476 (99.6)	1.44 (0.50)	494(99.8)	1.44 (0.50)	0.995
Rural	544 (55.9)			267 (55.9)		277(56.0)		
Urban	426 (43.8)			209 (43.7)		217 (43.9)		
Self-rated health	973 (100.0)	2.36 (0.81)		478 (100.0)	2.31 (0.87)	495 (100.0)	2.41(0.75)	0.59
In excellent health (1)	133 (13.7)			85 (17.8)		48 (9.7)		
In good health (2)	431 (44.3)			201(42.1)		230 (46.4)		
General health condition (3)	341 (35.0)			156 (32.6)		185 (37.3)		
In poor health (4)	64 (6.6)			32 (6.7)		32 (6.5)		
In very poor health (5)	4 (0.4)			4 (0.8)		0 (0.0)		
MPAI	930 (95.6)	36.03 (12.66)	17–80	455 (95.2)	34.06 (12.04)	475 (96.0)	37.91 (12.96)	<0.001
PHQ9	960 (98.7)	4.34 (4.15)	0–27	473(99.0)	4.00 (4.39)	487 (98.4)	4.67(3.88)	0.13
PSQI	921 (94.7)	5.46 (2.71)	0–17	450 (94.1)	5.12 (2.70)	471 (95.2)	5.79(2.68)	<0.001
Subjective sleep quality	966 (99.3)	0.95 (0.67)	0–3	473 (99.0)	0.93 (0.69)	493 (99.6)	0.98 (0.66)	0.27
Sleep latency	958 (98.5)	0.97 (0.81)	0–3	470 (98.3)	0.91 (0.80)	488 (98.6)	1.03 (0.81)	0.24
Sleep duration	965 (99.2)	1.10 (0.73)	0–3	474 (99.2)	1.10 (0.72)	491(99.2)	1.10 (0.73)	0.99
Habitual sleep efficiency	962 (98.9)	0.19 (0.52)	0–3	471 (98.5)	0.20 (0.53)	491 (99.2)	0.19 (0.51)	0.67
Sleep disturbance	941 (96.7)	0.86 (0.54)	0–3	462 (96.7)	0.78 (0.54)	479 (96.8)	0.93 (0.53)	<0.001
Use of sleep medication	968 (99.5)	0.06 (0.38)	0–3	476 (99.6)	0.05 (0.35)	492 (99.4)	0.08 (0.40)	0.20
Daytime dysfunction	968 (99.5)	1.35 (1.00)	0-3	475 (99.4)	1.16 (1.00)	493 (99.6)	1.53 (0.97)	<0.001

Analysis between male vs. female was performed with *t*-tests for continuous variables (normal distribution) and χ^2 test for categorical variables.
SD, Standard Deviation; MPAI, Mobile Phone Addiction Index; PHQ9, Patient Health Questionnaire- 9; PSQI, Pittsburgh Sleep Quality Index.

little interest or pleasure in doing things.", "Feeling tired or having little energy.", and "Loss of appetite or overeating."), the items are scored on a 4-point Likert scale (0 = Not at all, 1 = Several days, 2 = More than half of the days, and 3 = Nearly every day). Participants rated the frequency of depressive symptoms over the past 2 weeks (47). The PHQ-9 had been translated into Chinese, and the Chinese version of the PHQ-9 has been shown to be a valid and efficient tool for screening depression (48). The total score of the nine items ranges from 0 to 27, indicating severity of depression symptoms (0 indicating no depression symptoms and 27 indicating that all symptoms occur nearly daily). The Cronbach's alpha of the scale was 0.868, indicating good internal consistency of the measure.

Sleep disturbances (PSQI)

The Chinese version of the Pittsburgh Sleep Quality Index (PSQI) (49) was used in the study and its reliability was satisfactory (Cronbach's alpha = 0.81). The index is a self-administered questionnaire with 19 individual items which assesses sleep quality and sleep disturbances during a 1-month period. The 19 items are divided into seven components, including a participant's subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbance, use of sleep medication, and daytime dysfunction. A Likert 4-level scoring method was used for each dimension (0 = Not at all, 1 ≤ Once a week, 2 ≤ Twice a week, and 3 ≤ Three times a week), and the seven components form a global sleep quality score that ranges from 0 (good quality) to 21 (poor quality) (50). In this study, Cronbach's alpha was 0.801, and the value of 5 was used as the standard in selecting students with poor sleep quality.

Statistical analysis

First, a factor analysis was used for testing common method bias. Secondly, the descriptive statistics, Chi square test, *t*-tests, and Pearson's correlation analysis were conducted using Stata version 15.0 (Stata Corporation, TX, USA). *N* (%) indicated data for categorical variables, mean ± SD indicated data for numerical variables. Pearson's correlations were used to test our first hypothesis and to examine the relationships among mobile phone addiction, sleep disturbances, and depression symptoms. The third step was to test the mediation model and moderated mediation effect model. Model 4 of the PROCESS macro (version 3.4) of the Statistical Package for the Social Sciences (SPSS) version 23.0 (51) was used to test the mediating effect of

TABLE 2 Pearson's correlations among relevant study variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	1													
2. Gender	0.10	1												
3. Residence	0.00	−0.02	1											
4. Self-rated health	0.06	−0.09	0.03	1										
5. MPAI	0.16***	−0.03	0.06	0.17***	1									
6. PHQ9	0.08	0.05	−0.02	0.28***	0.45***	1								
7. PSQI	0.12**	0.04	0.02	0.27***	0.36***	0.57***	1							
8. Subjective sleep quality	0.04	−0.02	−0.02	0.27***	0.25***	0.41***	0.69***	1						
9. Sleep latency	0.08	0.07	−0.02	0.14***	0.18***	0.36***	0.68***	0.46***	1					
10. Sleep duration	0.00	−0.06	0.04	0.017	0.12**	0.12**	0.47***	0.18***	0.14***	1				
11. Habitual sleep efficiency	−0.02	0.01	0.02	0.00	0.02	0.12**	0.42***	0.11**	0.15***	0.27***	1			
12. Sleep disturbance	0.14***	0.04	−0.05	0.18***	0.24***	0.40***	0.58***	0.37***	0.31***	0.04	0.08	1		
13. Use of sleep medication	0.04	0.04	0.07	0.128***	−0.02	0.16***	0.2818***	0.10	0.12**	0.00	0.10	0.10	1	
14. Daytime dysfunction	0.19***	0.05	0.03	0.26***	0.43***	0.54***	0.73***	0.40***	0.33***	0.16***	0.11	0.41***	0.11**	1

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
MPAI, mobile phone addiction index; PHQ9, patient health questionnaire-9; PSQI, Pittsburgh Sleep Quality Index.

TABLE 3 Testing the mediation model of sleep disturbances.

	PSQI				PHQ9			
			BOOSTRAP 5000 TIMES 95% CI				BOOSTRAP 5000 TIMES 95% CI	
	β	S.E.	LLCI	ULCI	β	S.E.	LLCI	ULCI
Constant	−2.31	1.6	−5.46	0.84	−6.86***	2.06	−10.89	−2.82
MPAI	0.07***	0.01	0.06	0.08	0.09***	0.01	0.07	0.11
PSQI	–	–	–	–	0.64***	0.04	0.556	0.73
Age	0.19*	0.08	0.03	0.34	0.169	0.1	−0.03	0.37
Residence	−0.06	0.17	−0.39	0.27	−0.39	0.22	−0.81	0.03
Self-rated health	0.77***	0.11	0.57	0.98	0.75***	0.14	0.48	1.02
		R^2		=0.18		$R^2 = 0.41$		
		F = 48.41***				F = 122.25***		

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Variables have been normalized. 95% CI estimated using bootstrap method. Bootstrap sample size = 5,000.
CI, confidence interval; β, standardized regression coefficient; S.E., standard error; LLCI, lower level confidence interval; ULCI, upper level confidence interval; MPAI, mobile phone addiction index; PHQ9, patient health questionnaire-9; PSQI, Pittsburgh Sleep Quality Index.

sleep disturbances. Model 7 of the PROCESS macro (version 3.4) was used to test the moderating role of gender on the mediation effect. In order to eliminate the units of measurement differences and make the relative strength of different variables comparable, we standardized all continuous variables in the model (52).

Results

Common method biases

To avoid common method biases, this study was carried out by collecting anonymous responses and scoring some items in reverse. And the common method biases was tested by Harman's single-factor test. Study findings showed that the KMO value is 0.896, the significance of Bartlett test is $P < 0.001$, and there were 11 factors with the original root >1. The first factor could explain 23.138% of the cumulative variance, and the critical value was <40%. It indicated that there is no serious common method bias in this study.

Descriptive and correlational analyses

Before data analysis, the missing data were handled by mean imputation in Stata. Controlling for the effects of age, gender, residence, and self-rated health, partial correlation analysis was used. The descriptive statistics and correlation matrix are displayed in Table 2. Positive correlations were found between mobile phone addiction and depressive symptoms, the total score of sleep disturbances, sub-dimensions of sleep disturbances (subjective sleep quality, sleep latency, sleep duration, sleep disturbance, and daytime dysfunction). Depressive symptoms were positively correlated with the total score of sleep disturbances and seven dimensions of sleep disturbances. Age has significant positive correlations with mobile phone addiction and sleep disturbances, sub-dimensions of sleep disturbances (sleep disturbance, daytime dysfunction), but has no significant correlation with other variables. There were significant positive correlations between self-rated health and mobile phone addiction, depressive symptoms, the total score of sleep disturbances, sub-dimensions of sleep disturbances (subjective sleep quality, sleep latency, sleep disturbance, use of sleep medication, daytime dysfunction).

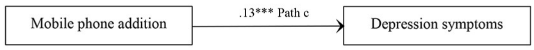

FIGURE 1
(Hypothesis 1) Total effect models: effect of mobile phone addiction on depression symptoms ***$p < 0.001$.

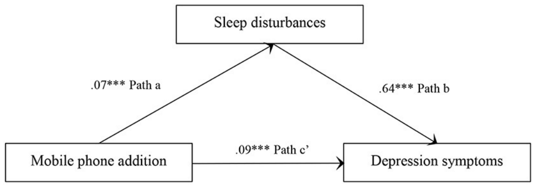

FIGURE 2
(Hypothesis 2) Mediation models: effect of mobile phone addition on depression symptoms with the mediation of sleep disturbances ***$p < 0.001$.

Mediation effect analysis

Model 4 from the SPSS macro PROCESS 3.4 was used to test for the existence of mediation. In the absence of the mediator, mobile phone addiction was positively associated with depression symptoms after controlling for age, residence, and self-rated health. As shown in Table 3, mobile phone addiction significantly positively correlated with sleep disturbances. Both mobile phone addiction and sleep disturbances significantly positively correlated with depression symptoms. These results indicated that sleep disturbances partially mediated the relationship between mobile phone addiction, and depressive symptoms, which was consistent with hypothesis 1 and hypothesis 2.

Figures 1, 2 show the total effect model and the mediation model. The results indicated that the three simple path coefficients (paths a, b, and c) were statistically significant. The results from 5,000 bootstrapping samples presented that all indirect effects were statistically significant, with the bootstrapping 95% CI excluding zero. The total effect of mobile phone addiction on depression symptoms was 0.13 ($p < 0.001$). The indirect effect of sleep disturbances was 0.04, 95% CI (0.03, 0.06), accounting for 33.09% of the total effect.

Subsequently, we further examined the parallel mediating effect of seven dimensions of sleep disturbances on the relationship between mobile phone addiction and depressive symptoms. As presented in Figure 3, there was a significant positive correlation between mobile phone addiction and five dimensions of sleep disturbances (subjective sleep quality, sleep latency, sleep duration, sleep disturbance, and daytime dysfunction). Four dimensions of sleep disturbances (subjective sleep quality, sleep latency, sleep disturbance, and daytime dysfunction) had a significant mediating effect on the relationship between mobile phone addiction and depressive symptoms, while other factors had no significant mediating effect. The indirect effect of subjective sleep quality was 0.01, 95% CI (0.00, 0.01); the indirect effect of sleep latency was 0.01, 95% CI (0.00, 0.01); the indirect effect of sleep disturbance was 0.01, 95% CI (0.00, 0.02); the indirect effect of daytime dysfunction was 0.03, 95% CI (0.02, 0.05).

Moderated mediation effect analysis

Age, residence, and self-rated health were controlled, Model 7 from the SPSS macro PROCESS was applied to test for the proposed moderated mediation model with sleep disturbances as mediator and gender as a moderator. The relations between variables were illustrated in Figure 4. As shown in Table 4, mobile phone addiction positively correlated with sleep disturbances. Sleep disturbances and mobile phone addiction significantly positively correlated with depression symptoms. These results indicated that sleep disturbances partially mediated the relationship between mobile phone addiction and depression symptoms. However, the interaction between sleep disturbances and gender was not correlated with mobile phone addiction. These results indicated that gender could not moderate the relationship between mobile phone addiction and sleep disturbances, which is inconsistent with hypothesis 3 in our study.

Discussion

Although there have been many studies on the association between mobile phone addiction and depressive symptoms,

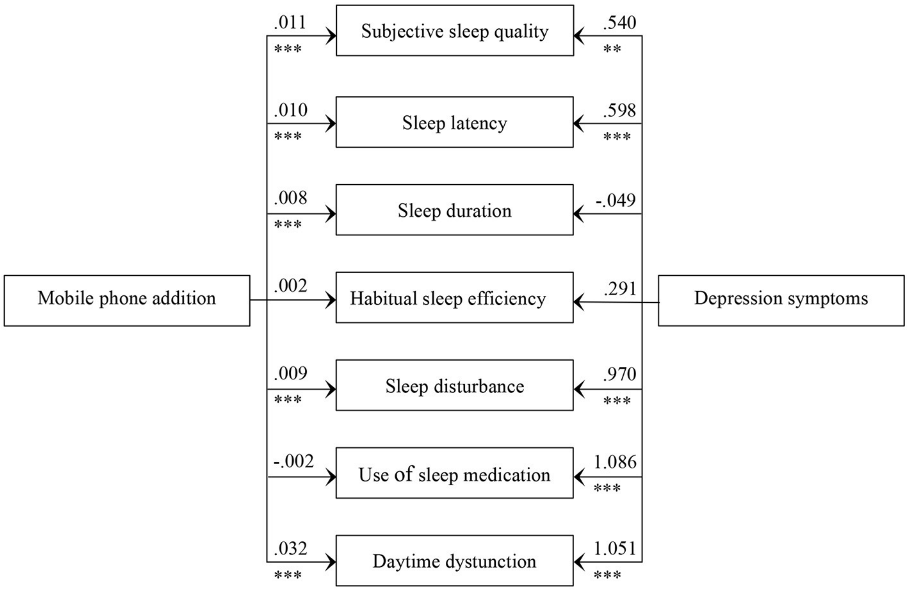

FIGURE 3
Mediating role of seven components of sleep disturbances on the relationship between mobile phone addiction and depression symptom $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

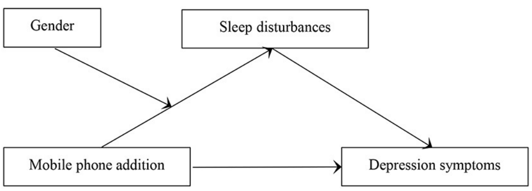

FIGURE 4
(Hypothesis 3) Moderated-mediation model: effect of mobile phone addiction on depression symptoms with sleep disturbances as a mediator and gender as a moderator.

the potential mechanisms underlying this process remain to be explored. Therefore, we proposed a moderated mediation model to examine the role of sleep disturbances and gender in this process. The results indicate that mobile phone addiction could significantly predict depressive symptoms. Besides, sleep disturbances played a mediating role in the relationship between mobile phone addiction and depressive symptoms, but the mediating role was not moderated by gender among Chinese University students.

Firstly, consistent with our hypothesis, the results indicate that mobile phone addiction could be a risk factor for depressive symptoms. Mobile phone addiction becomes more compulsive during the process of reinforcement, which could cause individuals to start experiencing negative emotions when they are not engaging in the behavior (53). Worry, anxiety, and other negative emotions are displayed when not using mobile phones. According to the study of dysfunctional mental processes, irrational beliefs (about the self) can be identified in the context of excessive mobile phone use. For example, low self-esteem occurs when you cannot reach your significant other on your mobile phone, which translates into frequent irrational or distorted cognitions (e.g., "I'm not worthy of love") (54). Such feelings of inferiority, insecurity, and fluctuating self-esteem are important factors in depressive symptoms.

Secondly, our study found that sleep disturbances partially mediated the relation between mobile phone addiction and depressive symptoms. Mobile phone addiction involves cognitive and behavioral disorders (55). On one hand, our results are in line with previous findings, which suggest a link between mobile phone addiction and sleep disturbances. From a physiological point of view, the timing of melatonin onset at night is affected by screen use, as mobile phones emit large amounts of blue light, and controlling the secretion of melatonin is a key factor in regulating health and circadian rhythms (56, 57). Persistent sleep deprivation caused by mobile phone addiction may harm one's immune system, leaving them vulnerable to various diseases (58). Another possible explanation is the large-scale phenomenon of "emotional contagion" in the era of the digital Internet (59). Mobile phones are an important channel to access the social networking space, browsing social media sites before bedtime could potentially have an impact on their mood, leading to sleep disturbances. On the other hand, this study advanced our understanding of how mobile phone addiction could lead to

TABLE 4 Testing the moderated mediation effect of mobile phone addiction on depression symptoms.

	PSQI				PHQ9			
			BOOSTRAP 5000 TIMES 95% CI				BOOSTRAP 5000 TIMES 95% CI	
	β	S.E.	LLCI	ULCI	β	S.E.	LLCI	ULCI
Constant	−0.036	1.59	−3.16	3.08	−3.62	2.04	−7.61	0.38
MPAI	0.090***	0.02	0.05	0.13	0.09***	0.01	0.07	0.11
PSQI	–	–	–	–	0.64***	0.04	0.56	0.73
Gender	0.342*	0.17	0.01	0.678	–	–	–	–
MPAI × Gender	−0.01	0.01	−0.04	0.01	–	–	–	–
Age	0.17*	0.08	0.02	0.33	0.17	0.10	−0.03	0.37
Residence	−0.05	0.17	−0.38	0.28	−0.39	0.22	−0.81	0.03
Self-rated health	0.76***	0.11	0.55	0.96	0.75***	0.14	0.48	1.02
	$R^2 = 0.43$				$R^2 = 0.41$			
	F = 33.27***				F = 122.25***			

	Direct effect of MPAI on PHQ9			
			BOOSTRAP 5000 TIMES 95% CI	
	β	S.E.	LLCI	ULCI
	0.09***	0.01	0.07	0.11

	Conditional indirect effect at gender values			
			BOOSTRAP 5000 TIMES 95% CI	
	β	BootS.E.	BootLLCI	BootULCI
M – 1 SD	0.05	0.01	0.04	0.06
M	−0.01	0.01	−0.03	0.01
M + 1 SD	0.04	0.01	0.03	0.05

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Variables have been normalized. 95% CI estimated using bootstrap method. Bootstrap sample size = 5,000.
CI, confidence interval; β, standardized regression coefficient; S.E., standard error; LLCI, lower level confidence interval; ULCI, upper level confidence interval; MPAI, mobile phone addiction index; PHQ9, patient health questionnaire-9; PSQI, Pittsburgh Sleep Quality Index.

depressive symptoms. In general, the more time people spend on mobile phones, the less interaction they have in real life, which may lead to feelings of loneliness and depression. In addition, prolonged and excessive use of social media may evoke social comparisons, which have been shown to lead to negative emotions and depression (60). Our results supported the "I-PACE" model, which states that the disorder caused by addictive behavior is the consequence of the interaction between an individual's core characteristics and several moderating and mediating variables, and these variables are dynamic (38).

Finally, our study found that gender does not play a moderating role in the relationship between mobile phone addiction and sleep disturbances. It is consistent with the findings of Salehan and Negahban that the moderating effect of gender on mobile phone use is inconclusive (43). One possible reason is that discussing gender differences in the context of social orientation can explain differences between males and females in cognition, behavior, and how they view their social roles. Under the guidance of social orientation, different genders will develop their own behavior patterns and social roles, thus producing different emotions (61). While previous studies have selected young people as samples, there are significant differences in education level, occupation, and marital status (16). Our research samples were University students from western China who share a common social role as "students" in the campus setting, with similar educational level and marital status. They also bear similar social expectations, so they show similarities in the relationship between mobile phone addiction and sleep disturbances. Another possible reason is as follows: previous studies have demonstrated that higher rates of Internet and computer addiction among males (44), while higher rates of mobile phone addiction among females (62). In China, for undergraduates, most universities have a system that requires the lights and power to be turned off regularly on weekday nights. In addition, students in the dormitories need to take care of their roommates' sleeping schedules. These reasons may limit male students from using laptops at night. Due to the advantages of convenience, high performance and accessibility, mobile phones can replace computers in many functions. For example, the latest generation of smartphones allow individuals to participate in a wide range of online activities, such as browsing social networks, watching videos, and playing online games. As an important terminal of mobile Internet, the functions of mobile phones are constantly being updated. Therefore, under the restrictions of the campus environment, the proportion of mobile phone addiction among males may increase, while the gap with the ratio of mobile phone addiction among females will narrow. So, the moderating effect of gender was not found between mobile phone addiction and sleep disturbances.

Our findings have both theoretical and practical implications for reducing mobile phone addiction, depressive symptoms, and sleep disturbances. Theoretically, our study has preliminarily clarified the cross-sectional correlations and direction of effects among mobile phone addiction, seven dimensions of sleep disturbances, and depressive symptoms, and explored the mediating effect of sleep disturbances between mobile phone addiction and depressive symptoms. These efforts offered the foundation for the next step in the study of the association mechanism. Our findings broaden the objects of the maladaptive coping style in sleep disturbances and depressive symptoms. From a practical perspective, our findings have implications for the prevention of depression. Depression symptoms worsen over time, so early intervention is needed. Interventions for sleep disturbances may be appropriate to alleviate mental health problems. There are three strategies to help correct mobile phone addiction: capacity-enhancing strategies (i.e., enhanced self-discipline and rational management ability), behavior reinforcement strategies (i.e., focus on real social networks that can interact face to face), information-enhancing strategies (i.e., support from friends can improve addictive behavior for those who fully understand the risks of mobile phone use) (63). Based on this, we propose the following suggestions for interventions.

First, technology-based interventions are necessary. Mobile software developers should further develop effective strategies to intervene in the link between mobile phone addiction and mental health problems. For example, they could create programs to limit the amount of time a mobile phone can be used. By providing the user with periodic reminders, warning signs that a running application is about to exit, or forced dormancy. Restrict mobile phone access during certain hours, such as at night or when users need to concentrate. To urge mobile phone addicts to better understand their phone usage habits, the application can regularly give users feedback on their daily phone usage, daily usage, duration, and unlock times of the phone. So that users can understand the daily duration of mobile phone use and the reasons and motivations behind mobile phone addiction. The direction of future software developers should be to provide personalized digital interventions based on the mobile phone usage habits of different users (64).

Second, University educators should publicize the potential hazards of mobile phone addiction, sleep disturbances, and depression symptoms. At the same time, University students are encouraged to sleep regularly, exercise moderately, control the use and dependence of mobile phones by improving self-control. University educators could present relevant coping strategies, such as encouraging students to set goals to reduce mobile phone use, sleep on time, and make efforts to stick to those goals. Through class meetings, lectures, psychological counseling, and other relevant practices, strengthen communication, timely relief of negative emotions. Meditation and self-control training may also be beneficial. One of the pathways leading to problematic mobile phone use is the extroversion pathway, where an individual's mobile phone addictive behavior is driven by a strong constant desire to communicate with others and establish new relationships (6). Therefore, we suggest that increasing communication and interaction with others in real life and finding catharsis ways can help improve mobile phone addiction behaviors.

Third, students could try to mobilize social support, such as mobilizing roommates to help each other, or establishing mutual aid groups in the class or dormitory. Classmates or dormitory members remind each other to exercise regularly and sleep on time, which may form a supervision mechanism among students and help them gradually develop good living habits. Guiding students to pour out troubles to families or friends is a good way of easing off pressure, reduce negative emotions, and improve sleep disturbances. For individuals with high social support, the association between problematic mobile phone use and negative emotions became insignificant (35).

There are some limitations to our research. First, in this study the measurements of MPAI, PSQI, and PHQ9 reported by participants, which naturally generates some reliability and validity questions, including the problem of recall bias and response style bias. Future studies can adopt multiple methods and include more information providers in the sample. The second limitation is that this was a University sample, which may add to the limitations of generalizability of the results to other samples. And we used measures of depressive symptoms rather than diagnostic assessments of depression, so any conclusions cannot be generalized to the clinical population. Further studies could examine these relationships using clinical populations. Thirdly, this was a cross-sectional design study, it could not detect causality due to the cross-sectional nature of the data. Longitudinal studies are expected in the future. Finally, our current study only considered depression symptoms, but sleep disturbances may mediate the association between mobile phone addiction and other psychological health concerns. Therefore, we recommend that future studies consider issues such as stress, loneliness, and anxiety. Despite these limitations, however, this study further examined the parallel mediating effect of seven dimensions of sleep disturbances on the relationship between mobile phone addiction and depressive symptoms. It also provides a new intervention strategy from the perspective of sleep disturbances to reduce depressive symptoms.

Conclusion

Overall, mobile phone addiction is an important public health problem related to depressive symptoms and sleep disturbances. The result of the current study revealed that mobile phone addiction can be a risk factor for depressive symptoms of University students. Furthermore, this relationship could be mediated by sleep disturbances. Besides, gender did not moderate the indirect pathway between mobile phone addiction and depressive symptoms. Implications of the findings were discussed in the context of mobile phone addiction and psychological problems among University students. Identifying the key factors in the relationship between mobile phone addiction and depressive symptoms is important for more effective and well-targeted health interventions to prevent and treat depression across the life course. Our results also suggest the importance of early intervention among University students with mobile phone addiction, especially among those with sleep disturbances.

Data availability statement

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

Ethics statement

The study protocol was reviewed and approved by Biomedical Ethics Committee of Xi'an Jiaotong University, China. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

Author contributions

CL designed the research, created the protocol, obtained ethical approval, contributed to the data analysis, and participated in revising the manuscript. ML provided support toward the design of the study, analyzed the data, and produced and revised the research manuscript. All authors read and approved the final manuscript.

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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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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.965135/full#supplementary-material

References

1. Sapacz M, Rockman G, Clark J. Are we addicted to our cell phones? *Comput Hum Behav.* (2016) 57:153–9. doi: 10.1016/j.chb.2015.12.004

2. Omar S, Mohsen K, Tsimonis G, Oozeerally A, Hsu JH. M-commerce: the nexus between mobile shopping service quality and loyalty. *J Retailing Consum Serv.* (2021) 60:102468. doi: 10.1016/j.jretconser.2021.102468

3. AlTameemy F. Mobile phones for teaching and learning: implementation and students' and teachers' attitudes. *J Educ Technol Syst.* (2017) 45:436–51. doi: 10.1177/0047239516659754

4. Pai RR, Alathur S. Assessing awareness and use of mobile phone technology for health and wellness: insights from India. *Health Policy Technol.* (2019) 8:221–7. doi: 10.1016/j.hlpt.2019.05.011

5. Lian L, You X, Huang J, Yang R. Who overuses smartphones? Roles of virtues and parenting style in smartphone addiction among Chinese college students. *Comput Hum Behav.* (2016) 65:92–9. doi: 10.1016/j.chb.2016.08.027

6. Billieux J, Maurage P, Lopez-Fernandez O, Kuss DJ, Griffiths MD. Can disordered mobile phone use be considered a behavioral addiction?

An update on current evidence and a comprehensive model for future research. *Curr Addiction Rep.* (2015) 2:156–62. doi: 10.1007/s40429-015-0054-y

7. Kim JH, Seo M, David P. Alleviating depression only to become problematic mobile phone users: can face-to-face communication be the antidote? *Comput Hum Behav.* (2015) 51:440–7. doi: 10.1016/j.chb.2015.05.030

8. Oulasvirta A, Rattenbury T, Ma L, Raita E. Habits make smartphone use pervasive. *Person Ubiq Comp.* (2012) 16:105–14. doi: 10.1007/s00779-011-0412-2

9. Leung L. Linking psychological attributes to addiction and improper use of the mobile phone among adolescents in Hong Kong. *J Child Media.* (2008) 2:93–113. doi: 10.1080/17482790802078565

10. Chóliz M. Mobile phone addiction: a point of issue. *Addiction.* (2010) 105:373–4. doi: 10.1111/j.1360-0443.2009.02854.x

11. Liu Q, Zhou Z, Yang X, Kong F, Niu G, Fan C. Mobile phone addiction and sleep quality among Chinese adolescents: a moderated mediation model. *Comput Hum Behav*. (2017) 72:108–14. doi: 10.1016/j.chb.2017.02.042

12. Liu J, Liu C, Wu T, Liu BP, Jia CX, Liu X. Prolonged mobile phone use is associated with depressive symptoms in Chinese adolescents. *J Affect Disord.* (2019) 259:128–34. doi: 10.1016/j.jad.2019.08.017

13. Lemola S, Perkinson-Gloor N, Brand S, Dewald-Kaufmann JF, Grob A. Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. *J Youth Adolesc.* (2015) 44:405–18. doi: 10.1007/s10964-014-0176-x

14. Hughes N, Burke J. Sleeping with the frenemy: How restricting "bedroom use" of smartphones impacts happiness and wellbeing. *Comput Hum Behav.* (2018) 85:236–44. doi: 10.1016/j.chb.2018.03.047

15. Cui G, Yin Y, Li S, Chen L, Liu X, Tang K, et al. Longitudinal relationships among problematic mobile phone use, bedtime procrastination, sleep quality and depressive symptoms in Chinese college students: a cross-lagged panel analysis. *BMC Psychiatry.* (2021) 21:449. doi: 10.1186/s12888-021-03451-4

16. Thomée S, Härenstam A, Hagberg M. Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults: a prospective cohort study. *BMC Public Health.* (2011) 11:66. doi: 10.1186/1471-2458-11-66

17. Alhassan AA, Alqadhib EM, Taha NW Alahmari RA, Salam M, Almutairi AF. The relationship between addiction to smartphone usage and depression among adults: a cross sectional study. *BMC Psychiatry.* (2018) 18:148. doi: 10.1186/s12888-018-1745-4

18. Jun S. The reciprocal longitudinal relationships between mobile phone addiction and depressive symptoms among Korean adolescents. *Comput Hum Behav*. (2016) 58:179–86. doi: 10.1016/j.chb.2015.12.061

19. Lin YH, Chiang CL, Lin PH, Chang LR, Ko CH, Lee YH, et al. Proposed diagnostic criteria for smartphone addiction. *PLoS ONE.* (2016) 11:e0163010. doi: 10.1371/journal.pone.0163010

20. Demirci K, Akgönül M, Akpinar A. Relationship of smartphone use severity with sleep quality, depression, and anxiety in University students. *J Behav Addict.* (2015) 4:85–92. doi: 10.1556/2006.4.2015.010

21. Kaya F, Bostanci DN, Durar E. Smart phone usage, sleep quality and depression in University students. *Int J Soc Psychiatry.* (2021) 67:407–14. doi: 10.1177/0020764020960207

22. Ezoe S, Iida T, Inoue K, Toda M. Smartphone addiction and sleep quality associated with depression in University students in Japan. *IJCBPL.* (2019) 9:22–31. doi: 10.4018/IJCBPL.2019100102

23. Islam M. Link between excessive smartphone use and sleeping disorders and depression among South Korean University students. *Healthcare.* (2021) 9:1213. doi: 10.3390/healthcare9091213

24. Augner C, Hacker G. Associations between problematic mobile phone use and psychological parameters in young adults. *Int J Public Health.* (2011) 57:437–41. doi: 10.1007/s00038-011-0234-z

25. Boumosleh JM, Jaalouk D. Depression, anxiety, and smartphone addiction in University students-A cross sectional study. *PLoS ONE.* (2017) 12:e0182239. doi: 10.1371/journal.pone.0182239

26. Liu S, Wing YK, Hao Y, Li W, Zhang J, Zhang B. The associations of long-time mobile phone use with sleep disturbances and mental distress in technical college students: a prospective cohort study. *Sleep.* (2019) 42:zsy213. doi: 10.1093/sleep/zsy213

27. Li Y, Li G, Liu L, Wu H. Correlations between mobile phone addiction and anxiety, depression, impulsivity, and poor sleep quality among college students: a systematic review and meta-analysis. *J Behav Addict.* (2020) 9:551–71. doi: 10.1556/2006.2020.00057

28. Choksi ST, A. study to find out the correlation of mobile phone addiction with anxiety, depression, stress and sleep quality in the college students of Surat city. *Int J Curr Res Rev.* (2021) 13:137–42. doi: 10.31782/IJCRR.2021.13812

29. Yang J, Fu X, Liao X, Li Y. Association of problematic smartphone use with poor sleep quality, depression, and anxiety: a systematic review and meta-analysis. *Psychiatry Res.* (2020) 284:112686. doi: 10.1016/j.psychres.2019.112686

30. Zou L, Wu X, Tao S, Xu H, Xie Y, Yang Y, et al. Mediating effect of sleep quality on the relationship between problematic mobile phone use and depressive symptoms in College Students. *Front Psychiatry.* (2019) 10:822. doi: 10.3389/fpsyt.2019.00822

31. Bai C, Chen X, Han K. Mobile phone addiction and school performance among Chinese adolescents from low-income families: a moderated mediation model. *Child Youth Serv Rev.* (2020) 118:105406. doi: 10.1016/j.childyouth.2020.105406

32. Xu F, Cui W, Xing T, Parkinson M. Family socioeconomic status and adolescent depressive symptoms in a Chinese low- and middle- income sample: the indirect effects of maternal care and adolescent sense of coherence. *Front Psychol.* (2019) 10:819. doi: 10.3389/fpsyg.2019.00819

33. Bandura A. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice Hall (1986).

34. Chen L, Yan Z, Tang W, Yang F, Xie X, He J. Mobile phone addiction levels and negative emotions among Chinese young adults: The mediating role of interpersonal problems. *Comput Hum Behav*. (2016) 55 (Part B):856–66. doi: 10.1016/j.chb.2015.10.030

35. Gao L, Yang C, Yang X, Chu X, Liu Q, Zhou Z. Negative emotion and problematic mobile phone use: the mediating role of rumination and the moderating role of social support. *Asian J Soc Psychol.* (2021) 25:138–151. doi: 10.1111/ajsp.12471

36. Bozoglan B, Demirer V, Sahin I. Problematic internet use: functions of use, cognitive absorption, and depression. *Comput Hum Behav.* (2014) 37:117–23. doi: 10.1016/j.chb.2014.04.042

37. Kardefelt-Winther D. A conceptual and methodological critique of internet addiction research: towards a model of compensatory internet use. *Comput Hum Behav*. (2014) 31:351–4. doi: 10.1016/j.chb.2013.10.059

38. Brand M, Wegmann E, Stark R, Müllere A, Wölflingf K, Robbins TW, et al. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neurosci Biobehav Rev.* (2019) 104:1–10. doi: 10.1016/j.neubiorev.2019.06.032

39. Goel N, Kim H, Lao RP. Gender differences in polysomnographic sleep in young healthy sleepers. *Chronobiol Int.* (2005) 22:905–15. doi: 10.1080/07420520500263235

40. Chen B, Liu F, Ding S. Ying X, Wang L, Wen Y. Gender differences in factors associated with smartphone addiction: a cross-sectional study among medical college students. *BMC Psychiatry.* (2017) 17:341. doi: 10.1186/s12888-017-1503-z

41. Adams SK, Kisler TS. Sleep quality as a mediator between technology-related sleep quality, depression, and anxiety. *Cyberpsychol Behav Soc Netw.* (2013) 16:25–30. doi: 10.1089/cyber.2012.0157

42. Thomée S, Eklöf M, Gustafsson E, Nilsson R, Hagberg M. Prevalence of perceived stress, symptoms of depression and sleep disturbances in relation to information and communication technology (ICT) use among young adults: an explorative prospective study. *Comput Hum Behav.* (2007) 23:1300–21. doi: 10.1016/j.chb.2004.12.007

43. Salehan M, Negahban A. Social networking on smartphones: when mobile phones become addictive. *Comput Hum Behav*. (2013) 29:2632–39. doi: 10.1016/j.chb.2013.07.003

44. Bianchi A, Phillips JG. Psychological predictors of problem mobile phone use. *Cyberpsychol Behav.* (2005) 8:39–51. doi: 10.1089/cpb.2005.8.39

45. Spitzer RL, Kroenke K, Williams JBW, Group, PHQPCS. Validation and utility of a self-report version of PRIME-MD: The PHQ primary care study. *JAMA.* (1999) 282:1737–44. doi: 10.1001/jama.282.18.1737

46. American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders.* 4th ed. Washington, DC: American Psychiatric Association (1994).

47. Löwe B, Kroenke K, Herzog W, Gräfe K. Measuring depression outcome with a brief self-report instrument: sensitivity to change of the patient Health questionnaire (PHQ-9). *J Affect Disord.* (2004) 81:61–6. doi: 10.1016/S0165-0327(03)00198-8

48. Wang W, Bian Q, Zhao Y, Li X, Wang W, Du J, et al. Reliability and validity of the Chinese version of the patient Health questionnaire (PHQ-9) in the general population. *Gen Hosp Psychiatry.* (2014)36:539–44. doi: 10.1016/j.genhosppsych.2014.05.021

49. Tsai PS, Wang SY, Wang MY, Su CT, Yang TT, Huang CJ, et al. Psychometric evaluation of the Chinese version of the Pittsburgh Sleep Quality Index (CPSQI) in primary insomnia and control subjects. *Qual Life Res.* (2005) 14:1943–52. doi: 10.1007/s11136-005-4346-x

50. Buysse DJ, Reynolds CF III, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. *Psychiatry Res.* (1989) 28:193–213. doi: 10.1016/0165-1781(89)90047-4

51. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. New York, NY: Guilford Publications (2017).

52. Yang X, Wang P, Hu P. Trait procrastination and mobile phone addiction among Chinese college students: a moderated mediation model of stress and gender. *Front Psychol.* (2020) 11:614660. doi: 10.3389/fpsyg.2020.614660

53. Elhai JD, Dvorak RD, Levine JC, Hall BJ. Problematic smartphone use: a conceptual overview and systematic review of relations with anxiety and depression psychopathology. *J Affect Disord.* (2017) 207:251–9. doi: 10.1016/j.jad.2016.08.030

54. Billieux J, Philippot P, Schmid C, Maurage P, De Mol J, Van der Linden M. Is dysfunctional use of the mobile phone a behavioural addiction? Confronting symptom-based versus process-based approaches. *Clin Psychol Psychother*. (2015) 22:460–8. doi: 10.1002/cpp.1910

55. Jun S. Longitudinal influences of depressive moods on problematic mobile phone use and negative school outcomes among Korean adolescents. *Sch Psychol Int.* (2019) 40:294–308. doi: 10.1177/0143034319830452

56. Wood AW, Loughran SP, Stough C. Does evening exposure to mobile phone radiation affect subsequent melatonin production? *Int J Radiat Biol.* (2006) 82:69–76. doi: 10.1080/09553000600599775

57. Oh JH, Yoo H, Park HK, Do YR. Analysis of circadian properties and healthy levels of blue light from smartphones at night. *Sci Rep.* (2015) 5:11325. doi: 10.1038/srep11325

58. Shek DTL, Sun RCF, Yu L. Internet addiction. In: Pfaff DW, editors. *Neuroscience in the 21st Century*. New York, NY: Springer (2013). p. 2775–811.

59. Coviello L, Sohn Y, Kramer ADI, Marlow C, Franceschetti M, Christakis NA, et al. Detecting emotional contagion in massive social networks. *PLoS ONE.* (2014) 9:90315. doi: 10.1371/journal.pone.0090315

60. Pantic I, Damjanovic A, Todorovic J, Topalovic D, Bojovic-Jovic D, Ristic S. Association between online social networking and depression in high school students: behavioral physiology viewpoint. *Psychiatr Danub.* (2012) 24:90–3.

61. Chen C, Zhang KZ, Gong X, Zhao SJ, Lee MK, Liang L. Examining the effects of motives and gender differences on smartphone addiction. *Comput Hum Behav*. (2017) 75:891–902. doi: 10.1016/j.chb.2017.07.002

62. Hong F-Y, Chiu S-I, HuangD-H. A model of the relationship between psychological characteristics, mobile phone addiction and use of mobile phones by Taiwanese University female students. *Comput Hum Behav.* (2012) 28:2152–9. doi: 10.1016/j.chb.2012.06.020

63. Busch PA, McCarthy S. Antecedents and consequences of problematic smartphone use: A systematic literature review of an emerging research area. *Comput Hum Behav*. (2021) 114:106414. doi: 10.1016/j.chb.2020.106414

64. van Velthoven MH, Powell J, Powell G. *Problematic Smartphone Use: Digital Approaches to an Emerging Public Health Problem*. London: SAGE Publications Sage UK (2018). p. 1–9.

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A study on the impact and buffer path of the internet use gap on population health: Latent category analysis and mediating effect analysis

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Background: The development of Internet information technology will generate an Internet use gap, which will have certain adverse effects on health, but internet information dependence can alleviate these negative effects.

Objective: This article is to demonstrate the negative impact of the internet use gap on population health in developing countries and to propose improvement paths.

Methods: This article used the 2018 China Family Tracking Survey database ($N = 11086$). The research first used Latent class analysis (LCA) to identify potential categories of users with different Internet usage situations, then used the Bolck, Croon, and Hagenaars (BCH) method to perform latent class modeling with a continuous distal outcome, and finally built an intermediary model about Internet information dependence based on the model constraint function in Mplus software.

Results: (1) The Internet users can be divided into light-life users (C1: $N =$ 1,061, 9.57%), all-around users ($N =$ 1,980, 17.86%(C2: $N =$ 1,980, 17.86%), functional users (C3: $N =$ 1,239, 11.18%), and pure-life users (C4: $N =$ 6,806, 61.39%). (2) We examined individual characteristics, social characteristics and different living habits, and health differences between the latent classes. For example, there are certain structural differences on the effect of different categories of Internet use on health (C1: $M = 3.089$, SE = 0.040; C2: $M = 3.151$, SE = 0.037; C3: $M = 3.070$, SE = 0.035; C4: $M = 2.948$, $SE = 0.016$; $P < 0.001$). (3) The Internet use gap can affect health through the indirect path of Internet information dependence, and some of the mediation effects are significant. When the functional user group (C3) was taken as the reference group, the mediating effect values of light-life users (C1) and all-around users (C4) on health were −0.050 (SE = 0.18, Est./SE = −3.264, $P = 0.001$) and −0.080 (SE = 0.010, Est./SE = −8.412, $P = 0.000$) through Internet information dependence, respectively. However, the effect of categories on health was not significant after adding indirect paths.

Conclusion: The Internet use gap has a significant effect on health, and Internet information dependence plays an intermediary role in this effect path. The study proposes that attention should be paid to the diversified development of Internet use, the positive guiding function of Internet information channels should be made good use of, and the countermeasures and suggestions of marginalized groups in the digital age should also be paid attention to and protected.

KEYWORDS

internet use gap, internet information dependence, population health, latent category analysis, regression analysis

Introduction

With the innovation and transformation of information technology and the in-depth expansion of application space, the Internet not only affects social progress and economic development but also changes the production and lifestyle of the population. According to the "Digital 2021: Global Overview Report" released by the DataReportal research institute, the current global Internet users account for 59.51% (4.66 billion/7.83 billion) of the global population, 5.22 billion mobile phone users, and the penetration rate is 66.6%. Internet users spend nearly 7 h online every day, and the penetration rate and application rate of the Internet have reached a new high (1). As the largest developing country, China has 1.032 billion Internet users, and its Internet penetration rate is as high as 73.0%. The daily Internet online time exceeds 4 h, which is much higher than the overall level of the global Internet penetration rate (The 49th "Statistical Report on Internet Development in China," 2022), and the status of China's Internet as the world's largest network has become increasingly prominent (2). Thanks to the accumulation and iteration of basic Internet resources and the rich innovation of digital application technology services, the Internet has penetrated people's daily life from multiple dimensions such as study, work, social interaction, and entertainment. The frequency of activities and information dependence have been continuously strengthened. The digitalization of the earth's inhabitants is irreversible, and the Internet is one of the social determinants of health (3). Improving population health is one of the important goals of digital governance(4).

The results of Internet development have created differentiation, gaps, and even gaps between the digital and non-digital groups, and this differentiation is called the Digital Divide (5). The concept of the Digital Divide proposed by the OECD includes two dimensions, namely, "Whether Internet access (Have)" and "Whether there is a difference in Internet use (Use)" (6, 7). The "Internet use gap" (IUG) is the difference in Internet use and one of the important manifestations of digital inequality (8). The current Digital Divide is mainly manifested in the differences in digital skills and user behavior. According to the different purposes of using Internet, Internet users can be divided into "researchers," "consumers," "expressers," and "entertainers" (9). Different ways of using the Internet will produce different social benefits, and recreational and social use of the Internet have more significant effects on health, affecting life satisfaction and well-being (7, 10, 11). Internet use is affected by individual, cultural, technological and social factors such as gender, race, registered residence, geographical location and socio-economic status (12), which can directly affect health. According to the empirical analysis results of China's typical micro database (Charles), self-rated health status is significantly related to Internet use, and narrowing the digital divide can reduce health inequality (12). Problematic Internet Use (PIU) caused by COVID-19 is even more serious. There are country differences in this situation, which will aggravate loneliness, damage self-esteem, and cause psychological distress. It is necessary to be alert to adverse consequences for health caused by differences in using Internet. (13). The above research conclusions show that more and more scholars are paying attention to the important impact of the Internet on population health, but there are still some theoretical differences in the relationship between the two (14, 15), especially since few studies are focusing on the effect of the IUG on health, and only a few scholars have proposed that narrowing the digital divide can reduce health inequality (16).

The Internet can affect health from multiple domains, one of which is information (17, 18). Through the analysis of Knowledge Gap Theory, it is found that the Digital Divide causes unequal opportunities for information interaction, and the ability to search and utilize information will affect the use of the Internet by affecting human capital, thereby deepening the IUS (18). The Internet brings about the explosive growth of information, which greatly improves the utilization effect

Abbreviations: CFPS, China family panel studies database; IUG, internet use gap; IID, internet information dependence; CV, control variable; DV, dependent variable; IV, independent variable; ICV, individual characteristic variables; DE, direct effect; IE, intermediary effect; LCA, latent class analysis; PIU, problematic internet use; MP, mediation percentage; LHV, living habits variables; SCV, social characteristic variables.

of information, especially medical and health information, and makes it develop into one of the important ways to obtain health information and knowledge (19), forming the "Internet information dependence" (IID) of health capital. IID can affect both the digital divide and population health. On the one hand, the development of Internet information technology can enhance the digital dividend, and it may also cause an information gap due to the difference in the possession and utilization of information technology, thereby increasing the digital divide (20). On the other hand, the rapid ingestion of Internet information can improve the ability to participate in information, meet information needs, enhance self-esteem experience and alleviate the fear of the unknown (21). IID has two dividing dimensions, namely, the availability of information and the usefulness of information (22). The former affects health behaviors through as much information as possible, and the latter ultimately affects health decisions through information screening. The improvement of Internet health information literacy is an important condition to ensure mental health. However, the low threshold for Internet information access will cause information risks, and the diversity, extensiveness, misleading and uncertainty of information will cause anxiety and tension to a certain extent, and affect health (20). Based on the above analysis, it is found that IID can affect health through direct and indirect paths, but its indirect effect paths are more diverse, and few people have paid attention to the positive role of IID in the negative effect of IUS on health. The collaborative research on the three is relatively scarce and needs to be further deepened from the theoretical level.

At present, the research on the impact of the Internet on health has mostly focused on the use of smartphones and social media (23). The research methods are mostly qualitative surveys such as statistical regression (24) and focus interviews (25), and the key groups of concerning are special groups such as adolescents (26) and the elderly (24). Thus, quantitative research results for developing countries are relatively scarce. This study used the 2018 China Family Panel Studies Database (CFPS) as the research data source extracting relevant measurement indicators such as population health, IUG, IID, etc. According to the data types and characteristics of the questionnaire, Mplus 8.0 software was used to carry out LCA with distal outcomes and mediation test. The findings of this study have important implications for reducing the negative effects of the IUG on population health in low- and middle-income countries.

Methods

Data source

The research data came from China's 2018 CFPS cross-sectional database released by the China Social Science Survey Center (N = 11086), which covered 31 provinces/cities/autonomous regions of China and had the characteristics of national, systematic, social and continuous, etc. The data is permanently tracked with a two-year survey cycle. Since the nationwide survey in 2010, a total of 8 rounds of data collection have been carried out, including the preliminary survey. It is an important micro-database for studying Chinese social issues. This study selected the content of family questionnaires and adult questionnaires as the main data sources, and the survey content covered multiple dimensions such as income, education, society, medical care, and health.

Analytic strategy

The data analysis is divided into three stages. The main goal of the first stage is to identify the Internet use subtypes of different users through five Internet use variables which is used as the IUG variable. Then the second stage is to examine individual characteristics, social characteristics, living habits and health differences between the latent classes. The main goal of the third-stage analysis was to observe the mediating effect of IID on the population health pathway of the IUD.

LCA is a method of parameter estimation based on the principle of probability distribution and the joint probability of individuals on explicit variables (27), which can reorganize explicit variables of specific Internet-use behavior into categorical variables of Internet use behavior patterns. The key explanatory variable of this study is the IUG, which consists of five explicit variables, namely the frequency of Internet study, work, social interaction, entertainment and business activities (divided into high-frequency and low-frequency categories according to the questionnaire information), and they are denoted as A, B, C, D, and E, respectively. The corresponding latent variable model is constructed as:

$$\pi_{fghij}^{ABCDE} = \sum_{n=1}^{N} \pi_n^X \pi_{fn}^{A|X} \pi_{gn}^{B|X} \pi_{hn}^{C|X} \pi_{in}^{D|X} \pi_{jn}^{E|X} \qquad (1)$$

In formula (1), f, g, h, j, and k are the values of five explicit variables corresponding to specific Internet use behaviors, respectively. $\pi_{\mathrm{fghij}}^{ABCDE}$ represents the joint probability of a latent Internet use category model, and π_{n}^{X} is the latent class probability, that is, the probability that a latent class X belongs to class n, $n = 1, 2 ... \mathrm{N}$. $\pi_{\mathrm{fn}}^{A|X}$ is the conditional probability, that is, the probability that an individual belonging to the nth latent category responds to the fth level of the observed variable A. The subsequent interpretation of the conditional probability is similar to this, so it will not be explained one by one.

The Bolck, Croon, and Hagenaars (BCH) approach of LCA was used to predict distal outcomes, which modeled all covariates and distal outcomes simultaneously in the final LCA solution (28). This analytical method has significant advantages, which indicates that modal posterior probability assignment is used to reflect respondents to their most likely latent class and performs the subsequent weighted multi-categorical analysis. This stepwise approach can not only provide overall significance testing of associations between latent class membership and outcomes but also perform pairwise differences testing between classes in the means of continuous outcomes (29). In addition, this method can fully consider the influence of covariates on dependent variables so that the effects of latent class membership are controlled by those covariates (30).

Moreover, we used the model constraint function in Mplus to build a mediation model. After controlling for covariates such as individual characteristics, with the latent class variable of IUG as independent variable, we observed IID as intermediary variable, and population health as the dependent variable. We examined whether the mediation effect of Internet information dependence is established.

All models were done by using Mplus version 8 and State 16.

Variable selection

Dependent variable (DV)

The dependent variable is population health. According to the question "how do you think your health status" in the personal questionnaire QP201, the score is 1–5, and the higher the value is, the higher the health level is.

Independent variable (IV)

The independent variables mainly analyze two factors, the IUG and IID.

(1) Internet use gap (IUG). According to the frequency of Internet study, work, social interaction, entertainment, and business activities, a categorical variable of Internet use with significant explanatory power was constructed, and it was used as an integrated variable for the IUG. Use Mplus 8.0 software to fit the data many times, and compare the fitting effects of different models, then finally determine the best fitting model according to the Log-Likelihood G2, AIC and BIC. Use Entropy (value 0–1) to evaluate the accuracy of the classification, and focus on the values of AIC, BIC, and aBIC. The smaller the values are, the better the fitting effect of the classification results is (31).

(2) Internet information dependence (IID). The measurement of IID in previous research was mostly carried out from the perspectives of Internet access such as Internet coverage and mobile phone penetration. A small number of scholars used the time of using Internet to measure the degree of Internet use (32), and some scholars comprehensively analyzed the availability and effectiveness of Internet information (22). This study mainly focuses on the gap and information dependence based on Internet use and focuses more on the usefulness of Internet information. Therefore, the question of QU802 "Importance of the Internet for you to obtain information" is selected as the explanatory variable of IID, and the values are assigned from 1 to 5, and the degree of importance increases gradually.

Control variable (CV)

To minimize the problems of endogeneity and heteroscedasticity, the study further selected factors that may affect health from different dimensions such as individual characteristics, social characteristics and living habits, as covariates in the analysis framework. Among them, individual characteristics include variables such as gender, age, marital status, years of education and chronic disease prevalence, and social characteristics include variables such as income, employment status and family size. Drinking, exercise and smoking are used as indicators of living habits.

The basic description and statistics of the variables are shown in Table 1. In order to avoid the possible multicollinearity of the multiple explanatory variables of the cross-sectional data from affecting the regression results as much as possible, the Tolerance (Tol) and the Variance Inflation Factor (VIF) were tested respectively, and it was found that the Tol values were much >0.1 and VIF values were all <5, which indicated that the selected explanatory variables have passed the multicollinearity test and can be further analyzed.

According to the results of Table 1, the selected survey sample's health level is high as a whole ($M = 3.015$, $SD = 1.183$), and there is only a small part of the chronic disease ($M = 0.14$, $SD = 0.345$), of which Pure-Life uses group is the most ($N = 6806$, Category Probability = 6806/11086 = 61.39%) and Light-life users' group is the least ($N = 1061$, Category Probability = 1061/11086 = 61.39% = 9.57%). At the same time, the sex ratio of the investigated population is balanced ($M = 0.50$, $SD = 0.500$), of which the age is relatively high ($M = 45.12$, $SD = 14.869$), and most of them are married ($M = 0.81$, $SD = 0.396$) and working ($M = 0.82$, $SD = 0.383$). However, their education level is low, and the average years of schooling is only 8.33, most of them lack healthy habits, and the average weekly exercise frequency is only 2.55. The proportion of people who smoke ($M = 0.68$, $SD = 0.465$) and drink ($M = 0.84$, $SD = 0.368$) is relatively large.

Results

Latent class identification

The potential category analysis of the IUG is mainly completed through the Mplus 8.0 software. See Table 2 for the

TABLE 1 Variable description and descriptive statistics.

Variable	Name	Description	Mean	SD
Health	Health	Score ranges: 1–5. The larger score, the healthier	3.015	1.183
IUGV	First class	Light-life users, $N = 1061$, C1	0.10	0.294
	Second class	All-around users, $N = 1980$, C2	0.18	0.383
	Third class	Functional users, $N = 1239$, C3	0.11	0.315
	Fourth class	Pure-life users, $N = 6806$, C4	0.61	0.487
IIDV	INT infomation	Importance of the Internet for you to obtain information Value ranges: 1–5	3.185	1.6154
ICV	Gender	Gender: Male = 1, Female = 0	0.50	0.500
	Age	Age: actual age. Value ranges: 16–96	45.12	14.869
	Marriage	marital status: with spouse = 1, without spouse = 0	0.81	0.396
	Education	Years of education, from illiterate to doctorate. Value ranges: 0–22	8.33	4.732
	Chronic	chronic disease: Do you have the chronic disease? Yes = 1, No = 0	0.14	0.345
SCV	Employ	Working status: employed = 1, unemployed = 0	0.82	0.383
	Family number	Family size: number of family members. Value ranges: 1–17	4.09	1.997
	Income	Income: logarithm of per capita household income (annual income/family size)	9.490	0.998
LHV	Exercise	Exercise: the frequency of physical exercise in the last week. Value ranges: 0–50	2.55	3.271
	Smoke	Smoking: Smoking in the past month? Yes = 1, No = 0	0.68	0.465
	Drink	Drinking: 3 times per week in the past month? Yes = 1, No = 0	0.84	0.368

IUGV, Internet use gap variable; IIDV, Internet information dependence variable; ICV, Individual characteristic variables; SCV, Social characteristic variables; LHV, Living habits variables; same below.

specific analysis results. It can be seen from the analysis results that the likelihood ratio statistic G^2 gradually decreases with the increase of the number of categories, and the degree of freedom level increases, but the type4 has the smallest AIC (44302.367), BIC (44470.579) and aBIC (44397.487) values, and the Entropy value (0.735) is higher than that of the type 5 (0.718), so the study considers the latent category model of type 4 to be the optimal category model. Based on this, the study further analyzes the latent category probability and conditional answer probability of different Internet use classifications, and names the corresponding Internet use types according to the corresponding conditional answer probability. The results are shown in Table 3 and Figure 1. Users in category 1 are weak in other functions except for social and entertainment, so they are named "light-life users." Similarly, users in category 2 with a high frequency of five functions are named "all-around users." Users in category 3 have relatively high frequencies except for the low frequency of working, which is named "functional users." Users in category 4 have a very low frequency of functional usage except for the very high frequency of social entertainment, and they are named "pure-life users." The latent category probabilities of the four types of users are 9.57, 17.86, 11.18, and 61.39%, respectively. Different types of Internet users not only reflect differences in individual Internet use but also directly reflect the Internet digital divide. It is proved that differences in Internet use patterns create an IUG.

Class characteristics

Individual characteristics, social characteristics and living habits for the four classes are displayed in Table 4. We tested whether classes differed in individual characteristics, social characteristics, living habits, IIDV and health. Smoking status and IID did not differ significantly among potential subcategories of Internet use. Different Internet use categories

TABLE 2 Latent category model indicator evaluation of internet use categories.

Type	Likelihood ratio statistic G^2	*P* Value	*AIC*	*BIC*	*aBIC*	Entropy	Degrees of freedom
Type 1	−25116.997	0.000	50243.993	50280.561	50264.672	0	5
Type 2	−22669.355	0.000	45360.711	45441.16	45406.203	0.841	11
Type 3	−22196.292	0.000	44426.584	44550.914	44496.893	0.775	17
Type 4	−22128.184	0.000	44302.367	44470.579	44397.487	0.735	23
Type 5	−22108.162	0.000	44374.332	44486.422	44398.263	0.718	29

TABLE 3 Latent category probability and conditional answer probability of internet use model (%).

	Latent category			Light-life users	All-around users	Functional users	Pure-life users
	Category probability			9.57%	17.86%	11.18%	61.39%
Conditional probability	Study	Internet use frequency	Low↓	0.929	0.067	0.408	1.000
			High↑	0.071	0.933	0.592	0.000
	Work		Low↓	0.923	0.000	0.532	0.713
			High↑	0.077	1.000	0.468	0.287
	Social Interaction		Low↓	0.419	0.031	0.002	0.000
			High↑	0.581	0.969	0.998	1.000
	Entertainment		Low↓	0.478	0.190	0.017	0.007
			High↑	0.522	0.810	0.983	0.993
	Business		Low↓	0.934	0.471	0.262	1.000
			High↑	0.066	0.529	0.738	0.000

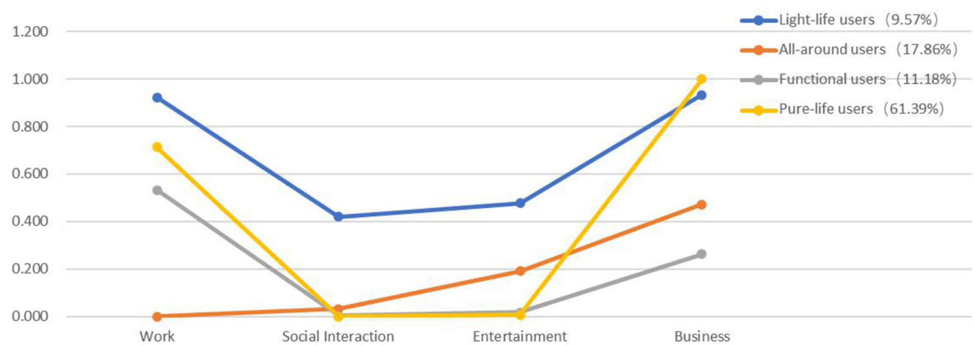

FIGURE 1
Item response probabilities and prevalence for the four-class model.

have significant between-group differences in multiple variables and have their characteristics.

Based on research needs, focus on observing whether there are significant differences in the health level and IID of different potential categories of Internet users. According to LCA with distal outcome, there are significant differences in the health level (C1: M = 3.089, SE = 0.040; C2: M = 2.948, SE = 0.016; C3: M = 3.070, SE = 0.035; C4: M = 2.948, SE = 0.016) and IID (C1: M = 3.070, SE = 0.050; C2: M = 3.571, SE = 0.051; C3: M = 3.555, SE = 0.048; C4: M = 3.002, SE = 0.022) of different potential categories of Internet use. Furthermore, the characteristics of C2 and C4 users are the most prominent. C2 users' educational level educational level (M = 10.073, SE = 0.171) and income level (M = 9.599, SE = 0.036) are higher than other categories of Internet users, but the age is lower (M = 40.607, SE = 0.480). C4 users have the longest age (M = 47.511, SE = 0.204), but their family size (M = 3.780, SE = 0.026) was minimum.

TABLE 4 ICV, SCV, LHV, health and IIDV of latent classes.

	Variable	M(SD)/Prob(OR)			
		Light-life users (C1)	All-around users (C2)	Functional users (C3)	Pure life users (C4)
	Number	1061	1980	1239	6806
ICV	[B]Gender[a]** = 1	0.531 (1.225)	0.503 (1.096)	0.516 (1.154)	0.480 (1.000)
	[A]Age[a]***	44.765 (0.421)	40.607 (0.480)	41.125 (0.426)	47.511 (0.204)
	[A]Edu[a]***	7.890 (0.146)	10.073 (0.171)	8.461 (0.146)	7.958 (0.062)
	[B]Marriage[a]*** = 1	0.883 (1.747)	0.743 (0.671)	0.777 (0.810)	0.811 (1.000)
	[B]Chronic[a] *** = 1	0.136 (0.884)	0.118 (0.757)	0.115 (0.735)	0.151 (1.000)
SCV	[A]Family number[a]***	4.443 (0.065)	4.367 (0.068)	4.645 (0.066)	3.780 (0.026)
	[B]Employ[a]*** = 1	0.921 (0.009)	0.855 (1.812)	0.903 (2.858)	0.766 (1.000)
	[A]Income[a]***	9.349 (0.032)	9.599 (0.036)	9.515 (0.032)	9.489 (0.013)
LHV	[A]Exercise[a]***	2.220 (0.102)	2.633 (0.103)	2.322 (0.102)	2.667 (0.045)
	[B]Smoke = 1	0.670 (0.959)	0.715 (1.186)	0.689 (1.047)	0.679 (1.000)
	[B]Drink[a]*** = 1	0.843 (0.992)	0.875 (1.286)	0.780 (0.653)	0.844 (1.000)
IIDV	[A]IIDV[a]***	3.070 (0.050)	3.571 (0.051)	3.555 (0.048)	3.002 (0.022)
Health	[A]*Health******	3.089 (0.040)	3.151 (0.037)	3.070 (0.035)	2.948 (0.016)

Note: Significant differences between all groups, where $^{***}p < 0.001$.
[A]Indicates that the variable is continuous and reports M (SE).
[B]Indicates that the variable is categorical and reports Prob (OR).
[a]Indicates significant differences between C1 and the rest of the groups. *M*, means; OR, Odds Ratio.

Intermediary effect validation

We further examined whether differences between the functional user's group and the three internet use groups in IID explained differences in health. Thus, multi-categorical weighted mediation analyses (33) were performed to determine whether differences in the degree of dependence on internet information between each internet use class and the functional users class accounted for health of the IUG after controlling for covariates.

Tests of indirect effects via IID were examined in the same model (see Figure 2 and Table 5). As seen in Figure Group A, for internet users of Light-life (C1), higher dependence on internet information ($b_{indirecteffect} = -0.050$, SE $= 0.18$, Est./SE $= -3.264$, $P = 0.001$), partially explained differences in health relative to the Functional users class. However, the effect of class on health was not significant after adding indirect paths ($b_{indirecteffect} = 0.197$, SE $= 0.141$, Est./SE $= 1.399$, $P = 0.162$). Although health was not significantly higher for C2 than for C3 after accounting for all other measures, the extent to which health was higher in All-around users' class was not accounted for by different degree of dependence on internet information. As seen in Figure Group B, for internet users of All-around (C2), evidencing greater health was not explained by the dependence on internet information ($b_{indirecteffect} = 0.003$, SE $= 0.014$, Est./SE $= 0.202$, $P = 0.840$) in the Functional users group. Consistent with Group A, the effect of class on health was not significant after adding indirect paths ($b_{indirecteffect} = -0.016$, SE $= 0.163$, Est./SE $= -0.099$, $P = 0.921$). As seen in Figure Group C, in Pure-life users group (C4), lower dependence on internet information relative to the Functional users group fully explained the extent to which people had reduced health ($b_{indirecteffect} = -0.080$, SE $= 0.010$, Est./SE $= -8.412$, $P = 0.000$). However, the effect of class on differences in health was not significant after adding indirect paths ($b_{indirecteffect} = -0.066$, SE $= 0.105$, Est./SE $= -0.631$, $P = 0.528$).

Discussion

The Internet is the core technical element and production element for the life and development of modern people and affects health. According to the empirical analysis of the 2018 CFPS database, the research analyzes the mechanism of the IUG and IID on health. First of all, by analyzing the latent categories of various ways of using the Internet, the users who use the Internet can be divided into light-life users, all-around users, functional users, and pure-life users. There are obvious differences in the latent category probabilities of different user types, which reflect the IUG, indicating that IUG exists objectively. Different latent categories of Internet users present certain individual and social characteristics. Secondly, the IUG has a direct effect on health. According to the results of the BCH approach for LCA with distal outcomes, it is found that there are significant differences in the health level of Internet users in different potential categories(C1: $M = 3.089$, SE $= 0.040$; C2: $M = 2.948$, SE $= 0.016$; C3: $M = 3.070$, SE $= 0.035$; C4: $M =$

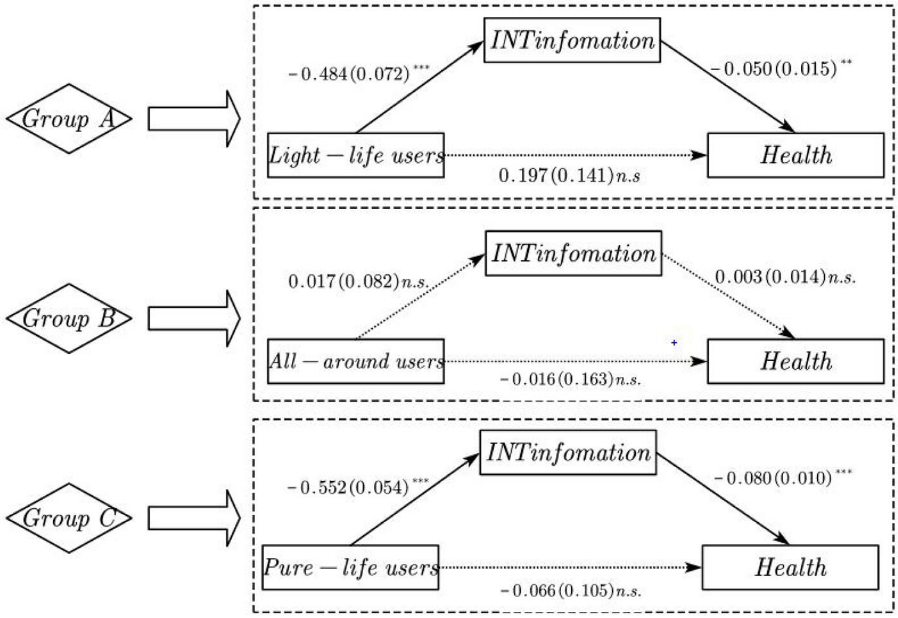

FIGURE 2
Multigroup mediation model relative to the Functional users (C3). Note: **(Group A)** Comparison of Light-life users class (C1) against the Functional users class (C3). **(Group B)** Comparison of All-around users class (C2) against Functional users class (C3). **(Group C)** Comparison of Pure-life users class (C4) against Functional users class (C3). Significant directional paths are represented in solid lines and non-significant paths in dashed lines. Our statistical model included health at covariates (*P < 0.05. **P < 0.01. ***P < 0.001).

TABLE 5 Class differences relative to the functional users (C3).

Variable	M(SE)		
	Light-life users(C1)	All-around users(C2)	Pure life users(C4)
Take C3 as the reference group			
Class(x) - Health	0.197 (0.141)	−0.016 (0.163)	−0.066 (0.105)
Class(x) - IIDV	−0.484 (0.072)***	0.017 (0.082)	−0.552 (0.054)***
IIDV - Health	−0.050 (0.015)**	0.003 (0.014)	−0.080 (0.010)***

ICV, SCV, LHV are controlled, and results for one dependent variable control for theother dependent variables (i.e., class differences in health for IIDV).
ICV, Individual characteristic variables; SCV, Social characteristic variables; LHV, Living habits variables; IIDV, Internet information dependence variable. *P < 0.05, **P < 0.01, ***P < 0.001.

2.948, SE = 0.016). This shows that theIUG formed by different Internet usage does have different effects on population health. In addition, by analyzing the mediating effect of the model constraint function in Mplus, it is found that the mediating effect of Internet information dependence on the healthy path of the Internet use gap exists.

Based on the above research conclusions, corresponding policy recommendations are put forward. First, pay attention to the diversified, life-oriented, and balanced development of Internet use. When analyzing the classification characteristics of potential subclasses formed by different Internet use situations, it is found that C2 Internet users have higher social, economic status and health status, while C4 Internet users have the opposite, which indicates that C4 Internet users have certain limitations and limit the positive impact of the Internet on population health. It is necessary to consider the production and life functions of Internet use, maximize the social benefits of the Internet's digital dividends, be alert to the negative effects of the IUG on health, and prevent the Internet's "technological addiction," "entertainment addiction" and "social addiction." Second, make good use of the positive guiding function, transmission function, and interactive function of Internet information channels. The intermediary effect test proves that the intermediary effect of IID on the healthy path of the impact of the IUG does exist, which indicates that the information transmission function of the Internet is very important. The Internet is an epoch-making change in information dissemination. It promotes the global dissemination and sharing of information and affects people's personality psychology, value orientation, and way of life in an all-around way. Opportunities and challenges of Internet information dissemination should be treated with caution. On the one hand, we should build a strong supervision network for Internet information, strictly punish the dissemination of harmful information and Internet information crimes, and guide correct, positive, and healthy network information to occupy the network position. On the other hand, pay attention to the guidance of ideology and the propaganda on the correct use of Internet information, and improve the people's information literacy and information network screening ability. Third, pay attention to and protect marginalized groups in the digital age. C2 Internet users are the dominant group of Internet users. They are generally younger and better at using the Internet to create health benefits and social benefits, However, C4 Internet users' high age and low education levels restrict their ability to use the Internet, resulting in low health benefits and social benefits. Due to insufficient Internet accessibility and technical requirements for usability, disadvantaged groups in digital development such as the elderly, female groups, and rural groups are formed, making it difficult to absorb digital dividends and even causing double cumulative disadvantages. For such disadvantaged groups, individualized and tendentious Internet resource platform development and technical support are needed to ensure the fairness of opportunities and the fairness in their Internet use.

Advantage

Research has certain innovations and advantages. First, the research object is typical, and the research data is scientific. Select China, which has the characteristics of the largest developing country and the largest number of Internet users, as the research object, and select the 2018 CFPS database as the data source ($N = 11086$). The database is a typical representative micro-database in China, with a wide range of survey objects. The survey content includes social fields, people's livelihood fields, and individual characteristics. It provides a first-hand data source for empirical analysis and ensures the integrity and feasibility of the research program. Second, the research perspective is innovative. The Internet is one of the social determinants that affect health (3), and there are still some theoretical differences in the relationship between the Internet and health. Previous studies have focused on the effects of social media usage and information technology development on health. Few studies have paid attention to the different effects that the diversity of Internet use may have on health. The research studies the effect of the Internet on health based on the IUG and provides new research thoughts and research strategies for related topics. Third, The BCH method was used to perform latent class modeling with a continuous distal outcome, which is robust to violations of analysis model assumptions in comparison to other stepwise approaches (34). Furthermore, this approach also allows the inclusion of covariates so that the effects of latent class membership are controlled by those covariates (35). In addition, building a mediation model about Internet information dependence through the model constraint function in Mplus is more perfect than the simple potential category analysis, which makes the research contains more completely.

Limitation

This research also has a few limitations. Firstly, the research data in this study are cross-sectional data. There may be a time lag in the effect of the Internet on health, which affects the explanatory power of the regression results. At the same time, the selection of research and analysis indicators is based on the principle of convenient sampling, which is subjective, and there are potential psychological characteristics to confuse the relationship between independent variables and dependent variables (36). In addition, the research data has a certain time lag. Limited by the availability of data, the research can only use the latest research data (2018CFPS) currently available for research, which has a certain time difference from the current time, and may be different from the current actual situation, which needs to be released at a later stage. Timely update data when the latest data is available to further improve research recommendations.

Conclusions

The COVID-19 epidemic continues to spread around the world, further creating an urgent health need (37). However, the spread of the COVID-19 epidemic is accompanied by a surge in the frequency of Internet use. The resulting problems of Internet addiction and overuse may pose a major public health threat. It is necessary to be alert to the adverse consequences caused by differences in Internet use (13). The research results show that there are significant differences in the health level of different potential types of Internet users. At the same time, the individual characteristics, social characteristics and living habits of different groups also have obvious group differences. In addition, Internet information dependence does play a mediating role in the process of Internet use gap affecting population health. It inspires for developing countries to improve the level of national health. Future research should further examine the time lag of the impact of the IUG and IID on health.

Data availability statement

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

Author contributions

Study design, data cleansing, and statistical analysis: YH and LZ. Supervision: LZ and XX. Writing—original draft: LZ and JuL. Writing—review editing: YH and JiL. Financial support: LZ. 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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References

1. Kemp S. *Digital 2021: Global Overview Report*. (2021). *DataReportal*. Available online at: https://datareportal.com/reports/digital-2021-global-overview-report.

2. Zhang B. *Digital Transformation Has Become the Driving Force of Industry Development*. China Press, Publication, Radio and Television News (2021) 9. doi: 10.28907/n.cnki.nxwcb.2021.003578

3. Lancet T. Mental health: time to invest in quality. *Lancet*. (2020) 396:1045. doi: 10.1016/S0140-6736(20)32110-3

4. Sharma MK, John N, Sahu M. Influence of social media on mental health: a systematic review. *Curr Opin Psychiatry*. (2020) 33:467–75. doi: 10.1097/YCO.0000000000000631

5. Zhang JJ, Liu TS. Does Internet use make rural residents happier?—Evidence from CFPS2018. *Dong Yue Lun Cong*. (2020) 41:172–9.

6. Bonfadelli H. The internet and knowledge gaps: a theoretical and empirical investigation. *Eur J Commun*. (2002) 17:65–84. doi: 10.1177/0267323102017001607

7. Helsper EJ. The social relativity of digital exclusion: applying relative deprivation theory to digital inequalities. *Commun Theory*. (2017) 27:223–42. doi: 10.1111/comt.12110

8. Dimaggio P, Hargittai E. *From the 'Digital Divide' to 'Digital Inequality': Studying Internet Use as Penetration Increases*. Princeton: Princeton University, School of Public and International Affairs, Center for Arts and Cultural Policy Studies, Working Paper (2001).

9. Norris P, Jones D. Virtual democracy. *Harvard Int J Press Polit*. (1998) 3:1–4. doi: 10.1177/1081180X98003002001

10. Hargittai E, Hinnant A. Digital inequality: differences in young adults'use of the internet. *Commun Res*. (2008) 35:602–621. doi: 10.1177/0093650208321782

11. Rochat L, Wilkosc-Debczynska M, Zajac-Lamparska L, Rothen S, Andryszak P, Gaspoz J, et al. Internet use and problematic use in seniors: a comparative study in Switzerland and Poland. *Front Psychiatry*. (2021) 12:609190. doi: 10.3389/fpsyt.2021.609190

12. Hong YA, Zhou Z, Fang Y, Shi L. The digital divide and health disparities in china: evidence from a national survey and policy implications. *J Med Internet Res*. (2017) 19:e317. doi: 10.2196/jmir.7786

13. D'Onofrio G, Ciccone F, Placentino G, Placentino M, Tulipani C, Prencipe A, et al. Internet-based psychological interventions during SARS-CoV-2 pandemic: an experience in South of Italy. *Int J Environ Res Public Health*. (2022) 19:5425. doi: 10.3390/ijerph19095425

14. Xie L, Yang HL, Lin XY, Ti SM, Wu YY, Zhang S, et al. Does the internet use improve the mental health of Chinese older adults? *Front Public Health*. (2021) 9:673368. doi: 10.3389/fpubh.2021.673368

15. Gjoneska B, Potenza MN, Jones J, Corazza O, Hall N, Sales CM, et al. Problematic use of the internet during the COVID-19 pandemic: good practices and mental health recommendations. *Compr Psychiatry*. (2022) 112:152279. doi: 10.1016/j.comppsych.2021.152279

16. Xu QH. Digital inequality: a review of research on social class and internet use. *Work Univ Libraries*. (2017) 37:16–20.

17. Zanatta ET, Wanderley GP, Branco IK, Pereira D, Kato LH, Maluf EM. Fake news: the impact of the internet on population health. *Rev Assoc Med Bras*. (2021) 67:926–30. doi: 10.1590/1806-9282.20201151

18. Yan H, Zhang YH, Han LQ. Research progress on mobile digital divide. *Library Inf Work*. (2014) 65:1–8.

19. Ma Q, Sun D, Cui F, Zhai Y, Zhao J, He X, et al. Impact of the internet on medical decisions of Chinese adults: longitudinal data analysis. *J Med Internet Res*. (2020) 22:e18481. doi: 10.2196/18481

20. Lu JH, Wei XD. Analysis framework, concept and path selection of digital divide governance for the elderly: based on the theoretical perspective of digital divide and knowledge gap. *Populat Res*. (2021) 45:17–30.

21. Wu L, Yang Y. The psychological value of digital technology in promoting active aging. *J Northwest Normal Univ Social Sci Edn*. (2021) 58:65–77.

22. Wang ZM, Ren BY, Peng W. Internet information dependence and heterogeneous household consumption: the perspective of financial assets allocation. *J Manage.* (2020) 33:52–65.

23. Abi-Jaoude E, Naylor KT, Pignatiello A. Smartphones, social media use and youth mental health. *CMAJ.* (2020) 192:E136–41. doi: 10.1503/cmaj.190434

24. Gao J, Zheng P, Jia Y, Chen H, Mao Y, Chen S, et al. Mental health problems and social media exposure during COVID-19 outbreak. *PLoS ONE.* (2020) 15:e0231924. doi: 10.1371/journal.pone.0231924

25. Vaingankar JA, van Dam RM, Samari E, Chang S, Seow E, Chua YC, et al. Social media-driven routes to positive mental health among youth: qualitative enquiry and concept mapping study. *JMIR Pediatr Parent.* (2022) 5:e32758. doi: 10.2196/32758

26. Alonzo R, Hussain J, Stranges S, Anderson KK. Interplay between social media use, sleep quality, and mental health in youth: a systematic review. *Sleep Med Rev.* (2021) 56:101414. doi: 10.1016/j.smrv.2020.101414

27. Lazarsfeld PF, Henry NW. Latent structure analysis. *Am Sociol Rev.* (1968) 34:293–4. doi: 10.2307/2092222

28. Bolck A, Croon M, Hagenaars J. Estimating latent structure models with categorical variables: onestep vs. three-step estimators. *Polit Anal.* (2004) 12:3–27. doi: 10.1093/pan/mph001

29. Asparouhov T, Muthen B. Residual associations in latent class and latent transition analysis. *Struct Equ Model.* (2015) 22:169–177. doi: 10.1080/10705511.2014.935844

30. Kong J, Martire LM, Tate AM, Bray BC, Almeida DM. Different types of childhood experience with mothers and caregiving outcomes in adulthood. *Fam Relat.* (2020) 70:1090–101. doi: 10.1111/fare.12511

31. Neuhaus V, Ring DC. Latent class analysis. *J Hand Surgery.* (2013) 38:1018–20. doi: 10.1016/j.jhsa.2013.01.024

32. Zhou GS, Liang Q. Internet use, market friction and household risk financial asset investment. *Financial Res.* (2018) 1:84–101.

33. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. *Biometrica.* (1983) 70:41–55. doi: 10.1093/biomet/70.1.41

34. Bakk Z, Vermunt JK. Robustness of stepwise latent class modeling with continuous distal outcomes. *Struct Equ Model Multidisciplin J.* (2016) 23:20–31. doi: 10.1080/10705511.2014.955104

35. Ugarte E, Narea M, Aldoney D, Weissman DG, Hastings PD. Family risk and externalizing problems in chilean children: mediation by harsh parenting and emotional support. *Child Dev.* (2021) 92:871–88. doi: 10.1111/cdev.13464

36. He Y, Zhou L, Li J, Wu J. An empirical analysis of the impact of income inequality and social capital on physical and mental health - take China's micro-database analysis as an example. *Int J Equity Health.* (2021) 20:241. doi: 10.1186/s12939-021-01560-w

37. Liese BH, Gribble R SF, Wickremsinhe MN. International funding for mental health: a review of the last decade. *Int Health.* (2019) 11:361–9. doi: 10.1093/inthealth/ihz040

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The temperature of internet: Internet use and depression of the elderly in China

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Introduction: Depression has become one of the most prevalent mental illnesses affecting the elderly in aging countries, i. e., in countries of the world whose population is slowly aging. It has become an important topic for scientists and policymakers to analyze how best to improve the elderly's mental health and save them from depression. The aim of this paper was to investigate whether and to what extent internet use may affect depression in the elderly. The heterogeneous effects of internet use on the elderly's depression across age, gender, and occupation were also investigated.

Methods: The data used in the present study were gathered from the China Health and Retirement Longitudinal Study that was conducted in 2018. The propensity score matching technique and the endogenous switch regression model were employed in this study to address potential endogeneity caused by both observed and unobserved factors.

Results: The results of the present study show that the elderly who are relatively young, male, well educated, live in an urban area, or have a small family are more likely to use the internet. The elderly who have healthy eyes or good eyesight, those who are not employed in the agricultural sector, or those who are retired, and those who are not eligible to receive any subsistence allowance or drink wine have a higher probability of using the internet. We also find that internet use significantly reduces the elderly's depression status by 3.370 points, which is roughly equivalent to a reduction of 37.19%. Heterogeneity analysis on internet use reveals that the health effect is particularly effective for agricultural workers, female, or the older elderly.

Conclusion: The results of the present study highlight the significant welfare effects brought about by the development of internet infrastructure. To improve the mental health of the elderly, the government should encourage them to adopt the internet. In particular, the needs of the elderly who are older, female, or have agricultural work should be paid more attention to motivate them to use the internet more to alleviate depression.

KEYWORDS

internet use, mental health, propensity score matching, endogenous switching regression, depression

Introduction

Various health problems faced by several elderly people have attracted a lot of attention from people all around the globe, including scientists and policymakers. As regards the elderly, deterioration in physical function, disability, chronic diseases, cognitive impairment, and other health problems seriously reduce the quality of their life and increase medical expenditure of their families (1). As the population of aged people continues to grow so do their health problems, putting tremendous pressure on social insurance programs to meet the rising costs of the elderly's health problems, which may further undermine a country's economic development (2). China, as one of the most populated nations of the world, has the largest elderly population and probably the highest old-age dependency ratio in the world (3). The Chinese seventh census survey shows that the Chinese population over the age of 60 years exceeded 260 million in 2020, which accounted for ∼18.7% of the total population.

Although depression has become one of the most prevalent mental illnesses affecting the elderly, it has in fact received much less attention than other health issues (4). It is reported that ∼17–27% of the Chinese elderly suffer from depression, which is a much higher value than the values observed in many other countries of the world (5). Depression reduces the elderly's happiness and satisfaction in life, and even causes a number of other health problems such as chronic diseases and provoking suicidal thoughts, thereby bringing a heavy burden to the elderly's families and the society at large (6). Thus, it has become an important topic for both scientists and policymakers alike to study in depth how to reduce the likelihood of depression among the elderly and save them from depression.

While we can attribute various causes for depression among the elderly groups, the lack of social participation serves as an important cause for triggering depression (7–9). For example, empirical evidence shows that participation by the elderly in leisure activities helps to improve their mental health to a large extent (10). In particular, engaging them in leisure social participation such as playing cards or chess has a remarkable effect on their mental wellbeing. However, social participation is not confined to specific forms. The form of people's social participation may affect mental health differently. For the elderly, continuous social participation often has a larger inhibitory effect on depression than occasional participation (7, 11). While voluntary participation in community activities may have positive effect on the elderly's mental health, forced participation may bring about negative effects (12).

In particular, the use of internet is often recognized as a vital form of social participation (13). With the progress in internet technology and the intensification of the aging process, the elderly groups have become an important force to reckon with among internet users (14). Indeed, information technology assists the elderly who struggle from physical inconvenience to shop, socialize, and form close relationships with the society (15). As a simple, convenient, and low-cost means of social participation, internet use reduces the incidence of depression (16, 17).

In this paper, we propose that there are at least two mechanisms through which internet use may drastically alter the elderly's depression status. First, internet use may allow the elderly to maintain the hitherto cordial relationship with relatives and friends, or even establish an alternative relationship network by striking a rapport with new friends (18). Indeed, usually the elderly's access to social participation is often restricted due to their nagging physical health issue (19). But internet comes to their succor by dispensing with such restrictions that arise from space, cost, and other conditions that are very much required for any social participation, and thereby allows the elderly to communicate hassle-free with the outside world. In fact, such a means of communication plays an important role in delaying anxiety, improving their sense of belonging, and reducing their loneliness, and it is equally effective in reducing depressive symptoms (20). In China, where the so-called "empty nest elderly" are popular, the use of internet can effectively reduce their loneliness and life pressure (21).

Second, internet use may maintain or improve the elderly's cognitive ability, which is an important predictor of depression (22). The common logic behind use of the internet is that its use allows the elderly to retrieve the hitherto gained memory on disease prevention and health-related knowledge, which indirectly improves their health status (23). In addition, active internet use requires the elderly to conduct a number of mental activities, such as to search, to think, or to calculate, which train the elderly's brain frequently and eventually improve their cognitive ability. Evidence from an experiment shows that training the elderly to use tablet devices increases their episodic memory and data processing ability (16). Another study finds that internet use lowers the prevalence of dementia in the elderly (24).

However, if internet use were too frequent, bordering the case of internet addiction, the internet use may then worsen the depression status of the elderly. When we generally speak of internet addiction, we usually associate it with young people only. For example, existing literature shows that internet addiction is often positively associated with the incidence of depression among the youngsters (25, 26). Yet, for the elderly mentioned in our paper we do not think internet addiction is applicable. Indeed, in China, internet addiction mainly occurs in the younger groups, e.g., teenagers and students (27). Nevertheless, in this paper, we don't think that internet addiction has a significant impact on the elderly. Overall, we expect internet use to lower the prevalence of depression in the elderly in China.

The objective of this paper was to investigate whether and to what extent internet use may affect the mental health of the elderly. The data used in the study were drawn from the China Health and Retirement Longitudinal Study (CHARLS) conducted in 2018. We employ the propensity score matching (PSM) technique to address the concern of selection bias caused by the observed factors. The endogenous switching regression (ESR) model is employed to further address the potential selection bias due to factors which are unobservable. We also examine the heterogeneous effects of internet use on the elderly across age, gender, and occupation.

Methods

Data

This paper uses the data from the China Health and Retirement Longitudinal Survey (CHARLS) 2018 for analysis. The CHARLS project is led by the Peking University, which aims to collect a large and representative sample of the population aged 45 years and above in China. Specifically, the CHARLS 2018 covers ∼150 counties, 450 communities or villages in China, and consists of ∼23,000 respondents in 28 provinces. The sample was selected following the probability proportional to the size sampling strategy. Due to their high-quality nature, these data have been widely used in scientific research and have generated many publications.

In the questionnaire, 10 questions from the CES-D (Center for Epidemiological Studies-Depression) are designed and drawn up for the depression test (Supplementary Table A1). For example, the respondent was asked if in the past week he/she was bothered, depressed, fearful, lonely, or always had trouble in mind, felt hard to do anything, could not sleep well or get going. The answer options for each question were "little or no," "not much," "sometimes or half the time," and "most of the time," which were assigned with values of 0, 1, 2, and 3, respectively. Out of the 10, there were two opposite questions, i.e., "I am full of hope for the future" and "I am very happy," with the same answer options. We used the reverse scoring method for the answers to the two questions. The scores of the 10 questions were then summed to generate the CES-D score as the outcome variable. The respondent with a CES-D score ≥10 is often defined as having symptoms of depression (28). Our results show that the overall incidence of depression among the Chinese elderly was ∼33.84% in 2018.

Besides the module of health status, the questionnaire also collected information about individual and family characteristics, e.g., age, gender, education, marriage status, family size, living habits, and daily activities. In particular, a question on learning about the respondent's behavior of internet use is designed. In that question, the respondent was asked if he/she had used the internet in the past month, with two answer options of "yes" or "no." We used the information from this question to generate our explanatory variable. During the data cleaning process, we excluded those observations of persons whose age was below 45 years. We also removed those observations that had missing values in our selected variables. The final sample for analysis in this paper has 17,365 observations.

Empirical strategies

A. Propensity score matching

The major challenge in identifying the effect of internet use on the elderly's depression status pertains to the fact that the elderly's behavior of internet use could be endogenous, i.e., internet use and depression might be affected by many common factors. This endogenous behavior on the part of the elderly may result in the concern of selection bias, if internet users are compared to non-users directly (29). To address such concern of selection bias, we employed the propensity score matching (PSM) technique. The PSM technique eliminates the impact of covariates by resembling the randomized assignment to treatment, to create conditions of a random experiment (30). The PSM has been widely employed in empirical work (31–33). Specifically, the following probit model is estimated in the first stage:

$$INT_i{}^* = X_i\alpha + \varepsilon_i \text{ with } INT_i = \begin{cases} 1 & if\ INT_i{}^* > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

where INT_i^* is a latent variable that indicates the utility of respondent i's choice of internet use. If the utility exceeds 0, we observe that the respondent chooses to use the internet ($INT_i = 1$); otherwise, the respondent does not use the internet ($INT_i = 0$). X_i is a set of exogenous variables, which affects the respondent's choice of internet use. Estimation from Equation (1) reports the determinants of the elderly's choice of internet use and allows us to predict the propensity score of each observation to use the internet.

The predicted propensity scores are then used to find one or more matching partners for internet users from non-users. We use the popular matching algorithms, i.e., nearest neighbor, radius, and kernel matching, to find matching partners (34). Taking advantage of the large sample, we select one, five, and ten matching partners in the nearest neighbor matching for robustness tests. A matching caliper of 0.001 is set to reduce potential matching bias. After matching, we compute the average treatment effect on the treated (ATT) of internet use on depression status following Equation (2):

$$ATT = E\left(Y_1|INT_i = 1\right) - E\left(Y_0|INT_i = 1\right) \tag{2}$$

where Y_1 and Y_0 are the elderly's depression statuses of the matched internet users and non-users, respectively.

The validity of PSM depends on three assumptions. First, before matching there must be a sufficient overlap of propensity scores between internet users and non-users. Second, after matching, the covariates must statistically have no difference between internet users and non-users. Third, in the selection function there is no omitted variable that is correlated with internet use and the elderly's depression status (35). In the Results section, we present supportive evidence for the satisfaction of these assumptions.

B. Endogenous switching regression

A major problem of the PSM is that it can only mitigate selection bias due to observables but not due to unobservables. We therefore employ the endogenous switching regression (ESR) model, which accounts for selection bias from both observables and unobservables, to complement the PSM. The ESR model has also been widely employed in empirical work (36–39). The typical ESR model has three equations. The first equation, as shown in Equation (1), determines two regimes that a respondent may fall into, namely, using the internet or not. The rest of the two equations explain the outcome variable, i.e., the depression status, under different regimes:

$$\text{Regime 1}: \ Y_{1i} = Z_i\beta_1 + \eta_{1i} \ \text{ if } \ INT_i = 1 \tag{3a}$$

$$\text{Regime 2}: \ Y_{0i} = Z_i\beta_0 + \eta_{0i} \ \text{if} \ INT_i = 0 \tag{3b}$$

where Y_{1i} and Y_{0i} are the measures of a respondent's depression status, which are observed only under regimes one and two, respectively. Z_i contains all the variables in X_i and at least one instrumental variable. The error terms ε_i, η_{1i}, and η_{0i} presumptively follow a joint normal distribution. In the estimation process, two inverse Mills ratios λ_{1i} and λ_{0i} are predicted using Equation (1) for internet users and non-users, respectively. The outcome equations are then updated by including the inverse Mills ratios:

$$\text{Regime 1}: \ Y_{1i} = Z_i\beta_1 + \lambda_{1i}\delta_1 + \eta_{1i} \text{ if } INT_i = 1 \tag{4a}$$

$$\text{Regime 2}: \ Y_{0i} = Z_i\beta_0 + \lambda_{0i}\delta_0 + \eta_{0i} \text{ if } INT_i = 0 \tag{4b}$$

where δ_1 and δ_0 are the parameters to be estimated for the inverse Mills ratios. To estimate the selection and outcome equations simultaneously, a full information maximum-likelihood method should be employed (40). The estimated parameters in the outcome equations are then used to predict the expected depression status.

$$E\left(Y_{1i}|INT_i = 1\right) = Z_i\beta_1 + \lambda_{1i}\delta_1 \tag{5a}$$

$$E\left(Y_{0i}|INT_i = 1\right) = Z_i\beta_0 + \lambda_{0i}\delta_0 \tag{5b}$$

where $E\left(Y_{1i}|INT_i = 1\right)$ is the expected depression status of the elderly who use internet and $E\left(Y_{0i}|INT_i = 1\right)$ is the expected depression status of the elderly in the counterfactual scenario. The average treatment effect on the treated is then computed following Equation (6):

$$ATT = E\left(Y_{1i}|INT_i = 1\right) - E\left(Y_{0i}|INT_i = 1\right) \tag{6}$$

TABLE 1 Variable definitions.

Variables	Definitions
Depression	The score was calculated according to the CES-D scale
Internet use	1 = use the Internet; 0 = not use the Internet
Age	Age of respondents
Male	1 = male; 0 = female
Urban	1 = have a Urban Hukou; 0 = otherwise
Primary	1 = if the highest education is primary school or below; 0 = otherwise
Junior	1 = if the highest education is junior high school; 0 = otherwise
Senior	1 = if the highest education is senior high school or above; 0 = otherwise
Family size	The number of family members
Married	1 = married; 0 = not married
Sleep time	The time when you sleep every night (hours)
Vision	1 = good vision; 0 = otherwise
Agricultural work	1 = engaged in agricultural work; 0 = otherwise
Retirement	1 = withdrawal from the labor market; 0 = otherwise
Subsistence allowance	1 = subsidized; 0 = no subsidy
Drinking	1 = ever smoked before; 0 = otherwise
Smoking	1 = ever drank alcohol last year; 0 = otherwise

Authors' own design.

Heterogeneous effects of internet use on depression status are estimated by restricting Equation (6) to sub-group samples.

C. Variable definitions

Table 1 presents the variable definitions. The outcome variable is the CES-D score, which is a reliable and widely used measure of the depression status in clinical practices and epidemiological studies (41, 42). The explanatory variable is internet use, defined as 1 if the respondent used the internet in the last month, and 0 otherwise.

The variables included in the selection function are important. Some scholars propose that the variables should be theoretically important for outcomes (43). Whereas some other scholars argue that they should be simultaneously associated with selection and outcomes (34). In practice, empirical studies using PSM may choose variables that are important for selection (44), outcomes (45), or both (30, 46). In this paper, we follow the literature and select a set of variables, e.g., age, gender, education, martial status, family size, and living habits, which are associated with internet use and mental health to better predict the choice of internet use and mental health (47, 48).

The selected instrumental variable is the ratio of internet use by other elderly in the same communities. We propose that the ratio of internet use by other elderly in the same communities should be correlated with a respondent's behavior of internet use due to the peer effect (49). Besides, internet use by other people is simply their personal behavior, which is unlikely to have an impact on a specific elderly's depression scores. Such choice of instrumental variable has been proved valid in many empirical studies (30, 50, 51).

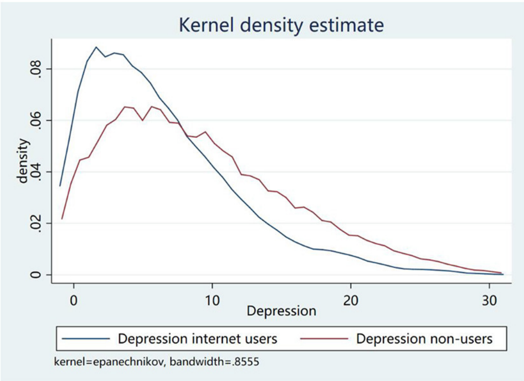

FIGURE 1
Depression scores between internet users and non-users.

Results

Descriptive analysis

Figure 1 shows the differences in depression scores between internet users and non-users. In general, the depression scores of the elderly who use the internet are smaller than those of the non-users. Table 2 further reports differences in the average depression scores between the elderly who are internet users and non-users. We find that the average CES-D score for the full sample is 8.709, while for the sub-samples of the internet users and non-users, the average CES-D scores are 6.374 and 9.061, respectively. That is, compared with the elderly who do not use the internet, those who use the internet score lower in the depression measure. The difference in depression score between the two groups is significant at 1%. These results tend to suggest to us that internet users have a lower risk of depression than non-users.

There are also differences in covariates between internet users and non-users. Generally, the young, male, highly educated, and married respondents are more likely to use the internet than their counterpartners. Respondents with an urban Hukou have a higher probability of using the internet than those respondents with a rural Hukou. Internet users often have a smaller family size and better eyesight than non-users. Besides, internet users tend to get retired, less likely to have agricultural work, and more likely to receive basic subsistence allowance

TABLE 2 Summary statistics.

Variables	Mean	S.D.	Mean of non-users (A)	Observations	Mean of users (B)	Observations	Difference (A–B)
Depression	8.709	6.443	9.061	15,092	6.374	2,273	2.687***
Age	61.37	9.589	62.269	15,092	55.366	2,273	6.903***
Male	0.475	0.499	0.463	15,092	0.553	2,273	−0.090***
Urban	0.204	0.403	0.166	15,092	0.451	2,273	−0.285***
Primary	0.653	0.476	0.712	15,092	0.259	2,273	0.454***
Junior	0.223	0.416	0.203	15,092	0.357	2,273	−0.155***
Senior	0.124	0.330	0.085	15,092	0.384	2,273	−0.299***
Family size	3.197	1.851	3.212	15,092	3.092	2,273	0.121***
Married	0.797	0.402	0.791	15,092	0.839	2,273	−0.048***
Sleep time	6.200	1.971	6.182	15,092	6.317	2,273	−0.136***
Vision	0.283	0.451	0.261	15,092	0.432	2,273	−0.171***
Agricultural work	0.481	0.500	0.506	15,092	0.313	2,273	0.193***
Retirement	0.179	0.383	0.160	15,092	0.309	2,273	−0.150***
Subsistence allowance	0.073	0.260	0.081	15,092	0.020	2,273	0.061***
Drinking	0.267	0.442	0.253	15,092	0.358	2,273	−0.105***
Smoking	0.416	0.493	0.412	15,092	0.439	2,273	−0.027**

The standard t-test was used to calculate the average difference between the two groups. ** and *** indicate the significance levels of 5 and 1%, respectively.

from the government. Internet users also drink and smoke more often than non-users.

The above results give a preliminary indication about internet use to prove that it is highly associated with the elderly's depression status. However, since there are also significant differences in many covariates, we cannot confidently conclude that there is a causal effect of internet use on the incidence of depression in the elderly. It is therefore necessary to further address the concern of potential selection bias in the rest of the analysis.

Determinants of internet use

Table 3 reports the determinants of the elderly's choice of internet use from Equation (1). The regression coefficients are reported in column (1). As shown in column (2), we also computed the average marginal effects of the variables. We find that age has a significant and negative impact on the probability of internet use. A 1-year increase in the respondent's age decreases the probability of using the internet by 0.8%. The probability of using the internet for men is 1.5% higher than that for women. The elderly who have an urban Hukou are more likely to use the internet. Compared with the elderly who have an education of primary school or below, those who have a higher level of education are more likely to use the internet, implying that education increases the likelihood of using the internet. Besides, the elderly person who has a larger family is less likely to use the internet, probably because internet use, as a substitution of social communication, is less necessary for the elderly in such large families.

Vision has a significant and positive impact on internet use. It is intuitive that good vision is a prerequisite for using the internet, especially for the elderly who often suffer from eye diseases in China. The elderly who are engaged in agricultural work are less likely to use the internet. Apart from the reason that access to the internet remains limited in a rural area, another reason could be attributed to the fact that farmers may have limited knowledge of internet and may evince less interest in internet use in China.

The retired respondents have a higher probability of using the internet than the respondents who have not retired from active service, probably because the retired have more time available at their disposal for leisure. The elderly who receive subsistence allowance from the government, arguably the poor people, are unlikely to use the internet. Indeed, internet use could cost a lot of money for the poor in China, which excludes the poor elderly from internet use. The elderly who drink alcohol are more likely to use the internet, probably because wine is a luxury good and drinking alcohol may also represent the income level.

TABLE 3 Determinants of the elderly's choice of internet use.

Variables	(1)	(2)
Age	−0.058***	−0.008***
	(0.002)	(0.000)
Male	0.110**	0.015**
	(0.045)	(0.006)
Urban	0.403***	0.064***
	(0.039)	(0.007)
Junior	−0.968***	0.087***
	(0.040)	(0.007)
Senior	−0.442***	0.209***
	(0.039)	(0.012)
Family size	−0.036***	−0.005***
	(0.008)	(0.001)
Married	−0.048	−0.007
	(0.039)	(0.005)
Sleep time	−0.006	−0.001
	(0.008)	(0.001)
Vision	0.160***	0.023***
	(0.030)	(0.004)
Agricultural work	−0.241***	−0.032***
	(0.031)	(0.004)
Retirement	0.270***	0.041***
	(0.040)	(0.007)
Subsistence allowance	−0.504***	−0.049***
	(0.081)	(0.005)
Drinking	0.108***	0.015***
	(0.035)	(0.005)
Smoking	−0.031	−0.004
	(0.043)	(0.006)
Observations	17,365	17,365
Pseudo R^2	0.251	0.251

The regression coefficients are reported in column (1). The average marginal effects are reported in column (2). Robust standard errors are given in parentheses. ** and *** indicate the significance levels of 5% and 1%, respectively.

The effect of internet use on depression from PSM

Table 4 reports the effects of internet use on the elderly's depression status from the propensity score matching. Different matching algorithms generate similar results. Overall, the elderly who use the internet have a lower depression score than those

TABLE 4 The effect of internet use on depression from propensity score matching (PSM).

Matching algorithm	Treated	Control	ATT	S.E.	T-statistics	Rosenbaum bounds
NN(1)	6.412	7.455	−1.042	0.208	−5.02***	1.75–1.76
NN(5)	6.412	7.395	−0.983	0.167	−5.88***	2.14–2.15
NN(10)	6.412	7.379	−0.967	0.164	−5.88***	2.20–2.21
Radius	6.412	7.328	−0.916	0.165	−5.53***	2.21–2.22
Kernel	6.374	7.319	−0.946	0.156	−6.08***	2.33–2.34

Authors' own calculation. *** indicates the significance level of 1%.

TABLE 5 Heterogeneity in health impacts of internet use by age.

Matching algorithm	Age $\leq$ 60				Age > 60			
	ATT	S.E.	T-statistics	Rosenbaum bounds	ATT	S.E.	T-statistics	Rosenbaum bounds
NN(1)	−0.671	0.242	−2.77***	1.61–1.62	−1.987	0.406	−4.90***	3.00–3.01
NN(5)	−0.699	0.200	−3.49***	1.98–1.99	−1.390	0.326	−4.26***	3.23–3.24
NN(10)	−0.647	0.197	−3.28***	1.98–1.99	−1.264	0.320	−3.95***	3.19–3.20
Radius	−0.679	0.197	−3.45***	2.04–2.05	−1.336	0.328	−4.07***	3.33–3.34
Kernel	−0.790	0.183	−4.31***	2.55–2.56	−1.535	0.281	−5.46***	4.31–4.32

Authors' own computation. *** indicates the significance level of 1%.

TABLE 6 Heterogeneity in health impacts of internet use by gender.

Matching algorithm	Male				Female			
	ATT	S.E.	T-statistics	Rosenbaum bounds	ATT	S.E.	T-statistics	Rosenbaum bounds
NN(1)	−0.691	0.255	−2.71***	1.72–1.73	−1.028	0.328	−3.13***	1.89–1.90
NN(5)	−0.684	0.212	−3.23***	2.09–2.10	−1.001	0.276	−3.63***	2.26–2.27
NN(10)	−0.755	0.210	−3.60***	2.21–2.22	−1.044	0.272	−3.84***	2.34–2.35
Radius	−0.730	0.211	−3.47***	2.22–2.23	−0.977	0.272	−3.60***	2.32–2.33
Kernel	−0.851	0.191	−4.46***	2.57–2.58	−1.012	0.249	−4.06***	2.55–2.56

Authors' own computation. *** indicates the significance level of 1%.

who do not use the internet. The size of the effects ranges from −0.916 to −1.042, which accounts for a reduction effect of ∼13% in the depression scores. The statistical significances are all set at the 1% level, regardless of the matching algorithms. These results support our expectation that internet use functions to reduce the incidence rate of depression in the elderly group in China.

Several tests are conducted to support the validity of our results. First, Supplementary Figure A1 shows that the overlap of propensity scores between internet users and non-users is sufficiently large, implying that most internet users can find a matching partner. Thus, our results can be generalized to the whole sample. Second, results from the balancing test (Supplementary Table A2) show that there is no significant difference in covariates between internet users and non-users after matching. Third, the sensitivity tests of the results report that the Rosenbaum bounds are all larger than 1.75, which implies that the significance of our results is not sensitive to omitted variables.

In this paper, we also test the heterogeneous effects across age. Specifically, we split the sample into two groups, namely the elderly aged 60 or below and the elderly aged over 60. We then estimate the impact of internet use on depression status using the PSM. Table 5 shows that, on average, the impact of internet use on depression status for the elderly aged 60 or below ranges from −0.647 to −0.790, while for the elderly aged over 60 it ranges from −1.264 to −1.987. That is, the reduction effect of internet use on the depression status is larger for the even older groups.

To test the heterogeneous effects across gender, we estimate the effects of internet use on the depression status for men and women separately. Table 6 reports the results. We find that the effect of internet use on depression score for the male elderly ranges from −0.684 to −0.851, using different matching

TABLE 7 Heterogeneity in health impacts of internet use by work.

Matching algorithm	Agricultural work				Non-agricultural work			
	ATT	S.E.	T-statistics	Rosenbaum bounds	ATT	S.E.	T-statistics	Rosenbaum bounds
NN(1)	−1.010	0.340	−2.97***	2.05–2.06	−0.854	0.253	−3.37***	1.74–1.75
NN(5)	−1.062	0.279	−3.80***	2.54–2.55	−0.742	0.211	−3.52***	2.08–2.09
NN(10)	−1.080	0.273	−3.95***	2.58–2.59	−0.752	0.208	−3.62***	2.14–2.15
Radius	−1.023	0.269	−3.80***	2.61–2.62	−0.768	0.212	−3.62***	2.17–2.18
Kernel	−0.970	0.254	−3.82***	2.70–2.71	−0.888	0.197	−4.52***	2.44–2.45

Author' computation. *** indicates the significance level of 1%.

algorithms, while the effect of internet use on depression score for the female elderly ranges from −0.977 to −1.028.

We also test the heterogeneous effects across occupation. We split the sample into two groups according to whether the elderly has any agricultural work or not. Table 7 reports the results. We find that the effects of internet use on depression status for the elderly with agricultural work range from −0.970 to −1.080. For the elderly who do not have any agricultural work, the effects range from −0.742 to −0.888.

The effect of internet use on depression from ESR

Table 8 reports the results from the endogenous switching regression (ESR) model. The *F*-statistic from tests on the strength of the instrumental variable in the selection function is 1,335.285 (*P*-value = 0.000), which exceeds the critical value of 10. This result implies that the concern of a weak instrumental variable should not be a problem in our work. Table 8 shows that the ESR model reports negative but larger effects of internet use on the elderly's depression scores. All the effects are statistically significant at 1% level. These results highlight the importance of addressing selection bias from unobserved confounds. On average, internet use reduces the elderly's depression scores by 3.370 points, which accounts for an approximate reduction of 37.19% from the average depression scores of the non-users.

Table 8 also shows that the general pattern derived from PSM still holds. That is, the effect of internet use on the depression status is larger for the older, female elderly, or the elderly who have agricultural work. Specifically, the effects of internet use on the depression status for the older and younger elderly are −3.772 and −3.251, respectively. The effects of internet use on the depression status for the male and female elderly are −3.145 and −3.648, respectively. While the effect on the elderly who have agricultural work is −3.627, for the elderly who have no agricultural work, it is −3.252. The *T*-statistics from tests over differences in the effects between different ages, genders, and employment status are −11.12, −12.85, and 8.74, respectively. The corresponding *P*-values are all smaller than 1%, which supports the heterogeneous effects of internet use.

TABLE 8 The effect of internet use on depression using the endogenous switching regression (ESR) model.

	ATT	S.E.	T-statistics
Main effects	−3.370	0.069	−48.768***
Age ≤ 60	−3.251	0.077	−42.090***
Age > 60	−3.772	0.148	−25.571***
Male	−3.145	0.084	−37.400***
Female	−3.648	0.099	−36.732***
Agricultural work	−3.627	0.122	−29.625***
No agricultural work	−3.252	0.080	−40.480***

Author' own computation. The F-statistic of the strength test of instrumental variables in the selection function is 1,335.285 (P-value = 0.000). T-statistics from tests over the differences in the effects of internet use on depression are −11.12 (P-value = 0.000) for age, −12.85 (P-value = 0.000) for gender, and 8.74 (P-value = 0.000) for agricultural work. *** indicates the significance level of 1%.

Discussion

This paper estimates the impact of internet use on the elderly's depression scores, using the data from the China Health and Retirement Longitudinal Survey in 2018. To address the concern of potential selection bias, the propensity score matching (PSM) and the endogenous switching regression (ESR) model are employed. Our main finding is that internet use significantly reduces the elderly's depression scores by 3.370 points, which accounts for a reduction of ∼37.19% of the average depression scores of the elderly who do not use the internet.

The health effect of internet use has been a big concern for scientists and policymakers alike. Generally, there are three different opinions that are voiced about the health effect of internet use, i.e., negative, neutral, and positive (52). For example, some studies voice skepticism on the internet use, based on its negative health effects on the teenagers

(25, 26). Some other studies find that the internet use is irrelevant to the health and living habits of the elderly (48). More studies, however, find that internet use is positively associated with the mental health of the elderly (47, 53). Our work supports the literature on the positive effect of internet use by linking internet use to the reduction in the elderly's depression scores, and by focusing on causality rather than association.

Our work is related to the literature on the effect of internet use and the determinants of elderly's mental health. Previous studies have investigated how the use of internet may affect the adoption of an environmentally friendly behavior (54, 55), household welfare and wellbeing (56), and agricultural production and marketing performance (57, 58). Some other studies have made effort to understand the diversity of elderly's mental health (11, 42, 59, 60). Yet, there is still limited knowledge about the relationship between the behavior of internet use and mental health.

As exceptions, two existing studies find a strong correlation between internet use and life satisfaction (61, 62). Another study finds that frequent internet use makes people feel lonely (63). These studies, however, only focus on some aspects of depression and investigate correlation rather than causality. Different from these studies, a recent work estimated the causal effect of internet use on residents' depression status (47), even though causality cannot be fully identified due to a flaw in selected method. Using an instrumental variable-based approach, another work finds a negative effect of internet access on young women's mental health (64). Our work complements the above strand of literature by measuring depression with a more comprehensive indicator. We also provide another effort to identify the causal effect of internet use on the elderly. The positive effects of internet use on the elderly's mental health in our research contradict with the negative effects of internet use on the young in previous research.

Another benefit of our work to the literature is that we investigated the heterogeneous effects of internet use. Existing studies on the health effects of internet use on the elderly's depression status often estimate its average effects (47, 53). But our work has brought out the fact that the health effects of internet use are larger for the older, female elderly, or those who have agricultural work than those for their counterpartners. These results provide supportive evidence for the opinion that internet use can function as a cost-effective type of social participation (65). Indeed, internet use, as the substitution of social participation, should be more important for even the older elderly, who have more difficulty in engaging in social participation (66). In addition, in the Chinese society, women often have less time for social participation than men (67). As a quick and low-cost approach to connect and communicate with other people, internet should have a larger substitution effect for women than for men. As regards occupation, working in the agricultural sector often implies that the elderly are probably living in a rural area, where the access to social participation is limited (68). On the contrary, the elderly who do not live in a rural area may have more choices for engaging in social participation other than surfing the internet.

Despite the larger health effect of internet use on the older, female, or the elderly who have agricultural work, the probability of internet use by these elderly is significantly lesser. Such results seem to reflect an awkward situation, that is, the potentially best beneficiaries have no access to the internet in China, which may have important implications for policymakers. There are also other determinants of internet use, such as education, family size, eye health, living habits, and so on, which are mostly in line with those of the existing studies (69, 70).

Conclusion

In aging countries, i.e., in countries of the world whose population is slowly aging, the prevalence of mental health problems in the elderly is challenging the sustainability of the societies at large. In this paper, we investigate the role of internet use in reducing the elderly's depression. We find that the internet use significantly reduces the incidence of depression in the elderly, especially for those who are older, female, and have agricultural work. Besides, the choice of internet use by the elderly is determined by age, gender, education, family size, eye health, working status, living habits, and some other individual or family characteristics.

Our findings have important policy implications. To improve the mental health of the elderly, the government should put in more effort to the adoption of the internet by the elderly. In particular, the needs of the elderly who are older, female, or have agricultural work should be satisfied. Specifically, restrictions imposed on the elderly to access the internet should be removed. More subsidies should be given to the poor elderly groups. Considering that a great number of the elderly have poor eyesight, it is necessary to create elderly oriented electronic devices and gadgets to motivate the elderly to continue to use the internet.

Our work may bring to light a few limitations. Due to data limitation, internet use is measured as a dummy that merely reflects whether the elderly use the internet or not. However, the frequency and the duration of internet use, which may have different impacts on the elderly's health, are not included and so ignored in our analysis. In addition, the purpose of internet use, e.g., to seek information, to communicate with friends, or to entertain themselves, may also lead to different impacts on the elderly. Thus, to gain a better understanding of the benefits of internet use, future work should investigate further the health effects of the frequency, the duration, and the purpose of internet use on the elderly.

Data availability statement

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

Author contributions

HG: conceptualization, formal analysis, and writing-original draft. SF: methodology, writing-review and editing, and resources. ZL: conceptualization, methodology, validation, writing-review and editing, and supervision. 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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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1076007/full#supplementary-material

References

1. Graham C, Zhou S, Zhang J. Happiness and health in China: the paradox of progress. *World Dev.* (2017) 96:231–44. doi: 10.1016/j.worlddev.2017.03.009

2. Lopreite M, Mauro M. The effects of population ageing on health care expenditure: a bayesian var analysis using data from Italy. *Health Policy.* (2017) 121:663–74. doi: 10.1016/j.healthpol.2017.03.015

3. Fang EF, Scheibye-Knudsen M, Jahn HJ, Li J, Ling L, Guo H, et al. A research agenda for aging in China in the 21st century. *Age Res Rev.* (2015) 24:197–205. doi: 10.1016/j.arr.2015.08.003

4. Levkoff SE, Macarthur IW, Bucknall J. Elderly mental health in the developing world. *Soc Sci Med.* (1995) 41:983–1003. doi: 10.1016/0277-9536(94)00434-U

5. Zhang L, Xu Y, Nie H, Zhang Y, Wu Y. The prevalence of depressive symptoms among the older in China: a meta-analysis. *Int J Geriat Psychiatry.* (2012) 27:900–6. doi: 10.1002/gps.2821

6. Roux TGD. Life and death during the great depression. *Proc Natl Acad Sci.* (2009) 106:17290–5. doi: 10.1073/pnas.0904491106

7. Croezen S, Avendano M, Burdorf A, Van Lenthe FJ. Social participation and depression in old age: a fixed-effects analysis in 10 European countries. *Am J Epidemiol.* (2015) 182:168–76. doi: 10.1093/aje/kwv015

8. Xue X, Reed WR, Menclova A. Social capital and health: a meta-analysis. *J Health Econ.* (2020) 72:102317. doi: 10.1016/j.jhealeco.2020.102317

9. Wang R, Chen Z, Zhou Y, Shen L, Zhang Z, Wu X. Melancholy or mahjong? Diversity, frequency, type, and rural–urban divide of social participation and depression in middle-and old-aged Chinese: a fixed-effects analysis. *Soc Sci Med.* (2019) 238:112518. doi: 10.1016/j.socscimed.2019.112518

10. Ma X, Piao X, Oshio T. Impact of social participation on health among middle-aged and elderly adults: evidence from longitudinal survey data in China. *BMC Public Health.* (2020) 20:1–8. doi: 10.1186/s12889-020-08650-4

11. Chiao C, Weng L-J, Botticello AL. Social participation reduces depressive symptoms among older adults: an 18-year longitudinal analysis in Taiwan. *BMC Public Health.* (2011) 11:1–9. doi: 10.1186/1471-2458-11-292

12. Hsu H. Does social participation by the elderly reduce mortality and cognitive impairment? *Aging Mental Health.* (2007) 11:699–707. doi: 10.1080/13607860701366335

13. Byun S, Ruffini C, Mills JE, Douglas AC, Niang M, Stepchenkova S, et al. Internet addiction: metasynthesis of 1996–2006 quantitative research. *Cyberpsychol Behav.* (2009) 12:203–7. doi: 10.1089/cpb.2008.0102

14. Zhu Z, Ma W, Sousa-Poza A, Leng C. The effect of internet usage on perceptions of social fairness: evidence from rural China. *China Econ Rev.* (2020) 62:101508. doi: 10.1016/j.chieco.2020.101508

15. Helsper EJ. Gendered internet use across generations and life stages. *Commun Res.* (2010) 37:352–74. doi: 10.1177/0093650209356439

16. Chan MY, Haber S, Drew LM, Park DC. Training older adults to use tablet computers: does it enhance cognitive function? *Gerontologist.* (2016) 56:475–84. doi: 10.1093/geront/gnu057

17. Berner J, Comijs H, Elmståhl S, Welmer A-K, Berglund JS, Anderberg P, et al. Maintaining cognitive function with internet use: a two-country, 6-year longitudinal study. *Int Psychogeriat.* (2019) 31:929–36. doi: 10.1017/S1041610219000668

18. Szabo A, Allen J, Stephens C, Alpass F. Longitudinal analysis of the relationship between purposes of internet use and well-being among older adults. *Gerontologist.* (2019) 59:58–68. doi: 10.1093/geront/gny036

19. Dave D, Rashad I, Spasojevic J. The effects of retirement on physical and mental health outcomes. *Southern Econ J.* (2008) 75:497–523. doi: 10.1002/j.2325-8012.2008.tb00916.x

20. Hong S-I, Hasche L, Bowland S. Structural relationships between social activities and longitudinal trajectories of depression among older adults. *Gerontologist.* (2009) 49:1–11. doi: 10.1093/geront/gnp006

21. Khalaila R, Vitman-Schorr A. Internet use, social networks, loneliness, and quality of life among adults aged 50 and older: mediating and moderating effects. *Qual Life Res.* (2018) 27:479–89. doi: 10.1007/s11136-017-1749-4

22. Yu D, Fiebig DG. Internet use and cognition among middle-aged and older adults in china: a cross-lagged panel analysis. *J Econ Age.* (2020) 17:100262. doi: 10.1016/j.jeoa.2020.100262

23. Liobikiene G, Bernatoniene J. The determinants of access to information on the internet and knowledge of health related topics in European countries. *Health Policy.* (2018) 122:1348–55. doi: 10.1016/j.healthpol.2018.09.019

24. Xavier AJ, Rafnsson SB, Steptoe A, Hogervorst E, Orrell M. Is use of the internet in midlife associated with lower dementia incidence? Results from the English longitudinal study of ageing. *Aging Mental Health.* (2018) 22:1525–33. doi: 10.1080/13607863.2017.1360840

25. Seki T, Hamazaki K, Natori T, Inadera H. Relationship between internet addiction and depression among Japanese University students. *J Affect Disord.* (2019) 256:668–72. doi: 10.1016/j.jad.2019.06.055

26. McDool E, Powell P, Roberts J, Taylor K. The internet and children's psychological wellbeing. *J Health Econ.* (2020) 69:102274. doi: 10.1016/j.jhealeco.2019.102274

27. Wang L, Luo J, Bai Y, Kong J, Luo J, Gao W, et al. Internet addiction of adolescents in China: prevalence, predictors, and association with wellbeing. *Addict Res Theory.* (2013) 21:62–9. doi: 10.3109/16066359.2012.690053

28. Lei X, Sun X, Strauss J, Zhang P, Zhao Y. Depressive symptoms and ses among the mid-aged and elderly in China: evidence from the China health and retirement longitudinal study national baseline. *Soc Sci Med.* (2014) 120:224–32. doi: 10.1016/j.socscimed.2014.09.028

29. Smith JA, Todd PE. Does matching overcome lalonde's critique of nonexperimental estimators? *J Econ.* (2005) 125:305–53. doi: 10.1016/j.jeconom.2004.04.011

30. Liu Z, Li J, Rommel J, Feng S. Health impacts of cooking fuel choice in rural China. *Energy Econ.* (2020) 89:104811. doi: 10.1016/j.eneco.2020.104811

31. Amin M, Islam AM. Does manager education play a role in the productivity of informal firms in developing economies? Evidence from firm-level surveys. *Rev Dev Econ.* (2022) 26:962–84. doi: 10.1111/rode.12864

32. Guha P. The effects of school-based management on indian government schools. *Rev Dev Econ.* (2022) 26:2090–108. doi: 10.1111/rode.12904

33. Wen L, Paudel KP, Chen Y, He Q. Urban segregation and consumption inequality: does hukou conversion matter in China? *Rev Dev Econ.* (2021) 25:2298–322. doi: 10.1111/rode.12805

34. Caliendo M, Kopeinig S. Some practical guidance for the implementation of propensity score matching. *J Econ Surv.* (2008) 22:31–72. doi: 10.1111/j.1467-6419.2007.00527.x

35. Imbens GW. Nonparametric estimation of average treatment effects under exogeneity: a review. *Rev Econ Stat.* (2004) 86:4–29. doi: 10.1162/003465304323023651

36. Liu M, Min S, Ma W, Liu T. The adoption and impact of E-commerce in rural China: application of an endogenous switching regression model. *J Rural Stud.* (2021) 83:106–16. doi: 10.1016/j.jrurstud.2021.02.021

37. Ma W, Zheng H, Yuan P. Impacts of cooperative membership on banana yield and risk exposure: insights from China. *J Agric Econ.* (2022) 73:564–79. doi: 10.1111/1477-9552.12465

38. Takam-Fongang GM, Kamdem CB, Kane GQ. Adoption and impact of improved maize varieties on maize yields: evidence from central cameroon. *Rev Dev Econ.* (2019) 23:172–88. doi: 10.1111/rode.12561

39. Zheng H, Ma W. Smartphone-based information acquisition and wheat farm performance: insights from a doubly robust ipwra estimator. *Elect Commer Res.* (2021) 628:1–26. doi: 10.1007/s10660-021-09481-0

40. Lokshin M, Sajaia Z. Maximum likelihood estimation of endogenous switching regression models. *Stata J.* (2004) 4:282–9. doi: 10.1177/1536867X0400400306

41. Li C, Jiang S, Zhang X. Intergenerational relationship, family social support, and depression among chinese elderly: a structural equation modeling analysis. *J Affect Disord.* (2019) 248:73–80. doi: 10.1016/j.jad.2019.01.032

42. Gaggero A, Fernández-Pérez A, Jiménez-Rubio D. Effect of the Covid-19 pandemic on depression in older adults: a panel data analysis. *Health Policy.* (2022) 126:865–71. doi: 10.1016/j.healthpol.2022.07.001

43. Heckman J, Navarro-Lozano S. Using matching, instrumental variables, and control functions to estimate economic choice models. *Rev Econ Stat.* (2004) 86:30–57. doi: 10.1162/003465304323023660

44. Liu Z, Rommel J, Feng S. Does it pay to participate in decision-making? Survey evidence on land co-management in Jiangsu Province, China. *Ecol Econ.* (2018) 143:199–209. doi: 10.1016/j.ecolecon.2017.07.023

45. Ameha A, Nielsen OJ, Larsen HO. Impacts of access and benefit sharing on livelihoods and forest: case of participatory forest management in Ethiopia. *Ecol Econ.* (2014) 97:162–71. doi: 10.1016/j.ecolecon.2013.11.011

46. Eyjólfsdóttir HS, Baumann I, Agahi N, Fritzell J, Lennartsson C. Prolongation of working life and its effect on mortality and health in older adults: propensity score matching. *Soc Sci Med.* (2019) 226:77–86. doi: 10.1016/j.socscimed.2019.02.026

47. Wang Y, Zhang H, Feng T, Wang H. Does internet use affect levels of depression among older adults in China? A propensity score matching approach. *BMC Public Health.* (2019) 19:1–10. doi: 10.1186/s12889-019-7832-8

48. Duplaga M. The association between internet use and health-related outcomes in older adults and the elderly: a cross-sectional study. *BMC Med Inform Dec Making.* (2021) 21:1–12. doi: 10.1186/s12911-021-01500-2

49. Conley TG, Udry CR. Learning about a new technology: pineapple in Ghana. *Am Econ Rev.* (2010) 100:35–69. doi: 10.1257/aer.100.1.35

50. Zhu Y, Wang Y, Liu Z. How does social interaction affect pro-environmental behaviors in China? The mediation role of conformity. *Front Environ Sci.* (2021) 9:690361. doi: 10.3389/fenvs.2021.690361

51. Liu Z, Rommel J, Feng S, Hanisch M. Can land transfer through land cooperatives foster off-farm employment in China? *China Econ Rev.* (2017) 45:35–44. doi: 10.1016/j.chieco.2017.06.002

52. Hunsaker A, Hargittai E. A review of internet use among older adults. *New Media Soc.* (2018) 20:3937–54. doi: 10.1177/1461444818787348

53. Cotten SR, Ford G, Ford S, Hale TM. Internet use and depression among retired older adults in the United States: a longitudinal analysis. *J Gerontol Seri B Psychol Sci Soc Sci.* (2014) 69:763–71. doi: 10.1093/geronb/gbu018

54. Ma W, Zhu Z. Internet use and willingness to participate in garbage classification: an investigation of Chinese residents. *Appl Econ Lett.* (2021) 28:788–93. doi: 10.1080/13504851.2020.1781766

55. Zhang J, Cheng M, Wei X, Gong X, Zhang S. Internet use and the satisfaction with governmental environmental protection: evidence from China. *J Clean Prod.* (2019) 212:1025–35. doi: 10.1016/j.jclepro.2018.12.100

56. Castellacci F, Tveito V. Internet use and well-being: a survey and a theoretical framework. *Res Policy.* (2018) 47:308–25. doi: 10.1016/j.respol.2017.11.007

57. Ma W, Wang X. Internet use, sustainable agricultural practices and rural incomes: evidence from China. *Aust J Agric Resour Econ.* (2020) 64:1087–112. doi: 10.1111/1467-8489.12390

58. Zheng H, Ma W, Wang F, Li G. Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy.* (2021) 102:102044. doi: 10.1016/j.foodpol.2021.102044

59. Pilania M, Yadav V, Bairwa M, Behera P, Gupta SD, Khurana H, et al. Prevalence of depression among the elderly (60 years and above) population in India, 1997–2016: a systematic review and meta-analysis. *BMC Public Health.* (2019) 19:1–18. doi: 10.1186/s12889-019-7136-z

60. Wanchai A, Phrompayak D. Social participation types and benefits on health outcomes for elder people: a systematic review. *Age Int.* (2019) 44:223–33. doi: 10.1007/s12126-018-9338-6

61. Pénard T, Poussing N, Suire R. Does the internet make people happier? *J Soc Econ.* (2013) 46:105–16. doi: 10.1016/j.socec.2013.08.004

62. Kavetsos G, Koutroumpis P. Technological affluence and subjective wellbeing. *J Econ Psychol.* (2011) 32:742–53. doi: 10.1016/j.joep.2011.05.004

63. Kraut R, Kiesler S, Boneva B, Cummings J, Helgeson V, Crawford A. Internet paradox revisited. *J Soc Issues.* (2002) 58:49–74. doi: 10.1111/1540-4560.00248

64. Golin M. The effect of broadband internet on the gender gap in mental health: evidence from Germany. *Health Econ.* (2021) 31:6–21. doi: 10.1002/hec.4570

65. Shklovski I, Kraut R, Rainie L. The internet and social participation: contrasting cross-sectional and longitudinal analyses. *J Comput Mediat Commun.* (2004) 10:JCMC1018. doi: 10.1111/j.1083-6101.2004.tb00226.x

66. Santini ZI, Jose PE, Koyanagi A, Meilstrup C, Nielsen L, Madsen KR, et al. Formal social participation protects physical health through enhanced mental health: a longitudinal mediation analysis using three consecutive waves of the survey of health, ageing and retirement in Europe (Share). *Soc Sci Med.* (2020) 251:112906. doi: 10.1016/j.socscimed.2020.112906

67. Zhao X, Zhang Q, Ji Y, Liu H, Lou VW. Influence of spousal caregiving and living arrangement on depression among husband caregivers in rural China. *Aging Mental Health.* (2022) 811:1–8. doi: 10.1080/13607863.2022.2089630

68. Ye J, Lu P. Differentiated childhoods: impacts of rural labor migration on left-behind children in China. *J Peasant Stud.* (2011) 38:355–77. doi: 10.1080/03066150.2011.559012

69. Ma W, Nie P, Zhang P, Renwick A. Impact of internet use on economic wellbeing of rural households: evidence from China. *Rev Dev Econ.* (2020) 24:503–23. doi: 10.1111/rode.12645

70. Birba O, Diagne A. Determinants of adoption of internet in Africa: case of 17 Sub-Saharan countries. *Struct Change Econ Dyn.* (2012) 23:463–72. doi: 10.1016/j.strueco.2012.06.003

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Effects of chronic stress on smartphone addiction: A moderated mediation model

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Introduction: Based on the compensatory Internet use theory and diathesis-stress model, the present study explores the effects of chronic stress on smartphone addiction (SPA). As intolerance of uncertainty and emotion-related variables are important factors that affect addictive behavior, we explore the mediating role of intolerance of uncertainty and the moderating role of emotion differentiation.

Methods: We conducted a questionnaire survey of 286 participants (13.64% female; M_{age} = 22.88; *SD* = 3.77; range = 17−39) on chronic stress, SPA, intolerance of uncertainty, and emotion differentiation. SPSS 28.0 was used to analyze the descriptive statistics and correlations and test the moderated mediation model.

Results: We find that (1) intolerance of uncertainty, SPA, and chronic stress are positively correlated with each other. Positive emotion differentiation is positively correlated with intolerance of uncertainty and negative emotion differentiation. (2) Intolerance of uncertainty plays a mediating role in chronic stress and SPA. (3) Positive emotion differentiation significantly moderates the relationship between chronic stress and SPA. Under the condition of low positive emotion differentiation, chronic stress is more effective in predicting SPA.

Discussion: These findings may contribute to intervention and prevention programs for SPA. Thus, the intervention and prevention of SPA can start from two directions-reduce the intolerance of uncertainty and enhance the ability to experience positive emotion differentiation.

KEYWORDS

chronic stress, smartphone addiction, intolerance of uncertainty, emotion differentiation, moderated mediation model

1. Introduction

With the progress and development of science and technology, the penetration rate of mobile phones in the population has increased from 33.9% in 2015 to 103.5% in 2017 (1). As a widely used medium among people, smartphone has brought many conveniences to people's lives. It has strengthened the connection between people (2), enriched daily entertainment, and improved people's life satisfaction and subjective happiness to a certain extent (3).

Excessive use of smartphones leads to smartphone addiction (SPA), also called problematic smartphone use (4–6), which is a type of behavioral addiction. Behavioral addiction is when individuals cannot control their desire for certain behaviors, leading to physical or psychological harm to themselves or others (7–9). Goodman (10) proposed that addiction has two aspects—repeated and uncontrollable behaviors—and it is difficult to stop the behavior even if it has significant negative effects on the individual (10). Although SPA has not been mentioned in The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) and International Classification of Diseases 11th Revision (ICD-11), one study conducted an exploratory factor analysis and proved the similarity between SPA and substance-related addictive disorders in DSM-5, including compulsive behavior, functional impairment, withdrawal, and tolerance (11). Furthermore, gaming disorder has been included in ICD-11. Mobile games have made smartphones an important device for playing games, and addiction to games is a crucial factor that leads to SPA (12). Although online content can be carried out through various devices, the use of smartphones promotes the occurrence of Internet use disorder (5). The effect size of SPA associated with problematic social media use is medium to large because social media use is mostly through smartphones (13). In summary, SPA is an extremely important concept in exploring digital behavioral addictions as it intersects with many addictive behaviors mentioned above.

SPA is considered one of the crucial causes of human health problems in the information-based society (14). For physical health, SPA might induce neck and hands uncomfortableness (15, 16), and sleep quality would be affected by SPA, leading to low self-regulation and bedtime procrastination (17). Regarding mental health, after studying a large number of university students, Demirci et al. (18) found that SPA is closely related to anxiety and depression (18). Therefore, it is necessary to research the influencing factors of SPA.

For working adults, working during non-working hours and overtime work have become the norm in most professions, leading to great work pressure (19). In daily life, interpersonal communication and family relations have also brought great psychological burden to young people, such as bank loans and interpersonal conflicts. Chronic stress refers to constant and long-term stress (20). Chronic stress and acute stress are corresponding. The key to distinguishing the two concepts lies in the duration of exposure to stressors. The first exposure to stressors may induce acute stress reaction, and the stressors may become chronic stressors with an increase in exposure time and frequency (21).

According to the compensatory Internet use theory, people overuse technologies, such as the Internet or smartphones, to mitigate the negative effects they feel in life and work (22). Some studies have found that a smartphone is like an "adult pacifier." Using a smartphone is considered a useful way of relieving pressure (3). Moreover, with the increase in work and life pressure of young people, the entertainment function of smartphones has received much attention, which has gradually extended the time of using smartphones, leading to SPA. SPA has a negative impact on mental health, making individuals have lower subjective and psychological wellbeing (23). However, subjective wellbeing is negatively correlated with perceived stress (24), so individuals are more inclined to use a smartphone to relieve stress (25). Therefore, chronic stress has a positive impact on SPA, and SPA, in turn, increases the pressure on individuals, thereby affecting their physical and mental health. However, there are few studies on the psychological mechanism between chronic stress and SPA, and the increasing phenomenon of SPA makes it extremely urgent to study the intervention of SPA. Therefore, it is essential to study the mechanism of the influence of chronic stress on SPA, and we put forward the following hypothesis:

> **Hypothesis 1 (H1).** *Chronic stress affects an individual's SPA, and the higher the chronic stress, the higher the SPA.*

Intolerance of uncertainty is one of the structures of a generalized anxiety disorder (26), which is closely related to worry (27) and refers to an individual's state when faced with ambiguous situations or stimuli (28). The relationship between intolerance of uncertainty and stress is complex, and the two can influence each other. Racial stress perceived by blacks can influence their state of worry, whereas intolerance of uncertainty can completely mediate the relationship between perceived racial stress and worry (29). A study on COVID-19 found that different personality traits have different intolerance of uncertainty, which affects the intensity of perceived stress (30). In addition, stress disorder is related to post-traumatic stress disorder, and the intolerance of uncertainty can predict the occurrence of post-traumatic stress symptoms (31). In summary, the above studies have demonstrated that stress and intolerance of uncertainty are closely related.

Numerous studies have revealed that intolerance of uncertainty affects SPA (32). Longitudinal studies suggest that the impact of intolerance of uncertainty on SPA is not entirely direct. Unsociable smartphone use is positively correlated with intolerance of uncertainty. Moreover, unsociable smartphone use mediates the intolerance of uncertainty and problematic smartphone use (33). Working remotely on the Internet during the COVID-19 pandemic has become mainstream. Intolerance of uncertainty increases people's pain (34), depression, and risk perception (35), which then increase their use of the Internet to ease pressure. Therefore, this study suggests that intolerance of uncertainty plays a mediating role in chronic stress and SPA. Therefore, we propose the following hypothesis:

> **Hypothesis 2 (H2).** *The influence of chronic stress on SPA is not entirely direct, and intolerance of uncertainty plays a mediating role in the relationship between them.*

The diathesis-stress model proposes that psychological state and coping styles in the face of pressure are different for subjects with different qualities (36). This indicates that not all people will be negatively affected by stress, and individual differences play an important role in coping with stress. Moreover, SPA may be one of the negative effects of chronic stress. According to this, some important abilities may moderate the negative effects of stress and play a key role in the relationship between chronic stress and SPA. In recent years, researchers put forward the diathesis-stress model of emotion differentiation and proved it through an interview study (37). Emotion differentiation refers to individual differences in emotional experience, which includes positive and negative emotion differentiation (38). Individuals with high emotion differentiation can better refine their perceived emotions, whereas individuals with low emotion differentiation can only describe experienced emotions in a general way. Individuals' perceived emotional states are associated with SPA. Negative emotion is significantly related to SPA (39). In addition, emotion regulation plays an important role in college students' SPA (40). Dysfunctional emotion regulation may lead to excessive smartphone use, contributing to problematic smartphone use (41). This suggests that an individual's ability for emotion differentiation may play a moderating role in the relationship between chronic stress and SPA.

The intolerance of uncertainty is closely related to an individual's emotional condition and emotion regulation ability. In adolescents

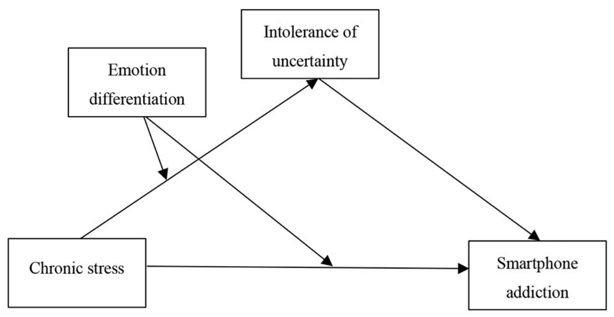

FIGURE 1
Hypothesized model.

with autism spectrum disorder, intolerance of uncertainty is influenced by emotion regulation, mediating emotion regulation, and symptoms of anxiety and depression (42). Negative emotion differentiation can mediate the relationship between stress and depression, and the lower the negative emotion differentiation, the stronger the predictive effect of stress on depression (37). Additionally, intolerance of uncertainty is closely related to depression (43), both of which have negative effects on stress. Therefore, based on the diathesis-stress model, the effect of chronic stress is influenced by individual diathesis (36). Thus, the relationship between chronic stress and intolerance of uncertainty may be affected by emotion differentiation, so the following hypothesis is proposed:

> **Hypothesis 3 (H3).** *Emotion differentiation regulates the relationship between chronic stress and SPA and its mediating mechanism. Thus, chronic stress has different relationships with SPA under different emotion differentiation conditions, and chronic stress has different relationships with intolerance of uncertainty, thus affecting SPA.*

Although many researchers have found a relationship between chronic stress and SPA, the psychological mechanism of how chronic stress affects SPA has not been investigated. From the perspective of the compensatory Internet use theory and the diathesis-stress model, the present study investigates whether chronic stress affects SPA and the mediating path and boundary conditions of chronic stress on SPA (see Figure 1).

2. Method

2.1. Participants

We randomly selected 293 enterprise employees from the northwest part of China. The questionnaires were answered by all participants. Participants who chose the same option in multiple scale questions in succession and spent too little time answering the questionnaires were excluded. A total of 286 participants (13.64% females; the participants' ages range from 17 to 39 years, with $M \pm SD = 22.88 \pm 3.77$ years) who completed the questionnaires were used for the analysis. Among the participants, 72 (25.2%) had a high school degree or below; 104 (36.4%) had a junior college degree; 103 (36.0%) had a bachelor's degree; and 7 (2.4%) had a master's degree or above. The participants are right-handed, with normal intelligence and no dyslexia. They all volunteered to participate in the study and signed the informed consent.

2.2. Procedure

The questionnaires were distributed to all participants in the same period. An online network survey was adopted, and the questionnaires were administered through WeChat. To ensure the authenticity and accuracy of the research data, each participant could only answer the questionnaires once. After being informed of the purpose, cautions, and confidentiality of the study, a total of 293 participants completed a self-administered questionnaire. In the questionnaires, first, the participants provided their demographic information. Second, the participants filled out the Perceived Stress Scale (PSS), the Smartphone Addiction Scale (SAS), and the Intolerance of Uncertainty Scale. Finally, the ability of emotion differentiation was measured.

2.3. Materials

2.3.1. Chronic stress

Chronic stress is assessed with PSS, which aims to measure participants' chronic stress intensity in the past month (44). It contains 14 items such as "In the last month, how often have you been upset because of something that happened unexpectedly?" Each item is rated on a five-point Likert scale, ranging from 0 (*never*) to *4* (*always*). Items 1, 2, 3, 8, 11, 12, and 14 are scored forward, where the higher the number, the greater the degree, whereas items 4, 5, 6, 7, 9, 10, and 13 are scored backward. The Cronbach's α of this scale is 0.75, and the construct validity is 0.88.

2.3.2. SPA

SPA is assessed using the Short Version of SAS (SAS-SV) (9, 45). It contains 10 items such as "Missing planned work due to smartphone use." Each item is rated on a six-point Likert scale ranging from 1 (strongly *agree*) to 6 (*strongly disagree*). All items are scored forward, with a higher number indicating a higher degree of SPA. The Cronbach's α for this scale is 0.92, and the construct validity is 0.90.

2.3.3. Intolerance of uncertainty

A Chinese version of the Intolerance of Uncertainty Scale is used in this study, which has good reliability and validity when applied to the Chinese context (46–48). It contains 12 items such as "The unexpected makes me restless." Each item is rated on a five-point Likert scale, ranging from 1 (*not at all*) to 5 (*extremely*). All items are scored forward, with a higher number indicating a higher degree of intolerance of uncertainty. The Cronbach's α for this scale is 0.90, and the construct validity is 0.90.

2.3.4. Emotion differentiation

Following previous studies (49–51), we asked the participants to complete a standard laboratory-based emotion differentiation task. The participants viewed 20 negative and 20 positive images from the Open Affective Standardized Image Set (52) and rated a series

TABLE 1 Descriptive statistics and correlations of all variables.

	M	*SD*	1	2	3	4	5
Chronic stress	21.65	7.52	1				
Smartphone addiction	18.14	9.29	0.34***	1			
Intolerance of uncertainty	27.75	9.64	0.33***	0.55***	1		
Negative emotion differentiation	0.70	0.29	−0.06	0.08	0.02	1	
Positive emotion differentiation	0.62	0.29	−0.06	0.06	0.15*	0.40***	1

M, mean; SD, standard deviations. *p < 0.05; ***p < 0.001.

TABLE 2 Mediation analysis.

Regression equation		Overall fitting index			Regression coefficient	
Outcome variable	Predictive variable	*R*	R^2	*F(df)*	β	*t*
Intolerance of uncertainty		0.33	0.11	$35.70^{***}_{(1)}$		
	Chronic stress				0.33	5.97***
Smartphone addiction		0.34	0.12	$37.71^{***}_{(1)}$		
	Chronic stress				0.33	6.14***
Smartphone addiction		0.57	0.33	$69.86^{***}_{(2)}$		
	Chronic stress				0.17	3.46***
	Intolerance of uncertainty				0.49	9.50***

All variables in the model were entered into the regression equation after standardization. ***p < 0.001.

of emotions on a 10-point scale, ranging from 1 (*not at all*) to 10 (*extremely*). Negative emotions (i.e., anger, ashamed, disgust, sadness, and scared) and positive emotions (i.e., calm, excitement, happiness, inspiration, and interested) were rated by the participants. Following prior work, each image was presented for 5 seconds, and the rating was self-paced.

The participants' negative emotion differentiation is investigated by calculating the average intraclass correlation coefficients (ICCs) of their ratings of 20 negative images. Lower ICCs indicate less similarity in how the participants use each emotion scale (51, 53). The final scores of ICCs are subtracted from one, so greater values represent higher emotion differentiation (54). The score of positive emotion differentiation is calculated in the same way.

2.4. Data analyses

All the data collected are processed using SPSS 28.0, which is used for descriptive statistics and correlation analysis. We take chronic stress as the independent variable, SPA as the dependent variable, intolerance of uncertainty as the mediating variable, and emotion differentiation as the moderating variable. PROCESS macro in SPSS 28.0 (55) is used to test the mediating and moderating effects. It is also used to explore the effect of chronic stress on SPA, the mediating role of intolerance of uncertainty, and the moderating role of emotion differentiation.

3. Results

3.1. Description and correlation

The descriptive statistics for each variable and the correlation analysis of the variables are presented in Table 1. The results of the correlation analysis indicate that SPA is positively associated with chronic stress. Intolerance of uncertainty, SPA, and chronic stress are positively correlated with each other. Moreover, the correlation coefficient between intolerance of uncertainty and SPA is moderate. In addition, positive emotion differentiation is positively correlated with intolerance of uncertainty and negative emotion differentiation.

TABLE 3 Testing the pathways of the mediation model.

	β	*SE*	95% confidence interval	
			Lower	Upper
Total effect	0.33	0.05	0.00	0.23
Direct effect	0.17	0.05	0.00	0.08
Indirect effect	0.16	0.03	0.10	0.23

3.2. Examination of the mediation model

To reveal the influence mechanism of chronic stress on SPA, PROCESS macro (Model 4) in SPSS 28.0 is used to investigate the mediating role of intolerance of uncertainty in the relationship between chronic stress and SPA. The results of the mediating effect are presented in Tables 2, 3. The results in Table 2 indicate that chronic stress can significantly predict SPA ($\beta = 0.33$, $t = 5.97$, $p < 0.001$). After adding the mediating variables, it is found that both chronic stress ($\beta = 0.17$, $t = 3.46$, $p < 0.001$) and intolerance of uncertainty ($\beta = 0.49$, $t = 9.50$, $p < 0.001$) positively predict SPA.

To assess the significance of the indirect effect, bias-corrected bootstrap tests are performed using 5,000 samples at the 95% confidence interval, and the results are presented in Table 3.

TABLE 4 Moderated mediation analysis.

Regression equation		Overall fitting index			Regression coefficient	
Outcome variable	Predictive variable	*R*	R^2	*F(df)*	*β*	*t*
Intolerance of uncertainty		0.33	0.11	$35.70^{***}_{(1)}$		
	Chronic stress				0.33	5.97^{***}
Smartphone addiction		0.58	0.34	$36.19^{***}_{(4)}$		
	Chronic stress				0.17	3.34^{***}
	Intolerance of uncertainty				0.49	9.43^{***}
	Positive emotion differentiation				0.00	0.07
	Positive emotion differentiation∗intolerance of uncertainty				−0.09	−2.01∗

All variables in the model were entered into the regression equation after standardization. $^*p < 0.05$; $^{***}p < 0.001$.

Intolerance of uncertainty has a significant indirect effect on the relationship between chronic stress and SPA ($\beta = 0.16$, $SE = 0.03$, *95% CI* = 0.10–0.23). The direct effect of chronic stress on SPA is also significant ($\beta = 0.17$, $SE = 0.05$, *95% CI* = 0.00–0.08).

3.3. Examination of the moderated mediation model

To reveal the mechanism of the effect of chronic stress on SPA, we use PROCESS macro (Model 8) in SPSS 28.0 to investigate the moderating effect of emotion differentiation in the relationship between chronic stress and intolerance of uncertainty, as well as between chronic stress and SPA. Negative emotion differentiation is used as a moderator variable, and the results reveal that the interaction of negative emotion differentiation and chronic stress has no significant predictive effect on intolerance of uncertainty ($\beta = -0.01$, $SE = 0.06$, $t = -0.18$, $p = 0.85$, *95% CI* = −0.13–0.11) and SPA ($\beta = -0.03$, $SE = 0.05$, $t = -0.66$, $p = 0.51$, *95% CI* = −0.14–0.07). When positive emotion differentiation is used as a moderator variable, the interaction between positive emotion differentiation and chronic stress has no significant predictive effect on intolerance of uncertainty ($\beta = -0.03$, $SE = 0.06$, $t = -0.53$, $p = 0.60$, *95% CI* = −0.14–0.08) and SPA ($\beta = 0.03$, $SE = 0.06$, $t = 0.70$, $p = 0.48$, *95% CI* = −0.06–0.13).

The interaction between chronic stress and emotion differentiation is not significant in predicting intolerance of uncertainty and SPA. Therefore, PROCESS macro (Model 14) in SPSS28.0 is used to construct a moderating mediation model to examine whether emotion differentiation plays a moderating role in the relationship between intolerance of uncertainty and SPA. Negative emotion differentiation is used as a moderator, and the results reveal that the interaction of intolerance of uncertainty and negative emotion differentiation has no significant effect on SPA ($\beta = -0.08$, $SE = 0.05$, $t = -1.72$, $p = 0.09$, *95% CI* = −0.18–0.01). The moderating effect of positive emotion differentiation is presented in Tables 4, 5 and Figure 2. The results in Table 4 indicate that the interaction of intolerance of uncertainty and positive emotion differentiation has a significant negative predictive effect on SPA ($\beta = -0.09$, $SE = 0.05$, $t = -2.01$, $p < 0.05$, *95% CI* = −0.19––0.00).

TABLE 5 Moderating effect of different positive emotion differentiation.

	β	*SE*	95% confidence interval	
			Lower	Upper
High positive emotion differentiation	0.13	0.03	0.07	0.20
Low positive emotion differentiation	0.19	0.04	0.11	0.28

According to Table 5, both low positive emotion differentiation and high positive emotion differentiation have different predictive effects on SPA. Low positive emotion differentiation ($\beta = 0.19$, $SE = 0.04$, *95% CI* = 0.11–0.28) is more predictive of SPA than high positive emotion differentiation ($\beta = 0.13$, $SE = 0.03$, *95% CI* = 0.07–0.20).

Figure 2 depicts the results of a simple slope analysis. Compared with a high emotion differentiation condition ($\beta = 0.40$, $SE = 0.07$, $t = 5.77$, $p < 0.001$, *95% CI* = 0.26–0.53), in a low emotion differentiation condition, intolerance of uncertainty has a greater positive predictive effect on SPA ($\beta = 0.58$, $SE = 0.07$, $t = 8.29$, $p < 0.001$, *95% CI* = 0.45–0.72). Figure 3 depicts the statistical model of this study.

4. Discussion

4.1. The relationship between the dimensions

Through correlation analysis, this study initially finds that chronic stress, SPA, and intolerance of uncertainty are positively correlated with each other. Consistent with previous findings, stress is a key factor in the emergence, development, and relapse of addictive behaviors (56, 57). Stress promotes excessive eating behavior, and adapting to stress and reward circuit promotes metabolic adaptation, which affects eating addiction behavior (56). With the development and popularization of the Internet, studies have found that gaming disorder is closely related to stress (58). In addition, stress is closely related to intolerance of uncertainty. Intolerance of uncertainty predicts the extent of post-traumatic stress symptoms associated with

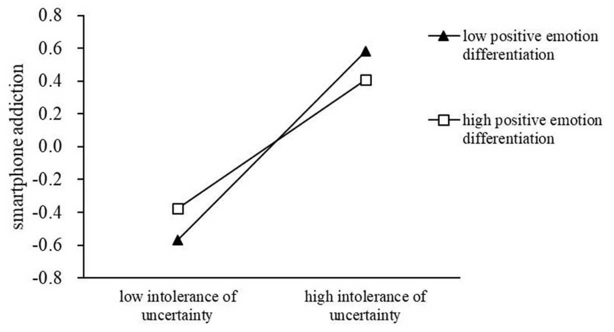

FIGURE 2
Simple slope plot of positive emotion differentiation.

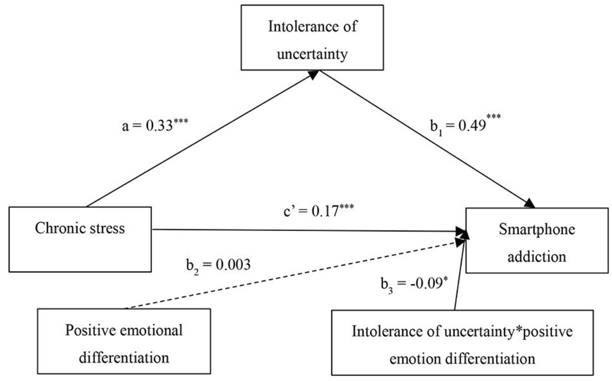

FIGURE 3
Statistic model.

negative stressful life events (59). There is also a strong relationship between intolerance of uncertainty and addictive behavior, and patients treated with opioids have higher intolerance of uncertainty (60). Therefore, the preliminary findings of this study indicate that there may be a complex relationship among the three variables, and we construct the relationship model among them.

4.2. The mediating role of intolerance of uncertainty

This study finds that chronic stress affects SPA through intolerance of uncertainty. The results of this study are consistent with those of other studies. Studies have demonstrated that chronic stress has a negative impact on mental health (61). Intolerance of uncertainty is closely related to worry, which closely reflects negative psychological wellbeing (27). Based on the ego depletion theory, stress promotes an individual's self-control to maintain the balance between the external pressure environment and their psychological wellbeing (62, 63). However, excessive self-control leads to self-depletion, psychological imbalance, or decline in self-control, which may have a negative impact on individuals (64).

The compensatory Internet use theory reveals that people release negative emotions and psychological pressure through the use of smartphones or the Internet (22). Intolerance of uncertainty is an important negative psychological feeling, and individuals can use smartphones or the Internet to alleviate negative psychological feelings. Therefore, the results of this study confirm the positive predictive effect of chronic stress on SPA and the mediating effect of intolerance of uncertainty on chronic stress and SPA.

4.3. The moderating role of emotion differentiation

The results of this study reveal that positive emotion differentiation plays a moderating role in the relationship between intolerance of uncertainty and SPA. Intolerance of uncertainty under low-level emotion differentiation is a greater positive predictor of SPA. The result of this study is consistent with that of other studies. Addicts have lower emotional wellbeing and intelligence, including emotion differentiation, than non-addicts (65, 66). Compared with non-alcoholics and abstainers, alcoholics have more difficulty in recognizing and expressing their feelings and have a lower emotion differentiation (67). Moreover, intolerance of uncertainty is a negative psychological state of individuals, which is closely related to their emotions. Therefore, individuals with low emotion differentiation are more vulnerable to the impact of intolerance of uncertainty, leading to SPA.

However, this study does not find the moderating effect of negative emotion differentiation. This could be because the original purpose of smartphone use is to seek positive emotions, such as happiness (3). Therefore, better recognition and expression of positive feelings can help individuals find the negative impact of positive emotions in the use of smartphones. This can help them avoid SPA caused by the excessive use of smartphones.

This study does not confirm H3, finding that neither positive nor negative emotion differentiation moderates chronic stress as a predictor of intolerance of uncertainty or SPA. Most studies have found the moderating role of negative emotion differentiation in chronic stress. High emotion differentiation alleviates anxiety and depression after exposure to stressful life events in adolescence (50). Rumination and constant attention to daily life are more strongly associated with depressive symptoms in individuals with low emotion differentiation (68). These findings are not consistent with the conclusion of this study. This may be because chronic stress reflects the degree of an individual's perceived stress in a certain period, whereas intolerance of uncertainty is an individual's negative psychological feeling, reflecting the negative emotions individuals feel when they are stressed. Moreover, emotion differentiation is the ability to recognize and distinguish emotions and can better adjust the influence of variables reflecting emotions. Further, the existing literature lacks mediating mechanism studies on the influence of chronic stress, but this study explores the mediating effect of chronic stress on SPA and further investigates the moderating effect of emotion differentiation. Therefore, the results of this study expand the research on the effects of chronic stress, and it is found that the moderating effect of emotion differentiation on the effects of chronic stress is mainly reflected in the negative effects.

4.4. Limitations and future research

There are several limitations in the present study. First, in the working environment, the relationship between leaders and employees, as well as leadership style, may have an important impact on the psychological feelings and behavior of employees (69, 70). Therefore, future studies can include relevant variables to explore their important role in individual psychological feelings and behavior to construct structural equation models. Second, the research method of this study is mainly a subjective assessment. This makes the results of the study subjective and subject to response bias. Thus, implicit behavioral research methods or cognitive neuroscience methods should be considered in future research to improve the objectivity and credibility of the study.

4.5. Strengths and implications

Despite these limitations, this study has the following strengths. First, it investigates the indirect effect of chronic stress on SPA, whereas previous studies mainly investigated the direct effect of chronic stress on SPA. Second, the important role of emotion differentiation in SPA is proposed for the first time. Third, the mechanism of positive emotion differentiation is disclosed by exploring the influences of both negative and positive emotion differentiation on SPA.

This study has significant implications. First, it is the first to examine the mediating role of intolerance of uncertainty in the relationship between chronic stress and SPA. It is revealed that the effect of chronic stress on SPA is indirect through intolerance of uncertainty. Second, the study finds that emotion differentiation plays a moderating role in the effect of chronic stress on SPA, providing support for future prevention and intervention. Individuals with high levels of positive emotion differentiation are less likely to suffer from chronic stress, thereby reducing the degree of SPA. Therefore, in future practice, cognitive behavior therapy or emotion regulation strategies can be used to reduce the intolerance of uncertainty that individuals feel when facing various types of pressure (42, 71). In addition, based on the moderating effect of emotion differentiation, mindfulness and other methods can be used to improve positive emotion differentiation (72), learn to better identify and express emotions, and reduce SPA.

5. Conclusion

In conclusion, the present study proposes a moderated mediation model to explain the effect of chronic stress on SPA and its mechanism. Specifically, chronic stress can significantly predict SPA, and intolerance of uncertainty plays a mediating role in the relationship between them. High chronic stress leads to high intolerance of uncertainty, resulting in SPA. In addition, positive emotion differentiation moderates the relationship between intolerance of uncertainty and SPA. Individuals with low positive emotion differentiation are more vulnerable to intolerance of uncertainty, leading to SPA.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

HQ: conceptualization, methodology, writing–original draft, and writing–review and editing. HL: conceptualization, validation, writing–review and editing, and investigation. JP, YZ, YM, and XW: investigation. CX: software. XZ: supervision, writing–review and editing, and investigation. All authors contributed to the article and approved the submitted version.

Conflict of interest

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

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References

1. Zhang J, Cheng M, Wei X, Gong X. Does mobile phone penetration affect divorce rate? *Evid China Sustain Basel.* (2018) 10:3701. doi: 10.3390/su10103701

2. Bian M, Leung L. Linking loneliness, shyness, smartphone addiction symptoms, and patterns of smartphone use to social capital. *Soc Sci Comput Rev.* (2015) 33:61–79. doi: 10.1177/0894439314528779

3. Melumad S, Pham MT. The smartphone as a pacifying technology. *J Consum Res.* (2020) 47:237–55. doi: 10.1093/jcr/ucaa005

4. Panova T, Carbonell X. Is smartphone addiction really an addiction? *J Behav Addict.* (2018) 7:252–9. doi: 10.1556/2006.7.2018.49

5. Montag C, Wegmann E, Sariyska R, Demetrovics Z, Brand M. How to overcome taxonomical problems in the study of internet use disorders and what to do with "smartphone addiction"? *J Behav Addict.* (2021) 9:908–14. doi: 10.1556/2006.8.2019.59

6. Horvath J, Mundinger C, Schmitgen MM, Wolf ND, Sambataro F, Hirjak D, et al. Structural and functional correlates of smartphone addiction. *Addict Behav.* (2020) 105:106334. doi: 10.1016/j.addbeh.2020.106334

7. Lin Y, Chiang C, Lin P, Chang L, Ko C, Lee Y, et al. Proposed diagnostic criteria for smartphone addiction. *PLoS ONE.* (2016) 11:e163010. doi: 10.1371/journal.pone.0163010

8. Albrecht U, Kirschner NE, Grüsser SM. Diagnostic instruments for behavioural addiction: an overview. *GMS Psycho Soc Med*. (2007) 4:1–11.

9. Kwon M, Lee JY, Won WY, Park JW, Min JA, Hahn C, et al. Development and validation of a smartphone addiction scale (SAS). *PLoS ONE.* (2013) 8:e56936. doi: 10.1371/journal.pone.0056936

10. Goodman A. Addiction: definition and implications. *Br J Addict.* (1990) 85:1403–8. doi: 10.1111/j.1360-0443.1990.tb01620.x

11. Lin YH, Chang LR, Lee YH, Tseng HW, Kuo TB, Chen SH. Development and validation of the Smartphone Addiction Inventory (SPAI). *PLoS ONE.* (2014) 9:e98312. doi: 10.1371/journal.pone.0098312

12. Liu C, Lin S, Pan Y, Lin Y. Smartphone gaming and frequent use pattern associated with smartphone addiction. *Medicine.* (2016) 95:e4068. doi: 10.1097/MD.0000000000004068

13. Marino C, Canale N, Melodia F, Spada MM, Vieno A. The overlap between problematic smartphone use and problematic social media use: a systematic review. *Curr Addict Rep.* (2021) 8:469–80. doi: 10.1007/s40429-021-00398-0

14. Ratan ZA, Parrish A, Zaman SB, Alotaibi MS, Hosseinzadeh H. Smartphone addiction and associated health outcomes in adult populations: a systematic review. *Int J Env Res Publ Health.* (2021) 18:12257. doi: 10.3390/ijerph182212257

15. AlAbdulwahab SS, Kachanathu SJ, AlMotairi MS. Smartphone use addiction can cause neck disability. *Musculoskeletal Care.* (2017) 15:10–2. doi: 10.1002/msc.1170

16. Baabdullah A, Bokhary D, Kabli Y, Saggaf O, Daiwali M, Hamdi A. The association between smartphone addiction and thumb/wrist pain. *Medicine.* (2020) 99:e19124. doi: 10.1097/MD.0000000000019124

17. Zhang MX, Wu AM. Effects of smartphone addiction on sleep quality among Chinese university students: The mediating role of self-regulation and bedtime procrastination. *Addict Behav.* (2020) 111:106552. doi: 10.1016/j.addbeh.2020.106552

18. Demirci K, Akgönül M, Akpinar A. Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *J Behav Addict.* (2015) 4:85–92. doi: 10.1556/2006.4.2015.010

19. Park Y, Liu Y, Headrick L. When work is wanted after hours: Testing weekly stress of information communication technology demands using boundary theory. *J Organ Behav.* (2020) 41:518–34. doi: 10.1002/job.2461

20. Ladewig J. Chronic intermittent stress: a model for the study of long-term stressors. *Biol Anim Stress*. (2000) 8:159–69. doi: 10.1079/9780851993591.0159

21. Rohleder N. Stress and inflammation – the need to address the gap in the transition between acute and chronic stress effects. *Psychoneuroendocrino.* (2019) 105:164–71. doi: 10.1016/j.psyneuen.2019.02.021

22. Kardefelt-Winther D. A conceptual and methodological critique of internet addiction research: towards a model of compensatory internet use. *Comput Hum Behav.* (2014) 31:351–4. doi: 10.1016/j.chb.2013.10.059

23. Horwood S, Anglim J. Problematic smartphone usage and subjective and psychological well-being. *Comput Hum Behav.* (2019) 97:44–50. doi: 10.1016/j.chb.2019.02.028

24. Schiffrin HH, Nelson SK. Stressed and happy? Investigating the relationship between happiness and perceived stress. *J Happiness Stud.* (2010) 11:33–9. doi: 10.1007/s10902-008-9104-7

25. Jeong S, Kim H, Yum J, Hwang Y. What type of content are smartphone users addicted to?: SNS vs. Games. *Comput Hum Behav.* (2016) 54:10–7. doi: 10.1016/j.chb.2015.07.035

26. Dugas MJ, Gagnon F, Ladouceur R, Freeston MH. Generalized anxiety disorder: a preliminary test of a conceptual model. *Behav Res Ther.* (1998) 36:215–26. doi: 10.1016/S0005-7967(97)00070-3

27. Osmanagaoglu N, Creswell C, Dodd HF. Intolerance of Uncertainty, anxiety, and worry in children and adolescents: a meta-analysis. *J Affect Disord.* (2018) 225:80–90. doi: 10.1016/j.jad.2017.07.035

28. Krohne HW. Vigilance and cognitive avoidance as concepts in coping research. In: Krohne HW, editor. *Attention and Avoidance: Strategies in Coping with Aversiveness*. Hogrefe and Huber Publishers (1993). p. 19–50.

29. Rucker LS, West LM, Roemer L. Relationships among perceived racial stress, intolerance of uncertainty, and worry in a black sample. *Behav Ther.* (2010) 41:245–53. doi: 10.1016/j.beth.2009.04.001

30. Bongelli R, Canestrari C, Fermani A, Muzi M, Riccioni I, Bertolazzi A, et al. Associations between personality traits, intolerance of uncertainty, coping strategies, and stress in Italian frontline and Non-Frontline HCWs during the COVID-19 pandemic—a Multi-Group Path-Analysis. *Healthcare.* (2021) 9:1086. doi: 10.3390/healthcare9081086

31. Oglesby ME, Boffa JW, Short NA, Raines AM, Schmidt NB. Intolerance of uncertainty as a predictor of post-traumatic stress symptoms following a traumatic event. *J Anxiety Disord.* (2016) 41:82–7. doi: 10.1016/j.janxdis.2016.01.005

32. Faghani N, Akbari M, Hasani J, Marino C. An emotional and cognitive model of problematic Internet use among college students: the full mediating role of cognitive factors. *Addict Behav.* (2020) 105:106252. doi: 10.1016/j.addbeh.2019.106252

33. Rozgonjuk D, Elhai JD, Täht K, Vassil K, Levine JC, Asmundson GJG. Non-social smartphone use mediates the relationship between intolerance of uncertainty and problematic smartphone use: Evidence from a repeated-measures study. *Comput Hum Behav.* (2019) 96:56–62. doi: 10.1016/j.chb.2019.02.013

34. Reizer A, Galperin BL, Chavan M, Behl A, Pereira V. Examining the relationship between fear of COVID-19, intolerance for uncertainty, and cyberloafing: a mediational model. *J Bus Res.* (2022) 145:660–70. doi: 10.1016/j.jbusres.2022.03.037

35. Luo R, Li Q, Meng G, Zheng Y, Hu K, Zhang X, et al. The association between intolerance of uncertainty and Internet addiction during the second wave of the coronavirus disease 2019 pandemic: a multiple mediation model considering depression and risk perception. *Psych J.* (2022) 11:383–91. doi: 10.1002/pchj.545

36. Monroe SM, Simons AD. Diathesis-stress theories in the context of life stress research: Implications for the depressive disorders. *Psychol Bull.* (1991) 110:406–25. doi: 10.1037/0033-2909.110.3.406

37. Starr LR, Hershenberg R, Shaw ZA, Li YI, Santee AC. The perils of murky emotions: Emotion differentiation moderates the prospective relationship between naturalistic stress exposure and adolescent depression. *Emotion.* (2020) 20:927–38. doi: 10.1037/emo0000630

38. Barrett LF, Gross J, Christensen TC, Benvenuto M. Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cogn Emot.* (2001) 15:713–24. doi: 10.1080/02699930143000239

39. Yue H, Zhang X, Sun J, Liu M, Li C, Bao H. The relationships between negative emotions and latent classes of smartphone addiction. *PLoS ONE.* (2021) 16:e248555. doi: 10.1371/journal.pone.0248555

40. Lee H, Bae S. Influence of stress, self factor and emotional factor on smartphone addiction level among college students. *J Korea Contents Assoc*. (2017) 17:326–36. doi: 10.5392/JKCA.2017.17.05.326

41. Rozgonjuk D, Elhai JD. Emotion regulation in relation to smartphone use: Process smartphone use mediates the association between expressive suppression and problematic smartphone use. *Curr Psychol.* (2021) 40:3246–55. doi: 10.1007/s12144-019-00271-4

42. Cai RY, Richdale AL, Dissanayake C, Uljarević M. Brief report: inter-relationship between emotion regulation, intolerance of uncertainty, anxiety, and depression in youth with autism spectrum disorder. *J Autism Dev Disord.* (2018) 48:316–25. doi: 10.1007/s10803-017-3318-7

43. Dar KA, Iqbal N, Mushtaq A. Intolerance of uncertainty, depression, and anxiety: Examining the indirect and moderating effects of worry. *Asian J Psychiatr.* (2017) 29:129–33. doi: 10.1016/j.ajp.2017.04.017

44. Cohen S, Kamarck T, Mermelstein R. A global measure of perceived stress. *J Health Soc Behav*. (1983) 24:385–96. doi: 10.2307/2136404

45. Kwon M, Kim D, Cho H, Yang S, Choi D. The smartphone addiction scale: development and validation of a short version for adolescents. *PLoS ONE.* (2013) 8:e83558. doi: 10.1371/journal.pone.0083558

46. Zhang YJ, Song JB, Gao YT, Wu SJ, Song L, Miao DM. Reliability and validity of the intolerance of uncertainty scale-short form in university students. *Chin J Clin Psychol.* (2017) 25:285–8. doi: 10.16128/j.cnki.1005-3611.2017.02.020

47. Carleton RN, Norton MAPJ, Asmundson GJG. Fearing the unknown: a short version of the Intolerance of Uncertainty Scale. *J Anxiety Disord.* (2007) 21:105–17. doi: 10.1016/j.janxdis.2006.03.014

48. Cheng SH, Zhang XY, Han YC. Relationship between fear of missing out and phubbing on college students: The chain intermediary cflect of intolerance of uncertainty and problematic social media nse. *China J Health Psychol.* (2022) 30:1296–300. doi: 10.13342/j.cnki.cjhp.2022.09.004

49. Nook EC, Sasse SF, Lambert HK, McLaughlin KA, Somerville LH. The nonlinear development of emotion differentiation: granular emotional experience is low in adolescence. *Psychol Sci.* (2018) 29:1346–57. doi: 10.1177/0956797618773357

50. Nook EC, Flournoy JC, Rodman AM, Mair P, McLaughlin KA. High emotion differentiation buffers against internalizing symptoms following exposure to stressful life events in adolescence: An intensive longitudinal study. *Clin Psychol Sci.* (2021) 9:699–718. doi: 10.1177/2167702620979786

51. Erbas Y, Ceulemans E, Lee Pe M, Koval P, Kuppens P. Negative emotion differentiation: Its personality and well-being correlates and a comparison of different assessment methods. *Cogn Emot.* (2014) 28:1196–213. doi: 10.1080/02699931.2013.875890

52. Kurdi B, Lozano S, Banaji MR. Introducing the open affective standardized image set (OASIS). *Behav Res Methods.* (2017) 49:457–70. doi: 10.3758/s13428-016-0715-3

53. Widdershoven RLA, Wichers M, Kuppens P, Hartmann JA, Menne-Lothmann C, Simons CJP, et al. Effect of self-monitoring through experience sampling on emotion differentiation in depression. *J Affect Disorders.* (2019) 244:71–7. doi: 10.1016/j.jad.2018.10.092

54. Tugade MM, Fredrickson BL, Barrett LF. Psychological resilience and positive emotional granularity: examining the benefits of positive emotions on coping and health. *J Pers.* (2004) 72:1161–90. doi: 10.1111/j.1467-6494.2004.00294.x

55. Hayes AF. *Process: A Versatile Computational Tool for Observed Variable Mediation, Moderation, and Conditional Process Modeling*. (2012). Available online at: http://claudiaflowers.net/rsch8140/Hayesprocess.pdf

56. Sinha R, Jastreboff AM. Stress as a common risk factor for obesity and addiction. *Biol Psychiat.* (2013) 73:827–35. doi: 10.1016/j.biopsych.2013.01.032

57. Sinha R. Chronic stress, drug use, and vulnerability to addiction. *Ann Ny Acad Sci.* (2008) 1141:105–30. doi: 10.1196/annals.1441.030

58. Rajab AM, Zaghloul MS, Enabi S, Rajab TM, Al-Khani AM, Basalah A, et al. Gaming addiction and perceived stress among Saudi adolescents. *Addict Behav Rep.* (2020) 11:100261. doi: 10.1016/j.abrep.2020.100261

59. Boelen PA. Intolerance of uncertainty predicts analogue posttraumatic stress following adverse life events. *Anxiety Stress Coping.* (2019) 32:498–504. doi: 10.1080/10615806.2019.1623881

60. Radell ML, Allen MT, Favaloro B, Myers CE, Haber P, Morley K, et al. Intolerance of uncertainty and conditioned place preference in opioid addiction. *PeerJ.* (2018) 6:e4775. doi: 10.7717/peerj.4775

61. Rosiek A, Rosiek-Kryszewska A, Leksowski A, Leksowski K. Chronic stress and suicidal thinking among medical students. *Int J Env Res Pub He.* (2016) 13:212. doi: 10.3390/ijerph13020212

62. Baumeister RF. Ego depletion and Self-Regulation failure: a resource model of Self-Control. *Alcohol Clin Exp Res.* (2003) 27:281–4. doi: 10.1097/01.ALC.0000060879.61384.A4

63. Maier SU, Makwana AB, Hare TA. Acute stress impairs Self-Control in Goal-Directed choice by altering multiple functional connections within the brain's decision circuits. *Neuron.* (2015) 87:621–31. doi: 10.1016/j.neuron.2015.07.005

64. Ackerman JM, Goldstein NJ, Shapiro JR, Bargh JA. You wear me out: the vicarious depletion of self-control. *Psychol Sci.* (2009) 20:326–32. doi: 10.1111/j.1467-9280.2009.02290.x

65. Salovey P, Mayer JD, Goldman SL, Turvey C, Palfai TP. Emotional attention, clarity, and repair: Exploring emotional intelligence using the trait meta-mood scale. In: Pennebaker JW, editor. *Emotion, Disclosure, & Health*. American Psychological Association (1995). p. 125–54. doi: 10.1037/10182-006

66. Naeim M, Rezaeisharif A. Comparison of emotional intelligence, attachment style, and mental health in addicted and nonaddicted people. *Addict Disord Their Treat.* (2021) 20:463–9. doi: 10.1097/ADT.0000000000000270

67. Bochand L, Nandrino J. Niveaux de conscience émotionnelle chez les sujets alcoolodépendants et abstinents. *L'Encéphale.* (2010) 36:334–9. doi: 10.1016/j.encep.2009.12.013

68. Starr LR, Hershenberg R, Li YI, Shaw ZA. When feelings lack precision: Low positive and negative emotion differentiation and depressive symptoms in daily life. *Clin Psychol Sci.* (2017) 5:613–31. doi: 10.1177/2167702617694657

69. Haar J, Schmitz A, Di Fabio A, Daellenbach U. The role of relationships at work and happiness: a moderated moderated mediation study of New Zealand managers. *Sustainability-Basel.* (2019) 11:3443. doi: 10.3390/su11123443

70. Ghadi MY, Almanaga'H KS. The role of job crafting in the relationship between empowering leadership and happiness at work: an empirical analysis. *Bus Theory Pract.* (2020) 21:244–51. doi: 10.3846/btp.2020.11109

71. Mahoney AEJ, McEvoy PM. Changes in intolerance of uncertainty during cognitive behavior group therapy for social phobia. *J Behav Ther Exp Psy.* (2012) 43:849–54. doi: 10.1016/j.jbtep.2011.12.004

72. Tong EMW, Keng S. The relationship between mindfulness and negative emotion differentiation: a test of multiple mediation pathways. *Mindfulness.* (2017) 8:933–42. doi: 10.1007/s12671-016-0669-7

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Reliability and validity of the problematic TikTok Use Scale among the general population

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Introduction: This study aims to provide a scale for measuring problematic TikTok use levels by adapting items from the Instagram Addiction Scale.

Methods: The 372 participants were determined by a convenience sampling method, and data were collected through Google online forms. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were performed for construct validity and criterion-related validity analysis. Criterion-related validity for the Problematic TikTok Use Scale (PTTUS) was tested using correlation analysis between the Bergen Social Media Addiction Scale and Social Media Use Disorder Scale.

Results: EFA indicated that a three-factor structure should be formed. The first factor is the sub-dimension of obsession and consists of 4 items, the second factor is the escapism sub-dimension and consists of 6 items, and the third factor is the lack of control sub-dimension and consists of 6 items. The model fit for adapting the PTTUS into Turkish was examined with first-level CFA, $\chi 2$/sd, RMSEA, CFI, GFI, AGFI, and SRMR, the obtained values show that the three-factor structure of the scale provides acceptable fit. Reliability analyses showed that Cronbach's alpha internal consistency reliability coefficient ranged from 0.83 to 0.90; McDonald's Omega reliability values was 0.84 to 0.90, and test–retest correlation coefficient ranged from 0.68 to 0.73, indicating sufficient internal consistency and test–retest reliability.

Conclusion: Based on this information, PTTUS is a measurement tool with sufficient psychometric properties that can be applied to determine individuals' levels of problematic TikTok use.

KEYWORDS
validation, reliability, social media, psychology, TikTok, problematic use

Introduction

The first smartphones began to enter people's lives in the early 2000s, offering ease of use without limitations of time and place. They have since become a necessity in many areas of life; smartphone use has become widespread, and its importance has gradually increased. Internet usage on smartphones now exceeds the rate of internet usage on other devices, such as computers and tablets, reaching 95.5%. Social media is the most common type of smartphone internet use.

Among social media applications, YouTube (23.7%) is the most popular, followed by Facebook (23.6%) and TikTok (19.6%) in terms of time spent. There has been a significant increase in social media use, especially during the COVID-19 (Coranavirus) Pandemic (1).

Behavioral addiction is a person's actions and activities that cause physiological, psychological and social problems and continue to be done uncontrollably despite the person's desire to quit, thus considering this behavior as unimportant and continuing to do it even if it harms herself/himself and her/him environment. Behavioral addiction according to DSM-5; It has features such as being overly preoccupied with behavior, decreased ability to control behavior, developing tolerance for behavioral, exhibiting excessive negative emotions when trying to avoid behavior, and causing negative psychological problems such as stress and depression.

TikTok was launched in 2016 by the China-based company ByteDance, under the name Musical.ly; it was renamed "TikTok" a year later (2). The TikTok application is used by downloading it to a smartphone and allows users to record videos of less than 3 min, which users can edit themselves (3). Some features include adding audio and images, making live broadcasts, and earning a certain amount of income based on users' number of followers. It differs from other social media platforms in that it can add audio and images to videos, produce content in line with followers' interest with short videos, enable more interaction, and involve users in an interactive process. TikTok allows people to both entertain and earn income while producing content and trying to attract followers' attention, which increases its use.

TikTok was downloaded more than 2 billion times in 2021, and most users are adolescents and young adults (16–35 years old) (4). According to the statistical data, 68.97% of TikTok users are under the age of 24, and 73.69% are under the age of 30 (5). Social media defines the phenomena it creates with the name of the social media network. For example, someone who is famous on YouTube is called a YouTuber, someone who is famous on Instagram is an Instagrammer, and someone famous on TikTok is defined as TikToker. TikTokers prepare and share content for reasons such as social acceptance, feeling comfortable, and satisfaction (6), which contributes to increasing TikTok usage.

It has been reported that social media have negative physical, psychological, emotional, and social effects on individuals (7–10). Previous studies have investigated and defined Facebook (11–13), Twitter, and YouTube (14, 15) addiction. Social media addiction is accepted as a subtype of internet addiction, which is one of the behavioral addiction types (8, 10, 12). Some recent studies emphasize that many symptoms seen in internet addiction are also included in social media addiction. In addition, in recent years, social media, which has increased its use, can make individuals more addicted. In previous years, there are many studies on social media addictions such as Facebook Addiction, Twitter Addiction, Youtube Addiction, and what these addiction types are has been defined. For example, there is the Social Media Addiction (SMD) scale, which was developed by Tutkun-Ünal (16) and whose reliability and validity studies were conducted, in order to detect social media addiction. This scale was developed to measure the social media addictions of university students in various ways such as gender, age, class level, applications used, school where they study, social media usage tools, people they live with, and duration of use of social networks. Another social media addiction scale was adapted into Turkish by Demirci (17). The scale aims to determine the mental pursuit, mood change, tolerance, deprivation, conflict and unsuccessful attempts of individuals to use social media. There are also social media addiction scales developed on different samples (18, 19). Scale adaptation studies were also carried out in order to measure Facebook addiction, another social media platform. The "Facebook Addiction Scale" was developed by Kimberly Young in 1998 to measure internet addiction and was adapted to Facebook by Çam (20) and translated into Turkish. There is also a facebook addiction scale developed by Turkyilmaz (13) and Akın et al. (11). As a result, it is seen that a wide variety of scales have been developed or adapted to determine the sub-types of technology or the levels of addiction in various social media platforms. However, it is stated that the TikTok application, which has become widespread in recent years, is now at the level of addiction. In the literature review, no scale was found to measure problematic TikTok use. In this respect, the absence of scale for the problematic TikTok use emerges as an important deficiency in the field.

Today, TikTok, one of the social media platforms today, has become an problematic due to its increasing usage rate. Today, problematic TikTok use has also become a concern, and can be defined as spending excessive time on one's own page to increase the number of followers; increasing the amount of time spent using the application day by day; the inability to control the time spent; and eventually getting bored of real life and coming to seeing one's virtual identity as real and arranging one's lifestyle accordingly. Moreover, individuals who are addicted may feel tense, restless, stressed, and lonely when they cannot use it.

India has the highest number of TikTok users, followed by the United States and Turkey. The average monthly TikTok usage time in Turkey is 18.8 h (1). Since problematic TikTok use is a relatively new phenomenon, there is comparatively little research investigating it, and it can be difficult to determine problematic TikTok use. While there are scales measuring other types of social media addiction in the literature, there is no scale for specifically measuring problematic TikTok use. Thus, this study aims to provide a scale for measuring problematic TikTok use.

Method

Before starting reliability and validity studies of the new scale, the necessary permissions were obtained from the author of the scale *via* email. And then the development process of the scale, necessary permissions were obtained from Pamukkale University Social and Human Sciences Ethics Committee in accordance with the decision of Document Date: 31.05.2022 and Number of Documents: E-93803232-622.02-211,894. After the items of the original scale were adapted for the PTTUS, they were sent to three experts working on the subject for content validity. In line with the suggestions from each expert, the item list of the scale was finalized and a pilot application was made. This indicated that the items of the scale worked well, and the trial phase began. Data were obtained *via* Google forms.

Participants and procedures

Participants were 500 Turkish adults who were determined by convenience sampling. Data were collected using Google forms.

Forms were distributed over the internet to Pamukkale University students, their relatives, and university staff. Responses with missing or extreme data were excluded from the analysis, leaving a final sample of 372 (74.4%). The construct validity of the scale was examined by confirmatory analysis. For factor analysis, according to Tabachnick and Fidell (21), 300 people in the research group is considered good, and 500 people is considered very good. In this respect, it can be said that the student group in which the studies are carried out is sufficient in terms of the number of personnel required by statistical analysis. The first page of the form included the purpose of the study, the ages and genders of the researchers, and the voluntary participant consent form. The second page of the form contained the scale items, which were scored using Likert-type scales. Participants knew about and used TikTok, and came from 52 cities in 7 regions of Turkey.

Measures

All rating scales were delivered to the participants and all data were collected within 2 weeks. In addition, the scale was sent to the same participants after a two-week break for test–retest reliability. Participants were asked to add their email addresses before submitting their questionnaires (used for informational purposes for the study only, and the information was deleted immediately after the analysis) for use in the test–retest analysis. A total of 215 participants; therefore, the test–retest was carried out with data from 215 participants.

The original form of the Problematic TikTok Use Scale

The PTTUS was developed by adapting D'Souza et al. (22) Instagram Addiction Scale, whose psychometric properties were determined by Kavaklı and İnan (23) (Supplementary Material S1). Permission was obtained from both the authors of the scale and the social and human sciences ethics committee of the university before adapting the scale. After the items of the Instagram Addiction Scale were adapted for the PTTUS, expert opinion was sought for the scale items and suggested corrections were made. The original Instagram Addiction Scale consisted of 21 items, 16 of which were adapted for the PTTUS. Originally, a 21-item PTTUS was presented to participants. However, as a result of EFA, five items whose factor load was not sufficient to be included in any factor were removed from the scale. Items were scored using a 5-point Likert-type scale (1 = *never* and 5 = *always*). One sample item is "I often upload videos to TikTok." Higher scores indicate higher levels of problematic TikTok use. In the current study, the Cronbach's Alpha reliability of the scale was 0.90; the Cronbach's Alpha reliability of the sub-dimensions; 0.84 for obsession sub-dimension; 0.90 for escapism sub-dimension and 0.85 for lack of control sub-dimension. In the current study, the McDonald's Omega reliability of the scale was 0.90; the McDonald's Omega reliability of the sub-dimensions; 0.84 for obsession sub-dimension; 0.90 for escapism sub-dimension and 0.85 for lack of control sub-dimension.

Bergen Social Media Addiction scale

The BSMAS scale was developed by Schou Andreassen et al. (24) and adapted into Turkish by Demirci (17). The scale consists of six items measuring mental exertion, mood change, tolerance, withdrawal, conflict, and unsuccessful attempts to quit. Items are scored using a 5-point Likert-type scale; higher scores reflect higher dependence on social network sites. Total scores range from 6 to 30. In the adaptation study, the Cronbach alpha internal consistency reliability coefficient of the scale was found 0.83. In this current research, the Cronbach alpha internal consistency reliability coefficient of the scale was found 0.857, and McDonald's Omega reliability value was calculated as 0.860.

Social Media Disorder scale

Developed by Van den Eijnden et al. (25) to measure individuals' social media addiction levels, the SMD scale was adapted into Turkish by Sarıçam and Adam-Karduz (26) using a nine-item form. Each item measures a different sub-dimension (occupation, endurance, deprivation, insistence, escape, problems, deception, displacement, conflict). In the present study, the internal consistency coefficient of the scale was 0.75 and Cronbach's alpha reliability coefficient was 0.82. In the adaptation study, the Cronbach alpha internal consistency reliability coefficient of the scale was found 0.75. In this current research, the Cronbach alpha internal consistency reliability coefficient of this scale was found 0.879, and McDonald's Omega reliability value was calculated as 0.883.

Statistical analysis

We examined the construct validity and reliability of the Turkish version of the PTTUS. Normality assumption was tested based on skewness and kurtosis of each item. To check the sampling adequacy and data suitability, the Kaiser–Meyer–Olkin (KMO) value and Bartlett's test of sphericity were checked. The Exploratory Factor Analysis (EFA) with Varimax technique was used to determine the factor structure of the PTTUS. Factors with an eigenvalue above 1 were defined as acceptable. Confirmatory Factor Analysis (CFA) with the diagonally weighted least squares method was carried to check the factor structure of the PTTUS, and a satisfactory model fit for the model was defined by a standardized root-mean square residual (SRMR) value ≤0.05, root-mean-square-error of approximation (RMSEA) value ≤0.10, and comparative fit index (CFI) and Tucker–Lewis index (TLI) values ≥0.90. The Cronbach's alpha method was preferred in the reliability analysis of the scale. The BSMAS and SMD scale were used for criterion-related validity. The receiver operating characteristic (ROC) analysis was performed to explore the appropriate cut-off score of the PTTUS on accordance with addiction (excessive or problematic use of social media and spending at least 8.5 to 21.5 h a week online). Validity and reliability analyses were conducted using the SPSS 22 and AMOS 20 package programs.

Results

All 500 participants who knew about and used TikTok from 52 cities in 7 regions of Turkey responded to the survey. A total of 201 (54.04%) participants were female, and the age range was 18–40 ($\bar{x}$ = 24.35; sd: 2.3).

Analysis of exploratory factors

In the EFA, Kaiser-Meyer-Olkin (KMO) and Bartlett's Sphericity tests were performed to test the suitability of the obtained data for factor analysis. Considering the analysis results, the KMO was 0.87 and the Approximate Chi-Square (χ^2) result was 2918.35 ($p < 0.001$). Since the KMO was higher than 0.60 and the Barlett's Sphericity test was significant, the dataset in the research group was considered to be suitable for factor analysis. (27) Findings related to the EFA were tested in the validity analysis. Varimax technique was used to determine the factor structure of the scale, so the factor number of the scale, the load values of each item, and the correlation of the items with the whole scale (Item-total correlation) were determined. Factors with an eigenvalue above 1 were accepted as the basis in the analysis (21).

In the adapted scale, a 3-dimensional structure with the sub-dimensions of obsession, escapism, and lack of control was obtained. Items 1–4 are in the first sub-dimension, items 5–10 are scored in the second sub-dimension, and items 11–16 are scored in the third sub-dimension. The eigenvalues and explanatory variances of the factor structures obtained as a result of the EFA are given in Table 1.

As a result of the EFA, the obtained three-factor structure explained 62.99% of the total variance. When the explanation rates of the factors were examined, factor 1 explained 24.23% of the total variance, factor 2 explained 21.84%, and factor 3 explained 16.92%.

Analysis of confirmatory factors

CFA was performed to determine the scale's structure (28, 29). Fit indices frequently used in CFA include Chi-square fit ($\chi2$) and ratio of Chi-square to degrees of freedom ($\chi2$/sd), Root Mean Square Errors of Approximation (RMSEA), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Goodness-of-Fit Index (GFI), and Standardized Root-Square Means (SRMR) (30). The data of the CFA performed to determine the construct validity of the PTTUS are presented in Table 2 and Figure 1. Item-total correlation and Cronbach's alpha if item deleted reliability coefficient for each item are also shown (Table 2).

Looking at the scale's sub-dimensions, factor 1 is the obsession sub-dimension comprising items 1–4; factor 2 is the escapism sub-dimension comprising items 5–10; and factor 3 is the lack of control sub-dimension comprising items 11–16. The item factor load distributions for the overall scale are shown in Table 2. To determine the item validity of the PTTUS, the item-total correlation results were examined. It is seen that the item-total correlation values vary between 0.40 and 0.70. Considering that items with an item-total correlation value of 0.30 and above are considered sufficient in terms of distinguishing the quality to be measured (27), all the items in the scale are sufficiently related to the scale's total score and the scale item validity is ensured.

Confirmatory factor analysis

While adapting PTTUS, model fit was examined using first-level CFA. The fit index values of the PTTUS were calculated $\chi2 = 1036.86$, $p < 0.01$, χ^2/sd = 4.19, RMSEA = 0.10, CFI = 0.88, GFI = 0.86, AGFI = 0.81, SRMR = 0.09 as before covariance. After was made covariance the fit indices of the PTTUS seem to be sufficient [CFA: $\chi2 = 1036.86$, $p < 0.01$, χ^2/sd = 4.14, RMSEA = 0.08, CFI = 0.95, GFI = 0.89, AGFI = 0.85, SRMR = 0.08]. Considering the statistical values of fit, a value of $\chi2$/sd below 5 indicates acceptable fit, a RMSEA value between 0.00 and 0.05 indicates good fit, and a value between 0.05 and 0.08 indicates acceptable fit (31, 32). The factor loads of the items in the scale range between 0.44 and 0.93. The analysis of the first-level CFA is presented in Table 3.

Criterion-related validity

For the criterion-related validity, correlations between the BSMAS and SMD scale were calculated and the analysis results are given in Supplementary Table S1.

When the relationships between PTTUS and BSMAS and SMD scale were examined, the following positive and significant relationships were found: between the PTTUS total score and BSMAS ($r = 0.56$, $p < 0.01$) and SMD scale ($r = 0.49$, $p < 0.01$); between the obsession sub-dimension and BSMAS ($r = 0.35$, $p < 0.01$) and SMD scale ($r = 0.30$, $p < 0.01$); between the escapism sub-dimension and BSMAS ($r = 0.52$, $p < 0.01$) and SMD scale ($r = 0.39$, $p < 0.01$); between the lack of control dimension and BSMAS ($r = 0.45$, $p < 0.01$) and SMD scale ($r = 0.49$, $p < 0.01$). Considering the analysis results align with the theoretical framework, it can be said that the PTTUS has criterion-related validity.

Reliability analysis

In this study, Cronbach's alpha internal consistency coefficient and test–retest reliability analysis were performed at two-week intervals to determine the reliability of the scale; the findings are presented in Supplementary Table S2.

Cronbach's alpha internal consistency coefficient and test–retest reliability analysis were used to determine the reliability of the PTTUS. The analysis showed Cronbach's alpha reliability coefficient of the total scale was calculated as 0.90. Reliability was 0.83, 0.90, and 0.85 for the obsession, escapism, and lack of control sub-dimensions, respectively. McDonald's Omega reliability coefficient of the total scale was calculated as 0.90. Reliability for the obsession sub-dimension of the scale was 0.84; for the escapism sub-dimension, the reliability was 0.90; for the lack of control sub-dimension, the reliability was

TABLE 1 Ratios of variance explained by eigenvalues obtained as a result of exploratory factor analysis.

	Initial eigenvalues			Rotation sums of squared loadings		
Factor	Total	% of variance	Cumulative (%)	Total	% of variance	Cumulative (%)
1	6.10	38.14	38.14	3.88	24.23	24.23
2	2.13	13.31	51.45	3.50	21.84	46.07
3	1.85	11.54	62.99	2.71	16.92	62.99

TABLE 2 Item factor loads for the Prpblematic TikTok Use Scale.

Item No.	Factor 1	Factor 2	Factor 3	Item-total correlation	Cronbach's alpha if item deleted	McDonald's Omega	Mean	SD
Item 1	0.74			0.45	0.90	0.90	1.60	0.90
Item 2	0.59			0.42	0.90	0.90	1.54	0.87
Item 3	0.81			0.56	0.89	0.90	1.59	1.06
Item 4	0.83			0.55	0.90	0.90	2.10	1.39
Item 5		0.59		0.66	0.89	0.90	2.25	1.30
Item 6		0.77		0.64	0.89	0.89	2.33	1.30
Item 7		0.86		0.65	0.89	0.89	2.85	1.38
Item 8		0.93		0.70	0.89	0.89	2.55	1.34
Item 9		0.74		0.64	0.89	0.89	2.04	1.26
Item 10		0.70		0.67	0.89	0.89	2.77	1.44
Item 11			0.87	0.53	0.90	0.90	1.53	0.96
Item 12			0.84	0.48	0.90	0.90	1.45	0.89
Item 13			0.77	0.57	0.89	0.90	1.55	0.93
Item 14			0.55	0.55	0.89	0.90	1.70	1.05
Item 15			0.62	0.62	0.89	0.89	0.51	0.97
Item 16			0.43	0.40	0.90	0.90	1.89	1.17

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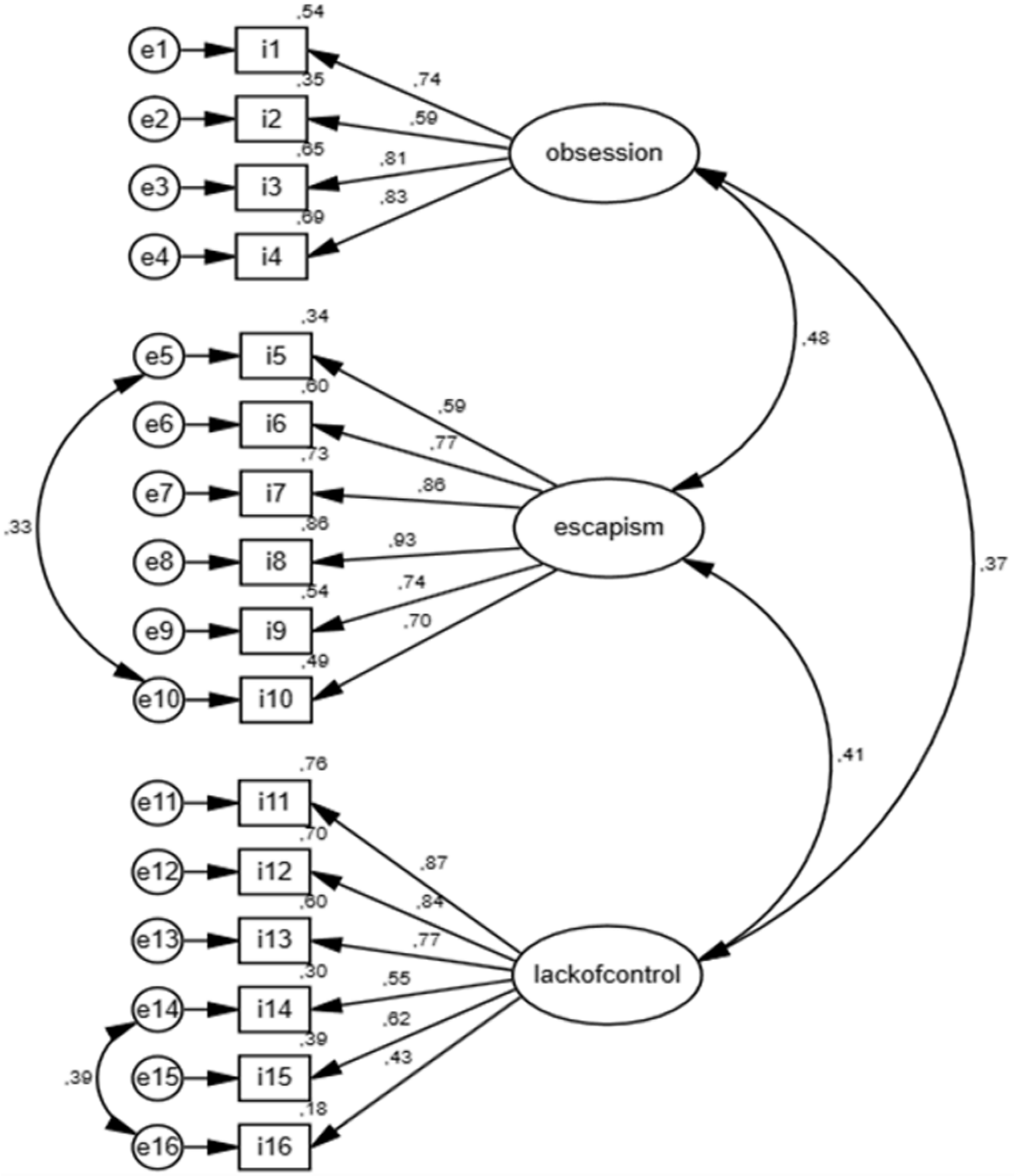

FIGURE 1
Path diagram and factor loads of the Problematic TikTok Use Scale.

TABLE 3 Model fit indices for the Problematic TikTok Use Scale.

	χ^2/sd	RMSEA	CFI	GFI	AGFI	SRMR
Good fit values	<3	0.00–0.05	≥0.97	≥0.90	≥0.90	≤0.05
Acceptable fit	≤3–5	0.05–0.08	≥ 0.95	0.89–0.85	0.89–0.85	0.05–0.08
Model fit indices	4.14	0.08	0.95	0.89	0.85	0.08
Model fit indices for male	2.69	0.08	0.93	0.88	0.85	0.08
Model fit indices for female	2.78	0.08	0.95	0.87	0.85	0.08

calculated as 0.85. The test–retest reliability analysis coefficients were 0.73 for the total scale, 0.68 for obsession, 0.68 for escapism, and 0.70 for lack of control. Considering that reliability coefficients of 0.70 and above are considered reliable in the scale adaptation process (33), it can be said that the internal consistency and test–retest reliability coefficients of the PTTUS are sufficient.

The receiver operating characteristic

We performed the analysis of ROC and the area under the curve (AUC) for determining the PTTUS. Supplementary Table S3 shows the analysis of ROC with the parameters required. The cut-off value obtained for the PTTUS was ≥31.5, with sensitivity and specificity percentages of 88.9 and 37.5%, respectively. Subjects are diagnosed as experiencing problematic TikTok use if their score is ≥32.

Discussion

The current study aimed to develop the PTTUS. For this purpose, the items of the Instagram Addiction Scale were adapted for Problematic TikTok Use. The TikTok application is closer to the Instagram application than the Facebook application due to its intended use and the developable content it allows. However, it is said that Instagram and TikTok applications tend to be used mostly on smartphones. In addition, it is seen that the use of Facebook application tends towards a more restricted age group. In addition, it has been determined that individuals use more interactive and instant sharing applications on social media (34). However, as the items of the Instagram addiction scale were evaluated to be more useful for measuring problematic TikTok use, it was deemed appropriate to use the items of the Instagram Addiction Scale. The Instagram addiction scale is a more inclusive scale since the number of items is 16. At the same time, the Instagram addiction scale was preferred because it is a more up-to-date scale. Language validity and content validity were performed for the obtained scale. In addition, EFA and CFA were performed for construct validity and criterion-related validity analysis was calculated. Cronbach's alpha internal consistency, McDonald's Omega value and test–retest coefficients were performed at two-week intervals to test the scale's reliability.

The language validity of the scale was ensured in line with expert opinions obtained during the adaptation of the original scale items to TikTok. Before the EFA and CFA analysis, the dataset's suitability for factor analysis was tested using KMO and Barlett tests. The dataset was considered suitable for factor analysis if the KMO was higher than 0.60 and the Barlett Sphericity test was significant. (27, 35) EFA and CFA showed that a three-factor structure consisting of 16 items explained 62.99% of the total variance, and the structure of the scale was confirmed. It can be said that PTTUS has a sufficient total variance explanation rate.

The CFA indicated that a three-factor structure is formed. The first factor comprises the obsession sub-dimension and consists of four items; the second factor is the escapism sub-dimension and consists of six items, and the third factor is the lack of control sub-dimension and consists of six items. The item factor load distributions of the scale showed load values ranging between 0.43 and 0.93. Considering that the item factor load value should be >0.32 (21) and if an item is included in more than one factor, there should be a difference of at least 0.10 in the item load between the factors (36), it can be said that the item factor load values of the three-factor PTTUS are sufficient. The model fit for adapting the PTTUS into Turkish was examined with the first-level CFA. $\chi 2$/sd, RMSEA, CFI, GFI, AGFI and SRMR values obtained as a result show that the three-factor structure of the scale provides acceptable fit.

In the study, correlations between BSMAS and SMD scale were calculated for criterion-related validity. The results showed that the total score and sub-dimensions of PTTUS had significant relationships with BSMAS and SMD scale. Considering the analysis results and the theoretical framework of PTTUS, it can be said that PTTUS has criterion-related validity. Corrected item-total correlations ranged from 0.40 to 0.70. The Cronbach's alpha internal consistency and test–retest analyses were used to determine the scale's reliability. Cronbach's alpha internal consistency reliability coefficient ranged from 0.83 to 0.90, and test–retest correlation coefficient ranged from 0.68 to 0.73; it can be said that the internal consistency and test–retest reliability of the PTTUS are sufficient.

In recent years, internet usage has become widespread in Turkey and worldwide, and social media is one of the most concentrated areas of use. Social media allows people to interact with each other and share their opinions, thoughts, photos, and videos through applications such as YouTube, Facebook, Instagram, and TikTok. However, dependence on these applications can cause individual and interpersonal problems. The literature indicates that as addiction to social media applications increases, negative mood disorders such as anxiety, neuroticism, and depression and the time spent using social media increase (37–43). Some studies have shown that the relationship between addiction to social media applications and anxiety symptoms is higher than the relationship between symptoms of depression and anxiety (24, 25). It can be said that TikTok, which is mostly used by adolescents and young adults (16–35 years old), is likely to cause negative effects. Therefore, it is necessary to have a scale for measuring problematic TikTok use. In addition, it is recommended to develop interventions to prevent and reduce problematic TikTok use so that individuals experience less anxiety, depression, and other negative effects. Based on this information, PTTUS is a measurement tool with sufficient psychometric properties that can be applied to determine individuals' levels of problematic use. The scale measures three sub-dimensions, and both the total score and the scores of the sub-dimensions can be obtained. Higher scores obtained from the scale indicate higher levels of problematic use.

The study was conducted online using a university population. Online data collection is being used increasingly, especially in social science. So large amounts of data were accessed quickly and at a low cost (44). Online data collection is as valid and reliable as traditional data collection methods. In addition to this strength, this study has several limitations. First, the participants were recruited using convenience sampling, so a more representative sample of the population is needed to generalize the findings. Second, data were obtained through self-report, so it may not be free from social desirability and recall biases. Future studies are needed to validate the PTTUS using an objective rating method rather than self-report. Third, the study was conducted in a non-clinical population. Further research is needed in clinical samples. Fourth, because this study only included participants in Turkey, there was no comparison of the PTTUS results between Western and Eastern countries, which could have important implications for healthcare professionals.

Nevertheless, this study provides initial support for using PTTUS as a reliable and valid measure of problematic TikTok use in Turkish adolescents and young adults. This easy-to-use scale has good psychometric properties and allows mental health professionals to screen for problematic TikTok use. It may also be useful for other researchers conducting studies related to problematic TikTok use in Turkey. Future studies are needed to demonstrate the usefulness of the scale for various age groups and problematic TikTok use behaviors in Türkiye.

Data availability statement

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

Ethics statement

The studies involving human participants were reviewed and approved by Ethics Committee: Pamukkale University, Social and Human Sciences Research and Publication Ethics Committee Document Decision Date and Number: 31.05.2022-E.211894. The patients/participants provided their written informed consent to participate in this study.

Author contributions

AG, TO, and SC: conceptualization. AG and TO: data curation, formal analysis, and visualization. AG, TO, SY, and SC: methodology. All authors, writing—original draft and review and editing. All authors contributed to the article and approved the submitted version.

Conflict of interest

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

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2023.1068431/full#supplementary-material

References

1. WEARESOCIAL. Digital. Another year of bumper growth. Available online at: https://wearesocial.com/uk/blog/2022/01/digital-2022-another-year-of-bumper-growth-2/ (2022).

2. Xiong Y, Ji Y. From content platform to relationship platform: analysis of the attribute change of Tiktok short video (citation has been translated from Chinese7 language). *View Publish*. (2019) 4:29–34. doi: 10.54097/ehss.v5i.2901

3. Wang Y. Humor and camera view on mobile short-form video apps influence user experience and technology-adoption intent, an example of TikTok (DouYin). *Comput Hum Behav*. (2020) 110:106373. doi: 10.1016/j.chb.2020.106373

4. Montag C, Yang H, Elhai JD. On the psychology of TikTok use: a first glimpse from empirical findings. Front. *Public Health*. (2021) 9:641673. doi: 10.3389/fpubh.2021.641673

5. Yang S, Zhao Y, Ma Y. Analysis of the reasons and development of short video application -taking TikTok as an example In: . *2019 9th international conference on information and social science (ICISS 2019)*. Francis Academic Press, UK (2019). 340–3. doi: 10.25236/iciss.2019.062

6. Lodice R, Papapicco C. To be a TikToker in COVID-19 era: an experience of social influence. *Online J Comm Media Technol*. (2021) 11:1–12. doi: 10.30935/ojcmt/9615

7. Kawada T. Comment on "smartphone addiction proneness is associated with subjective-objective sleep discrepancy in patients with insomnia disorder". *Psychiatry Investig*. (2022) 19:595–6. doi: 10.30773/pi.2022.0024

8. Kim SS, Bae SM. Social anxiety and social networking service addiction proneness in university students: the mediating effects of experiential avoidance and interpersonal problems. *Psychiatry Investig*. (2022) 19:462–9. doi: 10.30773/pi.2021.0298

9. Lim YJ. Exploratory structural equation modeling analysis of the social network site use motives scale. *Psychiatry Investig*. (2022) 19:146–53. doi: 10.30773/pi.2021.0092

10. Shin NY. Psychometric properties of the Bergen social media addiction scale in Korean Young adults. *Psychiatry Investig*. (2022) 19:356–61. doi: 10.30773/pi.2021.0294

11. Akin A, Demirci I, Kara S. The validity and reliability of Turkish version of the Facebook addiction scale. Academic perspective international refereed journal of. *Soc Sci*. (2017) 59:65–72.

12. Kuss DJ, Griffiths MD. Online social networking and addiction--a review of the psychological literature. *Int J Environ Res Public Health*. (2011) 8:3528–52. doi: 10.3390/ijerph8093528

13. Turkyilmaz M. The translation of Facebook addiction scale into Turkish and impact of Facebook addition to reading ability. *J Acad Soc Sci Stud*. (2015) 6:265–80. doi: 10.9761/JASSS2942

14. Kircaburun K. Effects of gender and personality differences on Twitter addiction among Turkish undergraduates. *J Educ Pract*. (2016) 6:265–42. doi: 10.9761/JASSS2942

15. Moghavvemi SA, Binti Sulaiman A, I JN, Kasem N. Facebook and YouTube addiction: the usage pattern of Malaysian students In: . *2017 international conference on research and innovation in information systems (ICRIIS)*. Langkawi, Malaysia (2017). 1–6. doi: 10.1109/ICRIIS.2017.8002516

16. Tutgun-Ünal A. *Social media addiction: A study on university students*. İstanbul: Marmara University, Institute of Social Sciences (2015).

17. Demirci I. The adaptation of the Bergen social media addiction scale to Turkish and its evaluation of relationships with depression and anxiety symptoms. *Anatolian J Psychiatry*. (2019) 20:1–22. doi: 10.5455/apd.41585

18. Orbatu D, Eliaçık K, Alagayut D, Hortu H, Demirçelik Y, Bolat N, et al. Development of adolescent social media addiction scale: study of validity and reliability. *Anatolian J Psychiatry*. (202) 1:56–61. doi: 10.5455/apd.77273

19. Özgenel M, Canpolat Ö, Ekşi H. Social media addiction scale for adolescents: validity and reliability study. *Addicta*. (2019) 0:629–62. doi: 10.15805/addicta.2019.6.3.0086

20. Çam E. *Educational and general purpose facebook uses and Facebook addictions of teacher candidates (SAU education faculty example)*. Sakarya: Sakarya University Institute of Educational Sciences (2012).

21. Tabachnick BG, Fidell LS. *Using multivariate statistics*. New York: Allyn and Bacon (2007).

22. D'Souza L, Samyukta A, Bivera TJ. Development and validation of test for Instagram addiction (TIA). *Int J Ind Psychol*. (2018) 6:4–14. doi: 10.25215/0603.81

23. Kavaklı M, İnan E. Psychometric properties and correlates of the Turkish version of Instagram addiction scale (IAS). *J Clin Psychol Res*. (2021) 5:86–97. doi: 10.5455/kpd.26024438m000037

24. Schou Andreassen C, Billieux J, Griffiths MD, Kuss DJ, Demetrovics Z, Mazzoni E, et al. The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: a large-scale cross-sectional study. *Psychol Addict Behav*. (2016) 30:252–62. doi: 10.1037/adb0000160

25. van den Eijnden RJJM, Lemmens JS, Valkenburg PM. The social media disorder scale. *Comput Hum Behav*. (2016) 61:478–87. doi: 10.1016/j.chb.2016.03.038

26. Sarıçam H, Karduz FFA. The adaptation of the social media disorder scale to Turkish culture: validity and reliability study. *Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi*. (2018) 9:117–36. doi: 10.21031/epod.335607

27. Filed A. *Discovering statistics using SPSS*. London: SAGE Publications Ltd. (2009).

28. Çokluk Ö, Şekercioğlu G, Büyüköztürk Ş. *Multivariate statistics for social sciences: SPSS and LISREL applications*. Ankara: Pegem Academy Publishing (2014).

29. Seçer İ. *Practical data analysis with SPSS and LISREL*. Ankara: Anı Publishing (2015).

30. Brown TA. *Confirmatory factor analysis for applied research*. New York, US: Guilford Press (2006).

31. Kline RB. *Principles and practice of structural equation modeling*. New York: The Guilford Press (1998).

32. Schermelleh-Engel K, Moosbrugger H, Müller H. Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures. Methods of psychological research. *Online*. (2003) 8:23–74.

33. Robinson JP, Shaver PR, Wrightsman LS. *Criteria for scale selection and evaluation in measure of personality and social psychological attitudes*. San Diego: California Academic Press (1991).

34. Kuss D, Griffiths M. Social networking sites and addiction: ten lessons learned. *Int J Environ Res Public Health*. (2017) 14:311–28. doi: 10.3390/ijerph14030311

35. Pallant J. *SPSS survival manual: A step by step guide to data analysis using SPSS for windows*. Australia: Australian Copyright (2005).

36. Büyüköztürk S. *Data analysis handbook for social sciences*. Ankara: Pegem Akademi Publishing (2008).

37. Andreassen CS, Torsheim T, Brunborg GS, Pallesen S. Development of a Facebook addiction scale. *Psychol Rep*. (2012) 110:501–17. doi: 10.2466/02.09.18.PR0.110.2.501-517

38. Koc M, Gulyagci S. Facebook addiction among Turkish college students: the role of psychological health, demographic, and usage characteristics. *Cyberpsychol Behav Soc Netw*. (2013) 16:297–84. doi: 10.1089/cyber.2012.0249

39. Lin CY, Brostrom A, Nilsen P, Griffiths MD, Pakpour AH. Psychometric validation of the Persian Bergen social media addiction scale using classic test theory and Rasch models. *J Behav Addict*. (2017) 6:620–9. doi: 10.1556/2006.6.2017.071

40. Lin CY, Ganji M, Pontes HM, Imani V, Brostrom A, Griffiths MD, et al. Psychometric evaluation of the Persian internet disorder scale among adolescents. *J Behav Addict*. (2018) 7:665–75. doi: 10.1556/2006.7.2018.88

41. Pantic I, Damjanovic A, Todorovic J, Topalovic D, Bojovic-Jovic D, Ristic S, et al. Association between online social networking and depression in high school students: behavioral physiology viewpoint. *Psychiatr Danub*. (2012) 24:90–3.

42. Uygur OF, Uygur H, Chung S, Ahmed O, Demiroz D, Aydın EF, et al. Validity and reliability of the Turkish version of the Glasgow sleep effort scale. *Sleep Med*. (2022) 98:144–51. doi: 10.1016/j.sleep.2022.06.022

43. Yang SC, Tung CJ. Comparison of internet addicts and non-addicts in Taiwanese high school. *Comp Human Behav*. (2007) 23:79–96. doi: 10.1016/j.chb.2004.03.037

44. Young KS. Cognitive behavior therapy with ınternet addicts: treatment outcomes and implications. *CyberPsychol Behav*. (2007) 10:671–9. doi: 10.1089/cpb.2007.9971

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Social media consumption and depressive symptoms during the COVID-19 lockdown: the mediating effect of physical activity

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Introduction: Social media platforms played a critical role during the COVID-19 pandemic. This study aimed to explore: (1) the changes in social media consumption patterns, physical activity levels/sedentary behavior, and depressive symptoms, and (2) how the changes in social media consumption patterns predict the changes in depressive symptoms while investigating the mediating role of changes in physical activity levels/sedentary behavior between before, and after the COVID-19 lockdown among U.S. adults with different age clusters.

Methods: A total of 695 U.S. participants completed an online questionnaire via MTurk, and participants were asked to recall their social media consumption patterns, physical activity/sedentary behavior, depressive symptoms in January and May of 2020 while covariates included non-physical activity health behavior including diet quality, alcohol consumption, smoking, and sleep quality.

Results: The results of Bayesian significance testing of changes showed that the older participants tended to spend more time with content-focused social media platforms during the lockdown. While significantly increased sitting time was reported by all age clusters, no significant changes were found in activity levels. Additionally, the middle-aged and older participants reported significantly higher depressive symptoms. The findings of a multigroup structural analysis showed the significant mediating effect of moderate-to-vigorous physical activity on the relationship between changes in social media consumption and depressive symptoms.

Discussion: This study highlights the need for targeting specific social media platforms for older adults and the importance of moderate-to-vigorous physical activity to alleviate the mental health issues resulting from social media consumption. The result of this study also highlights the need for sport-based intervention programs in the future and the need for more social media campaigns at the institution/organization levels established by public health stakeholders and policy makers to promote physical activity and maximize population perception and reach during the pandemic.

KEYWORDS

social media consumption, depressive symptoms, physical activity, COVID-19, social media, mental health

1 Introduction

Social media platforms played a critical role during the COVID-19 pandemic. As a consistently available communication tool, various information was generated, disseminated, and consumed via different types of social media platforms (1). Each social media platform served as a source for up-to-date information on progress regarding the pandemic and for entertainment while non-pharmaceutical interventions (e.g., shelter-in-place policies or stay-at-home-orders) were enacted. Since the COVID-19 outbreak, increases in social media use have been reported across the world – roughly 4.55 billion users in October 2021, compared to 3.8 billion users in January 2020. Notably, North America has the highest social media saturation rates (2, 3). Moreover, it was reported that there was a significant spike in the average time spent on social media among U.S. users in 2021, with 65 min daily compared to 54 min daily in 2019 (4).

The effects of social media consumption on mental health outcomes are well-known as a double-edged sword. During the pandemic, several studies of adults showed that increased social media consumption was related to lower loneliness (3), higher psychological well-being and happiness (2). Conversely, some studies found that increased social media consumption was associated with higher odds of anxiety (5), higher depression (5–7), higher psychosocial distress (8), higher loneliness (9), decreased life satisfaction (10), and overall poorer mental health (11). While these contradicting studies were consistent in their exploration of the direct relationships between social media consumption and various mental health outcomes, one of the most critical mediators, individual physical activity level, was overlooked.

It is well-known that the COVID-19-related lockdowns negatively impacted individual mood, feelings, and mental well-being (12). The COVID-19 lockdown also impacted patterns of physical activity, exercise, and sport participation due to closed facilities, gyms, and recreational centers (13). Interestingly, the findings of changes in physical activity during the pandemic have been mixed. An expected result has been a decrease in physical activity due to increased screen time resulted from increased use of smartphones, tablets, televisions, and video games, along with higher use of video chatting (14). Conversely, some studies found increased levels of physical activity resulting from more free time and home workout opportunities (14). In particular, social media platforms such as Twitter, Instagram, and TikTok have emerged as one type of technology-mediated means to promote the public's active lifestyle even at home through collaborative fitness. The social platforms have facilitated user engagement by stimulating one's social and hedonic values of active lifestyle (15). For instance, athletes all around the world posted positive videos promoting various types of fitness activity by using social campaigns such as "#fitnesschallenge," "#plankchallenge," or "#squatchallenge." In addition, major sport organizations such as the International Olympic Committee and Australian Olympic Committee continued to engage with fans and participants by initiating social campaigns titled "train like an Olympian at home" (16).

We identified three major research gaps in the studies of changes in social media consumption, physical activity, and mental health after the COVID-19 outbreak. First, several studies investigated the direct relationship between changes in social media and mental health without considering the potential mediating role of physical activity on this relationship. For instance, while individual social media consumption may relate to decreased levels of physical activity, social media intervention studies confirmed that social media usage can positively change physical activity and health behaviors (17, 18). Thus, it is essential to take physical levels and sedentary behaviors into consideration to grasp the complete picture on the relationship between social media consumption and mental health.

We specified one's physical activity level as a mediator based on the existing body of literature that social media can be an effective intervention to increase physical activity [e.g., (18)] and the therapeutic effect of physical activity participation on mental health [e.g., (19)]. Second, many studies in social media usage during the pandemic tended to disregard the unique nature of each platform by measuring social media usage as one construct instead of investigating each platform's usage (20, 21). Moreover, most studies related to social media consumption during the pandemic investigated the limited types of social media platforms including Twitter (22), or WeChat (23), even though there are more types of platforms such as YouTube, TikTok, or Reddit. Notably, Masciantonio et al. (24) found different relationships between use of different social media platforms and well-being during the COVID-19 pandemic lockdown. For instance, while active Facebook usage and TikTok usage was not related to social support or satisfaction with life, active Instagram usage and Twitter usage related to satisfaction with life through positive social support. Yet, most social media and mental health studies either investigated the usage of one social media platform or categorized all media platforms as one category. Lastly, scholars have not considered the different population characteristics among adults – particularly age – when investigating the relationships among social media usage, physical activity, and mental health. Most of all, previous studies tended to focus on younger populations such as children, adolescents, or young adults when it comes to social media use, physical activity, and mental health (25–27). Additionally, as Fukukawa et al. (28) argued that age should be considered when examining the effect of physical activity on mental health among adult populations, there is a lack of research on the associations between social media use, physical activity, and mental health among different adult populations during the COVID-19 pandemic lockdown.

In sum, to fill these gaps, this study's primary research purposes are to (1) explore the changes in social media consumption patterns (i.e., social media usage, social media intensity, problematic social media usage, usage based on each social media platform), physical activity levels, and depressive symptoms and (2) investigate how the changes in social media consumption patterns (i.e., total social media usage, social media intensity, problematic social media usage) predict the changes in depressive symptoms while investigating the mediating role of changes in physical activity levels (i.e., sitting, light physical activity, moderate-to-vigorous physical activity) between before, and after the COVID-19 lockdown among different age clusters (i.e., young adults, middle-aged adults, older adults) (see Figure 1 for the proposed research model). Here, social media usage is defined as the duration and frequency of social media use (29), whereas social media intensity is defined as a social media user's level of activity and engagement with social media (30). Problematic social media usage refers to a detrimental effect that occurs as a result of preoccupation and compulsion to excessive use in social media platforms (31). Among several mental illness indicators, we focused on depressive symptoms which is one of the most prevalent outcomes after experiencing traumatic events (32).

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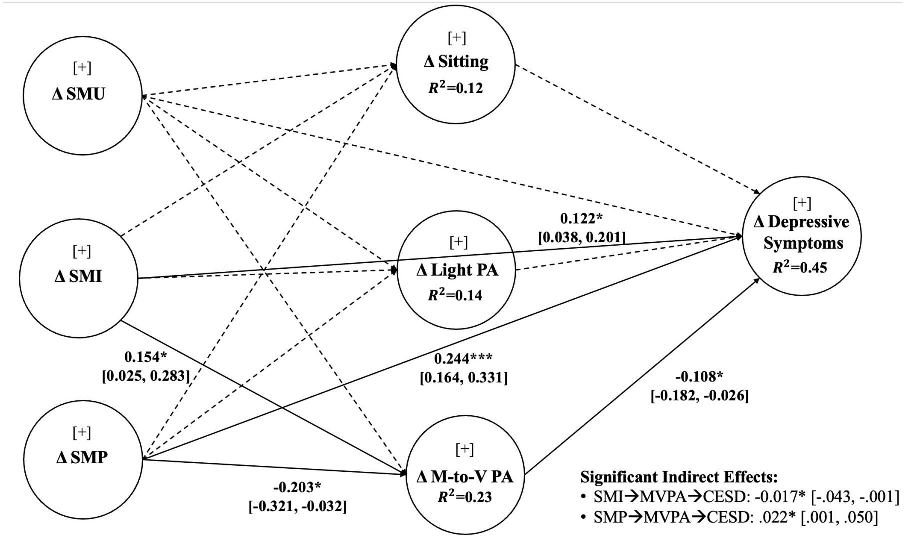

FIGURE 1
Research model.

2 Materials and methods

2.1 Participants and study design

Participants were invited to recall their social media consumption, physical activity participation, and depressive symptoms in January 2020 and May 2020 via Amazon's Mechanical Turk (MTurk). The platform has been useful as a data collection method for web-based research in health and medical research due to its higher reachability, higher reliability, and higher completion rate compared to conventional data collection methods such as paper-, telephone-, or in-person-based data capture approaches (33). In the present study, we employed a retrospective cross-sectional design. After obtaining consent, through Qualtrics, respondents answered screening questions about the respondent's United States residency and age. As an attention question, we included "To continue with the survey", please select "Somewhat agree" in the middle of the questionnaire. In the first week of June of 2020, the respondents were asked to recall their social media consumption, physical activity level, depressive symptoms, and non-health-behavior (i.e., diet quality, alcohol consumption, smoking, sleep quality) retrospectively at two timepoints: (1) January of 2020, which was immediately prior to the initial outbreak of the COVID-19 pandemic in the United States, and (2) May of 2020, which marked the peak of the first wave of infections and nationwide lockdowns (15). Three survey pools for young (18–39 years old), middle-aged (40–59 years old), and older (60 years and older) were created (34).

We used *a priori* Power Analysis to calculate the required sample size using the statsmodels in Python setting with the desired alpha at 0.05 and beta at 0.8 with an effect size equating to 0.5 (35) and the results yielded a minimum sample size of 695. Among 865 recorded responses who passed the screening questions, a total of 170 responses (55 young, 79 middle-aged, 36 older adults) were excluded because they failed to pass the attention question. In sum, a total of 695 responses (264 young, 234 middle-aged, 197 older adults) were included for further analysis. Survey respondents were from all states except for four states in the Midwest, including Montana, Wyoming, South Dakota, and Nebraska. Considering that COVID-19 least influenced these rural communities in the early period of the pandemic (36), the sample was reasonably representative for conducting the subsequent statistical analyses. This study protocol was approved by the Institutional Review Board at Florida State University (ID: STUDY00001406).

2.2 Measures

2.2.1 Social media consumption pattern

For social media consumption pattern, we adopted three previously validated measures: social media usage [i.e., duration and frequency; (29)], social media intensity (30), and problematic social media use (31). For duration, we asked "Approximately how much time per day did you spend on social media for personal, non-work-related use in January 2020?," whereas for frequency, we asked, "How often did you visit (social media platform name) in January 2020?" across twelve prominent social media platforms (i.e., Facebook, Instagram, Pinterest, LinkedIn, Twitter, Snapchat, YouTube, TikTok, WhatsApp, Reddit, Tumblr, and Vine). For social media intensity, a 6-item scale developed by Ellison et al. (30) was used. A sample item was "Social media was part of my everyday activity in January 2020" with a 5-point Likert scale from 1 = *strongly disagree* to 5 = *strongly agree*. For problematic social media use, we adopted a 6-item social media addiction scale originally developed by Andreassen et al. (31). A sample item was "How often did you spend a lot of time thinking about social media or planned use of social media in January 2020?" with a 5-point Likert scale from 1 = *very rarely* to 5 = *very often*. All questions included two sets of questions for January 2020 and May 2020, respectively.

2.2.2 Physical activity

The International Physical Activity Questionnaire-Short Form (IPAQ-SF), a validated self-reported measurement tool for physical activity among various adult population surveys, was used (37). This 7-item questionnaire included the frequency and duration of four different levels of weekly physical activities: vigorous activity (such as heavy lifting or aerobics), moderate activity (such as doubles tennis), light activity (including walking), and sitting for January 2020 and May 2020, respectively.

2.2.3 Depressive symptoms

To assess individual depressive symptoms, the 10-item Center for Epidemiologic Studies Depression Scale (CES-D-10) was employed. The reliability and validity of this scale has been consistently supported by previous large-scale survey studies (38, 39). The items reflect the respondents' feelings and the respondents answered 10 items for both January 2020 and May 2020. A higher score indicates a higher level of depressive symptoms.

2.2.4 Control variables

We included personal characteristics (i.e., age, marital status, household income, education, occupation, BMI, and Zip code) and non-physical-activity health behavior (i.e., diet quality, alcohol consumption, smoking, and sleep quality) as control variables. With acceptable validity and reliability, we used four items to assess one's daily intakes of fruit and vegetables, weekly intakes of fast food and soft drinks (40). Alcohol consumption was evaluated by the validated 3-item AUDIT Alcohol Consumption Questions [AUDIT-C; (41)] including questions about frequency and intensity of regular drinking and heaving drinking. The validated 8-item Fagerstrom Test for Nicotine Dependence (FTND) was employed to assess one's smoking status including frequency, amount, and dependency of smoking (42). The validated 3-item Pittsburg Sleep Quality Index (PSQI) was adopted to evaluate one's sleep quality which includes average daily hours of sleep, overall sleep quality, and sleep latency (43). Similar to social media consumption patterns, physical activity levels, and depressive symptoms, the respondents provided answers for two sets of questions for both the January 2020 and May 2020 timeframe.

2.3 Analyses

First, for testing significant changes in social media consumption patterns, physical activity, and depressive symptoms in each age group, Bayesian significance testing of changes was employed using the R2WinBUGS package in R (44). More specifically, we used the mean and standard deviation of the data recalled in January 2020 to specify distributions of informative priors in our Bayesian analysis. Next, we defined the precision of a normal distribution as the inverse of the squared standard deviation, where we assumed that the observations at both time points derive from normal distributions with the same precision tau. Then, we specified parameters for running the Markov Chain Monte Carlo (MCMC) simulation in R2WinBUGS to ensure the chain convergence was established for the estimated posterior distributions, with the number of chains equating to 10 and the total number of MCMC iterations per chain set at 20,000, while discarding the first 1,000 iterations as burn-in. The Bayesian approach was used due to its tendency to be less sensitive to the influence associated with missing values and asymptotic assumptions. Subsequently, a multigroup structural analysis was employed to evaluate the global empirical model within the component/variance-based Structural Equation Modeling framework using SmartPLS 4.0.

3 Results

Table 1 shows the descriptive statistics of respondents, and the baseline averages of the included parameters are shown in Table 2. While roughly 60% of respondents were male, most participants were Caucasian (70.2%), well-educated (74.8% with a 4-year college or more advanced degrees) and lived in a somewhat middle-class family with an annual household income between \$25,000 and \$75,000 as of 2019. Notably, the demographic breakdown was mostly consistent across three different age groups, except that more female respondents (65%) were identified in the older adult group.

The global results of the Bayesian significance testing of changes showed that social media usage, including individual's usage frequency in hours ($\Delta\mu = 1.49$, 95% CI [1.26, 1.72]), problematic consumption ($\Delta\mu = 0.21$, 95% CI [0.16, 0.26]), and usage intensity ($\Delta\mu = 0.19$, 95% CI [0.14, 0.24]), significantly increased among the respondents between January 2020 and May 2020 across all social media platforms (See Table 2). The greatest increase was observed in the usage of short-video platform TikTok ($\Delta\mu = 0.41$, 95% CI [0.30, 0.52]) while behavioral engagement in community-based Reddit ($\Delta\mu = 0.18$, 95% CI [0.08, 0.28]) experienced the least increase. Significant changes in social media usage were not universally applicable to all age segments; older adults showed a relatively small increase across the most social media platforms except for Meta, Instagram, Twitter, YouTube, and TikTok (see Table 2). Middle-aged adults showed an increase in widest range of social media platforms (all twelve social media platforms), whereas young adults showed significant increases in all but Twitter, Tumblr, and Vine. In terms of physical activity levels, despite slight decreases of hours in vigorous, moderate, and light physical activity (walking) globally, the changes were not statistically significant. Interestingly, except for the middle-aged respondents, young adults (Δ_SPA_ = 0.712, $p < 0.001$, 95% CI [0.394, 1.031]) and older adults (Δ_SPA_T = 0.331, $p < 0.05$, 95% CI [0.063, 0.598]) had a significantly increased sitting time, indicating an increased level of sedentary behavior during the COVID-19 lockdown. When it comes to depressive symptoms, there were no significant changes among young participants, whereas middle-aged (Δ_CESD_Total = 0.915, $p < 0.01$, 95% CI [0.278, 1.551]) and older participants (Δ_CESD_Total = 2.670, $p < 0.001$, 95% CI [2.077, 3.263]) had significantly higher levels of depressive symptoms after the lockdown (see Table 2 for further information) (see Table 3).

We also created a series of interaction terms between age groups and all major variables to test if changes in behavioral outcomes and depressive symptoms varied by age cohorts. The findings indicated that changes in social media usage differed significantly between young adults and older adults ($p < 0.001$), as well as between middle-aged adults and older adults ($p < 0.01$). Additionally, changes in depressive symptoms differed significantly between young adults and older adults ($p < 0.001$) and between middle-aged and older adults ($p < 0.001$). Notably, changes in self-reported use of different social media platforms significantly differed between middle-aged adults and older adults in terms of Instagram ($p < 0.05$), Pinterest ($p < 0.05$), LinkedIn ($p < 0.01$), TikTok ($p < 0.01$), Tumblr ($p < 0.05$), and Vine

TABLE 1 Descriptive statistics of sample demographic profiles.

Age groups	Parameter	Mean/Mode†	Frequency	Percent
Global sample ($n = 695$)	Age	45.85	n/a	n/a
	Std. deviation of age	15.42	n/a	n/a
	Ethnicity	Caucasian	488	70.20%
	Gender	Male	417	60.00%
	Education	4-Year College & Advanced Degrees	520	74.80%
	Income	$25,000 to $75,000	429	61.80%
	Job	Employed (Full-time + part-time)	570	82.00%
Young (18–39) ($n = 264$)	Age	29.78	n/a	n/a
	Std. deviation of age	4.08	n/a	n/a
	Ethnicity	Caucasian	161	61.00%
	Gender	Male	189	71.60%
	Education	4-Year College & Advanced Degrees	219	82.90%
	Income	$25,000 to $75,000	159	60.30%
	Job	Employed (Full-time + part-time)	253	95.80%
Middle aged (40–59) ($n = 234$)	Age	46.74	n/a	n/a
	Std. deviation of age	4.93	n/a	n/a
	Ethnicity	Caucasian	152	65.00%
	Gender	Male	158	67.50%
	Education	4-Year College & Advanced Degrees	193	82.40%
	Income	$25,000 to $75,000	154	65.80%
	Job	Employed (Full-time + part-time)	217	92.80%
Old (60+) ($n = 197$)	Age	66.00	n/a	n/a
	Std. deviation of age	4.50	n/a	n/a
	Ethnicity	Caucasian	175	88.80%
	Gender	Female	127	64.50%
	Education	4-Year College & Advanced Degrees	108	54.80%
	Income	$25,000 to $75,000	116	58.90%
	Job	Employed (Full-time + part-time)	100	50.80%

†Means were reported for continuous variables, and modes were displayed for ordinal (e.g., income) or categorical variables (e.g., gender); n/a = not applicable.

($p < 0.01$). Finally, changes in social media intensity, problematic social media use, and reported physical activity were not significantly different by age.

The results of the multigroup structural analysis (see Figure 1) showed a significant increase in social media intensity ($\beta = 0.122$, $p < 0.05$, 95% CI [0.038, 0.201]) and problematic social media usage ($\beta = 0.244$, $p < 0.001$, 95% CI [0.164, 0.331]) significantly led to a heightened level of depressive symptoms. Moderate-to-vigorous physical activity levels mediated both the relationship between social media intensity and depressive symptoms ($\beta = -0.017$, $p < 0.05$, 95% CI [−0.043, −0.001]) and between problematic social media consumption and depressive symptoms ($\beta = 0.022$, $p < 0.05$, 95% CI [0.001, 0.050]). That is, moderate and vigorous physical activity, such as participation in active sports, could alleviate the adverse effect of increased depressive symptoms resulting from increased social media consumption and addictive social media behaviors. No significant heterogeneity effect across different age cohorts were found (see Table 4) except for one path between social media intensity and depressive symptoms. The younger adults inclined to have a stronger relationship between social media intensity and depressive symptoms compared to older adults and middle-aged adults ($\beta = 0.232$, $p = 0.049$). No difference was found between middle-aged adults and older adults.

4 Discussion

The first purpose of this study was to explore changes in social media consumption patterns, physical activity levels, and depressive symptoms between before, and after the COVID-19 lockdown among young adults, middle-aged adults, and older adults. Regarding social media usage, older adults tended to spend more time with Instagram, Twitter, YouTube, and TikTok, which are content-focused social media platforms, whereas no significant changes were found in use of message-based platforms such as Snapchat or WhatsApp during the COVID-19 lockdown. Notably, middle-aged adults showed the most significant changes in use of social media platforms, spending more time with all twelve social media platforms. Younger respondents also

TABLE 2 The significance of changes by age groups using Bayesian analysis.

Age groups	Parameter	Baseline mean in January	Posterior			95% CI	
			Mean	S.D.	*p* (2-tailed)	Lower bound	Upper bound
Global sample (*n* = 695)	Δ_LPA	2.30	−0.084	1.932	0.251	−0.228	0.060
	Δ_MVPA	5.32	−0.060	3.258	0.626	−0.303	0.183
	Δ_SPA***	5.26	0.432	2.384	0.000	0.255	0.610
	Δ_CESD***	11.62	1.186	4.608	0.000	0.842	1.529
	Δ_SMU***	3.46	1.492	3.055	0.000	1.264	1.720
	Δ_SMP***	2.76	0.208	0.640	0.000	0.160	0.256
	Δ_SMI***	3.42	0.190	0.691	0.000	0.139	0.242
	Δ_Meta***	4.74	0.288	1.431	0.000	0.181	0.394
	Δ_Instagram***	3.95	0.355	1.405	0.000	0.251	0.460
	Δ_Pinterest***	3.38	0.279	1.372	0.000	0.177	0.381
	Δ_LinkedIn***	3.33	0.233	1.327	0.000	0.134	0.332
	Δ_Twitter***	3.93	0.292	1.484	0.000	0.181	0.403
	Δ_Snapchat***	3.10	0.335	1.396	0.000	0.231	0.439
	Δ_YouTube***	4.48	0.345	1.440	0.000	0.238	0.453
	Δ_TikTok***	3.17	0.413	1.489	0.000	0.302	0.524
	Δ_WhatsApp***	3.69	0.206	1.308	0.000	0.108	0.303
	Δ_Reddit***	3.36	0.183	1.342	0.000	0.083	0.283
	Δ_Tumblr***	2.95	0.199	1.289	0.000	0.102	0.295
	Δ_Vine**	2.98	0.180	1.408	0.001	0.075	0.285
Young (18–39) (*n* = 264)	Δ_LPA	2.89	−0.186	1.944	0.122	−0.422	0.051
	Δ_MVPA	6.05	0.172	3.134	0.372	−0.209	0.554
	Δ_SPA***	4.62	0.713	2.619	0.000	0.394	1.031
	Δ_CESD	15.15	0.318	4.354	0.236	−0.211	0.848
	Δ_SMU***	4.35	2.225	3.802	0.000	1.763	2.688
	Δ_SMP***	3.23	0.165	0.682	0.000	0.082	0.248
	Δ_SMI**	3.53	0.132	0.702	0.003	0.047	0.217
	Δ_Meta**	4.86	0.280	1.539	0.003	0.093	0.468
	Δ_Instagram***	4.71	0.424	1.568	0.000	0.234	0.615
	Δ_Pinterest**	3.98	0.318	1.607	0.001	0.123	0.514
	Δ_LinkedIn*	4.12	0.201	1.604	0.043	0.006	0.396
	Δ_Twitter	4.66	0.106	1.690	0.309	−0.100	0.312
	Δ_Snapchat***	4.00	0.417	1.693	0.000	0.211	0.623
	Δ_YouTube**	4.93	0.341	1.579	0.001	0.149	0.533
	Δ_TikTok***	4.16	0.417	1.613	0.000	0.220	0.613
	Δ_WhatsApp**	4.78	0.250	1.466	0.006	0.072	0.428
	Δ_Reddit*	4.13	0.227	1.543	0.017	0.040	0.415
	Δ_Tumblr	3.86	0.152	1.523	0.107	−0.034	0.337
	Δ_Vine	3.88	0.129	1.672	0.212	−0.075	0.332

(Continued)

TABLE 2 (Continued)

Age groups	Parameter	Baseline mean in January	Posterior			95% CI	
			Mean	S.D.	p (2-tailed)	Lower bound	Upper bound
Middle aged (40–59) (n = 234)	Δ_LPA	2.51	−0.048	2.121	0.728	−0.323	0.226
	Δ_MVPA	6.06	−0.369	3.723	0.131	−0.850	0.113
	Δ_SPA	4.88	0.202	2.451	0.209	−0.115	0.519
	Δ_CESD**	13.19	0.915	4.923	0.005	0.278	1.551
	Δ_SMU***	3.77	1.491	2.922	0.000	1.113	1.869
	Δ_SMP***	3.12	0.286	0.741	0.000	0.190	0.381
	Δ_SMI***	3.55	0.266	0.775	0.000	0.166	0.367
	Δ_Meta**	4.85	0.325	1.538	0.001	0.126	0.524
	Δ_Instagram***	4.50	0.479	1.578	0.000	0.274	0.683
	Δ_Pinterest***	3.88	0.410	1.483	0.000	0.218	0.602
	Δ_LinkedIn***	3.86	0.449	1.414	0.000	0.266	0.632
	Δ_Twitter***	4.32	0.517	1.624	0.000	0.307	0.727
	Δ_Snapchat***	3.61	0.491	1.495	0.000	0.298	0.685
	Δ_YouTube**	4.79	0.286	1.628	0.008	0.076	0.497
	Δ_TikTok***	3.74	0.611	1.725	0.000	0.388	0.834
	Δ_WhatsApp**	4.40	0.312	1.594	0.003	0.106	0.518
	Δ_Reddit*	3.88	0.252	1.564	0.014	0.050	0.454
	Δ_Tumblr***	3.44	0.389	1.464	0.000	0.199	0.578
	Δ_Vine***	3.50	0.402	1.589	0.000	0.196	0.607
Old (60+) (n = 197)	Δ_LPA	1.28	0.009	1.662	0.940	−0.226	0.244
	Δ_MVPA	3.47	−0.006	2.783	0.976	−0.399	0.387
	Δ_SPA*	6.55	0.331	1.896	0.015	0.063	0.598
	Δ_CESD***	5.01	2.670	4.198	0.000	2.077	3.263
	Δ_SMU***	1.91	0.511	1.344	0.000	0.321	0.701
	Δ_SMP***	1.71	0.173	0.404	0.000	0.116	0.230
	Δ_SMI***	3.12	0.178	0.551	0.000	0.100	0.255
	Δ_Meta**	4.45	0.254	1.119	0.002	0.096	0.412
	Δ_Instagram*	2.26	0.117	0.803	0.043	0.003	0.230
	Δ_Pinterest	1.96	0.071	0.718	0.166	−0.030	0.172
	Δ_LinkedIn	1.62	0.020	0.553	0.607	−0.058	0.098
	Δ_Twitter***	2.51	0.274	0.849	0.000	0.154	0.394
	Δ_Snapchat	1.27	0.041	0.523	0.277	−0.033	0.115
	Δ_YouTube***	3.52	0.421	0.915	0.000	0.292	0.551
	Δ_TikTok**	1.18	0.173	0.846	0.005	0.053	0.292
	Δ_WhatsApp	1.38	0.020	0.319	0.372	−0.025	0.065
	Δ_Reddit	1.72	0.041	0.493	0.249	−0.029	0.110
	Δ_Tumblr	1.14	0.036	0.383	0.194	−0.019	0.090
	Δ_Vine	1.15	−0.015	0.410	0.603	−0.073	0.043

Monte Carlo Sampling Seed: 200,000. CI = Bayesian 95% credible intervals; LPA, light intensity physical activity; MVPA, moderate and vigorous-intensity physical activity; SMU, social media usage; SMI, social media intensity; SMP, social media addiction; SPA, sitting; *p < 0.05; **p < 0.01; ***p < 0.001.

spent more time on the wide range of social media after the COVID-19 lockdown, reporting increased use of all platforms but Twitter, Tumblr, and Vine. Yet, it should be noted that the baseline Twitter usage was relatively high. The findings implied that specific social media platforms should be targeted to increase reach to older adults in particular.

TABLE 3 The results of structural analysis.

Paths	Bootstrapping sample mean	STDEV	T statistics	*p* values	Bootstrapping 95% CI	
Direct relationships						
Δ_LPA → Δ_CESD	−0.047	0.038	1.341	0.180	−0.120	0.008
Δ_MVPA → Δ_CESD*	−0.108	0.055	1.971	0.049	−0.182	−0.026
Δ_SMC → Δ_CESD	−0.001	0.042	0.155	0.877	−0.086	0.057
Δ_SMC → Δ_LPA	−0.016	0.087	0.265	0.791	−0.167	0.111
Δ_SMC → Δ_MVPA	−0.014	0.062	0.129	0.897	−0.101	0.104
Δ_SMC → Δ_SPA	0.049	0.061	0.796	0.426	−0.054	0.147
Δ_SMI → Δ_CESD*	0.122	0.050	2.446	0.015	0.038	0.201
Δ_SMI → Δ_LPA	0.063	0.074	0.986	0.324	−0.046	0.191
Δ_SMI → Δ_MVPA*	0.154	0.081	2.029	0.043	0.025	0.283
Δ_SMI → Δ_SPA	−0.055	0.070	0.830	0.406	−0.189	0.045
Δ_SMP → Δ_CESD***	0.244	0.051	4.859	0.000	0.164	0.331
Δ_SMP → Δ_LPA	−0.007	0.067	0.090	0.929	−0.120	0.104
Δ_SMP → Δ_MVPA*	−0.203	0.086	2.401	0.016	−0.321	−0.032
Δ_SMP → Δ_SPA	0.098	0.062	1.587	0.113	−0.007	0.197
Δ_SMU → Δ_CESD	−0.001	0.023	0.007	0.994	−0.037	0.040
Δ_SMU → Δ_LPA	−0.014	0.044	0.359	0.719	−0.088	0.057
Δ_SMU → Δ_MVPA	−0.008	0.049	0.204	0.838	−0.082	0.074
Δ_SMU → Δ_SPA	0.091	0.053	1.708	0.088	0.001	0.176
Δ_SPA → Δ_CESD	0.048	0.039	1.274	0.203	−0.013	0.113
Controls → Δ_CESD*	−0.270	0.136	1.981	0.048	−0.361	−0.011
Indirect relationships						
Δ_SMP → Δ_MVPA→Δ_CESD*	0.022	0.011	1.969	0.049	0.001	0.050
Δ_SMP → Δ_SPA→Δ_CESD	0.005	0.006	0.886	0.376	−0.009	0.020
Δ_SMU → Δ_MVPA→Δ_CESD	0.002	0.005	0.207	0.836	−0.007	0.011
Δ_SMU → Δ_LPA → Δ_CESD	0.001	0.003	0.310	0.757	−0.002	0.007
Δ_SMI → Δ_MVPA→Δ_CESD*	−0.017	0.009	1.966	0.050	−0.043	−0.001
Δ_SMC → Δ_MVPA→Δ_CESD	0.001	0.008	0.116	0.908	−0.011	0.014
Δ_SMC → Δ_SPA→Δ_CESD	0.003	0.004	0.540	0.589	−0.001	0.015
Δ_SMU → Δ_SPA→Δ_CESD	0.004	0.005	0.930	0.353	0.000	0.017
Δ_SMC → Δ_LPA → Δ_CESD	0.001	0.005	0.235	0.814	−0.004	0.015
Δ_SMI → Δ_LPA → Δ_CESD	−0.004	0.005	0.745	0.456	−0.019	0.001
Δ_SMI → Δ_SPA→Δ_CESD	−0.003	0.005	0.577	0.564	−0.019	0.001
Δ_SMP → Δ_LPA → Δ_CESD	0.000	0.004	0.079	0.937	−0.005	0.007

CI = 95% biased-corrected confidence intervals; CESD, depressive symptoms; MVPA, moderate and vigorous-intensity physical activity; LPA, light intensity physical activity; SMU, social media usage; SMI, social media intensity; SMP, social media addiction; SPA, sitting; $*p < 0.05$, $***p < 0.001$.

In terms of physical activity levels, while significantly increased sitting time was reported by all respondents regardless of age, no significant change was found in activity levels. This finding highlights the importance of effective social media campaigns to promote physical activity during the pandemic. For instance, during the COVID-19, two physician athletes of the United States initiated a social media campaign to promote physical activity among the general population with the #SocialDistancingFitnessChallenge (45). In March and April of 2020, these physicians posted a 5-day workweek and received positive feedback from social media users that those users engaged in physical activity during that time inspired by the posts (45). In spite of various types of individual-level campaigns during this time, organization-level campaigns have been lacking. For instance, between March 12 of 2020 (i.e., the day President Trump declared a national emergency concerning the COVID-19 outbreak) and December 2021, only 73 out of 4,137 postings (roughly 1.8%) of the Centers for Disease Control and Prevention (CDC) and only 160 postings out of 7,175 postings (roughly 2.2%) of the World Health

TABLE 4 Significant results of multigroup comparisons.

Path of hypothesis	Welch-Satterthwaite (W-S) significant testing†		
	Diff |Y-O|	*Diff* |Y-M|	*Diff* |M-O|
ΔSMI → ΔCESD	0.182*	0.100*	0.081 (n.s.)
	1.979	1.972	0.721

CESD, depressive symptoms, SMI, social media intensity, M, middle aged cohort, O, older cohort, Y, younger cohort; * $p < 0.05$, n.s. stands for non-significant. †The W-S test assumes unequal variances across age clusters. T-statistics of the W-S test were displayed for path differences.

Organization (WHO) were about physical activity. At the organization/institution levels, more social-media-based campaigns for physical activity may need to be designed and implemented to stimulate more active lifestyles regardless of the age of populations. In fact, the University of Milan conducted a social-media-based physical activity promotion campaign with "#StayHomeStayFit" providing useful general information and credible suggestions regarding physical activity and psychological support for the general population during the COVID-19 lockdown, attracting massive attention according to page views and reactions (46). This type of social media campaign, if established by public health stakeholders, policymakers and institutions, would maximize population perception and reach during the pandemic.

The significantly increased sitting time also indicates reducing sedentary behavior is critical. As Manini et al. (47) argued, interventions targeting sedentary behavior are distinctive from targeting physical activity. In particular, it is essential to consider a life course perspective that assumes sedentary behavior is age and life stage dependent. In this context, the importance of addressing environmental factors has been highlighted to reduce sedentary behavior. To fight against increased sedentary behavior during the COVID-19 lockdown, promoting environment change to reduce sedentary behavior seems critical. For instance, using new technology (e.g., standing desk, desk treadmills), new workspace ideas (e.g., active workstations at home), and developing specific policies (e.g., break times) might be effective interventions.

Consistent with expectations, the middle-aged and older respondents reported significant higher depressive symptoms, whereas no significant change was found among younger respondents. Nevertheless, it should be noted that the baseline of older respondents' depressive symptom was very low, while middle-aged (CESD_Total = 13.19) and younger adults (CESD_Total = 15.15) showed already relatively higher levels of depressive symptoms in January 2020. While this study solely focused on the negative mental health state, future studies may also need to investigate positive states such as happiness, optimism, or purpose in life.

Even though this study focused on social media use as an antecedent of mental health, it should be noted that some studies conducted in Italy contended that pre-existing mental issues could result in excessive and problematic social media use (48) among the Italian population. Sampogna et al. (48) found that people with mental disorders tended to consume significantly more hours on social media compared to the general population in Italy during the COVID-19 pandemic lockdown. Similarly, Volpe et al. (49) reported that general psychopathology, stress, anxiety, depression, and social isolation played a significant role on problematic social media use along with video gaming and internet use. Further studies with US adults, specifically patients with pre-existing mental health issues or disorders, may be beneficial to explore the nature of this relationship between social media consumption and mental health further.

The second purpose of this study aimed to investigate the mediating effect of changes in different levels of physical activity on the relationship between the changes in social media consumption and depressive symptoms during the COVID-19 lockdown. The findings highlight the importance of moderate-to-vigorous physical activity (MVPA; e.g., playing doubles tennis, running, cycling), implying potential differential effects compared to light physical activity (e.g., walking) on the relationship between media consumption and depressive symptoms. While some prior studies found that even light-intensity physical activity has positive mental health effects [e.g., (50)], some studies targeting the relief of depression via endorphin secretion is only associated with MVPA [e.g., (51)]. The findings of this study suggest that MVPA tended to alleviate the increased levels of depressive symptoms linked with the increased intensity of social media consumption and increased problematic social media behavior. Therefore, MVPA could be a potential coping strategy that can ease depressive symptoms resulting from excessive social media consumption. Considering the levels of MVPA was a significant mediator, further prospective and experimental studies would be helpful to examine what types of MVPA would be most effective on alleviating the mental health issues resulting from social media consumption.

When it comes to physical activity, there are three different types: physical activity [i.e., "bodily movement produced by skeletal muscles that results in energy expenditure," (52), p. 126], exercise [i.e., "physical activity that is planned, structured, repetitive, and purposive in the sense that improvement or maintenance of one or more components of physical fitness is an objective," (52), p. 128], and sport [i.e., "all forms of physical activity which, through casual or organized participation, aim at expressing or improving physical fitness and mental wellbeing, forming social relationships or obtaining results in competition at all levels," (53)]. Unlike unorganized physical activity, such as gardening or dog walking, and exercise, such as muscular strength training, sport is capable of achieving a result requiring physical exertion and/or physical skill, which, by its nature, is competitive and social (54). In fact, previous research supports the notion that the mental health effects of exercise may be different than that of sport. For instance, while Krogh et al. (55) concluded that the effects of exercise were insignificant on mental health outcomes, Asztalos et al. (56) concluded that only sport participation and no other type of physical activity was consistently related to lower stress and distress because sport is the only form of MVPA that aims for enjoyment and social interactions compared to other types such as exercise or biking to work. Therefore, further research may need to investigate the potential different effects of unorganized physical activity, exercise, and sport on the relationship between social media consumption and depressive symptoms.

Even though this study focused on the intensity and addictive behavior of social media consumption in general, different types of social media platforms were not considered. For instance, the addictive behavior with YouTube may have different effects on physical activity levels compared to the addictive behavior with Reddit. The type of consumed contents also should be considered. For example, consuming fitness-related content may have different effects than consuming food-related content. Lastly, the purpose of social media consumption also should be considered. Social media consumption can play various roles in one's life: information seeking, social networking, business transactions, and so forth. In particular, using social media platforms for social purposes (e.g., social support, social relationships) have been known to be beneficial for one's mental health during challenging times (57).

5 Limitations

The present study had several limitations that have implications for future research. First, our study should not be generalized to dissimilar populations considering our convenience samples featured a relatively healthy population with high levels of physical activity, low levels of depressive symptoms and an average or higher socioeconomic status. Moreover, the participants recalled their behavior 5 months following the first targeted recall date of January of 2020, which may result in recall bias. Though COVID-19 has been an influential global event that might prompt stronger recall of behaviors and moods connected to the pandemic, it is important to note that the present study was not immune from potential recall bias.

It is also should be noted that IPAQ does not differentiate between the different domains of physical activity such as work-related physical activity, household physical activity, leisure-time physical activity. Considering leisure-time physical activity has been recognized as a more significant predictor of mental health outcomes (58), the use of IPAQ might not capture the role of different types of physical activity. Additionally, this study did not consider the different types of social media usage. For instance, an active usage such as interacting directly with others through posting new content or adding comments to other posts can be distinguished from a passive usage such as reading, and skimming the content and posts of others. Some studies found that active social media usage tended to positively associate with one's well-being, whereas passive usage inclined to negatively associated with well-being (24, 59, 60). Thus, future research may need to consider the different types of social media usage when it comes to one's mental health and physical activity participation. Additionally, even though depressive symptoms have been identified as one of the significant mental health indicators related to traumatic events, there are other critical indicators such as anxiety or stress. These mental health indicators also need to be examined in the future research. Lastly, the present study examined only one outcome, depressive symptoms, which presents the negative state of one's emotions. More diversified psychological outcomes, including positive states such as positive psychological well-being (e.g., optimism, happiness, and contentment), should be investigated in the future.

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 humans were approved by Florida State University Office of Research. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

AK, JD, and DA contributed to the conception and design of the study and wrote sections of the manuscript. AK and DA organized the data collection. JD performed the statistical analyses. All authors contributed to the article and approved the submitted version.

Conflict of interest

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

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References

1. Tsao S-F, Chen H, Tisseverasinghe T, Yang Y, Li L, Butt ZA. What social media told us in the time of Covid-19: a scoping review. *Lancet Digit Health*. (2021) 3:E175–94. doi: 10.1016/S2589-7500(20)30315-0

2. Muñiz-Velázquez JA, Gómez-Baya D, Delmar JL. Exploratory study of the relationship between happiness and the rise of media consumption during Covid-19 confinement. *Front Psychol*. (2021) 12:566517. doi: 10.3389/fpsyg.2021.566517

3. Rosen AO, Holmes AL, Balluerka N, Hidalgo MD, Gorostiaga A, Gómez-Benito J, et al. Is social media a new type of social support? Social media use in Spain during the Covid-19 pandemic: a mixed methods study. *Int J Environ Res Public Health*. (2022) 19:3952. doi: 10.3390/ijerph19073952

4. Dixon S. (2022). Average daily time spent on social networks in the U.S. 2018–2022 [online]. Statista. Available at: https://www.statista.com/statistics/1018324/us-users-daily-social-media-minutes/ [Accessed].

5. Gao J, Zheng P, Jia Y, Chen H, Mao Y, Chen S, et al. Mental health problems and social media exposure during Covid-19 outbreak. *PLoS One*. (2020) 15:E0231924. doi: 10.1371/journal.pone.0231924

6. Longest K, Kang J-A. Social media, social support, and mental health of young adults during Covid-19. *Front Commun*. (2022) 7:828135. doi: 10.3389/fcomm.2022.828135

7. Orsolini L, Volpe U, Albert U, Carmassi C, Carrà G, Cirulli F, et al. Use of social network as a coping strategy for depression among young people during the Covid-19 lockdown: findings from the comet collaborative study. *Ann General Psychiatry*. (2022) 21:44. doi: 10.1186/s12991-022-00419-w

8. Zhang Y-T, Li R-T, Sun X-J, Peng M, Li X. Social media exposure, psychological distress, emotion regulation, and depression during the Covid-19 outbreak in community samples in China. *Front Psych*. (2021) 12:644899. doi: 10.3389/fpsyt.2021.644899

9. Johnson JMQ, Saleem M, Tang L, Ramasubramanian S, Riewestahl E. Media use during Covid-19: an investigation of negative effects on the mental health of Asian versus White Americans. *Front Commun*. (2021) 6:638031. doi: 10.3389/fcomm.2021.638031

10. Li S, Wang Y, Xue J, Zhao N, Zhu T. The impact of Covid-19 epidemic declaration on psychological consequences: a study on active Weibo users. *Int J Environ Res Public Health*. (2020) 17:2032. doi: 10.3390/ijerph17062032

11. Thygesen H, Bonsaksen T, Schoultz M, Ruffolo M, Leung J, Price D, et al. Social media use and its associations with mental health 9 months after the Covid-19 outbreak: a cross-National Study. *Front Public Health*. (2022) 18:752004. doi: 10.3389/fpubh.2021.752004

12. Ammar A, Mueller P, Trabelsi K, Chtourou H, Boukhris O, Masmoudi L, et al. Psychological consequences of Covid-19 home confinement: the Eclb-Covid 19 multicenter study. *PLoS One*. (2020) 15:E0240204. doi: 10.1371/journal.pone.0240204

13. Mutz M, Gerke M. Sport and exercise in times of self-quarantine: How Germans changed their behaviour at the beginning of the Covid-19 pandemic. *Int Rev Sociol Sport*. (2021) 56:305–16. doi: 10.1177/1012690220934335

14. Roberts K. Locked down leisure in Britain. *Leis Stud*. (2020) 39:617–28. doi: 10.1080/02614367.2020.1791937

15. Du J, Floyd C, Kim ACH, Baker BJ, Sato M, James JD, et al. To be or not to be: negotiating leisure constraints with technology and data analytics amid the Covid-19 pandemic. *Leis Stud*. (2021) 40:561–74. doi: 10.1080/02614367.2020.1862284

16. Hayes M. Social media and inspiring physical activity during Covid-19 and beyond. *Manag Sport Leisure*. (2022) 27:14–21. doi: 10.1080/23750472.2020.1794939

17. Todorovic J, Terzic-Supic Z, Dijakanovic B, Nesic D, Piperac P, Stamenkovic Z. Can social media intervention improve physical activity of medical students? *Public Health*. (2019) 174:69–73. doi: 10.1016/j.puhe.2019.05.030

18. Zhang J, Brackbill D, Yang S, Centola D. Efficacy and causal mechanism of an online social media intervention to increase physical activity: results of a randomized controlled trial. *Prev Med Rep*. (2015) 2:651–7. doi: 10.1016/j.pmedr.2015.08.005

19. Marconcin P, Werneck AO, Peralta M, Ihle A, Gouveia ER, Ferrari G, et al. The association between physical activity and mental health during the first year of the Covid-19 pandemic: a systematic review. *BMC Public Health*. (2022) 22:209. doi: 10.1186/s12889-022-12590-6

20. Geirdal A, Ruffolo M, Leung J, Thygesen H, Price D, Bonsaksen T, et al. Mental health, quality of life, wellbeing, loneliness and use of social media in a time of social distancing during the Covid-19 outbreak: a cross-country comparative study. *J Ment Health*. (2021) 30:148–55. doi: 10.1080/09638237.2021.1875413

21. Zhao N, Zhou G. Social media use and mental health during the Covid-19 pandemic: moderator role of disaster stressor and mediator role of negative affect. *Appl Psychol Health Well Being*. (2020) 12:1019–38. doi: 10.1111/aphw.12226

22. Valdez D, Ten Thij M, Bathina K, Rutter LA, Bollen J. Social media insights into us mental health during the Covid-19 pandemic: longitudinal analysis of twitter data. *J Med Internet Res*. (2020) 22:E21418. doi: 10.2196/21418

23. Ni MY, Yang L, Leung CMC, Li N, Yao XI, Wang Y, et al. Mental health, risk factors, and social media use during the Covid-19 epidemic and cordon sanitaire among the community and health professionals in Wuhan, China: cross-sectional survey. *JMIR Ment Health*. (2020) 7:E19009. doi: 10.2196/19009

24. Masciantonio A, Bourguignon D, Bouchat P, Balty M, Rime B. Don't put all social network sites in one basket: Facebook, Instagram, twitter, Tiktok, and their relations with well-being during the Covid-19 pandemic. *PLoS One*. (2021) 16:E0248384. doi: 10.1371/journal.pone.0248384

25. Alonzo R, Hussain J, Stranges S, Anderson KK. Interplay between social media, sleep quality, and mental health in youth: a systematic review. *Sleep Med Rev*. (2021) 56:101414. doi: 10.1016/j.smrv.2020.101414

26. O'kane SM, Lahart IM, Gallagher AM, Carlin A, Faulkner M, Jago R, et al. Changes in physical activity, sleep, mental health, and social media use during Covid-19 lockdown among adolescent girls: a mixed-methods study. *J Phys Act Health*. (2021) 18:677–85. doi: 10.1123/jpah.2020-0649

27. Precht L-M, Stirnberg J, Margraf J, Brailovskaia J. Can physical activity Foster mental health by preventing addictive social media use? A longitudinal investigation during the Covid-19 pandemic in Germany. *J Affect Dis Rep*. (2022) 8:100316. doi: 10.1016/j.jadr.2022.100316

28. Fukukawa Y, Nakashima C, Tsuboi S, Kozakai R, Doyo W, Niino N, et al. Age differences in the effect of physical activity on depressive symptoms. *Psychol. Aging*. (2004) 19:346–51. doi: 10.1037/0882-7974.19.2.346

29. Shensa A, Sidani JE, Dew MA, Escobar-Viera CG, Primack BA. Social media use and depression and anxiety symptoms: a cluster analysis. *Am J Health Behav*. (2018) 42:116–28. doi: 10.5993/AJHB.42.2.11

30. Ellison NB, Steinfield C, Lampe C. The benefits of Facebook "friends": social capital and college students' use of online social network sites. *J Comput-Mediat Commun*. (2007) 12:1143–68. doi: 10.1111/j.1083-6101.2007.00367.x

31. Andreassen CS, Torsheim T, Brunborg GS, Pallesen S. Development of a Facebook addiction scale. *Psychol Rep*. (2012) 110:501–17. doi: 10.2466/02.09.18.PR0.110.2.501-517

32. Ettman CK, Abdalla SM, Cohen GH, Sampson L, Vivier PM, Galea S. Prevalence of depression symptoms in us adults before and during the Covid-19 pandemic. *JAMA Netow Open*. (2020) 3:E2019686. doi: 10.1001/jamanetworkopen.2020.19686

33. Mortensen K, Hughes TL. Comparing Amazon's mechanical Turk platform to conventional data collection methods in the health and medical research literature. *J Gen Intern Med*. (2018) 33:533–8. doi: 10.1007/s11606-017-4246-0

34. Frayer C. D., Ostchega Y., Hales C. M., Zhang G., Kruszon-Moran D. (2017). Hypertension prevalence and control among adults: United States, 2015-2016 [online]. Available at: chrome-extension://Efaidnbmnnnibpcajpcglclefindmkaj. https://www.Cdc.Gov/Nchs/data/Databriefs/Db289.Pdf

35. Lakens D. *Sample Psize justification. Collabra: psychology*, vol. 8 (2022). 33267 p.

36. Zylla E., Hartman L. (2020). State Covid-19 data dashboards [online]. Available at: https://www.Shvs.Org/State-Covid-19-data-dashboards/ [accessed].

37. Lee PH, Macfarlane DJ, Lam TH, Stewart SM. Validity of the international physical activity questionnaire short form (Ipaq-sf): a systematic review. *Int J Behav Nutr Phys Act*. (2011) 8:115. doi: 10.1186/1479-5868-8-115

38. Baron EC, Davies T, Lund C. Validation of the 10-item Centre for epidemiological studies depression scale (Ces-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa. *BMC Psychiatry*. (2017) 17:6. doi: 10.1186/s12888-016-1178-x

39. Bradley KL, Bagnell AL, Brannen CL. Factorial validity of the center for epidemiological studies depression 10 in adolescents. *Issues Ment Health Nurs*. (2010) 31:408–12. doi: 10.3109/01612840903484105

40. Oftedal S, Kolt GS, Holliday EG, Stamatakis E, Vandelanotte C, Brown WJ, et al. Associations of health-behavior patterns, mental health and self-rated health. *Prev Med*. (2019) 118:295–303. doi: 10.1016/j.ypmed.2018.11.017

41. Barry AE, Chaney BH, Stellefson ML, Dodd V. Evaluating the psychometric properties of the Audit-C among college students. *J Subst Abus*. (2015) 20:1–5. doi: 10.3109/14659891.2013.856479

42. Hudmon KS, Pomerleau CS, Brigham J, Javitz H, Swan GE. Validity of retrospective assessments of nicotine dependence: a preliminary report. *Addict Behav*. (2005) 30:613–7. doi: 10.1016/j.addbeh.2004.08.006

43. Grandner MA, Kripke DF, Yoon I-Y, Youngstedt SD. Criterion validity of the Pittsburgh sleep quality index: investigation in a non-clinical sample. *Sleep Biol Rhythms*. (2006) 4:129–36. doi: 10.1111/j.1479-8425.2006.00207.x

44. Sturtz S., Liggers U., Gelman A. (2005). R2winbugs: A Package For Running Winbugs From R [Online]. Available at: https://cran.r-project.org/web/packages/r2winbugs/vignettes/r2winbugs.pdf [Accessed].

45. Stanford FC, Salles A. Physician athletes promoting physical fitness through social media during the Covid-19 pandemic. *Health Promot Pract*. (2021) 22:295–7. doi: 10.1177/1524839920988261

46. Lucini D, Gandolfi CE, Antonucci C, Cavagna A, Valzano E, Botta E, et al. #Stayhomestayfit: Unimi's approach to online healthy lifestyle promotion during the Covid-19 pandemic. *Acta Biomed*. (2020) 81:E2020037. doi: 10.23750/abm.v91i3.10375

47. Manini TM, Carr LJ, King AC, Marshall S, Robinson TM, Rejeski WJ. Interventions to reduce sedentary behavior. *Med Sci Sports*. (2015) 47:1306–10. doi: 10.1249/MSS.0000000000000519

48. Sampogna G, di Vincenzo M, Luciano M, Della Rocca B, Albert U, Carmassi C, et al. The effect of social media and Infodemic on mental health during the Covid-19 pandemic: results from the comet multicentric trial. *Front Psych*. (2023) 14:1226414. doi: 10.3389/fpsyt.2023.1226414

49. Volpe U, Orsolini L, Salvi V, Albert U, Carmassi C, Carrà G, et al. Covid-19-related social isolation predispose to problematic internet and online video gaming use in Italy. *Int J Environ Res Public Health*. (2022) 19:1539. doi: 10.3390/ijerph19031539

50. Loprinzi PD. Objetively measured light and moderate-to-vigorous physical activity is associated with lower depression levels among Odler us adults. *Aging Ment Health*. (2013) 17:801–5. doi: 10.1080/13607863.2013.801066

51. Saanijoki T, Tuominen L, Tuulari JJ, Nummenmaa L, Arponen E, Kalliokoski K, et al. Opioid release after high-intensity interval training in healthy human subjects. *Neuropsychopharmacology*. (2018) 43:246–54. doi: 10.1038/npp.2017.148

52. Caspersen CJ, Powell KE, Christenson GM. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. *Public Health Rep*. (1985) 100:126–31.

53. Councill Of Europe. *The European sports charter*. Brussels: Council Of Europe (2001).

54. Kim ACH, Du J, James JD. A social Epidmeiological perspective on local tennis league participation: a multigroup moderated-mediation structural analysis using Pls-Sem. *Int J Sports Mark Spons*. (2022) 23:437–61. doi: 10.1108/IJSMS-02-2021-0046

55. Krogh J, Hjorthoj C, Speyer H, Gluud C, Nordentoft M. Exercise for patients with major depression: a systematic review with Meta-analysis and trial sequential analysis. *BMJ Open*. (2017) 7:E014820. doi: 10.1136/bmjopen-2016-014820

56. Asztalos M, Wijndaele K, De Bourdeaudhuij I, Philippaerts R, Matton L, Duvigneaud N, et al. Specific associations between types of physical activity and components of mental health. *J Sci Med Sport*. (2009) 12:468–74. doi: 10.1016/j.jsams.2008.06.009

 10.3389/fpsyt.2023.1120230

57. Bekalu MA, Mccloud RF, Viswanath K. Association of social media use with social well-being, positive mental health, and self-rated health: disentangling routine use from emotional connection to use. *Health Educ Behav*. (2019) 46:69S–80S. doi: 10.1177/1090198119863768

58. White RL, Babic MJ, Parker PD, Lubans DR, Astell-Burt T, Lonsdale C. Domain-specific physical activity and mental health: a Meta-analysis. *Am J Prev Med*. (2017) 52:653–66. doi: 10.1016/j.amepre.2016.12.008

59. Shaw AM, Timpano KR, Tran TB, Joormann J. Correlates of Facebook usage patterns: the relationship between passive Facebook use, social anxiety symptoms, and brooding. *Comput Hum Behav*. (2015) 48:575–80. doi: 10.1016/j.chb.2015.02.003

60. Verduyn P, Lee DS, Park J, Shablack H, Orvell A, Bayer J, et al. Passive Facebook usage undermines affective well-being: experimental and longitudinal evidence. *J Exp Psychol Gen*. (2015) 144:480–8. doi: 10.1037/xge0000057