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Excessive internet use and its impact on mental health

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Excessive internet use and its impact on mental health

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Editorial: Excessive internet use and its impact on mental health

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KEYWORDS

social networking, online shopping, online gambling, internet-related addictions, mental health, behavioral addictions

Editorial on the Research Topic
Excessive internet use and its impact on mental health

The various forms of Internet use, including social networking, online shopping, gambling, and gaming are products of the time in which we live and represent an integral part of how we conduct and engage in social interaction. Internet platforms not only facilitate daily connection and efficient exchange of important information, but also provide educational functions and raise awareness of problems faced by individuals and societies globally. However, excessive use of Internet-related content has also increasingly been linked with mental health issues and aspects, such as addictive behavior, which is a central theme of this Research Topic.

Within this thematic unit, 51 papers were received, of which 20 were accepted for publication. It should be emphasized that distribution of the published articles by type was as following: 17 Original research, 2 Brief Research Report and 1 Hypothesis and Theory. The reviewers, who are distinguished scholars, helped a lot to successfully accomplish this Research Topic, and we thank them on this occasion as well.

The novel approaches, rigorous research methodologies and statistically significant findings, which are presented under this Research Topic, altogether speak in favor of the fact that Excessive Internet Use is quite problematic nowadays and that more care should be taken in how to deal with it. Although any internet-related addiction is not specifically identified in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) or International Classification of Diseases (ICD-11), the growing body of literature suggest it shares a common underlying etiological framework with other (substance or behavioral) addictions.

In this regard, the connections between the excessive use of the Internet (especially social networks) with pronounced occurrences of various symptoms of mental health, as well as health in general, were unequivocally established.

On other hand, it should be noted that some research showed that Internet use significantly enhances people's happiness (Sun et al.). Relatedly, it should be noted that this article was concerning older adults. In another cohort of the older adults in somewhat extensive Chinese study by Mu et al., it was shown that time spent on the Internet significantly reduces depressive and melancholic states. From this perspective, the two mentioned studies appear to be in line with regard to the reported, somewhat positive impact on mental health.

On the contrary, in a recent survey in the Republic of Serbia, which was based on a representative sample, it was found that excessive use of the Internet was significantly associated with obesity, psychological disturbances and social maladjustment (Novaković et al.).

Furthermore, Internet addiction has emerged as a serious concern, particularly among university students, affecting academic performance and having significant psychological implications. Nevertheless, even the "athlete" university students were shown to be at increased risk for depressive symptoms and Internet addiction and decreased healthy lifestyle behaviors, which was reported by the remarkable survey by Çelik and Haney. However, it was illustrated by Cai et al. that physical exercise, gender, and academic year have a significant impact on Internet addiction among university students. In their study, freshmen students were shown to be more susceptible to experiencing Internet addiction.

Anyway, more evidences were obtained that mobile phone addiction is a risk factor for insomnia symptoms and that physical activity had (as it was expected) a significant moderating effect between mobile phone addiction and social anxiety (Wang J. et al.).

Furthermore, moreover, significant associations were observed between smartphone addiction and spending more hours daily on smartphones, poor sleep quality, as well as elevated levels of stress, anxiety, and depression (Nikolic et al.; Wu et al.). Smartphone usage has witnessed an exponential rise globally, with projections estimating a staggering 7.8 billion smartphone users by 2028.

The association between social media use and health-related variables, including fruit and vegetable intake, physical activity, obesity, tobacco smoking, mental health, and stress levels among adults in the Saudi community was demonstrated by BinDhim et al.. In particular, it should be noted that the effectiveness of relapse prevention as a treatment for Internet gaming disorder was found to be superior to the usual treatment in terms of reduction of Internet gaming disorder symptoms (André et al.).

In another article, it was also shown that people who are more likely to be Internet addicted are at significant risk of suicide-related behaviors (Kang et al.). Psychological need thwarting has been shown to be closely related to problematic smartphone use, psychological distress, and perceived support (Liao et al.).

Online shopping addiction is a behavior that causes serious problems and has become increasingly prevalent in a modern society. Within the scope of the study by Erzincanli et al., it was identified that anxiety and depression positively affect online shopping addiction, whereas financial attitude has a negative effect.

Another study implemented Fear of Missing Out Scales, Loneliness Scale, Mobile Phone Addiction Index Scale, and Depression-Anxiety-Stress Questionnaire with purpose to investigate university students (Liu et al.). The results suggest that the fear of missing out significantly positively predicts mobile phone addiction. This direct effect could be mediated by depression, while the indirect effect of fear of missing out on mobile phone addiction could be moderated by loneliness. Additionally, with the use of valid instruments and accompanying appropriate statistical analysis, Wang W. et al. showed based on the sample from six universities in China that mobile phone addiction is also associated with suicide ideation and suicide attempt among university students.

Overall, it is of great importance that the research on the impact of internet usage on mental health continues and gains momentum. Comprehensive and interdisciplinary efforts toward clarification of the hidden patterns and elusive aspects on the population level as well as on the individual level are largely needed. Let it be that Internet itself does not occur as any danger for the wellbeing of each individual. However, the utilization of the Internet has become one of the most essential tools in our modern society. That is why the future research should resolve the causal relationships between Internet addiction and the psychosocial factors related to health.

Author contributions

AV: Conceptualization, Data curation, Formal analysis, Project administration, Validation, Writing – original draft, Writing – review & editing. KK: Conceptualization, Data curation, Formal analysis, Project administration, Validation, Writing – original draft, Writing – review & editing. ZT-Š: Conceptualization, Data curation, Formal analysis, Project administration, Validation, Writing – original draft. MS: Conceptualization, Data curation, Formal analysis, Project administration, Validation, Writing – original draft, Writing – review & editing.

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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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Internet use and depressive symptoms among Chinese older adults: Two sides of internet use

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Objective: To explore the relationship between internet use which includes time spent on the internet, internet skills, types of online activities, and depressive symptoms in older adults.

Methods: We used 2020 China Family Panel Studies (CFPS) data with 3,171 older adults aged 60 years. Depression symptoms were measured with the Center for Epidemiologic Studies Depression (CES-D), and internet use was measured by time spent on the internet, internet skills, and types of online activities. Multiple linear regression models were used to explore the relationship between internet use and depressive symptoms in older adults.

Results: Longer time spent on the internet was associated with higher scores of depressive symptoms ($\beta = 0.14$). Higher internet skills were associated with lower scores of depressive symptoms ($\beta = -0.42$). Watching short-form videos ($\beta = 1.34$) was associated with higher depressive symptom scores, and the use of the WeChat function ($\beta = -0.96$) was associated with lower depressive symptom scores, while online games and online shopping were not significant.

Conclusion: The effect of internet use on depressive symptoms in older adults is a double-edged sword. Controlling the time spent on the internet, improving internet skills, and guiding specific a type of online activities in older adults can improve depressive symptoms through rational use.

KEYWORDS

dark side of information technology use, internet use, depressive symptoms, aged, China, negative results

1. Introduction

Depression is a major threat to the mental health of older adults with an estimated prevalence of 4–9% worldwide (1), and the prevalence of depression among people aged 60 years and older in China is the highest of all ages groups, at 20.6 to 30.7% (2). With the deepening of aging and accelerated social transformation, the mental health pressure in older adults will be even greater, with a potentially large number of older adults with moderate to high levels of depressive symptoms (3). Besides, depression is associated with substantial morbidity and mortality due to potential underdiagnosis and under-treatment (1). A study showed that depression may exacerbate the clinical manifestations of combined symptoms such as diabetes or hypertension and is a risk factor for poor outcomes of these conditions (2). Thus, more attention should be paid to the depressive symptoms of older adults.

With the development of information technology and the improvement of residents' living standards, more and more older adults use the Internet. As of June 2022, the size of internet users aged 60 and above in China reached 119 million (4).

According to research data, about half of the middle-aged and older adults spends more than four hours a day online (5). Online activities have become rich and diverse, with instant messaging, short-form videos, online games, and online shopping becoming frequently used activities by older adults (5). In addition, Internet skills respond to the ability to use the Internet. People with stronger internet skills report greater willingness to adopt new technologies (5) as well as benefit from the Internet.

Evidence of the relationship between internet use and depressive symptoms in older adults is mixed. Some research found that internet use in older adults was associated with reducing depressive symptoms (6). Potential mechanisms for this association include providing a sense of self-esteem and control, maintaining and enhancing social relationships, providing leisure activities, and reducing feelings of isolation (7–11). The use of the internet by older adults in their daily lives provides new ideas for improving their depressive symptoms (7–9). However, Lifshitz et al. (12) found major online activities common among older adults, such as: information gathering, interpersonal communication, and leisure, were not associated with depressive symptoms. Moreover, Nie et al. (13) found that internet use among older adults in China was associated with higher depressive symptoms. Likewise, comparisons of internet users with others displayed a significantly higher level of depressive symptoms and anxiety among the former (14).

These contrasting findings can be explained by the macroscopic approach applied in many studies that have explored the association between internet use and depressive symptoms in older adults. On the one hand, Previous studies have used only a single indicator of whether or not they use the Internet to measure older adults' online behavior, ignoring older adults' rich internet use practices. On the other hand, Previous studies have not considered the stage-specific characteristics of Internet-generated benefits, i.e., internet use progressively generates benefits from internet access, time spent on the internet, internet skills, and types of online activities. When considering again the effect of internet use activities on depressive symptoms, the time spent on the internet and the internet skills of the sample need to be controlled.

Therefore, to remedy the shortcomings of these studies and to correctly reveal the relationship between internet use and depressive symptoms among older adults in China, time spent on the internet and internet skills should be considered, and on this basis, types of online activities in improving depressive symptoms should be examined. In this study, we conducted a data reanalysis based on the China Family Panel Studies (CFPS) data to explore the relationship between internet use and depressive symptoms in older adults, intending to provide an empirical basis for practices to improve depressive symptoms in older adults.

2. Methods

2.1. Sample and data collection

We performed a cross-sectional, secondary analysis using the data obtained from Wave 5 in 2020 of the China Family Panel Studies (CFPS), which is a national longitudinal survey started in 2010 by the Institute of Social Science Survey (ISSS) at Peking University (15). The CFPS collects individual (separate for children and adults), household, and community-level data through personal interviews (data recorded through computer-assisted personal interviewing techniques) for 25 provinces in China, which cover 95% of China's population. The CFPS interviewed a total of 14,960 households and 42,590 individuals, with a sample of individuals followed every two years.

The sample selection criteria and steps of this study: (1) Extraction of a nationally representative resample of 18,783. (2) There were 4,561 samples of older adults aged $\geq$60 years; (3) Missing samples of the Center for Epidemiologic Studies Depression Scale (CES-D) scores were excluded, and a final sample of 3171 was obtained.

2.2. Variables

2.2.1. Depressive symptoms

The eight-item Center for Epidemiologic Studies Depression Scale (CES-D) was used in CFPS to examine depressive symptoms, which is widely used in China (16) and has shown good validity and reliability (Cronbach's $\alpha = 0.815$) (17). In CFPS, respondents were asked to answer eight questions, namely, "I am in a low spirit" "I find it difficult to do anything" "I cannot sleep well" "I feel happy" "I feel lonely" "I have a happy life" "I feel sad" and "I feel that I cannot continue with my life" including two positive emotions items and six depression items. Response options for each are "Never" (equating to a score of 1), "Sometimes" (a score of 2), "Often" (a score of 3), "Most of the time" (a score of 4) and reverse scoring the results of positive answers. Then we merged these responses into a new indicator, namely depressive symptoms. Scores ranged from 8 to 32, and higher scores indicated greater severity of the depressive symptoms.

2.2.2. Internet use

Internet use was measured in three aspects of this study: time spent on the internet, internet skills, and types of online activities. Time spent on the internet (hours) was calculated by adding up the online duration of mobile devices and computers in a day; the value ranges from 0 to 24. In CFPS in 2020, participants were asked "Do you play online games," "Do you play online shopping," "Do you watch short-form videos" and "Do you use WeChat?" in the past week, and we set the answer to "yes" = 1 and "no" = 0. Internet skills of older adults were measured by summing these 4 items, ranging from 0 to 4, with higher scores representing higher internet skills. By the above question, types of online activities are divided into four items: online games, online shopping, short-form videos, and WeChat. Respectively, each type is treated as a dichotomous variable.

2.2.3. Covariates

Previous studies have found a set of variables associated with internet use and depressive symptoms (i.e., gender, age, education, marital status, monthly household income, place of residence, health status, and so on) (7, 18). What's more, Yu et al. (19) point out that lower memory ability at baseline was associated

TABLE 1 Definition/codes of the potential confounding variables.

Variable	Variable definition and assignment
Sociodemographic variables	
Age	Continuous variable
Gender	0 = Male; 1 = Female
Marital status	0 = Single; 1 = Married
Education attainment	0 = Illiterate; 1 = Primary school; 2 = Junior middle school; 3 = Senior high school; 4 = College and above
Residency	0 = Rural; 1 = Urban
Number of family members	Continuous variable
Household income	Monthly Household income of people living in the household (logarithmically transformed)
Health status	
Self-rated health	According to respondents' self-rated physical health status. 0 = Excellent; 1 = Very good; 2 = Good; 3 = Fair; 4 = Poor
Chronic diseases	Ever had a doctor-diagnosed Chronic disease? 0 = No; 1 = Yes
Degree of memory	0 = Only remember one thing; 1 = Only remember a few; 2 = Remember half the things; 3 = Remember most things; 4 = R remember everything

with worse depressive symptoms levels at follow-up. Therefore, to reduce the effects of confounding variables and provide stronger evidence of the association between internet use and depressive symptoms. We need to adjust for these variables, which include two main areas: sociodemographic variables and health status. The descriptive statistics of variables were shown in Table 1.

2.3. Statistical analysis

Demographic characteristics of the sample were studied using descriptive analysis. The mean value (SD) is used for continuous variables and the frequency distribution is used for categorical variables.

We used multiple linear regression to analyze the relationship between internet use and depressive symptoms. A total of seven models were included, model one only included control variables. In model two, we added the time spent on the internet, and internet skills variables were added in model three. Models four to seven added types of online activities (online games, online shopping, short-form videos, and WeChat) in turn. Analyses were done using R (version 4.0.3; The R Foundation), and the level of significance was set at $P < 0.05$.

3. Results

3.1. Descriptive statistics

The basic characteristics of the sample and the distribution of the study variables by internet use for this study are shown in Table 2. Most of the samples (2,627/3,171, 82.8%) were married.

TABLE 2 Sample characteristics of respondents.

Variable	Class	*n* (%)	Mean (SD)	Missing value (%)
Gender	Female	1,532 (48.3)		0 (0)
	Male	1,639 (51.7)		
Age			68 (5.8)	0 (0)
Residency	Rural	1,588 (50.3)		14 (0.44)
	Urban	1,569 (49.7)		
Educational attainment	Illiterate	1,294 (40.8)		0 (0)
	Primary school	713 (22.5)		
	Junior high school	659 (20.8)		
	Senior high school	417 (13.2)		
	College and above	88 (2.8)		
Marital status	Single	544 (17.2)		0 (0)
	Married	2627 (82.8)		
Number of family members			3.8 (2.2)	3 (0.09)
Household income (¥[a])			1958.33 (2778.26)	129 (4.07)
Self-rated health	Excellent	344 (10.8)		0 (0)
	Very good	346 (10.9)		
	Good	1149 (36.2)		
	Fair	556 (17.5)		
	Poor	776 (24.5)		
Chronic diseases	No	2,293 (72.4)		2 (0.06)
	Yes	876 (27.6)		
Degree of memory	Only remember one thing	952 (30.2)		18 (0.57)
	Only remember a few	580 (18.4)		
	Remember half the things	814 (25.8)		
	Remember most things	453 (14.4)		
	Remember everything	354 (11.2)		
Time spent on the internet			0.4 (1.3)	11 (0.35)
Depressive symptoms			13.6 (4.5)	0 (0)

[a]A currency exchange rate of US $1 = ¥6.79 is applicable.

N.B. The total percentage may not equal to 100 due to rounding.

There were slightly more males (51.7%) than females (48.3%), and the percentage of those living in rural areas is 50.3%. The average age of the sample was 68 (*SD* 5.8) years. There were 1294 samples who were illiterate. The mean monthly household income of the participants was ¥1958.33 (SD ¥2778.26; Mean US $288.41, SD US $409.17). The proportion of self-rated health as relatively good accounted for the most (1,149/3,171, 36.2%). There were 876 samples with chronic diseases. Regarding the degree of memory, there were 952 samples who only remembered one thing in the past week. The average online time was 0.4 (*SD* 1.3) h. As shown in Figure 1. The largest proportion of older adults with 0 Internet skills (2,507/3,170, 79.1%). While only 1.0% (33/3,170) of 4 Internet skills. As for different activities of internet use, the percentages of those using WeChat, short-form videos, online shopping, and online games were 19.7, 4.0, 4.9, and 1.5%, respectively (Figure 2). The average score for depression symptoms was 13.6 (*SD* 4.5).

3.2. Relationship between internet use and depressive symptoms

It shows the results of multiple linear regression models examining the associations between internet use and depression symptoms (Tables 3, 4). All models were statistically significant (for example, model one, $F = 49.3$, $P < 0.001$), and the independent variables could better explain the overall variation of depressive symptom scores (for example, Model one, $R^2 = 0.176$). The results of model one showed that male ($\beta = -0.63$, $P < 0.001$), older ($\beta = -0.05$, $P < 0.001$), living in urban ($\beta = -0.71$, $P < 0.001$), married ($\beta = -1.01$, $P < 0.001$), higher education (junior high school: $\beta = -0.58$, $P = 0.008$; High school: $\beta = -0.87$, $P < 0.001$), better household income ($\beta = -0.37$, $P < 0.001$), better memory ($\beta = -0.49$, $P < 0.001$) were associated with lower depressive symptoms; Chronic disease ($\beta = 0.6$, $P < 0.001$) and lower self-rated health score ($\beta = 0.84$, $P < 0.001$) were associated with higher depressive symptoms. The results of model two and three showed that the higher internet skills ($\beta = -0.42$, $P < 0.001$), the lower the depressive symptoms; the longer the online time ($\beta = 0.14$, $P = 0.03$), and the more severe the depressive symptoms. The positive association between the time spent on the internet and the aggravation of depressive symptoms was more obvious when considering the skills ($\beta = 0.31$, $P < 0.001$).

Taking into account control variables, time spent on the internet, and internet skills. The effect of different types of online activities on depressive symptoms needs to be considered (Table 4). The results showed that watching short-form videos ($\beta = 1.24$, $P = 0.049$) was associated with higher depressive symptoms, and using WeChat ($\beta = -0.96$, $P = 0.040$) was associated with lower depressive symptoms, while playing online games and online shopping had no significant effect.

4. Discussion

4.1. Principal findings

Taking into account the rich internet use of older adults in China and the phased characteristics of internet use, this study aims to reveal the complex association between internet use and depressive symptoms in older adults by using CFPS. The main conclusions are as follows: First, longer time of internet use is associated with higher depressive symptoms. Second, higher internet skills are associated with lower depressive symptoms. Third, watching short-form videos is associated with higher depressive symptoms, and using WeChat is associated with lower depressive symptoms. In general, the effect of internet use on depression symptoms in older adults is a double-edged sword. Previous studies have generally been optimistic about information technology use, but this study reveals the dark side of information technology use.

4.2. Possible explanations and relations to previous studies

The present study showed that being male, older, living in an urban, married, having higher education, and having better household income were associated with lower depressive symptoms. Our finding is consistent with the previous study that demographic-related variables are significantly related to depressive symptoms (7, 18). Lower levels of memory, chronic illness, and lower self-health scores were associated with higher depressive symptoms. Previous literature suggests older adults may experience an increase in depressed affect due to poor memory function (20). Yuan (7) pointed out depression symptoms sum scores increase with the diagnosis of chronic diseases.

The longer the Internet use, the worse the depressive symptoms. Our finding is consistent with a previous study on adolescents (21–23). Wu et al. (23) found adolescents spending more time online had a higher risk of experiencing depression symptoms. An increase of 1 h in average internet usage was related to an increase of 0.69 units in the severity of depressive symptoms (22). Excessive internet use can negatively affect individuals' lives (24–26), which may be explained by the fact that excessive internet use disconnects older adults from fundamental social interactions and activities, thereby impairing their mental health (26).

Our results found that older adults who have higher internet skills generally have lower depressive symptoms. The finding is consistent with previous studies showing the protective effects of higher internet skills on depressive symptoms (27) and the psychological wellbeing of older adults. By mastering internet skills, older adults can obtain required health information (e.g., using a medical website to learn about a health condition), social engagement (video conferencing to see distant relatives, sending text messages to friends or video chatting to buffer against loneliness) and so on to maintain mental health (28, 29).

Playing online games and online shopping have no significant relationship with depressive symptoms in older adults. However, Numerous studies have shown that involvement in leisure activities (e.g., playing online games) has a significant impact on older adults' psychological, improving their quality of life (30, 31). These possible explanations are that this study adopted a nationally representative sample, showing that the proportion of older adults playing online games and online shopping is small; only 1.5% of the sample played online games, and 4.9% shopped online.

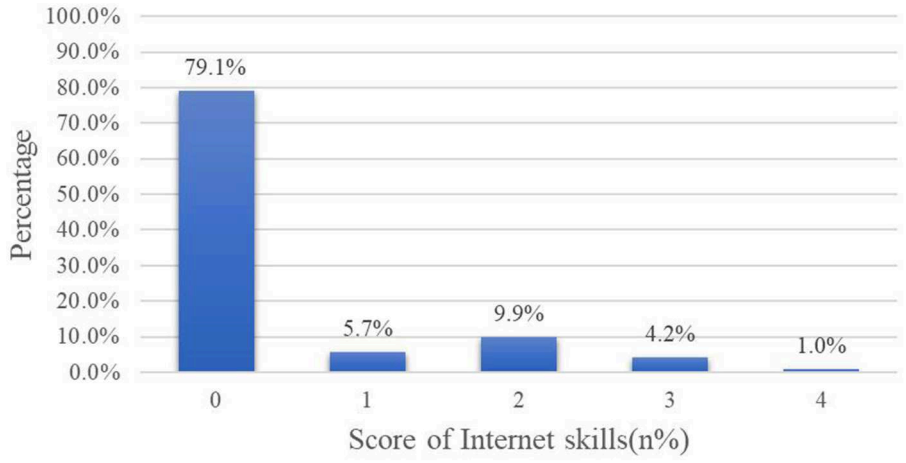

FIGURE 1
Percentage of different internet skills. N.B. The total percentage may not equal to 100 due to rounding.

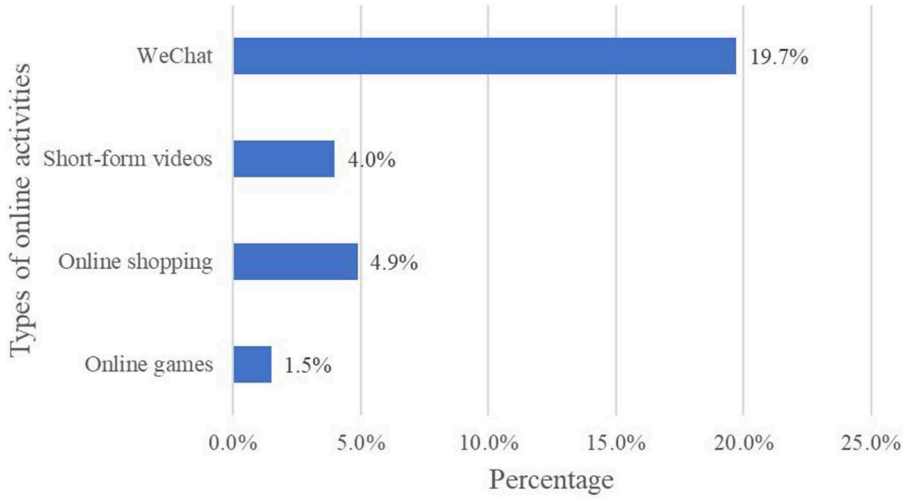

FIGURE 2
Percentage of using different types of online activities.

Besides, this study carefully controlled for time spent on the internet and internet skills effects. Online gaming and online shopping did not affect depression in older adults, at least at this stage.

As for watching short-form videos, it can aggravate depressive symptoms, which is consistent with Perlis et al. (32), who found TikTok usage was significantly associated with a greater risk of an increase in self-reported depressive symptoms. This finding was also consistent with practical observation. Considering the time spent on the internet and internet skills, using short-form videos by older adults may exacerbate depressive symptoms. The reason for this is that briefly stimulating, low-quality short videos in the current internet market are harmful to the mental health of older adults.

Social media use in older adults can potentially improve mental health in older adults (33–35). Qu et al. (34) used a multilevel logistic regression model for data analysis and found a significant reduction in the prevalence of depressive symptoms associated with WeChat use after adjusting for all possible covariates; the results of a review also found that online social networks can be used as a potential social therapy to alleviate depressive symptoms (35). Our findings reinforce previous findings, providing evidence that WeChat use is associated with lower CES-D scores, suggesting that social media use may be beneficial for depressive symptoms. For older populations, contacting family and friends when they were geographically separated and entering intergenerational communication with younger family members are much more

TABLE 3 Effect of time spent on the internet and internet skills on depressive symptoms.

Variable	Model 1			Model 2			Model 3		
	β	*SE*	*P*-value	*β*	*SE*	*P*-value	*β*	*SE*	*P*-value
Time spent on the internet				0.14	0.065	0.030	0.31	0.081	<0.001
Internet skills							−0.42	0.118	<0.001
Gender (reference: female)									
Male	−0.63	0.161	<0.001	−0.63	0.162	<0.001	−0.64	0.161	<0.001
Age	−0.05	0.014	<0.001	−0.05	0.014	0.001	−0.05	0.014	<0.001
Residency (reference: rural)									
Urban	−0.71	0.166	<0.001	−0.75	0.167	<0.001	−0.72	0.167	<0.001
Marital status (reference: single)									
Married	−1.01	0.212	<0.001	−1.00	0.213	<0.001	−1.00	0.212	<0.001
Educational attainment (reference: illiterate)									
Primary school	−0.38	0.202	0.061	−0.39	0.203	0.054	−0.37	0.202	0.068
Junior high school	−0.58	0.218	0.008	−0.62	0.220	0.005	−0.55	0.220	0.012
Senior high school	−0.87	0.262	<0.001	−0.99	0.269	<0.001	−0.84	0.272	0.002
College and above	−0.61	0.496	0.221	−0.72	0.504	0.153	−0.57	0.505	0.259
Number of family members	−0.06	0.034	0.067	−0.06	0.034	0.097	−0.06	0.034	0.079
Chronic diseases (reference: no)									
Yes	0.60	0.175	<0.001	0.59	0.176	<0.001	0.60	0.175	<0.001
Household income	−0.37	0.081	<0.001	−0.40	0.082	<0.001	−0.38	0.082	<0.001
Self–rated health	0.84	0.063	<0.001	0.84	0.063	<0.001	0.83	0.063	<0.001
Degree of memory	−0.49	0.058	<0.001	−0.49	0.059	<0.001	−0.48	0.059	<0.001
R^2	0.176			0.176			0.18		

important needs (36). Therefore, using WeChat can increase the chances of older adults' support of social exchange, reduce social isolation and loneliness, and thus improve the symptoms of depression.

4.3. Limitations

The findings should be interpreted with caution because of the following limitations. First, the data are cross-sectional design; it was impossible to conclude the causal relationship between internet use and depressive symptoms, and subsequent studies should use longitudinal analysis or randomized controlled trials to test the causal effect. Second, depressive symptoms used for the analyses were based on a self-report questionnaire, increasing the possibility of recall bias. Besides, the score of the CES-D scale can evaluate the depressive symptoms of older adults, which cannot be used to judge whether older adults suffer from depression. Third, owing to the limitations of the questionnaires, the analysis only included four types of online activities. The specific contribution of many common online activities to overall depressive symptoms during aging remains unclear. Fourth, the data reanalysis scheme inevitably has limitations in variable measurement. Although there is no clear standard on how to quantify internet skills, the variables selected and constructed in this study are still limited due to the limitations of the data itself, and subsequent studies should consider more accurate and in-depth measurement and analysis.

4.4. Implications for public health

This study finds that information technology is a double-edged sword, as it contributes to successful aging on the one hand and brings back harmful effects on the other. Therefore, how to let older adults thoroughly enjoy digital benefits and a better quality of life in old age while avoiding the dark side of the Internet is an essential issue that the whole society should discuss and solve together in the digital age. From the public perspective, the government, community, and families should participate together: the government should formulate relevant policies to provide institutional protection for older adults to use the Internet; the community should strengthen internet safety propaganda and actively organize internet use training; families should participate in improving internet use literacy of old persons, pay attention to

TABLE 4 Effects of types of online activities on depressive symptoms in older adults.

Variable	Model 4			Model 5			Model 6			Model 7		
	β	*SE*	*P*-value	*β*	*SE*	*P*-value	*β*	*SE*	*P*-value	*β*	*SE*	*P*-value
Online games (reference: no)												
Yes	0.54	0.690	0.434									
Online shopping (reference: no)												
Yes				−0.27	0.470	0.570						
Short–form videos (reference: no)												
Yes							1.24	0.069	0.049			
WeChat (reference: no)												
Yes										−0.96	0.462	0.040
Time spent on the internet	0.35	0.084	<0.001	0.31	0.083	<0.001	0.38	0.109	<0.001	0.33	0.082	<0.001
Internet skills	−0.50	0.133	<0.001	−0.43	0.143	0.003	−0.98	0.250	<0.001	−0.06	0.205	0.758
Gender (reference: female)												
Male	−0.64	0.163	<0.001	−0.63	0.161	<0.001	−0.65	0.172	<0.001	−0.65	0.161	<0.001
Age	−0.05	0.014	<0.001	−0.05	0.143	<0.001	−0.05	0.015	0.001	−0.05	0.014	<0.001
Residency (reference: rural)												
Urban	−0.72	0.168	<0.001	−0.72	0.166	<0.001	−0.79	0.176	<0.001	−0.72	0.167	<0.001
Marital status (reference: single)												
Married	−1.00	0.214	<0.001	−0.95	0.212	<0.001	−0.93	0.225	<0.001	−0.99	0.212	<0.001
Educational attainment (reference: illiterate)												
Primary school	−0.35	0.203	0.081	−0.36	0.202	0.071	−0.29	0.210	0.169	−0.36	0.202	0.079
Junior high school	−0.53	0.222	0.016	−0.55	0.220	0.012	−0.59	0.234	0.012	−0.52	0.221	0.019
Senior high school	−0.79	0.276	0.004	−0.91	0.272	<0.001	−0.71	0.300	0.018	−0.78	0.273	0.004
College and above	−0.50	0.521	0.341	−0.50	0.508	0.323	−0.09	0.570	0.869	−0.50	0.506	0.323
Number of family members	−0.06	0.035	0.077	−0.06	0.034	0.104	−0.07	0.036	0.069	−0.06	0.344	0.071
Chronic diseases (reference: no)												
Yes	0.60	0.177	<0.001	0.62	0.175	<0.001	0.69	0.167	<0.001	0.62	0.175	<0.001
Household income	−0.36	0.083	<0.001	−0.37	0.082	<0.001	−0.33	0.087	<0.001	−0.36	0.082	<0.001
Self–rated health	0.84	0.064	<0.001	0.81	0.063	<0.001	0.81	0.067	<0.001	0.83	0.063	<0.001
Degree of memory	−0.48	0.059	<0.001	−0.49	0.059	<0.001	−0.49	0.623	<0.001	−0.48	0.059	<0.001
R^2	0.179			0.182			0.174			0.181		

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internet use behavior of older adults, and reduce the infringement of certain internet use behaviors on the family network.

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

AM and SY planned the study, performed the data analysis, and wrote the paper. ZL provided comments on the changes. 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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The double-edged impact of Internet use on mental health outcomes among Filipino university students: the mediating role of online social support

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Introduction: Evidence supports both the positive and negative effects of Internet use on mental health outcomes, but it remains unclear on the role of online social support in this relationship. This study examined the link between daily hours of general Internet use and bidimensional mental health (BMMH) through the pathway of online social support (OSSS).

Methods: Drawing from a sample of 247 Filipino university students, this cross-sectional study tested two simple mediation models that considered mental wellbeing and psychological distress as outcome variables.

Results: Findings show that the total effect of Internet use is positive and negative for mental wellbeing and psychological distress, respectively. Online social support mediated the favorable effects of Internet use on BMMH outcomes. However, the introduction of OSSS as a mediator yielded residual direct effects with opposing signs for both models. The resultant inconsistent mediation in the models signifies the double-edged impact of Internet use on mental health, with favorable effects transmitted through online social support.

Discussion: Findings highlight the importance of online social support as a pathway to harness the positive effects of Internet on mental health. Recommendations to improve online social support for students are discussed herein.

KEYWORDS

Internet use, mental health, mental wellbeing, social support, students, psychological distress

1. Introduction

Since the dawn of the twenty-first century, the Internet has become an integral component of human life. Internet-based technologies have become increasingly ubiquitous in various aspects of social life, including education, work, commerce, health, family, community, and governance. Humanity's reliance on the Internet has been further compounded due to the novel coronavirus 2019 (COVID-19) pandemic, when in-person interactions and transactions had to be conducted online. In 2022, 4.95 billion (62.5%) of the total population are connected to the Internet (Kemp, 2022a). Due to the increasing necessity of the Internet in daily living, the United Nations (2016) declared that Internet access is a basic human right. However, despite its utility, the Internet has demonstrated negative consequences on individuals and society, which include concerns over data privacy and security, cybercrimes, widening of socioeconomic divides, physical and mental health, destabilization of social structures and institutions, and other threats to individual and collective wellbeing (Quaglio, 2020).

This study draws its focus on Filipino university students and was conducted during the period of COVID-19 pandemic-induced community quarantine and distance learning in the country. There were a total of 76 million Internet users in the Philippines recorded in January 2022 (Kemp, 2022b). The Internet penetration rate in the college-aged (18–24 years old) population is 86% (Statista, 2022). Kemp (2022b) has indicated an almost 3% increase in new Filipino Internet users from 2021 and 2022, arguably due to the online connectivity demands of the pandemic.

A particular research interest in the fields of digital determinants of health and digital sociology is digital mental health, particularly the influence of the Internet and other Internet-related technologies on mental health outcomes and the pathways where these effects are transmitted. Review evidence suggests that Internet use has both positive and negative outcomes for mental health among higher education students (Rouvinen et al., 2021). Local evidence suggests that increased use of particular Internet technologies (i.e., social media) among Filipino undergraduates is associated with mental health changes during the pandemic (Cleofas et al., 2022a). This study also found that whether college students demonstrate good or poor mental health is based on their problematic or reflective use of the Internet. Education-based research in the Philippines has also noted that poor digital access and tools were linked to poor academic and wellbeing outcomes among students (e.g., Cho et al., 2021).

However, research on the role of seeking and receiving social support online on mental health outcomes remains to be unclear, as suggested by Chang et al. (2022). The Philippines is often described as a collectivist culture (Flaming et al., 2010); hence, we argue that online social support is a potential salient mediator between Internet use and mental health, especially during the time of the pandemic, when Filipino students have become more reliant on Internet technologies to meet their social and intimacy needs due to COVID-induced physical distancing (Cleofas et al., 2022b). In this study, online social support is characterized as the experiences of students in socializing online in order to access benefits and fulfill their emotional, informational, companionship, and instrumental needs. These facets of social support in the online space has been indicated as promoters of mental health. Hence, this study attempts to determine the mediating role of online support on the relationship between Internet use and mental health outcomes.

2. Literature review and conceptual framework

2.1. Internet use and wellbeing theory

This study appeals to the theoretical framework of Castellacci and Tveito (2018) that suggests explanatory pathways wherein Internet use can improve wellbeing outcomes. They posit that Internet use exposes individuals to opportunities to improve the personal and work lives of individuals. The positive effects of Internet usage on the various domains of life can improve the culture, capabilities, and psychological functioning, which in turn optimizes wellbeing. This is confirmed by a review of higher education studies, which suggests that Internet use can promote physical, mental, social, and intellectual health among university students (Rouvinen et al., 2021). Moreover, Castellacci and Tveito's (2018) proposed that the Internet facilitates positive life outcomes by introducing changes in the overall use of time. Hence, the independent variable of interest for this study is daily hours of Internet use (DHIU), simply assessed through the self-reported average number of hours of Internet usage per day.

2.2. Bidimensional mental health

Castellacci and Tveito (2018) Internet use and wellbeing theory proposed that Internet use can enhance psychological functioning (i.e., mental health). Moreover, Rouvinen et al. (2021) suggested that Internet usage can influence the mental health of higher education students. The present study conceptualizes mental health using the bidimensional model (Renshaw and Bolognino, 2017). The bidimensional model (or dual-factor) of mental health (BMMH) explains that the assessment of mental health outcomes must be two-pronged and should include both positive and negative aspects of mental health. This study operationalizes the positive component of BMMH as ***mental wellbeing*** (Tennant et al., 2007), which refers to a eudemonic and hedonistic state where one feels optimistic, useful, relaxed, close to people, and able to think clearly, decide, and deal with one's problems. On the other hand, the negative component of BMMH is operationalized as ***psychological distress*** (Kessler et al., 2003), which refers to the extent one feels anxious, depressed, nervous, and restless. Mental wellbeing and psychological distress are the two dependent variables of interest in the present study.

On the other hand, in terms of the relationship between Internet use and mental health outcomes, results from the extant literature vary based on the measures used for the variables and the type/specificity of the Internet technology used (e.g., social media and Internet gaming). Rouvinen et al. (2021) suggest that Internet use in higher education can lead to promotive and/or detrimental effects on mental health. On the one hand, prior research among university students has evinced the link of various Internet-related technologies to positive mental health outcomes, such as higher mental wellbeing (Cleofas et al., 2022a), attainment of psychosocial developmental tasks (Cleofas et al., 2022b), satisfaction with daily habits (Austin-McCain, 2017), improved stress management (Saini et al., 2020), enhanced resilience (Sage et al., 2021), and engagement in psychological interventions (Lattie et al., 2019). On the other hand, findings from systematic reviews of studies among university students have demonstrated the association of Internet use with poor mental health outcomes, such as depression, anxiety, maladaptive cognitions, behavioral addictions, and loneliness (Rouvinen et al., 2021; Valkenburg et al., 2022). Hence, our hypotheses for the relationship between Internet use and mental health are non-directional:

H_{1a}: Daily hours of Internet use predicts mental wellbeing.
H_{1b}: Daily hours of Internet use predicts psychological distress.

2.3. Online social support

The theory of Castellacci and Tveito (2018) explains that the nature of the influence of Internet use on psychological functioning (i.e., mental health) is based on particular life domains where the Internet is used by an individual. Among the four domains identified by Castellacci and Tveito, the present study will focus specifically on ***social life***. For this study, the social domain of Internet use is operationalized as ***online social support*** (OSSS). Following Nick et al. (2018), OSSS is constituted of four types of social support received or experienced by individuals in an online environment. These include esteem and emotional support (e.g., receiving validation and care online), social companionship (e.g., experiencing a sense of belongingness online), informational support (e.g., sharing new information or perspectives and solving problems online), and instrumental support (e.g., receiving material support or services online). Online social support can exist in any online platform (Nick et al., 2018); hence our use of a generalized measure of Internet use as hours per day.

In particular, during the period of the COVID-19 pandemic when this study was conducted, research in the Philippines (Cleofas et al., 2022b) and elsewhere (e.g., Onat Kocabiyik, 2021; Bahfiarti and Arianto, 2022) have demonstrated the need for social connections and support as primary motivations for students to increase their use of Internet-based technologies. Previous research has indicated that those who spend more time online receive higher levels of online social support (Nick et al., 2018). Thus, we hypothesize that:

H_2: Daily hours of Internet use positively predicts online social support.

Furthermore, online social support has also been shown to have beneficial effects on mental health. For instance, Nick et al. (2018) have indicated that OSSS increases self-esteem and decreases depressive symptoms. In addition, Ali (2020) suggests that OSSS is a positive predictor of psychological wellbeing. Evidence from a systematic review has linked online social support with improved satisfaction with life and self-identity, and decreased social anxiety and loneliness (Zhou and Cheng, 2022a). Taken together, these studies indicate that OSSS is a facilitating factor of mental wellbeing and a protective factor against distress. Hence, we hypothesize that:

H_{3a}: Online social support positively predicts mental wellbeing.
H_{3b}: Online social support negatively predicts psychological distress.

Moreover, Castellacci and Tveito's (2018) also proposed that in terms of its relationship to psychological functioning and wellbeing, the Internet provides both opportunities to flourish and risks to flounder. This proposition is further evinced by the previous section that demonstrates the double-edged effect of Internet use on mental health outcomes. Castellacci and Tveito further posit that the social-domain-related function of the Internet can be examined as a channel through which the positive or negative impact of the Internet on psychological functioning (i.e., mental health) can be transmitted. This mediating role of social use of Internet is evinced by prior studies (Brailovskaia et al., 2021; Meshi and Ellithorpe, 2021; Chang et al., 2022). Thus, there is reason to suspect that online social support is a social domain that can mediate and further explain the relationship between Internet use and the BMMH outcomes among college students.

H_{4a}: Daily hours of Internet use has an indirect effect on mental wellbeing through the pathway of online social support.
H_{4b}: Daily hours of Internet use has an indirect effect on psychological distress through the pathway of online social support.

2.4. The present study

The aim of the present study is to examine the relationship between daily hours of Internet use and BMMH outcomes and the mediating role of online social support in this relationship among Filipino university students. Cognizant of the current state of literature that indicates the inconsistent association between general Internet use and mental health, we attempt to contribute by offering an explanatory pathway by including OSSS as a mediator, following the theoretical assertions of Castellacci and Tveito's (2018). Two simple mediation models representing the two BMMH outcomes (i.e., mental wellbeing and psychological distress) will be tested to address the hypotheses of the study (see Figure 1). While there had been studies in the past that tested similar models, they focused on offline or generalized social support (Glaser et al., 2018; Lin et al., 2021) and/or did not use BMMH as a framework to measure mental health as outcomes (Brailovskaia et al., 2021; Meshi and Ellithorpe, 2021; Chang et al., 2022). Additionally, these studies had inconsistent findings. We believe that specifying the type of social support (i.e., online) and assessing dual-factor mental health outcomes can help in drawing more nuanced insights about the variables and relationships being tested.

3. Methods

3.1. Research design and participants

This study utilized a quantitative, cross-sectional research design, specifically simple mediation analysis. A simple mediation study examines how the effect of an independent variable (i.e., Internet use) on a dependent/outcome variable (i.e., mental health outcome) is transmitted through a mediating variable (i.e., online social support) (Fritz and Mackinnon, 2007). The target participants for this study are undergraduate students from a selected private university in Manila, Philippines. The respondents were recruited regardless of their degree, college, or duration of curriculum. This is to ensure that all sectors of the student community are represented in the study. Following Fritz and Mackinnon (2007), the minimum sample size required to achieve 0.80 power for one simple mediation model using the variables in this study is 88 ($\alpha = 0.39$, $\beta = 0.59$, $\tau' = 0.39$). Hence, two mediation models will require at least 176 respondents. The final sample size of the study is 247. A plurality of the respondents are 21 years old (25.1%, $M = 20.06$, $SD = 1.40$). Males (51%) and females (49%) are approximately equal in representation.

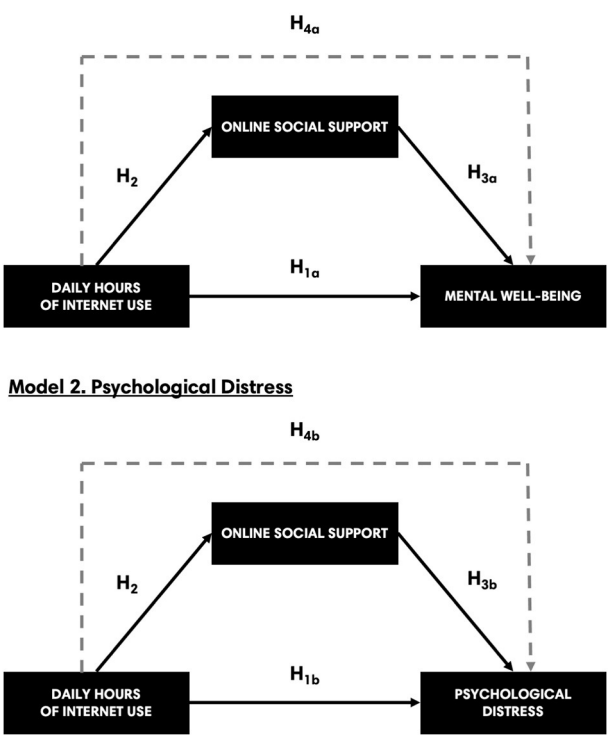

FIGURE 1
Two simple mediation models: Model 1 presents the hypothesized indirect effect of DHIU on mental wellbeing through OSSS; Model 2 presents the hypothesized indirect effect of DHI on psychological distress through OSSS.

3.2. Study procedure and ethical considerations

The data for this study was collected via an online survey (Google Forms) during the first quarter of 2022. Convenience sampling was employed to recruit respondents. The link was sent to the email addresses and social media accounts of the target participants. The study protocol is adherent to the principles of the Declaration of Helsinki and was granted administrative clearance for ethical conduct of research from the researchers' home department at the university. Informed consent was secured from all respondents through the first page of the online survey form. No private and personal details were collected from the participants. All data gathered were anonymized and secured in a double authenticated cloud storage.

3.3. Instruments

3.3.1. Daily hours of internet use

To measure self-reported DHIU, we asked, "on average, how many hours do you spend on the Internet daily?" on the survey. They were instructed to type in a number from 0 to 24 in the textbox provided with the question.

3.3.2. Online social support scale

OSSS is a 40-item scale developed by Nick et al. (2018) to measure the extent to which respondents receive social support in the forms of emotional, social companionship, informational and instrumental while they interacted with others on online platforms over the last 2 months. For each item, respondents were asked how often they experienced particular social interactions (e.g., "*When I'm online, I talk or do things with other people*") and were instructed to respond using a 5-point scale (0 = never, 4 = a lot). The OSSS exhibited high internal consistency (α = 0.94–0.95) and strong psychometric properties (see Nick et al., 2018). Scores ranged from 0 to 160. For this sample, the Cronbach alpha score for OSSS is 0.992. According to the developers' website, the use of the OSSS is free as long as attribution and citation of the authors are made.

3.3.3. Short Warwick-Edinburgh mental wellbeing scale

SWEMWBS is a 7-item scale that assesses positive aspects of mental health (Tennant et al., 2007). Participants were instructed to respond to each item that described experiences of mental wellbeing (e.g., "*I've been able to make up my own mind about things.*") in the last 2 weeks using a 5-point scale (1 = none of the time, 5 = all of the time). Scores were transformed based on developer instructions. SWEMWBS has demonstrated robust psychometric properties (e.g., Ringdal et al., 2018), including an acceptable reliability score in the Philippine population (α = 0.87, Cleofas and Oducado, 2022). The range of possible scores is from 7 to 35. For this sample, SWEMWBS garnered a Cronbach alpha value of 0.962. The use of this instrument has been registered at the developer's website.

3.3.4. Kessler psychological distress scale

K10 is a 10-item brief assessment for psychological distress developed by Kessler et al. (2003). K10 is a widely used scale to estimate the likelihood of mental health problems, such as depression, anxiety, stress, and agitation. The respondent was asked to rate each item (e.g., "*In the past 4 weeks, about how often did you feel restless or fidgety*?") using a 5-point scale (1 = none of the time, 5 = all of the time). K10 has been noted to have good internal consistency (α = 0.84) and construct validity (see Hoffman et al., 2022). Scores ranged from 10 to 50. For this sample, the Cronbach Alpha value for K10 is 0.968. Permission was sought for the use of this instrument.

3.4. Data analysis procedure

Mean and standard deviation was used to summarize the key variables. Bivariate correlations among the variables were tested using Pearson r correlation. Mediation analyses, including the computation of total, indirect and direct effects and path estimates, were carried out using the Mediation Module of JAMOVI version 2.0.0.0. Kolmogorov-Smirnov test results for the key variables signify normality. Bootstrapping using 5,000 replicates was performed in the mediation. R^2 scores for OSSS,

SWEMWBS, and K10 were computed using the Mediation Analysis module of JASP 0.16.1. Significance level was set at $p < 0.05$.

4. Results

4.1. Descriptive and bivariate statistics

Descriptive results in Table 1 indicate that college youth respondents spend an average of 10.312 h ($SD = 5.120$) on the Internet daily. Daily hours of Internet use (DHIU) ranged from 2 to 24 h. On the other hand, the mean score for online social support (OSSS) is 98.457 ($SD = 43.325$, Range = 16–160). As for mental health outcomes, average SWEMWBS scores indicate that respondents experience moderate mental wellbeing ($M = 21.112$, $SD = 6.739$), while K10 scores indicate that they are likely to have a moderate disorder ($M = 29.437$, $SD = 12.118$).

Bivariate statistical results indicate that DHIU is significantly positively correlated with OSSS ($r = 0.395$, $p < 0.001$). Moreover, SWEMWBS demonstrated significant positive correlations with DHIU ($r = 0.146$, $p = 0.021$) and OSSS ($r = 0.802$, $p < 0.001$). Meanwhile, psychological distress (K10) exhibited significant negative correlations with DHIU ($r = -0.194$, $p = 0.002$) and OSSS ($r = -0.742$, $p < 0.001$) (see Table 1). This means that higher usage of the Internet was observed among those with high online social support and mental wellbeing, and low psychological distress.

4.2. Simple mediation analyses results

The study carried out two simple mediation analyses, examining whether the relationship between Internet use and mental health outcomes (i.e., mental wellbeing and psychological distress) would be mediated by online social support. Table 2 presents the direct, indirect, and total effects among the key variables of the study.

Model 1 (mental wellbeing model) results suggest that without accounting for OSSS, the total effect of DHIU on SWEMWBS is significant and positive in nature ($B = 0.192$, $p = 0.009$). When we added OSSS as a mediating variable, the indirect effect of DHIU on SWEMWBS was significant and positive in nature ($B = 0.459$, $p < 0.001$); however, the residual direct effect of DHIU on SWEMWBS, although significant, became negative ($B = -0.267$, $p < 0.001$). The opposing signs of the direct and indirect effects suggest an *inconsistent mediation*. Path estimates indicate that DHIU positively predicts OSSS ($B = 3.345$, $p < 0.001$), and OSSS positively predicts SWEMWBS ($B = 0.137$, $p < 0.001$). Model 1 explains 15.6% of the variance of OSSS and 67.9% for SWEMWBS. This means that the effects of Internet on mental wellbeing may be positive and negative, with the positive effect coursing through online social support.

Model 2 (psychological distress model) results indicate that before accounting for OSSS, the total effect of DHIU to K10 is significant and negative in nature ($B = -0.460$, $p = 0.001$). When we included OSSS as a mediating variable, the indirect effect of DHIU on K10 was significant and negative in nature ($B = -0.737$, $p < 0.001$); however, the resulting residual direct effect of DHIU on K10, albeit significant, became positive ($B = 0.277$, $p < 0.020$). Like the first model, the competing signs of the direct and indirect effects in model 2 also indicate an *inconsistent mediation*. Path estimates suggest that DHIU positively predicts OSSS ($B = 3.345$, $p < 0.001$), and OSSS negatively predicts K10 ($B = -0.220$, $p < 0.001$). Model 2 explains 15.6% of the variance of OSSS and 56.2% for K10. This means that the effects of Internet on psychological distress may be positive and negative, with the negative effect coursing through online social support.

5. Discussion

The main objective of this study is to describe the role of online social support as a pathway through which Internet use can influence bidimensional mental health among Filipino students in a selected private university. Our research extends the literature by providing empirical evidence that links social-domain-related use of Internet-based technologies can explain how the Internet facilitates wellbeing. Similar to the outcomes of previous COVID-19 research done among Filipino adults (Egcas et al., 2021; Aruta, 2022; Cleofas et al., 2022a), the findings of the present study indicate that college student respondents have moderate mental wellbeing and are likely to experience moderate psychological distress symptoms. During the time this study was conducted, it was the second year of the pandemic and community quarantine in the Philippines. The sustained restrictions due to COVID-19 may explain the persistence of below optimal mental health of the students. These sustained levels in BMMH outcomes support the claim that the pandemic-induced societal disruptions can cause lasting effects on psychosocial health and developmental outcomes of young people during the latter periods of and even beyond the outbreak (Settersten et al., 2020).

Moreover, our findings confirm our first hypothesis: when unmediated, Internet use has a positive and negative total effect on mental wellbeing and psychological distress, respectively. This is consistent with prior evidence, which indicates the promotive influence of using Internet-based technologies on psychological functioning (Castellacci and Tveito, 2018) and mental health (Rouvinen et al., 2021). Moreover, Internet and gadget access were noted as protective factors against poor mental health among Filipino college students during the early months of the COVID-19 pandemic (Cleofas and Rocha, 2021).

5.1. Internet use facilitates online social support

As regards the second hypothesis of the study, our findings indicate a significant positive relationship between DHIU and OSSS. This corroborates the results of previous studies in the United States (Nick et al., 2018; Politte-Corn et al., 2022) and China (Chang et al., 2022). In the Philippines, Internet-based technologies, such as social media, have been used to meet belongingness needs, such as seeking help and receiving care from friends and family members and getting information from

TABLE 1 Descriptive statistics, internal consistency scores, and correlational analysis among key variables ($N = 247$).

Variables	Mean (SD)	Range	Cronbach's alpha	Correlation coefficients		
				(1)	(2)	(3)
(1) DHIU	10.312 (5.120)	2–24	–			
(2) OSS	98.457 (43.325)	16–160	0.992	0.395***		
(3) SWEMWBS[a]	21.112 (6.739)	7–35	0.962	0.146*	0.802***	
(4) K10[b]	29.437 (12.118)	10–50	0.968	−0.194**	−0.742***	−0.866***

*p < 0.05.
**p < 0.01.
***p < 0.001.
[a]Interpretation for SWEMWBS: low = 7–20; moderate = 21–27; high = 28–35.
[b]Interpretation for K10: likely to be well = 10–19; likely to have a mild disorder = 20–24; likely to have a moderate disorder = 25–29; likely to have a severe disorder = 30–50.

TABLE 2 Simple mediation analyses for daily hours of Internet use (DHIU), online social support (OSS), and bidimensional mental health outcomes (i.e., SWEMWBS and K10).

Paths	Estimates (95%CI)[a]		
	Direct effect	Indirect effect	Total effect
Model 1 (Mental wellbeing):			
DHIU → OSS	3.345 (2.425 to 4.276)***		
OSS → SWEMWBS	0.137 (0.126 to 0.149)***		
DHIU → SWEMWBS	−0.267 (−0.374 to −0.167)***		0.192 (0.031 to 0.330)**
DHIU → OSS → SWEMWBS		0.459 (0.325 to 0.598)***	
Model 2 (Psychological distress):			
DHIU → OSS	3.345 (2.377 to 4.191)***		
OSS → K10	−0.220 (−0.2416 to −0.199)***		
DHIU → K10	0.277 (0.046 to 0.515)*		−0.460 (−0.716 to −0.160)**
DHIU → OSS → K10		−0.737 (−0.966 to −0.516)***	

*p < 0.05.
**p < 0.01.
***p < 0.001.
[a]Bootstrapped estimates using 5,000 replicates.

classmates among undergraduate students during the period of COVID-19 (Cleofas et al., 2022b).

5.2. Online social support is linked to favorable mental health outcomes

Our third set of hypotheses is confirmed: online social support positively and negatively predicts mental wellbeing and psychological distress, respectively. The link between online social support and higher wellbeing outcomes has also been indicated by previous studies in Norway (Brandtzaeg and Lüders, 2021) and China (Zhou and Cheng, 2022b). On the other hand, studies in the United States (Nick et al., 2018; Polite-Corn et al., 2022) and Germany (Brailovskaia et al., 2021) suggested that OSSS is inversely correlated with mental health challenges such as stress, depression, anxiety, and behavioral addictions.

5.3. The double-edged impact of DHIU and BMMH outcomes when mediated by OSSS

For both the SWEMWBS and K10 models, two key findings emerged when OSSS was accounted for as a mediator between DHIU and BMMH outcomes. First is that online social support significantly mediates the relationship between Internet use and mental health, such that DHIU's positive effect on mental wellbeing and negative effect on psychological distress is strengthened when transmitted through OSSS. This finding confirms Castellacci and Tveito's (2018) proposition: the Internet affords individuals opportunities for social connections and community building, which improves their access to social support and, consequently, improves psychological functioning. Access to the Internet exposes university students to engage in socializing, expand social capital, academic support from other university entities, and receive informational support for health needs (Rouvinen et al., 2021; Cleofas et al., 2022b). These online-based social benefits of the Internet help promote mental wellness and decrease psychopathologies, as seen in prior research (Castellacci and Tveito, 2018; Nick et al., 2018), especially during the social distancing periods of the pandemic when most social interactions transitioned online (Brandtzaeg and Lüders, 2021; Cleofas et al., 2022a).

Second, after the inclusion of online social support as a mediator, estimates of the direct effect of DHIU on BMMH outcomes yielded signs that oppose the total and indirect effect estimates. On the one hand, Internet use transmitted through the channel of online social support increases mental wellbeing and decreases psychological distress. On the other hand, the unmediated residual direct pathway reveals detrimental effects of DHIU on BMMH outcomes. Similarly, studies have demonstrated various socio-behavioral variables as inconsistent or competing mediators of Internet technologies and psychological outcomes (Chan, 2014; Zeng et al., 2021; Chang et al., 2022; She et al., 2023).

This inconsistent mediation signifies the double-edged impact of Internet use on mental health and supports the theoretical claims of the Internet use and wellbeing theory, wherein Internet-based technologies can have both positive and negative effects on wellbeing based on how they are used, and the personal and social characteristics of individuals that use them (Castellacci and Tveito, 2018). This two-pronged nature of Internet-social/mental health relationships has also been noted in the university student population (Rouvinen et al., 2021).

5.4. Limitations

Our study has several limitations. First, ours is a non-random sample from a single university and culture, which may decrease the generalizability of our results. Second, we only used a regression-based strategy to test our mediation model instead of more robust statistical methods like structural equation modeling (SEM). Moreover, our study could have benefited from a more scale-based measure of Internet use instead of the simple self-reported number of hours of Internet use daily. Additional variables like social media use could not be included due to limitations of sample size. Future studies should consider more specific measures of Internet use, administer to a larger random non-student sample, include covariates and other mediating variables, and compute using more advanced statistical tools. Lastly, since this study is cross-sectional in nature, causality among the relationships could not be determined. Future research should design longitudinal protocols further examine the model forwarded in this study.

6. Conclusion

In conclusion, the findings of the present study indicate the double-edged impact of Internet use on bidimensional mental health among Filipino university students, and the role of online social support as a pathway that affords the benefits of the Internet on mental health. Internet use contributes to enhanced mental wellbeing and decreased psychological distress through increased online social support.

6.1. Implications

Theoretically, the present study contributes to the field of digital mental health by describing the opposing effects of Internet use on mental health outcomes and how its favorable impact on mental health is transmitted through online social support in the case of Filipino university students. The study also provided empirical evidence that demonstrates selected theoretical claims of the Internet use and wellbeing theory (Castellacci and Tveito, 2018), particularly the effect of Internet usage on psychological functioning through the channel of social life. Future research can further utilize the other life domains proposed by the theory, such as work and consumption, and other personal (i.e., capabilities and culture) and environmental factors (i.e., physical and social-institutional) that may help in explaining the pathway leading to negative effects on Internet on BMMH outcomes.

As regards practical implications, our study provides evidence that can inform mental health promotion practitioners in developing in-person and telepsychology interventions that empower students to positively exploit the social-support opportunities found in online platforms. Moreover, school administrators, teachers, and personnel should provide online and offline activities venues for students to socialize, gain social support and increase social capital. We also recommend the creation of programs and policies that can capacitate salient actors in the lives of students (i.e., family, friends, classmates, teachers, health, helping professionals, and community leaders) on how to provide effective social support online.

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 Department of Sociology and Behavioral Sciences, De La Salle University Manila. The patients/participants provided their written informed consent to participate in this study.

Author contributions

PA, AA, AG, and BS: conceptualization, protocol development, data gathering, initial data analysis, and writing of initial draft. JC: conceptualization, protocol development, final data analysis, and writing of final manuscript. 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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Children's Internet use and physical and psychosocial development

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Introduction: Internet use (IU) commonly refers to sedentary lifestyle and may be addictive, especially among children. The aim of this study was to investigate the relationship between IU and some aspects of child physical and psychosocial development.

Methodology: We conducted a cross-sectional survey by using a screen-time based sedentary behavior questionnaire and Strengths and Difficulties Questionnaire (SDQ)—among 836 primary school children in the Braničevo District. The children's medical records were analysed for vision problems and spinal deformities. Their body weight (BW) and height (BH) were measured and body mass index (BMI) was calculated as BW in kilograms divided by BH in meters squared (kg/m^2).

Results: The average age of respondents was 13.4 (SD 1.2) years. The mean duration of daily Internet use and sedentary behavior was 236 (SD 156) and 422 (SD 184) minutes, respectively. There was no significant correlation between daily IU and vision problems (near sightedness, farsightedness, astigmatism, strabismus), and spinal deformities. However, daily Internet use is significantly associated with obesity ($p<0.001$) and sedentary behavior ($p=0.01$). There was significant correlation between emotional symptoms with total Internet usage time, and total sedentary score ($p<0.001$ for both, $r=0.141$ and $r=0.132$, respectively). There was a positive correlation between the total sedentary score of children and hyperactivity/inattention ($r=0.167$, $p<0.001$), emotional symptoms ($r=0.132$, $p<0.001$), and conduct problems ($r=0.084$, $p<0.01$).

Conclusion: In our study, children's Internet use was associated with obesity, psychological disturbances and social maladjustment.

KEYWORDS

Internet use, schoolchildren, obesity, sedentary behavior, vision, spine deformities, physical development, psychosocial development

1. Introduction

The Internet has been increasingly used for obtaining information, entertainment, socialization and education. The Internet overuse among children may lead to an increase in sedentary habits and health problems such as the following: obesity, poor posture, psychological disturbances and eye disorders (1–3). The American Academy of Pediatrics (AAP) recommends that the time spent in front of screens on any digital device should not be longer than 2 h per day (4). The data obtained from the study, conducted in seven European countries including: Germany, Greece, Iceland, the Netherlands, Poland, Romania, and Spain, indicate an association between Internet use and overweight/obesity among adolescents (5). Asian countries also encounter similar problems with children's obesity, which may be connected to Internet addiction (6–8).

Internet overuse has been associated with developing cumulative musculoskeletal disorders (MSDs) and computer vision syndrome (CVS). MSDs are often characterized with muscle fatigue and discomfort, leading to pain (9, 10). A previous study on children confirmed the fact that there was an association between computer use and the occurrence of MSDs (11). Indeed, heavy use of digital devices is also associated with the new ophthalmic syndromes: "digital eye strain" (12) and "video game vision" (13). The findings of a recent study conducted among schoolchildren in Qatar revealed a higher prevalence of vision disorders among frequent Internet users and television viewers (14). However, The Collaborative Longitudinal Evaluation of Ethnicity and Refractive Error (*CLEERE*) Study Group showed that near work activities in myopic-children did not differ from the emmetropic ones (15). Sherwin et al. performed a meta-analysis and found that outdoor time might be protective against myopia (16). Epidemiological studies have indicated that musculoskeletal and visual problems in childhood might be tracked on into adulthood (17). Excessive Internet use (IU) has been associated whit adverse psychosocial development and functioning, including social isolation and impaired social skills among adolescents (18–20). Internet use has also been associated with attention deficit, hyperactivity disorder (21) and major depressive episodes (22).

The aim of our study was to investigate the relationship between excessive IU and some aspects of child physical and psychosocial development.

2. Materials and methods

2.1. Sampling

This cross-sectional study was performed on a sample of 836 children (response rate 98.6%) from two urban and two rural primary schools in the Braničevo district, Serbia. The study was carried out from April 2019 to May 2019.

2.2. Questionnaire

The examination of the connection between Internet use and physical and psychosocial characteristics of schoolchildren was designed as a cross-sectional observational study. All students from the fifth to the eighth grade in two villages and two city primary schools were included. All students with normal psychological development are included.

Before the start of the research, ethical approval was obtained from the management of the Institute of Public Health Požarevac. The survey was voluntary, and the respondents received detailed instructions from the research team how to fill out the questionnaire. Students and parents were informed about the methodology and purpose of the research, as well as the fact that their data will be kept confidential and used exclusively for research purposes. The questionnaire was anonymous, and additional confidentiality data is guaranteed by placing them in unmarked envelopes and boxes.

The children completed a questionnaire at home with parents. The questionnaire included three parts:

Socio-demographic data, Screen time-based sedentary behavior questionnaire, and Strengths and Difficulties Questionnaire. The third part of the Questionnaire consisted of the standardized Strengths and Difficulties Questionnaire (SDQ-Srp), which was completed by parents. The designed sedentary behaviors questionnaire was based on a previous study conducted in Belgium and Spain (23).

Children reported their habitual time devoted to several sedentary behaviors: (1) TV watching, (2) computer games, (3) console (video) games, (4) Internet for non-study reasons (hobbies), (5) Internet for study reasons, and (6) study time (out of scholar schedule). In a closed type of questionnaire, there were the six categories, following daily time: (I) 0 min, (II) >0–30 min, (III) >30–60 min, (IV) >60–120 min, (V) >120–180 min, (VI) >180–240 min and (VI) >240 min. Weekly time was calculated taking the median value in a selected category, and applying this formula: $[(\text{weekdays} \times 5) + (\text{weekend} \times 2)]/7$. A total sedentary score was obtained by summing up the time reported in each category.

The SDQ was used to assess participants' emotional and psychosocial adjustment (24). The SDQ includes 25 questions with answers scored from 0 to 2. The scales include: (1) Emotional symptoms subscale; (2) Conduct problems subscale; (3) Hyperactivity/inattention subscale; (4) Peer relationships problem subscale; (5) Prosocial behavior subscale. We excluded the Prosocial Scale, and the sum (range 0–40) of the remaining components constituted the Total Strengths and Difficulties score.

2.3. Anthropometry and medical records

Children's medical records were analyzed for vision problems and spine deformities. Their body weight (BW) and height (BH) were measured and body mass index was calculated as BW in kilograms divided by squared BH in meters. Anthropometric measurements were carried out at Public Health Institute Požarevac. Doctors and medical technicians with appropriate education performed the measurements. Body height was measured with an anthropometer and expressed in centimeters, with an accuracy of 1 cm. Body height was measured with subjects standing on a flat surface with their heels together. Body mass was measured with a medical decimal scale (Detecto 2,371 s) and was expressed in kilograms. During the measurement, the subjects were in underwear, without shoes.

Body Mass Index (BMI) is a number calculated from weight and height using WHO AnthroPlus software (25).

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2.4. Statistical analysis

Statistical analysis was performed using SPSS Statistics for Windows, Version 20.0. Descriptive statistics included proportions and percentages as summary statistics of the differences between the groups. In the end, the groups are compared based using proportion and percentages. The mean and SD were used to summarize distribution of numerical variables. Inferential statistics analysis was performed using Student *t*-test. Pearson correlation analysis was used to determine the correlation between continuous variables. In all statistical tests, p-value < 0.05 was considered as significance.

3. Results

Our study included 836 children, 520 from urban and 316 from rural schools. There were 431 boys and 405 girls who participated in the study. The age range was 11–16, with the average age of 13.4 ± 1.2 years. There were 175 fifth grade students, 250 sixth grade students, 204 seventh grade students and 200 eighth grade students.

The average age when children started with Internet use was 8.3 ± 2.24 years. Smartphones, desktop computers and laptops were used by 92.2, 76.3, and 40.6% of children, respectively. The purpose of IU was mostly electronic communication (65%), than electronic games (48%), and education (45%). The average daily duration of Internet use and sedentary behavior was 236 ± 156 and 422 ± 184 min.

This study indicated no significant differences according to the average daily use of electronic devices between children from rural and urban communities (Table 1). Daily duration of IU and total sedentary score were higher among boys compared to girls. The boys used Internet mainly for socialization and entertainment, while the Internet use among girls was mainly for educational purposes (Table 1).

The prevalence of wearing eyeglasses in the studied children was 16.9%, with an average age at diagnosis refractive errors of 8.7 ± 3.1 years. The most frequent refractive anomalies were nearsightedness and farsightedness (9.6 and 5%, respectively). There was no significant relationship between daily Internet use and refractive errors (Table 2). The study findings indicated that the prevalence of musculoskeletal deformities of spine and poor postures among children was 4.8 and 12.8%, respectively. There was no significant relationship between daily Internet use and poor body posture and spine deformities among children (Table 2).

The prevalence of obesity among the studied children was 6.9%. We found a significant association between the duration of total Internet usage time and total sedentary score with obesity among primary school students ($p < 0.001$ and $p < 0.05$, respectively; Table 2).

According to the children's answers from the questionnaires, 720 respondents (89.4%) have never visited the psychologist and/or psychiatrist, 23 (2.8%) considered the visit, while 88 (10.6%) went to see the psychologist and/or psychiatrist one or more times.

Concerning the total score of difficulties 4.6% of children had a borderline value, and 2.4% an abnormal total value. Hyperactivity-inattention, emotional symptoms, and conduct problems were correlated with daily IU. There was significant correlation between emotional symptoms with total Internet usage time, and total sedentary score ($p < 0.001$ for both, $r = 0.141$ and $r = 0.132$ respectively); when Internet usage time is higher and thus total sedentary score, emotional symptoms were more pronounced (Table 3).

There was a positive correlation between the total sedentary score of children and hyperactivity/inattention ($r = 0.167$, $p < 0.001$), emotional symptoms ($r = 0.132$, $p < 0.001$), and conduct problems ($r = 0.084$, $p < 0.01$). We have also found significant correlation between hyperactivity/inattention and Internet usage time and playing games (Table 3). Total strengths and difficulties score had positive significant correlation with playing mobile games ($p < 0.001$, $r = 0.137$), total Internet usage time ($p < 0.001$, $r = 0.184$) and total sedentary score ($p < 0.001$, $r = 0.147$). Furthermore, schoolchildren's prosocial behavior was negatively correlated with the use of the Internet ($p < 0.001$, $r = -0.134$), which means that Internet use was associated with negative prosocial behavior (Table 3).

TABLE 1 Purpose and average daily use of electronic devices among the studied children according to dwelling place and gender.

Variables (minutes per day)	Mean±SD	Mean±SD	*p**
	Dwelling place		
	Rural areas	Urban areas	
Playing computer games	60.4 ± 72.9	58.6 ± 73.7	0.624
Playing video game console	40.8 ± 61.6	43.3 ± 63.9	0.541
Playing mobile games	101.0 ± 117.6	101.8 ± 123.7	0.897
IU as a hobby	85.7 ± 70.2	89.7 ± 70.6	0.389
IU for educational purposes	53.3 ± 47.5	43.2 ± 44.3	<0.001
Other purpose the Internet usage	138.4 ± 95.1	132.8 ± 90.4	0.500
Total Internet usage time	239.6 ± 155.4	234.4 ± 155.8	0.484
Total sedentary score	423.3 ± 192.5	421.8 ± 179.4	0.857
	Gender		
	Girls	Boys	
Playing computer games	21.9 ± 45.4	99.0 ± 76.5	<0.001
Playing video game console	17.8 ± 40.7	68.4 ± 71.4	<0.001
Playing mobile games	39.5 ± 74.8	167.5 ± 126.7	<0.001
IU as a hobby	103.5 ± 72.4	71.9 ± 64.5	<0.001
IU for educational purposes	52.3 ± 49.1	41.3 ± 41.2	<0.001
Other purpose the Internet usage	155.5 ± 94.0	112.9 ± 84.9	<0.001
Total Internet usage time	194.8 ± 129.7	280.7 ± 168.3	<0.001
Total sedentary score	386.2 ± 168.5	461.0 ± 192.5	<0.001

*Student *t*-test.

4. Discussion

We have found no significant relationship between daily Internet use and vision problems (shortsightedness, farsightedness, astigmatism, and strabismus) and spine deformities. However, there is a significant association between daily duration of Internet use and children's obesity. We also detected and reported a positive

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TABLE 2 Associations between Internet use and sedentary score and wearing glasses, refractive errors, poor body posture, spine deformities and the prevalence of obesity among the studied children.

Variables (minutes per day)	Mean±SD	Mean±SD	*p**
	Wearing glasses		
	Yes	No	
Total Internet usage time	223.3 ± 145.1	239.0 ± 157.6	0.35
Total sedentary score	397.3 ± 172.7	427.5 ± 186.2	0.06
	Refractive errors		
	Yes	No	
Total Internet usage time	237.7 ± 157.2	225.3 ± 138.4	0.61
Total sedentary score	426.3 ± 184.2	397.9 ± 167.6	0.11
	Poor body posture		
	Yes	No	
Total Internet usage time	257.7 ± 166.0	232.2 ± 152.1	0.20
Total sedentary score	432.3 ± 181.3	419.9 ± 181.9	0.62
	Spine deformities		
	Yes	No	
Total Internet usage time	204.3 ± 146.5	237.0 ± 154.5	0.14
Total sedentary score	381.0 ± 164.1	423.3 ± 182.4	0.13
	Obesity		
	Yes	No	
Playing computer games	104.1 ± 88.1	56.7 ± 71.8	<0.001
Playing video game console	62.9 ± 78.6	40.9 ± 62.2	0.105
Playing mobile games	168.8 ± 147.6	97.5 ± 119.7	<0.001
Internet use as a hobby	91.7 ± 74.1	89.7 ± 70.2	0.992
Internet use for educational purposes	48.5 ± 40.3	47.4 ± 45.8	0.432
Other purpose the Internet usage	140.2 ± 82.8	136.7 ± 92.4	0.607
Total Internet usage time	309.3 ± 170.4	233.7 ± 152.3	<0.001
Total sedentary score	488.1 ± 194.6	421.4 ± 181.5	0.012

*Student *t*-test.

correlation between the duration of children's Internet use and hyperactivity-inattention, emotional symptoms, conduct problems and social maladjustment.

Our analysis has shown that boys use Internet more frequently than girls do and that is congruent with previous studies (26). Daily sedentary time was also longer among boys compared to girls. However, in a study conducted in Catalonia, boys scored higher than girls for physical activity (27). Average daily sedentary time was longer in our research compared with the previous studies (28, 29). These findings highlight the need for domain-focused strategies to decrease sedentary behavior. Current activity guidelines (4) recommend no more than 2 h per day of recreational screen time (i.e., watching TV, DVDs, or videos, playing video games, and computer use).

In our study, there was an association found between children's Internet use and sedentary time with obesity. The research conducted in Hunan (China) also found that middle school students with Internet addiction had a significantly higher prevalence of obesity compared to those without Internet addiction (30). Establishing a comprehensive management program that emphasizes behavioral modification is important for prevention of childhood obesity (31). Therefore, interventions should target reducing after-school sedentary behaviors and increasing physical activity. Studies in developed countries reported that only 33% of adolescents fulfil a recommended goal of at least 60 min of physical activity per day (32). Nearly half of the children in our study did not exercise any sport, which is similar to the situation among schoolchildren in other parts of Serbia (33) and in India (34). Sedentary behavior can negatively affect mental and cognitive health in children and adolescents with obesity (35).

Hence, in our study, there was no significant association between the Internet use and visual impairments, and this finding is in contrary to the report of the American Optometric Association that an individual who exceeds 2 h of computer use daily is at risk for developing computer vision syndrome (36). However, the studies conducted among children in Singapore found no evidence of refractive anomalies associated with increased computer viewing (37, 38). Increased time outdoors may be an effective measure in preventing the onset of myopia (39).

The prevalence of children's spinal deformities and bad posture, as reported in our study, was 4.8 and 12.8%, respectively. Data from the previous review indicated the prevalence of 0.47–5.2% for children's idiopathic scoliosis (40). In our research, there was no significant correlation found between daily Internet use and bad posture or spinal deformities. This finding is contrary to the reports confirming that musculoskeletal discomfort among American children may be associated with computer use (11). Additionally, a recent longitudinal study showed that more than 2 h per day of TV watching and computer use were associated with decreased musculoskeletal fitness (41).

The present study indicates that a significant number of adolescents suffer from emotional and psychosocial maladjustment, as assessed by the total SDQ score. In addition, Kormas et al. (19) and Critselis et al. (26) reported the correlation between Internet use and compromised psychosocial well-being. Few of previous studies have also showed that the increased Internet use is associated with an enhanced likelihood of hyperactivity and conduct problems among adolescents (3, 42). However, on the other hand, other results of other studies on prosocial and antisocial behavior associated with the Internet use are still controversial (43, 44).

There is compelling evidence showing that sitting by personal computer too much may impair physical, mental and cognitive health in children and adolescents (34, 45). In relation to our own contribution to the field, we found a statistically significant association between daily Internet use (sedentary lifestyle) and obesity, hyperactivity-inattention, emotional symptoms, conduct problems and social maladjustment.

We believe that greater involvement of multidisciplinary state institutions is necessary in overcoming the problem of excessive use of smart devices. Teachers, parents and children should be educated about the importance of setting clear limits on the time spent on smartphone. Parents and teachers, also, should be educated in order to detect possible problems in children's behavior early. In addition, the state should enable fostering healthy lifestyles, by increasing the availability and number of

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TABLE 3 Correlations between daily duration of Internet use and psychosocial distress among the studied children.

Variables (minutes per day)	Emotional symptoms	Conduct problems	Hyperactivity/ inattention	Peer relationships problems	Prosocial behavior	Total Strengths and Difficulties score
Playing computer games	−0.030	0.089*	0.216**	0.071*	−0.072*	0.111**
p	0.405	0.012	<0.001	0.045	0.040	0.002
Playing video game console	0.027	0.072*	0.177**	0.047	−0.090*	0.102**
p	0.440	0.043	<0.001	0.184	0.011	0.004
Playing mobile games	−0.002	0.116**	0.245**	0.061	−0.097**	0.137**
p	0.965	<0.001	<0.001	0.085	0.006	<0.001
IU as a hobby	0.176**	0.060	0.062	0.039	−0.093**	0.113**
p	<0.001	0.088	0.081	0.273	0.009	0.002
IU for educational purposes	0.082*	−0.094**	−0.051	0.064	0.046	−0.005
p	0.021	0.008	0.149	0.069	0.194	0.899
Other purpose the Internet usage	0.195**	0.016	0.030	0.061	−0.054	0.098**
p	<0.001	0.653	0.394	0.085	0.127	0.006
Total Internet usage time	0.141**	0.119**	0.201**	0.090*	−0.134**	0.184**
p	<0.001	<0.001	<0.001	0.011	<0.001	<0.001
Total sedentary score	0.132**	0.084**	0.167**	0.066	−0.122**	0.147**
p	<0.001	0.019	<0.001	0.064	<0.001	<0.001

**Correlation is significant at the 0.01 level, and * at the 0.05 level.

cultural and sports content. Parents and teachers should with a lot of love, understanding and respect, help children to find a balance between the time spent on smart devices and other activities. Children should reduce the use of the Internet and give priority to creative play without the presence of smart devices, to play sports and to spend more time in nature.

5. Conclusion

In our study, the children's Internet use and sedentary behavior were associated with obesity, but not with vision problems or spinal deformities. In addition, we found a positive significant relationship between children's Internet use and hyperactivity, emotional problems and social difficulties. It can be expected that the reduction in children's daily Internet use might have a positive effect on maintaining their mental health and normal body weight as well.

Since this research was done before the COVID-19 pandemic, it would be very important to repeat the study after the end of the pandemic and compare the results obtained.

6. Limitations of study

A precise electronic system was not used to measure time in front of the screen. The measurement is based on the assessment of parents and children about the amount of time spent using the smart devices. The parents together with the children did time estimation. Subjective assessment of children's time in front of the screen could not be excluded when filling out the SDQ questionnaire.

Possibility of confounding phenomena, because both excessive use of social networks and obesity can be consequences of the same thing, which is a sedentary lifestyle.

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

Ethical approval was provided by the Institute for Public Health Pozarevac. Written informed consent to participate was provided by the participants legal guardian.

Author contributions

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

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.

Publisher's note

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The relationship between depression, healthy lifestyle behaviors and internet addiction: a cross-sectional study of the athlete university students in Turkey

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Introduction: Mental health research exists for university students in the areas of prevalence and association of depression, internet addiction and healthy lifestyle behaviors. However, the studies examining prevalence rates and these relationships in athlete university students are needed. This study aimed to evaluate the relationship between depression, healthy lifestyle behaviors and internet addiction among athlete university students in Turkey.

Methods: A cross-sectional design was conducted, measuring depression using the Center for Epidemiologic Studies Depression Scale, healthy lifestyle behaviors (HPLP-II), and internet addiction (YIAT-SF). Predictive factors associated with depressive symptoms were estimated using binary logistic regression.

Results: Of the 501 participants, 61.3% were male, with a mean age of 21.45 years (SD: 3.19). Student-athletes were at risk of depressive symptoms (76.4%), internet addiction (34.4%) and had moderate healthy lifestyle behaviors (130.41 ± 22.93). No significant differences were found for age, smoking, time spent on social network, number of sports days, number of social networks use for depressive symptoms ($p > 0.05$), however significant differences were found for depressive symptoms by sex and living with family status ($p < 0.05$). Pathological internet addiction (OR: 12.74, 95% CI: 2.91–55.77) and low spiritual growth (OR: 0.854, 95% CI: 0.79–0.92) were found to be predictors of depressive symptoms within the athlete university students ($p < 0.001$).

Conclusion: The athlete university students are at increased risk for depressive symptoms and internet addiction and decreased healthy lifestyle behaviors. It is essential to establish programs to improve the mental health of students in universities and to strengthen the psychological counseling services offered to students. These findings can assist universities in establishing effective measures to improve mental health outcomes.

KEYWORDS

athlete students, depression, healthy lifestyle behaviors, internet addiction, Turkey

1. Introduction

Depression, which is characterized by sadness, loss of interest, hopelessness, anxious feelings, and even thought of suicide, increases during the transition from adolescence to adulthood; accordingly, depression is more common among university students than in the general population (1). University students are exposed to stress not only in their daily lives but also due to their education and additional stressors to which they are exposed in campus life. University students are a vulnerable group because they are in their developmental period, making efforts to adapt to a new environment, and trying to meet academic expectations (2). Recent studies report that approximately one third of university students displayed depressive symptoms (1). Studies show that the depression rates of Turkish university students are higher than those in the general population (3); these rates are also higher than those of university students in several other countries (4).

Many studies have found that depression among university students is associated with their lifestyle behaviors. According to these studies, behaviors such as cigarette smoking, hookah smoking, alcohol use, less healthy lifestyle habits, poor sleep quality, and internet addiction are associated with depressive symptoms (5–9). In addition, interventions that improve lifestyle play a role in reducing students' depressive symptoms (10). In recent years, internet use has increased significantly around the world and has become an indispensable part of life. According to Internet World Statistics, 67.9% of the global population use the internet (11). This increase in internet use worldwide has led to the problem of internet addiction (12). Internet addiction, which is a subtype of problematic internet use, is the uncontrolled, excessive, and obsessive use of the internet causing physiological, social, and emotional problems in the individual (13). Meta-analysis studies show that the rate of internet addiction among university students is 31.5–34.5% in Africa (14). Studies in the literature indicate that 13–17.4% of university students in Turkey have internet addiction problems (15, 16); that internet addiction causes psychosocial problems such as depression, anxiety, insomnia, and low self-esteem in young people (17); and that the prevalence of depression increases with the severity of internet addiction (18).

Athlete university students are a subset of undergraduate students included in mental health statistics, and these students have additional stressors linked to mental health problems. For example, fear concerning a professional future, uncertainty regarding a professional career, vigorous exercise, and physical or somatic stress associated with training programs all affect the mental health of student athletes (19, 20). Previous studies report that participation in sports during university education facilitates positive mental health characteristics such as self-confidence, commitment, social support, and positive self-esteem (21). Student athletes who are confident and have high self-esteem are also able to make better connections with their environment and can combat depression and anxiety by utilizing social support systems to cope with stress more effectively (21, 22). Previous studies show that the internet addiction levels among athlete students are lower than those of other non-athlete students (23), and that internet addiction negatively affects happiness of athlete adolescents (24). The literature contains a limited number of studies on internet addiction in individuals who regularly engage in sports (23, 25); however, no study has yet revealed the relationship between internet addiction, healthy lifestyle behaviors, and depression in student athletes. Therefore, the primary aim of this study is to determine the prevalence of depression and the relationship between depression and healthy lifestyle behaviors and internet addiction in athlete university students in Turkey. The second aim of this study is to reveal those factors affecting depression in athlete university students in Turkey.

2. Materials and methods

2.1. Participants

This cross-sectional study was conducted in the faculty of physical education and sports departments of three state universities in Turkey between February and April 2022. Data were collected with online survey due to SARS-CoV-2 through the social media in order to minimize face-to-face contact. In February, a list of all undergraduate students continuing their education in the physical education and sports departments of the three universities was made and an informed consent form and a link to the measurement tools were sent to all undergraduate athlete students via email.

The sample comprised a total of 501 undergraduate athlete students. No sample selection method was used and all students who volunteered to participate in the study were included in the study sample. Out of a total of 1,480 eligible students, 34% were included in this study. Permission was obtained from the ethics committee of the Osmaniye Korkut Ata University (Date: 17.02.2022, Decision no: 2022/3/3) to which the first author of this study was affiliated. Written consent was obtained from the students who agreed to participate in the present study.

2.2. Instruments

2.2.1. Demographic information form

This form, which was created by the researchers of the present study based on a review of the literature (12, 17), includes questions about the participants' age, sex, whether they live with their family, smoking status, duration of social network use (hour/day), number of social networks they use, and frequency of physical activity (day/per week).

2.2.2. Center for Epidemiologic Studies Depression Scale (CES-D)

The Center for Epidemiologic Studies Depression Scale (CES-D) is a self-report scale commonly used to monitor depressive symptoms in the general population (26). In this 20-item scale, participants are asked to evaluate the frequency of ideas and events over the past week and the answers are scored on a 4-point Likert-type scale (0 = rarely or none of the time, 3 = most of the time). Items 4, 8, 12, and 16 are scored inversely and total scale scores range from 0 to 60. A score of 0–15 indicates no depression, 16–20 indicates mild depression, 21–30 indicates moderate depression, and 30 and above indicates severe depression. The Cronbach's alpha of the Turkish form of the scale was between 0.75 and 0.90 (27).

2.2.3. Health Promoting Lifestyle Profile II (HPLP-II)

The health-related behaviors of students were assessed using the Health Promoting Lifestyle Profile II (HPLP-II) (28). The scale comprises 52 questions and six subscales: health responsibility (nine items), physical activity (eight items), nutrition (nine items), spiritual growth (nine items), interpersonal relations (nine items), and stress management (nine items). The frequency of participants' practice of health promotion behaviors was assessed using a 4-point Likert-type scale (1 = never, 4 = routinely). All scale items were included as positive statements, with the lowest possible total scale score being 52 and the highest total score being 208. A high scale score indicates positive health promotion behaviors. The Cronbach's alpha coefficient of the Turkish version of scale was 0.94 (29).

2.2.4. Young's Internet Addiction Test-Short Form (YIAT-SF)

The Young's Internet Addiction Test-Short Form (YIAT-SF) is one of the most widely used measures of internet addiction (30, 31). The scale consists of 12-items that are rated on a 5-point Likert-type scale (1 = never, 5 = very often); the scale contains no inversely scored items. The minimum and maximum scores obtainable from the scale are 12 and 60, respectively. Scores below 31 indicate normal internet use, scores of 31–37 indicate problematic internet use, and scores above 37 indicate pathological internet use (31). The Cronbach's alpha coefficient of the Turkish version of this scale was 0.91 for university students and 0.86 in adolescents (32).

2.3. Data analysis

Data were analyzed using SPSS 24.0. The demographic characteristics of the participants were presented using descriptive statistics (mean, standard deviation, and frequency). Normality of the data was evaluated using Kolmogorov–Smirnov test. Non-parametric tests were used in the study because the data were not normally distributed ($p < 0.05$). Comparison of categorical variables according to CES-D depression score was analyzed using the chi-square test. The relationship between the YIAT-SF and HPLP-II total and subscale scores and CES-D scores was assessed using Spearman correlation analysis. The comparison of YIAT-SF, HPLP-II totals and subscale scores with the CES-D depression scores was made using Mann–Whitney U test. The effect of demographic characteristics, internet addiction, and HPLP-II subscales on depressive symptoms was analyzed using binary logistic regression analysis. Values of $p < 0.05$ were considered statistically significant.

3. Results

3.1. Descriptive statistics

The students had a mean age of 21.45 years (SD: 3.19), and 61.3% of the students were male. The minimum and maximum age for male students were, respectively as 18, 38 and the minimum and maximum age for female students were, respectively as 18, 42. Of the 501 students, 55.1% were living with their families, 32.3% were smokers, 49.7% used social media 2–4 h a day, 39.9% did

TABLE 1 Characteristics of the participants.

Characteristics		Total *n*	%
Total		501	100.0
Age (year) (mean ± SD)		21.45 ± 3.19	
	20 and below	228	45.5
	21 and over	273	54.5
Sex	Female	194	38.7
	Male	307	61.3
Living with family	Yes	276	55.1
	No	225	44.9
Smoking	Yes	162	32.3
	No	339	67.7
Time spent on social network (hour/day)	<2 h	125	25.0
	2–4 h	249	49.7
	≥4 h	127	25.3
Number of sports days (day/per week)	0	39	7.8
	1–2 d	174	34.7
	3–4 d	200	39.9
	≥5 d	88	17.6
Number of social networks used	≤2	253	50.5
	≥3	248	49.5
CES-D scores (mean ± SD)		24.32 ± 10.99	
	Normal	118	23.6
	Mild	72	14.4
	Moderate	163	32.5
	Severe	148	29.5
HPLP-II total score (mean ± SD)		130.41 ± 22.93	
Health responsibility (item mean ± SD)		2.19 ± 0.57	
Physical activity (item mean ± SD)		2.48 ± 0.62	
Nutrition (item mean ± SD)		2.27 ± 0.52	
Spiritual growth (item mean ± SD)		2.84 ± 0.55	
Interpersonal relationships (item mean ± SD)		2.77 ± 0.49	
Stress management (item mean ± SD)		2.46 ± 0.51	
YIAT-SF (mean ± SD)		28.03 ± 9.00	
	Normal	329	65.6
	Problematic	96	19.2
	Pathologic	76	15.2

TABLE 2 The relationship between students' characteristics and depression.

Characteristics		CES-D		χ^2	*p*
		No depression (*n* = 118) *n* (%)	Depression (*n* = 383) *n* (%)		
Age	20 and below	52 (22.8)	176 (77.2)	0.129	0.719
	21 and over	66 (24.2)	207 (75.8)		
Sex	Female	35 (18.0)	159 (82.0)	5.341	0.021*
	Male	83 (27.0)	224 (73.0)		
Living with family	Yes	76 (27.5)	200 (72.5)	5.416	0.020*
	No	42 (18.7)	183 (81.3)		
Smoking	Yes	39 (24.1)	123 (75.9)	0.036	0.849
	No	79 (23.3)	260 (76.7)		
Time spent on social network (hour/day)	<2 h	38 (30.4)	87 (69.6)	6.002	0.050
	2–4 h	58 (23.3)	191 (76.7)		
	≥4 h	22 (17.3)	105 (82.7)		
Number of sports days (day/per week)	0	5 (12.8)	34 (87.2)	5.285	0.152
	1–2 d	38 (21.8)	136 (78.2)		
	3–4 d	48 (24.0)	152 (76.0)		
	≥5 d	27 (30.7)	61 (69.3)		
Number of social networks used	≤2	62 (24.5)	191 (75.5)	0.258	0.612
	≥3	56 (22.6)	192 (77.4)		

*$p < 0.05$, χ^2 = Chi-square test.

TABLE 3 The relationship between CES-D scores and subfactors and total scores on the HPLP-II and YIAT-SF.

	Spearman correlation with CES-D	No depression (mean ± SD)	Depression (mean ± SD)	*U*	*p*
HPLP II total score	−0.214**	139.20 ± 24.32	127.70 ± 21.82	4.869	<0.001**
Health responsibility	0.000	19.77 ± 5.54	19.74 ± 5.02	0.066	0.948
Physical activity	−0.149**	21.50 ± 5.32	19.33 ± 4.82	3.944	<0.001**
Nutrition	−0.089*	21.21 ± 5.10	20.27 ± 4.63	1.875	0.061
Spiritual growth	−0.351**	28.75 ± 4.97	24.69 ± 4.54	8.296	<0.001**
Interpersonal relationship	−0.250**	26.94 ± 4.65	24.38 ± 4.26	5.568	<0.001**
Stress management	−0.208**	21.01 ± 4.40	19.27 ± 3.99	4.044	<0.001**
YIAT-SF total score	0.445**	22.72 ± 6.31	29.67 ± 9.09	−9.337	<0.001**

*$p < 0.05$, **$p < 0.001$, U: Mann–Whitney U test.

sports 3–4 days a week, and 49.5% used 3 or more social networks. The Cronbach's alpha value was 0.89 for the CES-D, 0.94 for the HPLP-II, and 0.90 for the YIAT-SF. The mean CES-D score of the students was 24.32 ± 10.99. A total of 76.4% participants had depressive symptoms (14.4% mild, 32.5% moderate, 29.5% severe). The mean HPLP-II total score of the students was 130.41 ± 22.93 (ranging from 54 to 206). The mean item scores of HPLP-II subscales were as follows (from highest to lowest): spiritual growth 2.84 ± 0.55, interpersonal communication 2.77 ± 0.49, physical activity 2.48 ± 0.62, stress management 2.46 ± 0.51, nutrition 2.27 ± 0.52, and health responsibility 2.19 ± 0.57. The mean YIAT-SF score of the students was 28.03 ± 9.00. Of the students, 65.6% had no symptoms of internet addiction, 19.2% were addicted to internet at a problematic level, and 15.2% were addicted to internet at a pathological level. Detailed demographic information can be found in Table 1.

3.2. Relationship between depression and demographic characteristics

Table 2 shows the relationship between the students' demographic characteristics and their depression levels. The depression rate of female students (82%) was found to be significantly higher than that of male students (73%) ($p < 0.05$). Similarly, the depression rate of students who did not live with their families (81.3%) was found to be significantly higher than those who lived with their families (72.5%) ($p < 0.05$). No statistically

TABLE 4 Results of logistic regression analysis, factors associated with depression.

Characteristics	*B*	Wald	OR	95% CI	*p*
Age	−0.020	0.300	0.981	0.914–1.052	0.584
Sex (male, ref.)	0.298	1.200	1.347	0.791–2.294	0.273
Living with family (yes, ref.)	0.496	3.763	1.643	0.995–2.713	0.052
Smoking (no, ref.)	−0.297	1.141	0.743	0.431–1.282	0.286
Time spent on social network (<2 h, ref.)					
2–4 h	0.093	0.096	1.097	0.611–1.971	0.757
≥4 h	0.399	1.169	1.491	0.723–3.074	0.280
Number of sports days (≥5 d, ref.)					
0	0.110	0.026	1.116	0.295–4.224	0.871
1–2 d	−0.222	0.273	0.801	0.349–1.839	0.601
3–4 d	−0.140	0.154	0.870	0.433–1.747	0.695
Number of social networks used (≤2, ref.)	0.001	0.000	1.001	0.601–1.642	0.997
Internet addiction (normal, ref.)					
Problematic	0.797	5.082	2.220	1.110–4.441	0.024
Pathologic	2.545	11.439	12.74	2.91–55.77	<0.001*
HPLP-II					
Health responsibility	0.097	7.056	1.101	1.026–1.183	0.008
Physical activity	−0.061	2.369	0.941	0.871–1.017	0.124
Nutrition	−0.002	0.002	0.998	0.924–1.078	0.960
Spiritual growth	−0.158	16.308	0.854	0.79–0.92	<0.001*
Interpersonal relationships	−0.037	0.884	0.963	0.891–1.041	0.347
Stress management	−0.024	0.260	0.976	0.891–1.070	0.610
Constant	6.035	28.924	417.607		<0.001*

*$p < 0.001$, OR, odds ratio; CI, confident interval.

significant difference was found between the students' other demographic characteristics and their depression levels ($p > 0.05$).

3.3. Relationship between depression and healthy lifestyle behaviors and internet addiction

Table 3 shows the relationship between the students' depression and HPLP-II total, subscale, and YIAT-SF scores. The total mean scores of HPLP-II, physical activity, spiritual growth, interpersonal relationships, stress management subscale scores of the participants with depression were found to be significantly lower than those without depression ($p < 0.001$). The mean YIAT-SF score of the participants with depression (29.67 ± 9.09) was significantly higher than were the scores of those without depression (22.72 ± 6.31) ($p < 0.001$). Spearman correlation analysis showed a significant positive correlation between CES-D and YIAT-SF ($r = 0.445$) and a significant negative correlation between CES-D and total HPLP-II and its subscales scores (physical activity, nutrition, spiritual growth, interpersonal relationships, stress management; $r = -0.214$, $r = -0.149$, $r = -0.089$, $r = -0.35$, $r = -0.250$, and $r = -0.208$, respectively) ($p < 0.05$, $p < 0.001$).

3.4. Predictors of depression

Binary logistic regression analysis was applied by taking depressive symptoms as the dependent variable and the demographic characteristics, YIAT-SF, and HPLP-II subscales as independent variables (Table 4). Pathological internet addiction (OR = 12.74, 95% CI: 2.91–55.77) and low spiritual growth (OR = 0.854, 95% CI: 0.79–0.92) were found to be significantly associated ($p < 0.001$) with depressive symptoms.

4. Discussion

This study examined the relationship between depressive symptoms, healthy lifestyle behaviors, and internet addiction in Turkish athletic university students. The study results revealed that the prevalence of depressive symptoms was common (76.4%) among these students. In recent years, the prevalence of depression among university students has gradually increased (1). According to a meta-analysis study, in the literature the prevalence of depression among university students was 25% (33). Studies conducted with Turkish university students reported the prevalence of depression as 32.8–73.6% (34–36). A study comparing depression rates among university students in nine

countries found that students in Turkey had the highest risk of depression and anxiety (4). A systematic review study examining the prevalence of depression among student athletes revealed that rates of depression among this population varied between 3.7 and 39% (37). A study conducted in China showed that the rate of depression among athlete students was 49.1% (21). The results of the present study are similar to those related studies from the literature and confirm that depression is an important health problem for student athletes in Turkey. A study associated high levels of depressive symptoms in Turkish athlete students with fear of professional future, uncertainty concerning professional career, and physical or somatic stress associated with severe exercise training programs (19). Depressive symptoms in athlete students can reduce their performance (38) and lead to injuries (39) and school dropout (40).

The results of the present study show that female students were also at risk for depression. A systematic review meta-analysis study found that female gender consistently increased the risk of mental health problems (33). In studies conducted with general university students and athlete university students in Turkey, female gender was identified as at risk for depression (36, 41). Wolanin et al. (42) stated that the risk of depression symptoms for the girls was 1.844 times higher than was that for the boys in athlete university students. Some studies in the literature suggest that social relationship factors were a possible explanation for gender differences in depression (43). A longitudinal study conducted with university students reported that both social isolation and loneliness were associated with increased depression symptoms in female university students; however, the study found that only social isolation was associated with increased depression symptoms in male university students (44). According to this result, gender differences in depressive symptoms were partly attributed to women's experiences of more negative consequences of loneliness as compared to that of men's experiences. The results of the current study confirm those in the literature and show that female students are at greater risk of experiencing depressive symptoms compared with male students.

In the present study, students who did not live with their parents had higher depression scores. Studies in the literature report that students living on campus/in a student hostel have more depression symptoms than those living with their parents (45, 46) and that being away from home may increase risks such as lack of social support and poor economic status. In addition, some studies have reported that moving away from home leads to stress (46, 47). The present study showed that students who lived away from their families had higher levels of depression symptoms.

The results of this study showed that 49.7% of athlete students used the internet for 2–4 h a day and approximately one third of all students had different levels of internet addiction. Previous studies in the literature conducted in Turkey reported that internet addiction among athlete university students was 26.4% (48), that internet addiction among non-athlete university students was 7.5%, and that the rate of potential addiction among these students was 34.4% (49). According to a meta-analysis study in the literature, internet addiction among young adults is prevalent internationally and internet addiction is increasing among new generations (50). The same study drew attention to the role of factors such as increased individuality, lower socialization, and acculturation in internet addiction. In the current study, participants' internet addiction and depression scores were positively correlated, and the regression model showed that the risk of pathological internet addiction was 12.74 times higher among those with depression symptoms. The results of the current study are consistent with those of previous studies conducted with different student groups in Turkey. These studies reported that internet addiction was associated with high social anxiety, low self-esteem, and depression symptoms in medical faculty students (51), unhappiness in athlete high school students (24), and anger expression in athlete university students (52). According to the social-emotional model, negative emotions such as depression, anxiety, stress, and tendency to commit suicide also affect internet addiction (53). Internet addiction has also been found to be associated with a negative coping behavior of avoidance (54). The results of the present study confirmed that internet addiction in athlete university student was a risk factor for psychosocial problems such as depression.

The findings of the current study revealed that the HPLP-II total score of the athlete university students was moderate (130.41 ± 22.93), the highest healthy lifestyle behaviors were spiritual growth and interpersonal relationships, and the lowest behaviors were health responsibility and nutrition. Previous studies in the literature show that Turkish athlete university students had moderate HPLP-II scores, that the highest scores were spiritual growth/self-actualization, interpersonal relationships, and the lowest scores were physical activity, stress management, and nutrition (55, 56). In addition, this study also revealed a low-level negative correlation between HPLP-II total, physical activity, spiritual growth, interpersonal relationships, stress management scores, and depression scores of the participants. The results of present study are consistent with those of a study showing that healthy life behaviors are associated with depression, although the scale used to measure depression was different (57). The regression model showed that low spiritual growth posed 0.854 times more risk for depression symptoms. Inadequate self-actualization behaviors in university students are a risk factor for depression (12, 57). Spiritual growth refers to the individual's search for meaning in life, a sense of belonging, the ability to choose freely among options, and maximizing the potential of healthy life through studies toward goals in life (29). Accordingly, it can be argued that because of the negativities in students' efforts to find meaning in life and their efforts to attain belonging and personal goals in life, their general mental health status is negatively affected, especially as the severity of depressive symptoms increases.

Although this study is one of the few studies that evaluated the relationship between depression, healthy lifestyle behaviors and internet addiction among Turkish athlete university students, the study is not free from limitations and the findings should be discussed in line with these limitations. Firstly, even though the data of this study were obtained from athlete students of three universities in Turkey, the study sample represents a convenient sample of sports university students. Therefore, the study findings cannot be generalized to all athletic students. Future research should include a more representative sample. Secondly, the study sample was predominantly male students. Findings are limited to the sample of the study. Therefore, the obtained results may not be fully generalizable. Thirdly, due to the cross-sectional design of the study, it is not possible to establish a causal relationship between depression, healthy lifestyle behaviors and internet addiction. For the future, prospective studies are recommended to confirm the

causal relationships between depression, healthy lifestyle behaviors and internet addiction in sport university students. In addition, future studies that take the gender distribution as similar are more likely to explore gender differences.

5. Conclusion

To the best of our knowledge, this study provides the first estimation of the relationship between depression, healthy lifestyle behaviors and internet addiction among athletic university students in Turkey. Our findings indicate that approximately two-thirds of the athletic students had depressive symptoms, one-third had internet addiction, and their healthy lifestyle behaviors were insufficient. The findings emphasized that depressive symptoms were more common in female students and students who did not live with their families, and that pathological internet addiction and low spiritual growth were the predictives of depressive symptoms. While the findings of the study support the results regarding the prevalence of depressive symptoms among university students in Turkey and in other countries of the world, it provides a novel data in terms of the prevalence of depressive symptoms among athlete university students in Turkey. The results suggest that improving healthy lifestyle behaviors in these students may help reduce their depression symptoms. Athlete students who have depression have a higher risk of developing internet addiction. Therefore, it is very important for universities and authorities to develop effective strategies to reduce depressive feelings in female students and in students who live separately from their families as both these groups are at greater risk. Accordingly, it is recommended that programs to improve the mental health of students in universities are developed and that the psychological counseling services offered to athlete university students are strengthened.

Data availability statement

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

Ethics statement

The studies involving human participants were reviewed and approved by the Ethics Committee of the Osmaniye Korkut Ata University (protocol no: 2022/3/3 and date of approval 17.02.2022). The patients/participants provided their written informed consent to participate in this study.

Author contributions

Both authors contributed to the study's conception and design, performed the material preparation and analysis, wrote the first draft of the manuscript, commented on the previous versions of the manuscript, and 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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The impact of internet use on residents' happiness in China

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Using data from the 2018 Chinese General Social Survey (CGSS), this study investigates the impact of internet use on residents' happiness. Empirical results show that internet use significantly enhances residents' happiness. Considering the possible endogeneity problem, a two-stage tool variable estimation is carried out with ownership of a mobile phone as the tool variable. After overcoming the endogenous problem and conducting a series of robustness tests, the conclusion is still valid. The action mechanism finds that social interaction frequency and socioeconomic status (SES) play significant mediating effects in the process of internet use affecting happiness. Specifically, internet use significantly increases the social interaction frequency of residents and enhances their SES. The improvement of social interaction frequency and SES will significantly increase residents' happiness. Therefore, this paper gives policy recommendations from the perspectives of regulating and deepening internet use, increasing the frequency of communication among residents, and improving their SES to better enhance their happiness.

KEYWORDS

internet use, social interaction frequency, socioeconomic status, happiness, intermediary effect

1. Introduction

Since the 1960s, information technology has developed rapidly and internet applications have accelerated in popularity. This has brought unprecedented and profound changes to human production and lifestyle and even to all areas of the economy and society. As shown in Figure 1, in the past two decades, China's internet technology has developed rapidly, and as of December 2022, the number of internet users reached 1.067 billion and the internet penetration rate reached 75.6% (1). The popularity and use of the internet have greatly facilitated people's activities such as shopping, learning, entertainment, socializing and information acquisition (2–5), but at the same time, inappropriate internet use behaviors such as compulsive and problematic internet use and social media distraction have caused a series of psychological problems such as internet addiction and online procrastination (6–12). On this basis, the issue of how to use the internet properly and happily has attracted widespread attention in the academic community.

In recent years, the Chinese government has repeatedly mentioned in its work reports the need to "enhance people's happiness and sense of access" (13). The issue of "how to enhance the residents' happiness" has become a hot topic of concern for all sectors of society. So, what is "happiness"? Psychologists subdivide happiness into psychological well-being (PWB) and subjective well-being (SWB) (14), and consider subjective well-being as a comprehensive assessment of people's satisfaction with life and its various aspects, as well as the resulting psychological state with mainly positive emotions, "internal emotions" and "personal self-evaluation" (15); while psychological well-being refers to a good state of human psychological

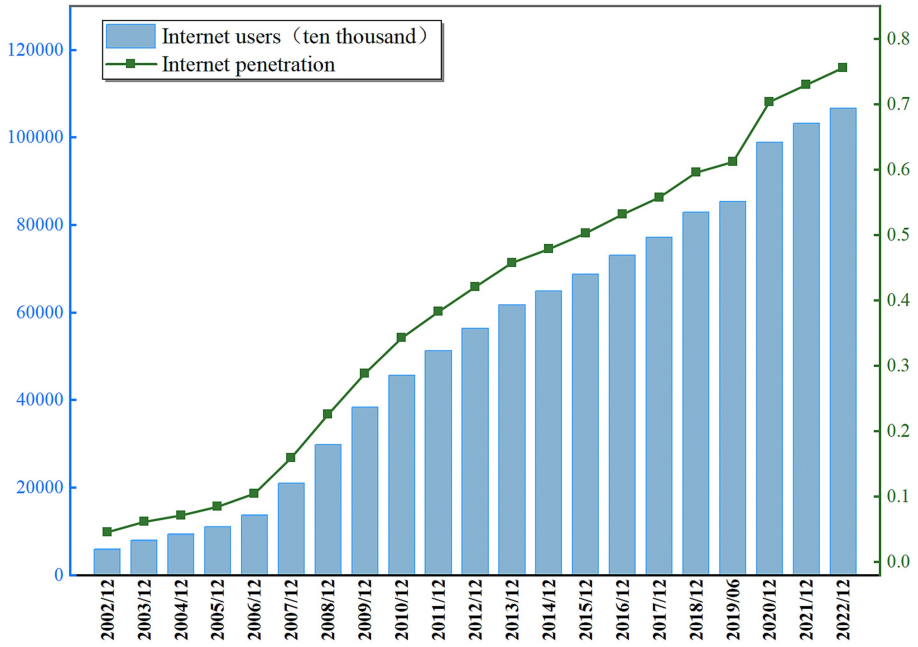

FIGURE 1
Scale of internet users and internet penetration rate in China, 2002–2022. Data source: China Internet Development Statistical Survey.

functioning, including six dimensions which are self-acceptance, positive relationships with others, functional autonomy, environmental control, life goals, and personal growth (16). Based on the hypothesis of rational man, happiness has been equated with maximum utility in traditional economic studies (17), whereas in the current economic context it is considered a manifestation of individual satisfaction (18). In general, although the definition of happiness varies from discipline to discipline, the core content of the existing studies is consistent in terms of research methods and empirical results: happiness is an individual's overall assessment of his or her quality of life and psychological state according to his or her own criteria, including the so-called happiness (19–21). For a long time, research on the happiness of residents has focused on income, education, social participation, family status and social environment (19, 22–26), and few studies have focused on the impact of the development of information technology on the happiness of residents in developing countries. In recent years, the harmful effects of excessive internet use on the mental health of adolescents and the older adult have been hotly debated (27–31), but this paper discusses the effects of internet use on overall happiness (including quality of life and psychological state) of Chinese residents compared to non-internet use. So, what exactly is the impact of internet use on residents' happiness? Scholars have discussed this issue extensively and profoundly from various fields, including psychology, economics, and sociology.

On the one hand, existing studies suggest that there is a "network gain effect" that makes internet use increase the level of happiness of residents (5, 32). First, the use of the internet promotes social participation and social capital accumulation, and in the process generates a large number of positive emotions that contribute to residents' happiness levels. For example, the emergence of Facebook, QQ, and WeChat has increased communication between people who are geographically distant (33), thereby strengthening relationships and social capital. In addition to maintaining and promoting existing interpersonal relationships, SNSs also assist in expanding social networks, which in turn increases social capital accumulation and enhances the happiness of users (34–37). Second, the internet provides more access to information. Pénard et al. (38) argue that the internet enables people to search for information more efficiently, which leads to cheaper goods, more diverse services, and better-matched job opportunities to improve their happiness. Through the internet, people can acquire relevant skills and knowledge to improve their human capital (39). For instance, with the emergence of mobile medical models, people are now able to acquire additional health information through the internet (40, 41). At the same time, the information property of the internet and the information benefits it brings have greatly reduced the cost of information search, enabling workers to obtain more employment information and expand their employment channels at a lower cost (42–45). Internet use has transformed individuals from passive consumers of information to active seekers, resulting in greater control over their lives and a greater sense of happiness (36). In addition, the internet has greatly improved work efficiency and enriched people's life experience. It allows the possibility of working online, which undoubtedly enhances work efficiency, job satisfaction, and individual happiness (46, 47). Furthermore, the internet facilitates the dissemination of information and the efficient exchange of information between colleagues, which can improve the quality of work (48, 49).

On the other hand, the "network substitution effect" in internet use may lead to social isolation and reduced social competence, as well as information overload, increased anxiety and stress, and thus reduced happiness (38, 50). The use of the internet will lead to an increase in online communication time. This outcome will partly replace face-to-face interaction between individuals, narrowing their social circles and reducing the frequency and quality of

communication between family members, thereby leading to disharmonious family relationships and negatively impacting people's welfare (32, 33, 51–54). A number of researchers have also argued that the use of the internet has significantly altered how individuals perceive and behave in social situations. The perception of an individual's situation is influenced by their judgment of their own circumstances, their comparisons with others, and their expectations of the future, all of which, in turn, affect their level of happiness (55, 56). When comparing themselves with people who are better off than they are, people experience psychological loss and relative deprivation, which can reduce their sense of happiness. People's social lives have expanded beyond their everyday lives due to the internet, allowing them to compare their experiences with people from different countries and backgrounds. By doing so, people may change their material desires, change their orientation toward their social class and relative income, and thus negatively affect the level of happiness (33, 57–62). At the same time, excessive use of the internet can also bring a series of negative effects on people's productive life, affecting people's mental health, such as social media distractions, online procrastination, etc., which may cause people to work less efficiently in the process of telecommuting, negatively affect productivity, job satisfaction, and general happiness (63, 64).

Although being addicted to the internet can reduce people's happiness, this study finds that using the internet as a whole will increase people's happiness compared to not using the internet. It is without doubt that internet use contributes significantly to individual happiness, but its direction and the mechanism by which it does so need to be further investigated empirically. On the basis of theoretical analysis, this study uses data from the 2018 China General Social Survey (CGSS) to empirically test the impact of internet use on the happiness of Chinese residents and its action mechanism. A marginal contribution of this study is that it provides novel empirical evidence as to how internet use affects residents' happiness. Unlike existing research that takes social capital and information access as intermediate transmission mechanisms, this study examines how social interaction frequency and socioeconomic status (SES) contribute to the impact of internet use on residents' happiness. By providing novel empirical evidence to further understand the relationship between internet use and residents' happiness we are able to gain a deeper understanding of this relationship.

The remainder of the paper is organized as follows: Section 2 presents our theoretical analysis and research hypotheses. Section 3 describes the data and methodology used in our research. Section 4 presents the estimation results. Section 5 analyzes the impact mechanisms. Section 6 presents research findings and policy implications.

2. Theoretical analysis and research hypotheses

2.1. Internet use and resident happiness

Numerous studies have demonstrated that internet use positively impacts the happiness of those who use it (36, 38, 65, 66). By facilitating access to and dissemination of information (38), the internet can enhance the utility level of the population. It will result in increased activities, such as online leisure, entertainment, shopping, and consumption (4, 5), which will in turn improve their welfare. Moreover, the use of the internet is often associated with the consumption of "relationship goods" (67) and an increase in social capital. Relational goods have proven to be a source of personal happiness (53, 68), and an increase in social capital plays the same role (69). The internet likewise helps improve residents' level of interaction with society as well as enhances their self-evaluation, self-efficacy, and sense of value, which in turn increases their sense of happiness (70–72).

However, it is undeniable that internet use may negatively affect residents' happiness. For example, it may increase people's loneliness by reducing the frequency of face-to-face communication and lower welfare; it may also weaken residents' happiness by increasing personal material aspirations and personal frustration and decreasing their relative income levels (60–62). The results of a comprehensive comparison analysis reveal that internet usage by Chinese residents tends to lead to higher levels of happiness. In light of this finding, we propose the first research hypothesis in this study.

> *H1*: The use of the internet significantly improves the happiness of residents.

2.2. Role of the frequency of social interaction in the effect of internet use on residents' happiness

Due to the increasing use of the internet, people's social interactions have changed rapidly, especially in terms of the frequency and scope of social interactions. The frequency of social interaction deals with the rate at which social contact occurs (73), which is an indicator of the number of times people interact in a certain amount of time. According to related research, higher frequency of social interaction is often thought to be associated with higher happiness. In the era of increasing internet usage, people's social interactions have undergone rapid changes. Many studies have examined the impact of the internet on residents' happiness without neglecting the importance of social interactions. As the first study to examine the effects of internet use on social interactions and well-being, Kraut et al. (74) concluded that internet use decreases social interaction with family and friends, thus increasing loneliness and decreasing well-being. Several early studies supported the view that internet usage reduces face-to-face interaction time, which negatively impacts the happiness of individuals (32, 33, 51–54, 75). According to more and more researchers, as ICTs have developed and the internet has become increasingly popular, particularly with the emergence of SNSs, the use of the internet does not entirely replace face-to-face communication with family and friends. By complementing existing social relationships, the internet provides the means of maintaining and developing existing relationships as well as establishing new social connections and making new friends (54, 76, 77). Thus, internet use strengthens and enhances people's social networks. As one of the manifestations of social capital, the expansion or strengthening of social networks will lead to an increase in social capital, which will in turn enhance residents' happiness (78, 79). In light of this, we propose the second research hypothesis in this study.

> *H2*: Internet use further enhances residents' happiness by increasing the frequency of their social interactions.

2.3. Role of socioeconomic status in the effect of internet use on residents' happiness

As a platform for the exchange and dissemination of information, the internet has the characteristics of anonymity and equality, which contribute to the transformation of existing social structures and the SES of individuals. SES is a complex and multidimensional concept that reflects the relative position of an individual in a society or group, including both objective measures (e.g., income or education) and subjective assessments of their position (80). SES has been shown to be an influential factor in determining residents' happiness and the higher the SES, the more resources residents will have at their disposal, resulting in a heightened degree of happiness (81–85).

Information technology, represented by the internet, has greatly influenced the production, lifestyle, and consumption patterns of residents. In some ways, the internet has reduced the cost of searching for information, thereby alleviating information asymmetry. Through it, search-matching costs on the labor market are reduced, residents have more access to information and technical resources, employment channels are expanded, opportunities and rewards on the labor market are enhanced, and their SES is improved. Note that this enhancement effect is pronounced for residents of low SES, which inevitably enhances their happiness (42, 86–88). Furthermore, the emergence of a platform economy built upon the internet has triggered structural changes in the labor market, which has widened the scope of labor employment and entrepreneurship on a global scale. According to Boston Consulting Group's report, "Year 2035: 400 Million Job Opportunities in the Digital Age," 415 million jobs will be created worldwide by 2035 in the digital economy sector (89). It is possible for internet technology to drive employment growth through the creation of new tasks, and even to create some new jobs in the process (90). It will also increase employment options for workers, allowing them to earn an adequate income while performing relatively flexible work tasks. This situation will raise their income levels, improve their SES, and ultimately increase their happiness (91). As a result of the above analysis, the third research hypothesis of this study is formulated as follows.

> *H3*: Internet use further enhances residents' happiness by improving their socioeconomic status.

3. Variables and data

3.1. Variable setting

3.1.1. Dependent variable

The text continues to use data to demonstrate the assumptions put forward earlier. Happiness has been described in many different ways in previous literature (92, 93). It is defined as a sense that includes the absence of negativity, a positive attitude, tranquility, personal development, luck, joy, desires, purpose, and belonging (94). Happiness covers how well individuals are doing in life, including the social, health, material, and subjective dimensions of well-being (95, 96).

As happiness cannot be visually observed and measured, this study uses the question "In general, do you think you are happy in your life?" to indicate the happiness of residents. The scale from 1 to 5 indicates very unhappy, relatively unhappy, unhappy, relatively happy, and very happy, respectively. It also means that as the number increases, the happiness of the residents gradually increases.

3.1.2. Explanatory variable

Internet use can be categorized into academic, social, and recreational (97). At the same time, there are a lot of devices for using the internet. Therefore, in this study, we chose the question "In the past 6 months, have you accessed the internet, including computers, cell phones, smart wear, and other devices?" to indicate internet use. If you use the internet, it is recorded as 1, and if not, it is recorded as 0.

3.1.3. Control variables

Reference is made to previous literature related to the study of the happiness of the population (98–101). To study the effect of internet use on the happiness of the population, we introduced control variables, including gender, age, age squared, ethnicity, religion, literacy, political affiliation, marital status, and household registration status. For gender, males were assigned a value of 1 and females a value of 0. The year of birth of the respondents was asked in the questionnaire, and the year of birth was subtracted from the year of the interview (i.e., 2018) to obtain the age of the respondent. Age was squared by dividing the age by 10 and then squared. For ethnicity, Han was assigned a value of 1 and minority was assigned a value of 0. For religion, having a religion was assigned a value of 1 and not having a religion a value of 0. For education, no education is assigned a value of 1; private schools, literacy classes, and elementary schools are assigned a value of 2; junior high schools are assigned a value of 3; high schools, junior colleges, and technical schools/vocational high schools are assigned a value of 4; university colleges (adult higher education) and university colleges (formal higher education) are assigned a value of 5; and university bachelor' s degrees and above are assigned a value of 6. In the political status variable, Communist Party (CCP) member is assigned a value of 1 and non-CCP member a value of 0. In the marital status variable, the unmarried and cohabitating are assigned a value of 0; the first married with a spouse, remarried with a spouse, separated and not divorced, divorced, and widowed are assigned a value of 1. In the household status variable, residents who have agricultural households are assigned a value of 0; otherwise, they are assigned a value of 1.

3.2. Description of data

The data used in this paper come from the Chinese General Social Survey (CGSS) released by the China Survey and Data Center of Renmin University of China. Started in 2003, the CGSS adopted a multi-order stratified unequal probability sampling method to survey individuals in 125 counties (districts), 500 streets (townships), 1,000 neighborhood (village) committees, and 10,000 households nationwide. In this study, the latest published CGSS data of 2018 were selected, forming a total of 12,787 valid samples. We normalized the raw data. On the one hand, the data in this paper is processed with positive criteria. For example, in the original questionnaire, "In the last 6 months, have you been on the internet, including using various devices such as computers, cell phones and smart wears?", which marks the answer "yes" as 1, and the answer "no" as 2. We replaced 2 with 0. In addition, happiness, gender, age, ethnicity, religion, education, political status, marital status, household status, frequency of social interactions and

socioeconomic status are all positive indicators. On the other hand, we use the mvdecode command to handle the special values in the questionnaire responses. According to Table 1, the correlation coefficient between internet use and residents' happiness reached 0.062, and the *p*-value between internet use and residents' happiness is 0, indicating a strong correlation between internet use and residents' happiness. This implies that the use of the internet will increase the happiness of the residents, verifying the basic hypothesis of this paper.

The statistical description of the variables is shown in Table 2. The happiness of the residents is measured between saying that they are not happy or unhappy and relatively happy; the percentage of residents who use the internet is 61.9%. In terms of demographic characteristics, the proportion of males was 46.7%, the average age was 52 years old, the proportion of Han Chinese was 92.7%, the proportion of those with religious beliefs was 10.7%, the education level was between college specialist and college or above; the proportion of political appearance was 11.1% for CCP members; the proportion of married was 87.8%; and the proportion of residents that do not have agricultural households was 45.3%.

4. Empirical analyses

4.1. Baseline regression results

This study first empirically tests the effect of internet use on residents' happiness using a least squares regression model. In addition, because the explanatory variables are ordered discrete variables, ordered logit and ordered probit models are used to regress the cross-sectional data on ordered discrete variables and test the robustness of the results. The corresponding regression equations are set as follows.

$$\text{Happiness} = \beta + \beta_1 * \text{Internet use} + \beta_2 * \text{Control} + \varepsilon \quad (1)$$

Happiness denotes residents' happiness; *internet use* denotes the internet use; *Control* denotes the control variables, including individual demographic characteristics variables (i.e., gender, age, square of age, nationality, religion, education, political status, marital status, and household status); and ε is the random error term.

Table 3 reports the corresponding regression results. Column (1) represents the results of the regression model using the ordinary least squares (OLS) method, which does not control for demographic characteristics of the population, showing that the positive effect of internet use on the happiness of the population is significant at the 1% level, but the adjusted *R*-squared is only 0.004. After controlling for the demographic characteristics of the population, as shown in column (2) of the table, the results are similar to those in column (1), with a higher value of adjusted *R*-squared. The coefficients of the happiness variable are also significantly positive in both the Ologit and Oprobit regressions, indicating that internet use significantly increases the happiness of the population.

The regression results for other control variables are generally consistent with the existing literature as well. First, the coefficient of gender is negative and significant at the 1% level, indicating that women's happiness is higher than that of men. In China, men can enjoy better education, higher employment rates and income. This results in higher social expectations for men. So men will face more pressure, which may reduce their happiness (102). For women, although they are more prone to negative emotions due to their physiology, it does not mean that they are unhappy (15). Moreover, society empowers women more, and higher income levels enhance their status in the family and give them more freedom (103). Second, the coefficient of age is positive and significant at the 1% level, indicating that the happiness of residents gradually decreases with age. The squared coefficient of age is significantly positive, indicating that age and happiness have a U-shaped relationship (104). Happiness decreases from a high point at a young age, reaches a low point at middle age, increases thereafter, and reaches another high point at old age. Third, the coefficient of ethnicity is not significant, indicating that the presence of ethnic minorities does not have an effect on the happiness of residents. Fourth, the coefficient of religiosity is significantly positive, indicating that residents with religious beliefs have a stronger sense of happiness. Religious beliefs have the function of guiding the thoughts and behaviors of individuals, and the spiritual protection function of religious culture is conducive to making human beings perceive happiness (105). Fifth, the coefficient of education is positive and significant at the 1% level, which indicates that the increase of education level will significantly improve the happiness of residents. Education not only enriches people's spiritual world and positively affects their self-esteem, self-confidence, and happiness, but also enhances their happiness by increasing their income level (106). Sixth, the coefficient of political affiliation is positive and significant at the 1% level, indicating that residents who are members of the CCP are happier. Being a CCP member is considered to be important social capital (107). Studies show that CCP and the Communist Youth League of China (CYLC) members are less money conscious than the masses and will be more self-conscious and participate more in social activities (108). Seventh, the coefficient of marital status is positive and significant at the 1% level, indicating that married residents are happier. After several years of follow-up and research development, marriage makes people happier. On the one hand, due to the national welfare policy, married couples can enjoy tax incentives (109); on the other hand, marriage alliances can be more rewarding (110). Eighth, a significantly positive household coefficient indicates that the happiness of non-rural household residents is stronger. Residents of urban households have better quality social services and health care coverage, while rural residents suffer from greater life stress, and overall, the happiness of rural household residents is significantly lower than that of non-rural households (111).

TABLE 1 Matrix of correlations.

Variables	(1)	(2)
(1) Internet use	1.000	
(2) Happiness	0.062***	1.000

*, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the values of the statistics are in parentheses.

4.2. Robustness test

Internet usage frequency is a good indicator of internet usage. Therefore, this study selected internet usage frequency as a proxy variable for the explanatory variable of internet usage. The question in the questionnaire asks, "In the past year, how often did you use the internet (including cell phone access)?" The answers from 1–5

TABLE 2 Statistical description of the variables.

Variables	Mean	Median	SD	Min	Max	*n*
Happiness	3.897	4.000	0.816	1.000	5.000	12751.000
Internet use	0.619	1.000	0.486	0.000	1.000	12745.000
Gender	0.467	0.000	0.499	0.000	1.000	12764.000
Age	51.855	52.000	16.936	18.000	118.000	12764.000
Age squared	29.757	27.040	17.745	3.240	139.240	12764.000
Nationality	0.927	1.000	0.259	0.000	1.000	12764.000
Religious belief	0.107	0.000	0.309	0.000	1.000	12764.000
Education	3.155	3.000	1.502	1.000	6.000	12735.000
Political status	0.111	0.000	0.314	0.000	1.000	12764.000
Marital status	0.879	1.000	0.327	0.000	1.000	12764.000
Household status	0.453	0.000	0.498	0.000	1.000	12764.000

TABLE 3 Baseline regression results of the effect of internet use on the happiness of Chinese residents.

	Ols (1)	Ols (2)	Ologit (3)	Ologit (4)	Oprobit (5)	Oprobit (6)
Internet use	0.105*** (7.05)	0.119*** (5.87)	0.184*** (5.08)	0.263*** (5.23)	0.115*** (5.68)	0.148*** (5.30)
Gender		−0.0531*** (−3.62)		−0.148*** (−4.11)		−0.0804*** (−3.97)
Age		−0.0241*** (−8.74)		−0.0586*** (−8.60)		−0.0326*** (−8.54)
Age squared		0.0265*** (10.52)		0.0653*** (10.44)		0.0362*** (10.37)
Nationality		−0.0159 (−0.56)		−0.0505 (−0.72)		−0.0250 (−0.64)
Religious belief		0.0583** (2.45)		0.178*** (3.02)		0.0944*** (2.88)
Education		0.0454*** (6.67)		0.0991*** (5.91)		0.0570*** (6.05)
Political status		0.123*** (4.99)		0.331*** (5.49)		0.192*** (5.58)
Marital status		0.198*** (7.34)		0.496*** (7.56)		0.265*** (7.17)
Household status		0.0453*** (2.65)		0.121*** (2.87)		0.0682*** (2.89)
Constant	3.833*** (327.62)	3.969*** (52.04)				
Adj R^2	0.004	0.033				
Pseudo R^2			0.001	0.015	0.001	0.015
n	12,732	12,703	12,732	12,703	12,732	12,703

*, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the values of the statistics are in parentheses (the next table is the same as).

indicate never, rarely, sometimes, often, and very often, respectively, which indicate the internet use of residents. Table 4 reports the regression results. The regression coefficients of happiness in the least squares regression model are all positive and significant at the 1% level. Similarly, the coefficients of happiness variables in the Ologit and Oprobit regressions are all significantly positive, indicating that the increase in the frequency of internet use significantly enhances the happiness of residents.

4.3. Endogenous issues

The estimated results may have endogeneity problems due to reverse causality and omitted variables. The endogeneity problem cannot be ignored because residents have more leisure time to use the internet when their happiness is stronger. In this study, we use an instrumental variable regression model to deal with the endogeneity problem; the selected instrumental variable is whether or not to own a cell phone independently. The question in the questionnaire is, "Do you have a cell phone that you use alone?" Since having a cell phone alone or not does not directly affect their happiness, but having a cell phone alone is associated with the internet use of residents, this instrumental variable is theoretically feasible.

Table 5 reports the results of the two-stage instrumental variable estimates of internet use on happiness. In the 2SLS regression results, the non-identifiable test statistic is 378.590, which rejects the original hypothesis that the instrumental variable is not correlated with the endogenous variable at the 1% significance level. The weak instrumental variable statistic is 389.889, which is greater than the critical value at the 10% bias level of 16.38 (112). Therefore, the original hypothesis of the existence of a weak instrumental variable is rejected; the *t*-value of the instrumental variable is 19.57, indicating that the instrumental variable is valid. From the first-stage regression results, the coefficient of independent cell phone ownership is significantly positive, indicating that independent cell phone ownership promotes internet use. The results of the second-stage regression indicate that internet use significantly enhances residents' happiness after controlling for endogeneity issues, so the results are robust. To further verify the rationality of the instrumental

TABLE 4 Effect of frequency of internet use on residents' happiness.

Explanatory variables	Ols (1)	Ols (2)	Ologit (3)	Ologit (4)	Oprobit (5)	Oprobit (6)
Internet usage frequency	0.0320*** (7.46)	0.0335*** (5.38)	0.0575*** (5.49)	0.0752*** (4.88)	0.0357*** (6.11)	0.0423*** (4.92)
Gender		−0.0546*** (−3.73)		−0.151*** (−4.20)		−0.0821*** (−4.06)
Age		−0.0224*** (−8.06)		−0.0547*** (−7.95)		−0.0305*** (−7.91)
Age squared		0.0248*** (9.90)		0.0614*** (9.88)		0.0340*** (9.81)
Nationality		−0.0172 (−0.61)		−0.0530 (−0.76)		−0.0264 (−0.68)
Religious belief		0.0586** (2.47)		0.180*** (3.04)		0.0946*** (2.89)
Education		0.0433*** (6.26)		0.0939*** (5.51)		0.0541*** (5.65)
Political status		0.126*** (5.12)		0.338*** (5.60)		0.196*** (5.70)
Marital status		0.200*** (7.42)		0.498*** (7.59)		0.267*** (7.24)
Household status		0.0490*** (2.87)		0.130*** (3.07)		0.0726*** (3.08)
Constant	3.805*** (264.88)	3.914*** (49.31)				
Adj R^2	0.004	0.032				
Pseudo R^2			0.001	0.015	0.001	0.015
n	12,745	12,716	12,745	12,716	12,745	12,716

*, **, and ***indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the values of the statistics are in parentheses.

TABLE 5 Internet use and happiness: two-stage instrumental variable estimates.

Explanatory variables	2SLS		IVoprobit	
	Internet use	Happiness	Internet use	Happiness
	(1)	(2)	(3)	(4)
Internet use		0.513*** (4.300)		0.641*** (4.210)
Ownership of cell phones	0.228*** (19.570)		0.229*** (19.830)	
Control variables	Yes	Yes	Yes	Yes
Unrecognizable test	378.590			
Weak instrumental variable test	389.889			
Wald test			13260.280	
atanhrho_12			−0.178*** (−3.210)	
Sample size	12,695	12,695	12,716	12,716

*, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the values of the statistics are in parentheses.

variable selection, the Oprobit instrumental variable model is used to test the robustness of the two-stage regression results, where atanhrho_12 is significant at the 1% level of significance, thus rejecting the original hypothesis that internet use is an exogenous variable. The Wald test statistic is 13260.28, which is significant at the 1% level, indicating that the instrumental variable has explanatory power. The results of the first-stage regression indicate that independent ownership of a cell phone significantly promotes internet use, and the results of the second-stage regression show the same significant positive effect of internet use on residents' happiness after controlling for endogeneity issues.

5. Analysis of intermediary effect mode

5.1. Model and variables

The results in the previous section show that internet use has a significant positive effect on residents' happiness. So how does internet use enhance residents' happiness? Based on the principle of the mediating effect test proposed by Baron and Kenny (113), the present study constructs the following mediating effect equation to empirically test the mechanism of the effect of internet use on residents' happiness:

$$\text{Happiness} = \delta + a_1 * \text{Internet use} + b * \text{Control} + \varepsilon \quad (2)$$

$$\text{Mediator} = \delta + c * \text{Internet use} + b * \text{Control} + \varepsilon \quad (3)$$

$$\text{Happiness} = \delta + a_2 * \text{Internet use} + e * \text{Mediator} + b * \text{Control} + \varepsilon \quad (4)$$

Eq. (2) tests the effect of internet use on residents' happiness which is the same as the baseline regression Eq. (1). The second step regresses model (3), and if the regression coefficient *c* is significant, it indicates that internet use has a significant effect on the mediating variable and then the third step regresses model (4). a_1 is the total effect of internet use on happiness, and a_2 is the direct effect of

internet use on happiness. If the coefficients c and e are significant, then it means there is a partial mediating effect of the mediating variable; if the coefficients c and e are significant but the coefficient a_2 is not significant, then it indicates that there is a full mediating effect of the mediating variable. In addition, this study further uses the Sobel method to test the existence and magnitude of the mediating effect. Since the explanatory variables in Eqs. (2)–(4) are all discrete variables, to enhance the reliability of the results, Ologit and Oprobit models are used, respectively, in this study for regression. The study likewise uses the Sobel method to further test the existence and magnitude of mediating effects.

This study analyzes the mechanism of social interaction frequency and SES. The frequency of social interaction is based on the questionnaire, "In a typical day, how many people, other than family members and relatives, do you have contact with in total through various means? Contact refers to one-to-one contact, including meeting, telephone, e-mail, WeChat, etc., whether you know them or not." The responses from 1–7 indicate 0, 1–4, 5–9, 10–19, 20–49, 50–99, and 100 or more times, respectively. For SES, this study uses the household economic status in the questionnaire to express "What is the economic status of your household in your region?" The responses from 1 to 5 indicate far below average, below average, average, above average, and far above average to measure the household economic status, respectively.

The statistical descriptions of the mediating variables are shown in Table 6. On average, the frequency of social interactions ranged from 5 to 19; SES was between below average and average.

5.2. Empirical results

The results of the mediating effects of social interaction frequency are shown in Table 7. The regression results of the Ologit and Oprobit models are consistent, indicating that the results are robust. In the first step, the baseline regression results indicate that the total effect of internet use significantly enhances residents' happiness. In the second step, the coefficients of internet use are also all significantly positive, indicating that internet use increases the frequency of social interactions among residents and enhances SES. In the third step, the coefficients before social interaction frequency and SES are both significantly positive, indicating that the increase in social interaction frequency and SES significantly improves residents' happiness. Meanwhile, the coefficients before internet use are significantly positive, implying that social interaction frequency and SES play a role of partial mediating effect between the effect of internet use on residents' happiness. There is a transmission mechanism in the process of internet use affecting residents' happiness which is internet use → social interaction frequency/SES → happiness. To further ensure the robustness of the regression results, this study uses the Sobel method for testing. The absolute value of Sobel Z size is 2.890 and 9.922, which are significant at the 1% significance level, where the mediating effect accounts for 0.064 and 0.445 of the total effect, indicating that there is a significant mediating effect of social interaction frequency and SES. Hence, the theoretical hypotheses 2 and 3 were verified.

TABLE 6 Statistical description of the mediating variables.

Variables	Mean	Median	SD	Min	Max	*n*
Frequency of social interactions	3.049	3.000	1.383	1.000	7.000	4431.000
socioeconomic status	2.577	3.000	0.729	1.000	5.000	12638.000

TABLE 7 Mediating effects of frequency of social interactions and socioeconomic status.

Variables	Ologit			Oprobit		
	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
	Happiness (1)	Inter-mediate variables (2)	Happiness (3)	Happiness (4)	Inter-mediate variables (5)	Happiness (6)
Internet use	0.263*** (5.23)	0.429*** (5.48)	0.284*** (3.31)	0.148*** (5.30)	0.256*** (5.71)	0.165*** (3.46)
Frequency of social interactions			0.076*** (3.35)			0.042*** (3.32)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.015	0.034	0.017	0.015	0.035	0.017
n	12,703	4,419	4,416	12,703	4,419	4,416
Internet use	0.263*** (5.23)	0.502*** (10.22)	0.141*** (2.77)	0.148*** (5.30)	0.291*** (10.38)	0.0821*** (2.89)
Socioeconomic status			0.690*** (25.99)			0.387*** (26.62)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.015	0.043	0.039	0.015	0.044	0.040
n	12,703	12,591	12,579	12,703	12,591	12,579

*, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the values of the statistics are in parentheses.

6. Research findings and policy implications

This study investigates the impact of internet use on residents' happiness based on data from the 2018 CGSS. The empirical results show that, first, internet use significantly enhances residents' happiness. A two-stage instrumental variable estimation is conducted using whether or not a person independently owns a cell phone as an instrumental variable, and the finding still holds after overcoming the endogeneity problem and conducting a series of robustness tests. Second, the mediating effect model test finds that there is a transmission mechanism in the process of internet use affecting residents' happiness which is internet use → social interaction frequency/SES → happiness. Internet use significantly increases the social interaction frequency of residents and enhances their SES, and the increase in social interaction frequency and SES significantly enhances residents' happiness.

The following recommendations are proposed based on the conclusions of this article:

Firstly, spread internet use more widely while giving individuals more internet literacy. As of June 2022, China's internet penetration rate was only 74.4%, which is still a large gap compared to developed countries such as Europe and the United States. Therefore, it is necessary to further increase the internet penetration rate and improve people's internet usage skills by improving internet infrastructure to solve the problem of internet usage difficulties for the poor and the old, lower tariffs, accelerate the cultivation of internet-related talents and popularise internet education, enabling more people to benefit from the convenience resulting from internet development and making internet usage an effective means of enhancing residents' happiness.

Secondly, the interactive effect of the internet should be brought into full play to increase the frequency of social interaction among residents. Internet popularization should differ depending on the age group of residents. For young people, digital teaching and high-quality digital resources should be developed, providing strong support for promoting the reform and development of basic education in the information era. For the older adult, the age-appropriate transformation of applications such as WeChat, Tiktok, Alipay, and so on can expand their family network and friend network, and reduce their sense of loneliness. Meanwhile, the disabled and other special groups could cross the "digital divide" and improve their sense of happiness with the help of the accessibility transformation of applications. In addition, "internet + tourism," "internet + medical," "internet + education" and other "internet +" platforms should be vigorously developed to provide people with convenience and enrich their spiritual and cultural lives so that people could feel happier as technology advances. Moreover, the internet, as a social media, plays a significant role in the development and maintenance of social relationships. As such, it is important to encourage individuals to engage in more social activities via the internet, expand their social networks, and strengthen their social capital, while also promoting pro-social behaviors.

Thirdly, it is important to develop individuals' understandings of the internet, to guide them in using the internet rationally, to create an upwardly mobile online environment, and to improve individual socioeconomic status. First and foremost, it is necessary to diversify the types and disciplines of online education, develop digital labor platforms, explore the potential of the internet to enhance work efficiency and flexibility. Assist people in using the internet rationally and scientifically in their studies, work, and daily lives to improve their skills and knowledge, to avoid playing online games or excessive use of virtual social networks, and to increase awareness of the possibility of promoting one's human capital quality through the internet, and to lay a solid foundation for social and economic improvement. Secondly, the relevant departments should grasp the importance of strict supervision, network platforms should consolidate the main responsibilities, and most internet users should improve their network literacy. It would allow people to reduce information asymmetry, broaden employment channels, and increase the income of urban and rural residents through the internet, resulting in an olive-shaped structure of income and wealth distribution with a large middle and two small ends. Expand the middle-income group and enhance the degree of common prosperity so that the internet can truly be used to improve the quality of life of people.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: http://www.cnsda.org/index.php?r=projects/view&id=35694191.

Author contributions

YS and XZ: conceptualization, validation, formal analysis, writing—review and editing, and supervision. YS, JG, XZ, and YC: methodology. JG and YC: software. YS, JG, and YC: data curation. YS and JG: writing—original draft preparation. YC: visualization. YS: project administration and funding acquisition. 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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Smartphone addiction, sleep quality, depression, anxiety, and stress among medical students

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Introduction: Studies consistently link excessive smartphone use to poor sleep quality, depression, anxiety, and stress. This study specifically aimed to investigate these associations among medical students in Belgrade and Nis (Central Serbia).

Materials and methods: The cross-sectional study included a sample of 761 students, who were selected from both the Faculties of Medicine at the University of Belgrade and the University of Nis. Questionnaires, including the International Physical Activity Questionnaire – Short Form (IPAQ-SF), Smartphone Addiction Scale – Short Version (SAS-SV), the Pittsburgh Sleep Quality Index (PSQI), and the Depression, Anxiety, and Stress Scale – 21 items (DASS-21), were completed by the participants. Statistical analysis techniques, such as the Chi-square test, student's *t*-test, and logistic regression, were employed to examine the relationship between smartphone addiction, physical activity, sleep quality, depression, anxiety, and stress.

Results: The findings indicated a prevalence of smartphone addiction among medical students at 21.7%, with rates of 22.9% among males and 21.1% among females. Females exhibited significantly higher scores on the SAS-SV scale compared to males ($p = 0.032$). Univariate logistic regression analysis revealed significant associations between smartphone addiction and spending over 4 h daily on smartphones (OR = 2.39; $p < 0.001$), poor sleep quality (OR = 1.65; $p = 0,005$), as well as elevated levels of stress (OR = 1.75; $p = 0.003$), anxiety (OR = 2.04; $p < 0.001$), and depression (OR = 2.29; $p < 0.001$). Multivariate regression analysis identified spending more than 4 h daily on smartphones (OR = 2.39; $p < 0.001$) and increased levels of depression (OR = 2.51; $p < 0.001$) as independent significant factors associated with smartphone addiction.

Conclusion: This study sheds light on the prevalence of smartphone addiction among medical students, with spending excessive time on smartphones and higher levels of depression standing out as significant factors. Future research should delve into the underlying mechanisms and causal relationships between smartphone addiction and these psychosocial factors. Understanding these connections will aid in developing effective interventions and strategies to tackle this growing public health concern.

KEYWORDS
smartphone addiction, sleep quality, depression, anxiety, stress

1. Introduction

A smartphone is a portable mobile phone with computer-like capabilities (1). Unlike traditional mobile phones that were primarily used for calls and SMS messages, smartphones now offer a wide array of functionalities, such as email, music, camera, web browsing, gaming, and a multitude of applications. Currently, around 6.6 billion people worldwide use smartphones, and this number is projected to reach 7.8 billion by 2028 (2).

The increase in smartphone usage has led to a surge in research investigating excessive and problematic smartphone use. Many studies indicate that a significant number of individuals engage in excessive phone use, leading to disruptions in their daily routines, safety, and general well-being (3–6). Furthermore, prolonged and excessive smartphone usage has been associated with negative effects on mental health and behavior (7–9).

Problematic smartphone use is often conceptualized as a behavioral addiction, exhibiting similarities to non-chemical addictions such as gambling addiction. This condition is characterized by a diminished ability to regulate phone use, accompanied by addiction-related symptoms such as tolerance, withdrawal, preoccupation, unsafe or prohibited phone usage, and adverse functional consequences (10). Despite the abundance of research highlighting the addictive characteristics of smartphones, smartphone addiction has not yet received official recognition in the Diagnostic and Statistical Manual of Mental Disorders (DSM) published by the American Psychiatric Association (11), nor in the International Classification of Diseases (ICD) (12). Nonetheless, although it lacks formal diagnostic status, criteria for smartphone addiction have been suggested (13). The criteria for smartphone addiction can be categorized into three sections: Part A, comprising six symptom criteria that delineate specific symptoms of smartphone addiction; Part B, focusing on functional impairments that arise from excessive smartphone use; and Part C, consisting of exclusion criteria that rule out manic episodes or obsessive-compulsive disorder (13). Research findings revealed significant overlaps between the characteristics of smartphone addiction and substance-related or behavioral addictive disorders (13). Additionally, Horvath et al. (14) provided evidence of specific structural and functional correlates associated with behavioral addictions in individuals who met the psychometric criteria for smartphone addiction.

Contrary to the prevailing notion of smartphone addiction, some studies have raised questions regarding its conceptualization (15, 16). Some authors argue that the debates surrounding the understanding and acceptance of technological and behavioral addictions are largely influenced by terminology. They note that while smartphone addiction may not have the same severity and health consequences as substance addiction, there is no alternative widely accepted term to describe the lack of self-control, attachment, overuse, and adverse outcomes associated with this behavior (15). Consequently, "addiction" has become an accepted umbrella term despite potential misrepresentation of the disorder's severity and the resulting implications for research and treatment efforts. The concept of "smartphone addiction" continues to be a subject of extensive debate in scientific literature, with ongoing controversies surrounding its terminology. Nevertheless, "smartphone addiction" has gained widespread acceptance and usage in the field's literature. Therefore, in alignment with existing conventions, this study employs the term "smartphone addiction" to characterize the excessive use of smartphones that adversely affects daily functioning.

Multiple studies have provided evidence of a positive correlation between smartphone addiction and stress, anxiety, and depression (8, 17), as well as associations with poor sleep quality, fatigue, difficulties in falling asleep, and shorter sleep duration (17–20). Moreover, in clinical settings, excessive smartphone use can serve as a significant distraction and lead to potential negligence and harm to patient health (21). To explore the relationship between "smartphone addiction" and various factors including physical activity, depression, anxiety, stress, and sleep quality, a cross-sectional study was conducted on a representative sample of students from the Faculty of Medicine in Belgrade and the Faculty of Medicine in Nis.

2. Materials and methods

This cross-sectional study was conducted between 1st and 31st December 2018 among students of medical faculties in Belgrade and Nis, Serbia. The study was reviewed and approved by the Ethics Committee of the Faculty of Medicine, University of Belgrade (No. 2650/XII-1). The Dean of the Medical Faculty at the University of Nis gave signed permission to conduct research among medical students in Nis. Students were offered the opportunity to voluntarily complete the questionnaire at the beginning of their classes. Informed consent was obtained from all participants before completing the questionnaire survey.

2.1. Participants

The study was conducted on a representative sample of medical students from the Faculty of Medicine University of Belgrade (MFUB) and the Faculty of Medicine University of Nis (MFUN), Republic of Serbia. Multi-stage sampling was used. The required sample size for MFUB student population was computed as 291 using Epi Info 7 (version 7.2.5.0) [population size: 3,055 medical students; expected frequency: 29.8% (22); acceptable margin of error: 5%; design effect: 1]. The required sample size for MFUN student population of 253 was computed using Epi Info 7 (version 7.2.5.0) [population size: 1198 medical students; expected frequency: 29.8% (22); acceptable margin of error: 5%; design effect: 1]. To address the possibility of incomplete questionnaires, a larger number of students was included in the study. A total of 761 students completed the questionnaire (383 students (50.3%) from the MFUB and 378 (49.7%) students from the MFUN).

TABLE 1 Factors associated with smartphone addiction among students of medical faculties: results of univariate logistic regression analysis.

	Not addicted *N* = 596 *N* (%)	Addicted *N* = 165 *N* (%)	OR (95%CI)	*p*-value
Sex, female	411 (69.0)	110 (66.7)	0.90 (0.62–1.30)	0.575
Age ≤ 21 years	284 (47.7)	74 (44.8)	0.89 (0.63–1.26)	0.523
Year of study ≤3	300 (50.3)	81 (49.1)	0.95 (0.67–1.34)	0.777
GPA ≥ 8.8	246 (51.2)	63 (45.7)	0.80 (0.55–1.17)	0.247
Residence during studies – With parents	244 (40.9)	77 (46.7)	1.26 (0.89–1.78)	0.188
Socio-economic status – Good	356 (59.7)	97 (58.8)	0.96 (0.67–1.37)	0.827
Parents' marital status – Married	485 (82.3)	139 (86.3)	1.36 (0.82–2.23)	0.231
Smoking	119 (20.0)	32 (19.4)	0.96 (0.62–1.49)	0.870
Alcohol consumption	391 (65.6)	120 (72.7)	1.40 (0.95–2.05)	0.086
Energy drink consumption	227 (38.2)	69 (41.8)	1.16 (0.82–1.66)	0.393
BMI categories[†]				
Underweight	55 (9.3)	17 (10.4)	1 (Ref.)	
Normal weight	445 (74.9)	122 (74.4)	0.89 (0.49–1.58)	0.685
Overweight	84 (14.1)	23 (14.0)	0.89 (0.43–1.81)	0.739
Obesity	10 (1.7)	2 (1.2)	0.65 (0.13–3.25)	0.597
Physical activity				
Low	120 (20.1)	31 (18.8)	1 (Ref.)	
Moderate	291 (48.8)	78 (47.3)	1.04 (0.65–1.66)	0.650
High	185 (31.0)	56 (33.9)	1.17 (0.71–1.92)	0.714

X, Mean; SD, Standard Deviation; OR, Odds Ratio; 95%CI, 95% Confidence Interval; GPA, Grade Point Average—average grade for students in their 2nd to 6th year of study; *p*-value for ULRA; BMI, Body Mass Index; [†]The body height or weight data of 3 students was not provided, rendering the calculation of their BMI unfeasible.

Students from 1st to 6th year of study were evenly distributed in the sample.

2.2. Instruments

Respondents completed various self-report questionnaires. A specifically developed questionnaire was utilized to collect sociodemographic characteristics of the participants, including gender, age, year of study, place of residence during studies (with parents/apartment/room/dorm/other), socioeconomic status (good/medium/poor), grade point average (GPA) (for students in their 2nd to 6th year of study; with the minimum grade being 6 and the maximum being 10), body mass (in kilograms), body height (in meters), smoking status (smokers/non-smokers), alcohol consumption (yes/no), and energy drinks consumption (yes/no). Additionally, participants were asked about their daily time spent on smartphones. In the logistic regression step (Tables 1, 2), the numerical variables age, year of study, GPA, and "time spent on smartphones" were dichotomized to identify predictors of smartphone addiction.

The level of smartphone addiction was assessed using the short version of the Smartphone Addiction Scale (SAS-SV) (23). The items on the SAS-SV were carefully selected from the original Smartphone Addiction Scale (SAS), which consisted of 33 items, based on their validity (24). The correlation between the SAS-SV and SAS was found to be 0.96. The SAS-SV is a validated scale comprising 10 items that participants rate on a 6-point Likert scale (ranging from 1 = strongly disagree to 6 = strongly agree). The total score on this scale can range from 10 to 60, with higher scores indicating a greater degree of smartphone addiction. The original SAS-SV demonstrated content and concurrent validity, as well as internal consistency (Cronbach's alpha of 0.91). The items on the scale encompass various aspects of addiction such as disruption in daily life, withdrawal symptoms, relationships centered around cyberspace, excessive use, and tolerance. The SAS-SV possesses the advantage of being able to identify a potentially high-risk group for smartphone addiction, both within educational settings and the broader community. For males, a cut-off value of 31 is considered indicative of addiction (with a sensitivity of 0.867 and specificity of 0.893), while for females, the corresponding cut-off value is 33 (with a sensitivity of 0.875 and specificity of 0.886). In this study, a translated and culturally adapted Serbian version was used, which proved to be a valid and reliable instrument for assessing smartphone addiction (25).

Depression, anxiety, and stress levels were evaluated utilizing the DASS-21 scale (Depression Anxiety and Stress Scale - DASS). The DASS-21 comprises three subscales designed for self-assessment of negative emotional states associated with depression, anxiety, and stress (26). In essence, the Depression subscale predominantly captures low positive affect, the Anxiety subscale focuses on physiological arousal, and the Stress subscale evaluates nonspecific negative affect (26, 27). Respondents indicate the extent to which they experienced each listed condition in the previous week using a four-point response scale. The responses for each subscale are then summed

TABLE 2 Factors associated with smartphone addiction among students of medical faculties: results of univariate* and multivariate** logistic regression analysis.

Characteristics	Not addicted $N = 601$	Addicted $N = 164$	OR (95%CI)*	*p* value*	OR (95%CI)**	*p* value**
Time spent on smartphone >4 h/day	181 (30.4)	81 (49.1)	2.21 (1.55–3.13)	**<0.001**	2.39 (1.66–3.43)	**<0.001**
Sleep quality						
Good	376 (63.1)	84 (50.9)	1.65 (1.16–2.33)	**0.005**		
Poor	220 (36.9)	81 (49.1)				
Stress						
Normal	449 (75.3)	105 (63.6)	1 (Ref.)			
Mild	69 (11.6)	16 (9.7)	0.99 (0.55–1.78)	0.977		
Moderate	53 (8.9)	33 (20.0)	2.66 (1.64–4.32)	**<0.001**		
Severe	19 (3.2)	9 (5.5)	2.03 (0.89–4.61)	0.092		
Extremely severe	6 (1.0)	2 (1.2)	1.42 (0.28–7.16)	0.667		
Increased stress†	147 (24.7)	60 (36.4)	1.75 (1.21–2.52)	**0.003**		
Anxiety						
Normal	408 (68.5)	85 (51.5)	1 (Ref.)			
Mild	47 (7.9)	17 (10.3)	1.74 (0.95–3.17)	0.072		
Moderate	83 (13.9)	29 (17.6)	1.68 (1.03–2.72)	**0.036**		
Severe	30 (5.0)	10 (6.1)	1.60 (0.75–3.40)	0.221		
Extremely severe	28 (4.7)	24 (14.5)	4.11 (2.27–7.45)	**<0.001**		
Increased anxiety†	188 (31.5)	80 (48.5)	2.04 (1.44–2.90)	**<0.001**		
Depression						
Normal	451 (75.7)	95 (57.6)	1 (Ref.)			
Mild	59 (9.9)	26 (15.8)	2.09 (1.25–3.49)	**0.005**		
Moderate	48 (8.1)	26 (15.8)	2.57 (1.52–4.35)	**<0.001**		
Severe	22 (3.7)	9 (5.5)	1.94 (0.86–4.35)	0.107		
Extremely severe	16 (2.7)	9 (5.5)	2.67 (1.14–6.22)	**0.023**		
Increased depression†	145 (24.3)	70 (42.4)	2.29 (1.59–3.29)	**<0.001**	2.51 (1.73–3.63)	**<0.001**

OR, Odds Ratio; 95% CI, 95% Confidence Interval; **p* value for ULRA; ***p* value for MLRA. Bold values indicate statistical significance. †Dichotomous variables (normal vs. increased).

and multiplied by two to ensure comparability with results obtained from the DASS-42 scale. Based on the scores, the subscales are categorized as follows: normal, mild, moderate, severe, extremely severe (28). To facilitate multivariate logistic regression analysis, the variables were classified into the following two distinct categories: normal and increased. The Serbian translation of the DASS-21 scale underwent psychometric testing on a sample of students (1,374 students) in Novi Sad (27). The results demonstrated that the Serbian version of DASS-21 is a reliable and valid measure of unpleasant emotional states.

Sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI), a questionnaire designed to measure subjective sleep quality over a one-month period (29). The PSQI consists of 19 self-rated questions, as well as five questions answered by a bed partner. The additional questions answered by another person, typically a partner or roommate, provide clinical information but are not included in the scoring process. The 19 items of the PSQI are divided into seven components, namely subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Each component is assigned a score, and the scores for the seven components are summed to obtain the global PSQI score. The global score ranges from 0 to 21, with higher scores indicating poorer sleep quality. The Serbian translation of the PSQI questionnaire has been validated and can be utilized as a reliable screening tool for assessing sleep quality in diverse populations (30). A cutoff score of 5 is commonly used to categorize respondents into two groups: those with good sleep quality (PSQI <5) and those with poor sleep quality (PSQI ≥5) (30).

The International Physical Activity Questionnaire-Short Form (IPAQ-SF), a reliable and validated tool, was employed to evaluate physical activity levels over the past week (31). The IPAQ-SF captures four levels of physical activity intensity: vigorous-intensity physical activity, which encompasses activities like heavy lifting, intense aerobic exercises, and using a bike or treadmill; moderate-intensity physical activity, including tasks such as carrying light loads, cycling at a regular pace, and engaging in yard work; walking time; and average sitting time on weekdays, including sedentary work. Furthermore, the IPAQ-SF provides information on the level of physical activity in terms of energy expenditure measured in metabolic equivalent (MET)-minutes per week (32). MET-min/week coefficients

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used for each type of physical activity were: 3.3 for walking, 4.0 for moderate physical activity, and 8.0 for vigorous physical activity. The total weekly energy expenditure, known as total physical activity, was determined by summing the MET-min/week values for walking, moderate physical activity, and vigorous physical activity. Based on the total MET score, respondents were categorized into three groups: high, moderate, and low physical activity levels. Respondents with a weekly energy expenditure of less than 600 MET-minutes were classified as having low physical activity, those with 600–3,000 MET-minutes fell into the moderate physical activity category, and individuals with more than 3,000 MET-minutes were categorized as engaging in high-intensity physical activity. A spreadsheet programmed with specific criteria was utilized to automatically calculate the scores (33).

The body mass index (BMI) was employed as a measure to evaluate the nutritional status of the participants. Participants provided their height and weight, and the BMI was calculated based on these values. All participants were classified into four groups based on their BMI: underweight (BMI < 18 kg/m^2), normal weight (BMI = 18–24.9 kg/m^2), overweight (BMI = 25.0–29.9 kg/m^2), and obesity (BMI ≥ 30 kg/m^2) (34).

2.3. Statistical analysis

The statistical analysis of the data was performed using the SPSS 23.0 program (SPSS Inc., Chicago, IL, United States) for data processing. Descriptive statistics methods were employed, including the calculation of mean values, standard deviations, medians, minimum and maximum values. For comparing two groups of subjects, either a parametric test (independent samples *t*-test) or a non-parametric test (χ^2 test) was applied. More specifically, the independent samples *t*-test was used to analyze numerical variables, while the Chi-square test was applied to investigate categorical variables. The observed differences were considered statistically significant if the *p*-value was less than 0.05. To identify predictors of smartphone addiction, both univariate logistic regression analyses (ULRA) and multivariate logistic regression analyses (MLRA) were conducted. The dependent variable in these analyses was smartphone addiction, assessed based on the recommended cut-off values of 31 for males and 33 for females. Independent variables in multivariate analysis included all variables that exhibited significance in the univariate analysis at a significance level of less than 0.05.

TABLE 3 Demographic characteristics of students from medical faculties.

Demographic characteristics	Total (*N* = 761)
Sex, *N* (%)	
Male	240 (31.5)
Female	521 (68.5)
Age, years (X±SD)	21.81 ± 2.15
Year of study, *N* (%)	
1	128 (16.8)
2	128 (16.8)
3	125 (16.4)
4	130 (17.1)
5	126 (16.6)
6	124 (16.3)
GPA, (X±SD)	8.75 ± 0.72
Residence during studies, *N* (%)	
With parents	321 (42.2)
Apartment/room/dorm/other	440 (57.8)
Socio-economic status, *N* (%)	
Good	451 (59.3)
Medium	291 (38.2)
Poor	19 (2.5)
Married parents, *N* (%)	632 (83.0)

X, Mean; SD, Standard Deviation; GPA, Grade Point Average—average grade for students in their 2nd to 6th year of study.

TABLE 4 Smartphone addiction prevalence among males and females in medical faculties.

	Males (*N* = 240)	Females (*N* = 521)	Total (*N* = 761)	*p*-value
SAS-SV score				
X±SD	23.65 ± 9.00	25.17 ± 9.17	24.69 ± 9.14	**0.032***
Median (min-max)	22 (10–58)	25 (10–58)	24 (10–58)	
Smartphone addiction				
Addicted	55 (22.9)	110 (21.1)	165 (21.7)	0.575**
Not addicted	185 (77.1)	411 (78.9)	596 (78.3)	

SAS-SV, Smartphone Addiction Scale – Short Version; X, Mean; SD, Standard Deviation; **p* value for Student's *t*-test; ***p* value for χ^2 test. Bold values indicate statistical significance.

3. Results

The study included 761 students (Table 3). The gender distribution consisted of 68.5% males and 31.5% females. The sample was evenly distributed among students from the 1st to the 6th year of study, with each year comprising 124–130 students. On average, the age of the students was 21.81 (±2.15) years. The students' average grade point average (GPA) was calculated to be 8.75 (±0.72). Around 42% of the students resided with their parents during their studies. Socio-economic status indicated that approximately 60% of the students had a good socioeconomic standing, 38% had a medium standing, and 2.5% had a poor standing. Approximately 83% of students in both faculties had parents who were married.

The mean value of the Smartphone Addiction Scale - Short Version (SAS-SV) score was found to be 24.69 (±9.14) (Table 4). The prevalence of smartphone addiction among the participants was determined to be 21.7%. Notably, females exhibited significantly higher scores on the SAS-SV scale compared to males. However, when considering the prevalence of smartphone addiction, no significant difference was observed between males and females.

The findings of the univariate analysis examining factors associated with smartphone addiction among students are presented in Table 1. Variables including sex, age, year of study, GPA, housing during studies, socio-economic status, parents' marital status, smoking, alcohol consumption, energy drink consumption, nutritional status and physical activity, were not

found to be significantly associated with smartphone addiction.

Based on the findings from the univariate logistic regression analysis, it was observed that spending more than 4 h daily on smartphones, poor sleep quality, elevated levels of stress, anxiety, and depression were significantly associated with smartphone addiction (Table 2). Multivariate logistic regression models were utilized to identify the factors independently associated with smartphone addiction. The independent variables included in the multivariate analysis were those that showed significance in the univariate analysis at a level of $p < 0.05$, namely: time spent on the smartphone (>4 h per day), sleep quality, stress (dichotomous), anxiety (dichotomous), and depression (dichotomous). According to the final model, the significant factors independently associated with smartphone addiction were spending more than 4 h daily on smartphones (OR = 2.39; $p < 0.001$) and increased levels of depression (OR = 2.51; $p < 0.001$).

4. Discussion

In our study, the prevalence of smartphone addiction among medical students was determined to be 21.7%. According to the SAS-SV scale, smartphone addiction rates were estimated to be 12% among Japanese students (35), 16.9% in Switzerland (36), 26.9% in Romania (37), 29.8% in China (22), 33.1% in Brazil (38), and 35.9% in Thailand (35). The highest prevalence of addiction was observed in Saudi Arabia, reaching 71.9% (39), followed by India at 73%, and Iraq at 78.3% (40). Variations in the prevalence of smartphone addiction among students across countries may stem from differing social and cultural environments and disparities in the development and accessibility of information and communication technologies. Additionally, the choice of threshold value can influence reported prevalence, emphasizing the need for further studies to establish appropriate thresholds in diverse populations and age groups.

When analyzing the scores obtained from the SAS-SV scale, it was observed in our study that women had significantly higher scores than men. The higher scores achieved by women on the SAS-SV scale justified the recommended higher cutoff value (in order to be considered indicative of addiction) in the original study (23). However, in our study, no significant difference was observed between males and females when considering the prevalence of smartphone addiction. This finding aligns with the study conducted by Chen et al. (22), which also utilized the SAS-SV scale to assess smartphone addiction among medical students in China, revealing no significant difference in addiction prevalence between men (30.3%) and women (29.3%). In contrast, some studies have reported a higher prevalence of "smartphone addiction" in women (39). A review by Yu and Sussman (10) found that gender was a significant predictor in 19 studies (18% of the total studies reviewed), indicating that women had a higher risk of being "smartphone addicted." Additionally, 16 studies demonstrated that women were more inclined to be addicted to social media, while men exhibited a greater likelihood of game addiction (10).

In our study, there was no difference in the prevalence of smartphone addiction across different age groups. Several studies have consistently demonstrated a higher prevalence of addiction among younger individuals (36). Notably, a substantial number of studies have focused on addiction in adolescents and young adults (19, 36). Within a comprehensive review encompassing 108 studies, a remarkable 78% of them specifically examined adolescents and young adults, consistently reporting higher prevalence rates of smartphone addiction among this age group compared to older adults (10). One crucial aspect contributing to the susceptibility of younger individuals to smartphone addiction is their developmental stage. Adolescence and young adulthood mark significant periods of identity formation and social interaction. During this time, young people are more likely to seek social validation, peer acceptance, and a sense of belonging. Smartphones offer a means to fulfill these needs by providing constant connectivity to social networks and online communities. The desire to stay connected and "fear of missing out" (FoMO) can drive excessive smartphone use as they strive to maintain social relationships and seek approval from their peers.

In our study, we observed no statistically significant distinction in the mean GPA scores between group of students classified as being addicted to smartphones and those classified as non-addicted. The findings from a study among college students revealed a significant association between increased cell phone usage and decreased academic achievement (6). Moreover, a comprehensive review encompassing 23 studies investigating the link between smartphone usage and academic performance in tertiary education institutions found that 18 studies (78.3% of the total) reported a significant negative correlation between smartphone use and academic achievement. The remaining five studies did not demonstrate a significant relationship (41). The research suggests that students predominantly perceive smartphones as recreational devices, primarily utilizing them for social networking, internet browsing, video consumption, and gaming (6, 42). Additionally, the constant need to remain connected and stay updated, driven by the "fear of missing out" (FoMO), can impair the focused attention required for achieving favorable academic results (43). Furthermore, due to a lack of academic motivation, students may experience boredom in class or during study periods, with smartphones and various applications offering a quick and tempting escape from this state of ennui (41, 44).

Based on the findings of our study, no significant differences were observed between students categorized as addicted and those categorized as non-addicted in terms of smoking behavior, alcohol consumption, and energy drink consumption. Conversely, numerous studies have reported a correlation between these behaviors and smartphone addiction. In a study conducted in China, it was demonstrated that current smokers and individuals who consume alcohol once a week or more frequently are at a higher risk of smartphone addiction (45). Both smartphone use and alcohol/cigarette consumption can serve as coping mechanisms for individuals dealing with stress, anxiety, or other emotional challenges. People may turn to their smartphones or alcohol/smoking as a way to escape from negative emotions or to seek temporary relief. In a study conducted among students in South Korea, factors such as female gender, alcohol consumption, internet addiction, and anxiety were identified as risk factors for smartphone addiction among students (46). This connection can be explained by a shared psychosocial process underlying excessive use of psychoactive substances and other addictions. Recognized risk factors associated with problematic phone use encompass various personality traits such as neuroticism, anxiety, depression, low self-esteem, low self-control, and impulsivity (16, 47, 48). These factors may create a vulnerability for individuals to engage

in excessive smartphone use and substance abuse as a means of self-medication or self-soothing.

In our study, a significant association was observed between spending more than 4 h daily on smartphones and smartphone addiction. The variable of spending over 4 h per day on smartphones emerged as an independent factor significantly associated with smartphone addiction. Other researchers have also found similar results, indicating that increased frequency and duration of phone usage pose a risk for addiction (24, 39, 49). This suggests that students who are addicted face difficulties in controlling excessive phone use. In a study conducted among young individuals in Switzerland, significant independent predictors of smartphone addiction included longer phone usage, shorter time until the first phone use after awakening, and the predominance of social media usage as the primary activity on the phone (36).

In our study, no statistically significant difference was observed in terms of physical activity levels or nutritional status between students classified as addicted and those classified as non-addicted. Smartphone usage predominantly involves sedentary behavior (50). Extended periods spent gazing at smartphone and tablet screens have been linked to reduced engagement in physical activity, leading to higher body mass index, decreased physical activity levels, and various health issues such as visual impairments and musculoskeletal problems (39, 51, 52). Notably, students addicted to smartphones exhibit lower levels of physical activity compared to non-addicted students, a pattern observed in children as well (53). A mini-review investigating the impact of phone use on physical activity deficits revealed a negative association between smartphone usage and physical activity in 9 out of 14 studies (51). In a study conducted among Chinese students, students classified as being at a higher risk of smartphone addiction, exhibited lower muscle mass and higher fat tissue mass compared to those who exhibited moderate phone usage (54).

While excessive smartphone use can contribute to sedentary behaviors and reduced physical activity, it's worth noting that smartphone use can also be leveraged to promote and improve engagement in physical activity. Smartphone applications designed for fitness tracking can monitor and record various physical activities, such as walking, running, cycling, or workout sessions. These apps can provide real-time feedback, track progress, set goals, and offer motivation, thereby encouraging individuals to engage in regular physical activity. Smartphone apps and social media platforms can provide a sense of community and social support for individuals pursuing physical activity goals. It's important to note that while smartphones can be helpful tools for promoting physical activity, it's crucial to find a balance and avoid excessive smartphone use that interferes with active and healthy lifestyles.

The present study revealed a significant association between smartphone addiction and various psychosocial factors, including poor sleep quality, elevated levels of stress, anxiety, and depression. These findings suggest that individuals who exhibit higher levels of smartphone addiction are more likely to experience compromised sleep patterns and increased psychological distress. But of all the factors listed, an increased level of depression was identified as an independent predictor of smartphone addiction. In a study conducted among college students in Turkey, a significant association was found between smartphone use and depression and anxiety, indicating that higher levels of phone use were correlated with increased symptoms of depression and anxiety (8). Similar findings were observed in a study conducted among students in Lebanon, where a positive association between smartphone addiction, anxiety, and depression was identified. Both depression and anxiety were found to be independent positive predictors of smartphone addiction (55). A systematic review conducted by Elhai et al. (56) demonstrated a consistent connection between excessive smartphone use, depression, anxiety, and stress. A meta-analysis investigating the relationship between problematic phone use and mental health, involving 41 studies with a total sample size of 41,871 children and youth, revealed that problematic smartphone use was associated with an increased risk of depression (OR = 3.17), anxiety (OR = 3.05), stress (OR = 1.86), and poor sleep quality (OR = 2.60) (57). These collective findings highlight the strong link between problematic smartphone use and mental health issues, emphasizing the need for further research and targeted interventions to address this growing concern.

In a broader context, the examination of the influence of the internet and technology reveals compelling evidence linking the co-occurrence of depression, anxiety, and stress to the development of technology addiction. For instance, individuals experiencing persistent stress may resort to internet-based video games as a coping strategy (58), whereas those suffering from depression may employ mobile phones as a means to alleviate negative emotions which leads to more time spent on phones (59). A follow-up study by Kang et al. (60) revealed that students experiencing depression and/or anxiety were more prone to engaging in addictive smartphone usage compared to individuals without mental health issues. In essence, the utilization of smartphones serves as a means to circumvent the engagement with unpleasant emotional content, thereby engendering a spectrum of potential consequences. Conversely, heightened engagement with technology can contribute to the onset of depression, anxiety, and stress. A cohort study involving students demonstrated that individuals classified as "high users," specifically those who extensively utilize computers, social networks, and mobile phones, exhibited elevated levels of chronic stress, depression, and sleep disturbances after a one-year follow-up (61). Furthermore, a bidirectional association can be observed between excessive phone usage and psychological disorders, wherein problematic phone use can contribute to the development of psychological disorders, and conversely, pre-existing psychological disorders can lead to problematic phone use (62, 63). It can be postulated that a reciprocal relationship exists between phone addiction and mental disorders, forming a cyclical pattern with reinforcing effects.

In our study, the findings from the univariate logistic regression analysis revealed a significant association between poor sleep quality and smartphone addiction among students. In a previous study conducted among medical students, more than half of the students (54.7%) experienced poor sleep quality. Additionally, approximately one in every four students reported increased fatigue, and almost half of the students exhibited elevated levels of sleepiness (64). According to a study conducted by Chung et al. (19), individuals classified as "at-risk users" showed 2.3 times higher levels of daytime sleepiness compared to users of "low-risk." Another study by Sohn et al. (65), which involved 1,043 students in London, found that 61.6% of the students had poor sleep quality. Among the participants, a significantly higher percentage of smartphone-addicted students, experienced poor sleep quality (68.7%) compared to non-addicted students (57.1%). This suggests that smartphone addiction is associated with poor sleep quality (OR = 1.41) (36).

Furthermore, even after adjusting for daily screen time, the association between poor sleep quality and smartphone addiction remained significant, indicating that the link between these factors is not solely explained by the duration of phone use. A systematic review of existing literature by Hale et al. (66). indicate that the majority of studies consistently demonstrate a negative relationship between screen-based media consumption and sleep health. This association primarily manifests through delayed bedtimes and reduced overall sleep duration. The underlying mechanisms that contribute to these associations are likely as follows: (1) time displacement, where screen usage replaces time that could have been allocated to sleep and other activities; (2) psychological stimulation derived from the content of the media; and (3) the impact of the light emitted by electronic devices on circadian rhythm, sleep patterns, and wakefulness (67). Additionally, problematic smartphone use can contribute to the development of depression and/or anxiety, conditions that are known to be associated with sleep difficulties (8). Another way in which smartphones can have a negative impact on sleep quality is by causing nocturnal awakenings or interruptions during sleep. In today's society, it is commonly assumed that almost everyone possesses a smartphone, and there is an expectation for individuals to be constantly accessible. Communication with others often persists even after retiring to bed (68).

It is important to consider the limitations of the study when interpreting the findings. The limitations of this study stem from its cross-sectional study design. Causal relationships cannot be established in cross-sectional studies, including the direction of the associations. Specifically, it cannot be concluded whether individuals with higher levels of stress, depression, and anxiety and poorer sleep quality are more prone to smartphone addiction, or if excessive smartphone use among individuals leads to increased levels of these negative emotional states and worsened sleep quality. Adequately designed longitudinal and clinical studies are necessary to investigate this association. Another limitation of the current study is that it relied on retrospective subjective reports. Therefore, it is recommended that future research include objectively recorded data on smartphone usage, body weight and height and physical activity. The study used the cut-off values of the SAS-SV score recommended by the questionnaire authors. Although the recommended cut-off values are widely used in research studies on different populations, it is advisable to assess the predictive value of this scale and the cut-off values in collaboration with psychiatrists and psychologists. However, despite the mentioned limitations, the SAS-SV scale is among the most commonly used and translated instruments for assessing smartphone addiction.

5. Conclusion

In our study, we found that the prevalence of smartphone addiction among medical students was determined to be 21.7%. The significant factors independently associated with smartphone addiction were spending more than 4 h daily on smartphones and increased levels of depression. It is crucial for future research to delve deeper into the underlying mechanisms and causal relationships between smartphone addiction and these psychosocial factors. This will enable the development of effective interventions and strategies to address this growing public health concern.

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 Ethics Committee of the Faculty of Medicine, University of Belgrade (No. 2650/XII-1). 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

SS, AN, DK, and ZP contributed to the conception and design of the study. The database was organized by AN, MVu, NL, JG, MVr, and IK. AN, BB, and SS performed the statistical analysis. AN wrote the first draft of the manuscript. AN, MVu, NL, and JG wrote sections of the manuscript. SS, BB, and ZP reviewed and edited the manuscript. SS was responsible for project administration and funding acquisition. 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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Problematic social media use and mental health risks among first-year Chinese undergraduates: a three-wave longitudinal study

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Introduction: The association between social media use and mental health risks has been widely investigated over the past two decades with many cross-sectional studies reporting that problematic social media use (PSMU) is associated with higher mental health risk such as anxiety and depression. The present study examined the relationship between PSMU severity and mental health risks (depression, anxiety, stress, and loneliness) using a three-wave longitudinal design.

Methods: A total of 685 first-year Chinese undergraduate students (Mean age = 19.12 years, SD = 0.92) completed surveys at three times points with intervals of 3 to 4 months. Results revealed that PSMU was positively correlated with all the mental health risk variables over the three time points.

Results: The prevalence of PSMU increased over the three research waves. Cross-lagged models identified bi-directional relationships between PSMU and mental health risks, while such links were not consistent between different mental health risk variables and can change over different research intervals.

Discussion: This study indicates that PSMU and mental health risks could predict each other in a vicious loop, but the differences between specific mental health risks and the research context (e.g., different term times and experiences in university) should not be ignored. Further research attention should be paid to the prevalence of PSMU and mental health conditions among Chinese first-year undergraduates who appear to have difficulties in adapting to university life.

KEYWORDS

problematic social media use, mental health risks, first-year Chinese undergraduates, longitudinal study, cross-lagged analysis

Introduction

There are more than 5 billion internet users and 4.7 billion social media users worldwide (1, 2). In 2022, China had 983.3 million active social media users which ranked it at first place globally (1, 2). Studies have frequently pointed out that social media use, especially problematic social media use (PSMU) or social media addiction, can be associated with mental health risks such as anxiety and depression (3, 4). PSMU, often regarded as one type of specific problematic internet use, can be defined as the compulsive or excessive use of social media applications (e.g., Twitter and Facebook) with addictive characteristics (e.g., mood modification, withdrawal symptoms and conflicts) that lead to functional impairments or negative consequences (5–8). However, the relationship between social media use and mental health conditions remains debatable since some studies also suggest that social media use is not linked with mental health issues and people's decreased well-being might not be directly caused by their social media usage (9, 10). Furthermore,

researchers have warned that daily behaviours should not be overpathologized as addictions (11). Several longitudinal studies have shown that there might be bi-directional relationship between addictive internet use or smartphone use and mental health risks [e.g., anxiety and depression (12, 13)]. Anxiety, depression, stress, and loneliness are among the most significant mental health risks associated with problematic social media use (PSMU) or internet addiction (3, 4, 14, 15). For example, among 1,052 participants, Ostovar et al. (14) identified that anxiety, depression, stress, and loneliness are the four significant mental health risks associated with internet addiction in a structural equation model. Because of the important association between the four variables and problematic internet use identified in many empirical studies, the present study aimed to explore the link between PSMU and anxiety, depression, stress, and loneliness using a longitudinal design. Several recent longitudinal investigations have examined the link between problematic social media use (PSMU) and mental health risks among different populations [e.g., (6, 16, 17)]. Li et al. (18) found a bi-directional link between social media addiction and depression among adolescents in China. It remains unknown whether this link can be identified in specific groups of young people, for example, first-year undergraduates who were found to have difficulties in adapting to college life (19). Overall, it is necessary to conduct longitudinal studies to track the changes of the severity of PSMU and explore the relationship between PSMU and mental health risks, especially among the first-year Chinese undergraduates during their adaptation period in university.

Literature review

Problematic social media use and mental health

Earlier studies tended to use the term internet addiction to describe excessive online behaviours with negative outcomes (20). Davis (21) believed that pathological internet use should be described as generalized and specific. Problematic or addictive behaviours on specific online functions or applications such as social media, online games, online gambling, and online shopping were then widely investigated in various contexts (8, 22–24). Theoretically, the Interaction of Person-Affect-Cognition-Execution (IPACE) model concludes that psychopathological variables are the possible predisposing factors of specific addictive behaviours such as problematic gaming, gambling, and compulsive shopping (25). This link can be bi-directional since addictive behaviours could in turn intensify personal characteristics such as mental health risks (25). The pathway model of problematic mobile phone use also suggests that mental health problems such as anxiety and loneliness can be predicting factors for problematic use of mobile phones (11).

Social media has been defined as the "web 2.0 capabilities of producing, sharing, and collaborating on content online" including a wide range of social applications such as weblogs, social networking sites (mainly for connecting people) and virtual games (8), p. 2. The overuse of social media can become addictive and cause negative consequences in life (7, 8). Many cross-sectional studies found that PSMU was associated with mental health risks such as anxiety and depression (3, 4, 14). A recent systematic review based on 1,747 papers identified a strong and bi-directional relationship between problematic social media use and anxiety or depression (4). For the Chinese context, a systematic review by Hussain et al. (3) further revealed that most studies identified the link between PSMU and depression, but the effect sizes between PSMU and anxiety were larger. It is therefore important to further explore the relationships between PSMU and different types of mental health risks besides anxiety and depression. Hussain et al. (3) observed that more studies, especially longitudinal studies, on social media use and psychopathological variables among Asian groups are needed since Asian social media users were found to show more social media use disorder symptoms than their Western counterparts (3, 19, 26).

Longitudinal studies

The longitudinal studies that have investigated the relationship between different types of problematic internet use (e.g., smartphone use, gaming, and social media use) and mental health risks and/or well-being, have obtained diverse results (6, 12, 13, 16–18, 27–33). In a three-wave longitudinal study among Chinese undergraduates, problematic smartphone use was found to be predicted by earlier stressful life events and mediated by mental health problems (33). A large-scale longitudinal study among 7,434 Chinese undergraduates revealed that psychosocial factors such as depressive symptoms, social anxiety, academic stress, and loneliness were the risk factors for problematic smartphone use (12). It thus seems that mental health issues were the key antecedents for problematic internet use, particularly smartphone use.

However, studies also revealed that the relationship between problematic internet use and mental health can be bi-directional or in a reversed direction (problematic internet use first, mental health issues later). In a three-wave longitudinal study, Teng et al. (29) revealed that earlier internet gaming disorder negatively predicted subsequent psychosocial well-being (self-esteem, life satisfaction, and social support) but not vice versa. A two-wave study among Chinese adolescents found a bi-directional relationship between internet addiction and depression but not anxiety. Earlier depression predicted subsequent internet addiction and vice versa (13). Similarly, Li et al. (18) found a bi-directional relationship between social media addiction and depression among 4,237 Chinese adolescents in a two-wave study. Therefore, the association between problematic internet use and mental health risks appears to be complex, which might be different in terms of different types of internet use (e.g., gaming, social media) and kinds of mental health risks (e.g., anxiety and depression). There is a need for more longitudinal research studies that investigate specific problematic online behaviours (e.g., PSMU) and associations with mental health risks.

Many recent longitudinal studies have investigated the relationship between PSMU and mental health risks among different groups (16, 34–37). Several longitudinal studies conducted among school children identified the link between PSMU or social media addiction and psychological distress (34, 35, 37). For example, Chen et al. (35) found that increased PSMU were associated with greater psychological distress (anxiety, depression and stress) among young school children. Besides, several studies obtained similar findings among university students using longitudinal designs [e.g., (16, 36)].

However, additional longitudinal studies on such links (PSMU and mental health risks) among first-year undergraduate students in China are still further needed to better understand the complex mechanisms of social media use and how they may facilitate the development of problematic use. Some studies have explored internet gaming disorder or problematic smartphone use among freshmen in university [e.g., (12, 29)], a focus on PSMU is needed to better understand the phenomenon. Given the potential impact of the sharp change from high school to university on Chinese first-year undergraduates' technology use and well-being (19), it is necessary to explore the link between PSMU and mental health among first-year college students in education transition in China. This age-group tends to be technologically adept and could be prone to maladaptive behaviours, thus it is important to investigate this population.

The present study

Given that the relationship between problematic internet use (either generalized or specific use) and mental health risks remains unclear, and that most studies have adopted cross-sectional designs, it is important to investigate the relationship between PSMU (one of the most popular specific online behaviours) and multiple mental health risks utilizing a longitudinal study design. In the Chinese context, previous studies reported that Chinese first-year undergraduate students had difficulties in adapting to a "more relaxed university life" after stressful high school years (19). It is thus necessary and reasonable to focus on these freshmen in their educational transition from high school to university. Given the cross-sectional nature of previous research and a lack of studies examining social media use amongst first-year Chinese students, the present study utilised a three-wave longitudinal study design to investigate PSMU and associations with the mental health risks of depression, anxiety, stress and loneliness amongst first-year Chinese students. The aforementioned variables were examined at three time points during the first year of university study. The study research hypotheses were as follows.

> *H1*: The levels of problematic social media use severity will increase during the first year of university studies.
>
> *H2*: Problematic social media use severity in earlier times will positively and significantly predict subsequent mental health risks.
>
> *H2a*: Problematic social media use severity at time 1 (T1) will positively and significantly predict mental health risks at time 2 (T2).
>
> *H2b*: Problematic social media use severity at T2 will positively and significantly predict mental health risks at time 3 (T3).
>
> *H3*: Mental health risks in earlier times will positively and significantly predict subsequent problematic social media use severity.
>
> *H3a*: Mental health risks at T1 will positively and significantly predict problematic social media use severity at T2.
>
> *H3b*: Mental health risks at T2 will positively and significantly predict problematic social media use severity at T3.

The hypothesized model for the longitudinal associations between problematic social media use and mental health risks are shown in Figure 1.

Methods

Design

The study utilised a three-wave longitudinal design, data was gathered at three time points. The variables under investigation were PSMU, depression, anxiety, stress, and loneliness.

Participants

A total of 685 Chinese first-year undergraduates completed all the three waves of surveys. The average age was 19.12 years (SD = 0.92). There were 221 males and 464 females.

Measures

The surveys consisted of demographic questions and the following psychological scales which were translated into Mandarin.

Bergen social media addiction scale

The Bergen social media addiction scale [BSMAS (22)] based on the component model (38) was used to measure PSMU severity. In this study, the validated Chinese version of the BSMAS (39) was adopted. The scale consists of 6 items that assess symptoms of addiction over the past 12 months, participants rate all items on a 5-point Likert scale (where 1 = very rarely, 2 = rarely, 3 = sometimes, 4 = often, 5 = very often). Example items include "How often during the last year have you tried to cut down on the use of social media without success?" and "How often during the last year have you used social media in order to forget about personal problems?." Total scores are obtained by summing participant ratings of each item, with higher scores indicating higher PSMU severity. To identify PSMU in the current study, a cut-off point of 24 was used. This was based on previous social media research among Chinese adolescent (40). The Cronbach's alpha of the scale in this study was 0.85 (T1), 0.85 (T2), and 0.86 (T3), respectively.

Depression anxiety stress scale

The 21-item depression anxiety stress scale (DASS-21) developed by Lovibond and Lovibond (41) and validated in Chinese by Gong et al. (42) was used to measure symptoms of depression, anxiety, and stress. The DASS-21 includes 37-item subscales for depression, anxiety, and stress, respectively, rated on a 4-point Likert scale ranging from 0 (did not apply to me) to 3 (applied to me very much, or most

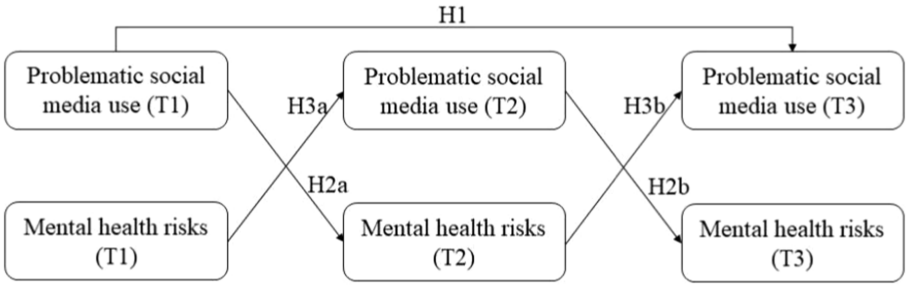

FIGURE 1
The hypothesized model.

of the time). Example items are: "I felt that life was meaningless" (depression), "I felt scared without any good reason" (anxiety), "I felt that I was rather touchy" (stress). Scores are summed with high scores indicating elevated depression, anxiety, and stress symptoms. The Cronbach's alpha of the sub-scales in this study were all above 0.70: depression (T1: 0.84, T2: 0.85, T3: 0.86), anxiety (T1: 0.79, T2: 0.82, T3: 0.82) and stress (T1: 0.78, T2: 0.82, T3: 0.82).

Loneliness scale

Loneliness was measured using the 6-item Chinese version of UCLA loneliness scale [ULS-6 (43)] developed from the 20-item UCLA loneliness scale (44). Participants rate items using a 4-point Likert scale ranging from 1 (never) to 4 (always). Example items include "People are around me but not with me," "I feel left out," and "I lack companionship." Loneliness is measured by calculating the average score across the 6 items. Higher scores indicate higher levels of loneliness. The Cronbach's alpha in this study was 0.85 (T1), 0.86 (T2), and 0.87 (T3).

Procedure

The ethics committee of the first author's university approved the study. The study was conducted in three universities in South China and three waves of identical online surveys were distributed to the same participants. Data were collected from October 2021 to May 2022, with four-month intervals between each wave. The baseline survey (time 1, T1) recruited 822 first-year undergraduate students and 699 of them completed the second survey at time 2 (T2). In the third wave at time 3 (T3), 685 participants remained in this study and completed the third survey with 3 participants' age missing.

All participants were presented with consent forms at the beginning of each survey, informed consent was obtained from all participants, and study participation was voluntary. As the questionnaires were anonymous, all the participants were asked to provide the last 6 digits of their phone number for the purpose of data matching. After completing all the three rounds of surveys, the participants received 20 Chinese RMB for study participation.

Analytic strategy

Descriptive statistics and Pearson's product-moment correlation coefficients were calculated using IBM SPSS version 23. One-way repeated measures ANOVA was conducted to compare the differences in the variables across time. Cross-lagged analysis was conducted using structural equation modelling in AMOS version 24. We tested the link between the sum scores (besides the separate scores) of mental health risks and PSMU because we intended to explore whether overall and specific mental health risks are differentially associated with PSMU. The evaluation of the model fit was done with standard criteria: comparative fit indices (CFI/TLI; values >0.90 indicated an acceptable fit with the data), and root mean square error of approximation (RMSEA; values <0.08 indicated a good fit with the data) (45, 46). Additionally, the χ^2 test was used to check the data derivation of the defined model. However, before analysing the structural equation model all relevant variables were checked to see if they correlated with each other (47).

Results

Descriptive statistics and correlations

Table 1 shows the descriptive statistics and Pearson's correlation coefficients of the main study variables in the three waves. There was a rise in PSMU severity over the three waves of the study. The percentages of the participants who scored higher than 24 on the BSMAS were 2.5% (T1), 3.6% (T2), 4.7% (T3) respectively. PSMU severity at T1, T2 and T3 were significantly and positively correlated with each other ($p < 0.01$). In each wave, PSMU severity was significantly and positively correlated with all the mental health risks variables (depression, anxiety, stress, and loneliness) ($p < 0.01$). To assess whether PSMU, loneliness, depression, stress, and anxiety differed over time, one-way repeated measures ANOVA were conducted. For PSMU, the main effect of time was significant, F (2, 1368) = 9.292, $p < 0.001$, $\eta^2 = 0.013$. Specifically, the level of PSMU severity at T3 was significantly higher than T1. For loneliness, the main effect of time was significant but with a small effect size, F (2, 1368) = 4.915, $p = 0.008$, $\eta^2 = 0.007$, which indicated that the level of loneliness at T3 was significantly lower than T1 and T2. For depression, the main effect of time was also significant, F (2, 1368) = 14.894, $p < 0.001$, $\eta^2 = 0.021$, which indicated that the level of depression at T1 was significantly lower than T2 and T3. Similarly, participants' perceived stress at T3 was significantly higher than T2, F (2, 1368) = 3.664, $p = 0.026$, $\eta^2 = 0.005$. For anxiety, the main effect of time was not significant, F (2, 1368) = 2.272, $p > 0.05$. The skewness and kurtosis values show that all scores were normally distributed (see Table 1). The values for skewness and kurtosis between −2 and +2 are considered acceptable in order to prove normal univariate distribution (48). Hair

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TABLE 1 Correlations between problematic social media use (PSMU) and mental health risks at three time points.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. PSMU (T1)	—														
2. PSMU (T2)	0.53**	—													
3. PSMU (T3)	0.54**	0.58**	—												
4. Depression (T1)	0.22**	0.22**	0.15**	—											
5. Depression (T2)	0.18**	0.34**	0.21**	0.61**	—										
6. Depression (T3)	0.21**	0.29**	0.34**	0.59**	0.70**	—									
7. Anxiety (T1)	0.28**	0.28**	0.23**	0.71**	0.49**	0.46**	—								
8. Anxiety (T2)	0.21**	0.38**	0.24**	0.50**	0.76**	0.58**	0.61**	—							
9. Anxiety (T3)	0.20**	0.31**	0.36**	0.46**	0.58**	0.77**	0.57**	0.68**	—						
10. Stress (T1)	0.33**	0.29**	0.24**	0.68**	0.49**	0.47**	0.78**	0.57**	0.52**	—					
11. Stress (T2)	0.23**	0.43**	0.27**	0.48**	0.74**	0.55**	0.55**	0.82**	0.61**	0.61**	—				
12. Stress (T3)	0.24**	0.34**	0.40**	0.47**	0.56**	0.75**	0.51**	0.60**	0.83**	0.56**	0.65**	—			
13. Loneliness (T1)	0.24**	0.24**	0.20**	0.50**	0.35**	0.35**	0.49**	0.36**	0.35**	0.50**	0.36**	0.36**	—		
14. Loneliness (T2)	0.18**	0.33**	0.18**	0.43**	0.54**	0.44**	0.40**	0.49**	0.41**	0.40**	0.52**	0.43**	0.58**	—	
15. Loneliness (T3)	0.16**	0.31**	0.28**	0.41**	0.48**	0.55**	0.39**	0.44**	0.52**	0.41**	0.46**	0.55**	0.57**	0.66**	—
M	15.93	16.33	16.68	4.07	4.59	4.73	4.84	4.60	4.65	6.18	5.87	6.18	13.22	13.19	12.86
SD	4.89	4.77	4.78	3.71	3.90	3.98	3.46	3.57	3.61	3.72	3.92	3.90	3.73	3.80	3.71
Skewness	0.00	−0.07	0.05	1.33	1.05	1.19	1.00	1.03	1.13	0.57	0.64	0.58	−0.01	−0.01	0.09
Kurtosis	−0.40	−0.38	−0.07	1.86	0.86	1.55	1.34	1.05	1.69	0.26	0.19	0.29	−0.32	−0.40	−0.18

**$p < 0.01$, $N = 685$, M = mean values, SD = standard deviation.

et al. (49) and Byrne (50) argued that data is considered to be normal if skewness is between −2 to +2 and kurtosis is between −7 to +7.

Attrition analyses

We conducted attrition analysis following the approaches in previous studies (51). Our attrition analyses did not show any significant differences between participants who dropped out (16.7%) and those who took part in all three surveys when considering all the variables: gender, $\chi^2(1) = 1.25$, $p = 0.26$; age, $t(817) = 0.58$, $p = 0.56$; PSMU, $t(820) = -0.25$, $p = 0.80$; loneliness, $t(820) = 1.64$, $p = 0.10$; stress, $t(820) = 1.00$, $p = 0.32$; depression, $t(820) = 1.24$, $p = 0.21$; anxiety, $t(820) = 1.05$, $p = 0.30$. Therefore, there was no need to conduct data imputation for further analysis.

Structural equation modelling

Table 2 shows the cross-lagged model fits for the longitudinal relationship between PSMU severity and mental health risks (anxiety, depression, stress, and loneliness). The model fit indices were acceptable at good levels and indicate that all the models fitted the data well. As shown in Figure 2, the model including PSMU scores and the total scores of mental health risks obtained a good model fit ($\chi^2/df = 2.17$, CFI = 0.999, TLI = 0.991, RMSEA = 0.041). PSMU in earlier times did not significantly predict mental health risks in subsequent times from T1 to T2 and from T2 to T3. Mental health risks positively and significantly predicted PSMU from T1 to T2 ($\beta = 0.15$, $p < 0.001$) but not from T2 to T3 ($\beta = -0.26$, $p < 0.001$). However, mental health risks positively and significantly predicted PSMU in T3 ($\beta = 0.38$, $p < 0.001$). Furthermore, PSMU in earlier times positively and significantly predicted subsequent PSMU, mental health risks in earlier times positively and significantly predicted subsequent mental health risks.

When replacing the total scores of mental health risks by the scores of depression, anxiety, stress, and loneliness, the models were similarly structured and obtained good model fits (see Table 2). The models were differently modified according to modification indices to reach good model fits. For the model of depression (see Figure 3), depression positively and significantly predicted PSMU from T1 to T2 ($\beta = 0.11$, $p < 0.001$), and PSMU significantly predicted depression

from T2 to T3 ($\beta = 0.06$, $p < 0.05$). For the model of anxiety (see Figure 4), anxiety positively and significantly predicted PSMU from T1 to T2 ($\beta = 0.14$, $p < 0.001$). For the model of stress (see Figure 5), stress positively and significantly predicted PSMU from T1 to T2 ($\beta = 0.13$, $p < 0.001$) but not from T2 to T3 ($\beta = -0.17$, $p < 0.001$). PSMU positively predicted stress from T2 to T3 ($\beta = 0.06$, $p < 0.05$). For the model of loneliness (see Figure 6), loneliness at T1 significantly predicted PSMU at T2 ($\beta = 0.12$, $p < 0.001$), and PSMU at T2 could predict the level of loneliness at T3 ($\beta = 0.09$, $p < 0.01$).

Discussion

Summary of the findings

The present study examined the relationship between PSMU and mental health risks (depression, anxiety, stress, and loneliness) using a three-wave longitudinal design. The results showed an increase in PSMU severity over time among first-year Chinese undergraduate students. PSMU severity at T3 was significantly higher than PSMU severity at T1, which supported H1. Overall, the correlational analysis revealed positive longitudinal associations between PSMU severity and mental health risks. However, in the cross-lagged models, this relationship was different over the two intervals. Earlier PSMU severity did not significantly predict subsequent mental health risks which reject H2a and H2b. Mental health risks significantly and positively predicted PSMU severity from T1 to T2 but not from T2 to T3, which support H3a and reject H3b. In T3, mental health risks positively and significantly predicted PSMU severity. It is possible that there was a suppressor effect in the model (52), which indicates that mental health risks in the same research waves were more powerful predictors of PSMU severity compared with earlier mental health risks. This can be seen from the correlational analysis that most of the contemporaneous coefficients between PSMU severity and mental health risks were larger. Another reason for the negative path from T2 mental health risks to T3 PSMU might be the role of stress which negatively predicted PSMU from T2 to T3 (see Figure 5). It possibly indicates that those first-year undergraduates who faced increasing levels of stress in the second half of the year (as shown in our ANOVA) had limited free time for social media and perceived lower PSMU subsequently. The longitudinal associations were different when replacing the total scores of mental health risks by depression, anxiety, stress, and loneliness separately (see models 2 to 5). Bi-directional longitudinal relationships between PSMU severity and the four variables were identified but not consistent across all the three waves of studies.

TABLE 2 Model fits of the cross-lagged models for PSMU and mental health risks (anxiety, depression, stress and loneliness).

Model	Mental health risks in the model	χ^2/df	CFI	TLI	RMSEA
1	Total score	2.17	0.999	0.991	0.041
2	Depression	1.28	0.999	0.997	0.020
3	Anxiety	2.89	0.998	0.982	0.053
4	Stress	1.62	0.999	0.994	0.030
5	Loneliness	1.79	0.999	0.992	0.034

The total score was computed by summing up the scores of anxiety, depression, stress and loneliness.

Theoretical and practical implications

The present study supports the theories of specific internet use disorder and PSMU. The I-PACE model suggest that psychopathological variables can be the predicting factors for addictive behaviours (25). In line with this, the present study proved that PSMU severity was consistently positively correlated with mental health risks in all the three waves of the study. Mental health risks in T1 significantly predicted PSMU severity in T2, which also proves that existing mental health problems could act as the risk factors for subsequent PSMU. These findings are similar to the findings of previous longitudinal studies that reported problematic internet use can be predicted by psychopathological variables such as anxiety and

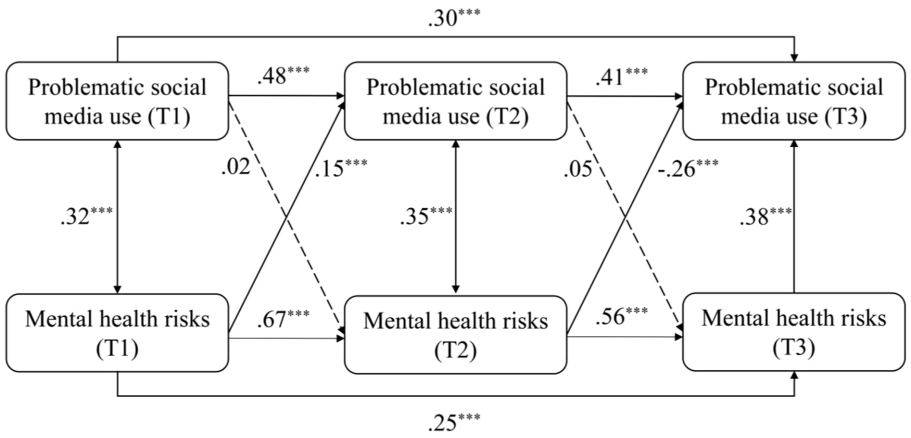

FIGURE 2
Model 1: the cross-lagged model of PSMU and mental health risks. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, $N = 685$.

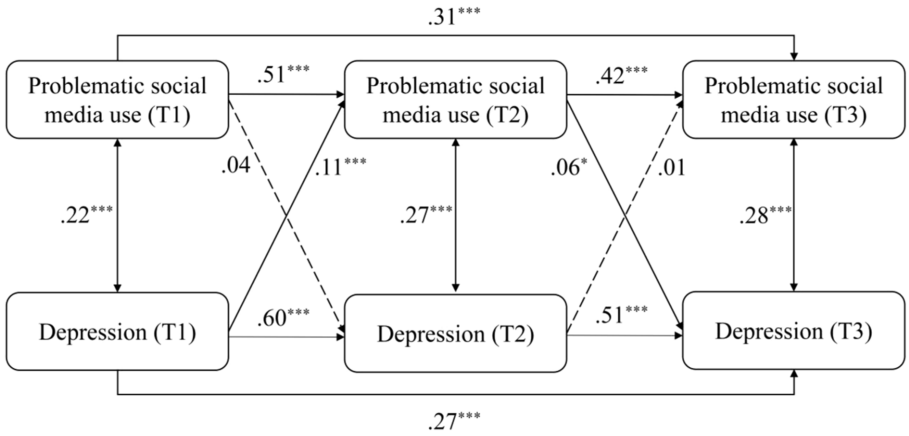

FIGURE 3
Model 2: the cross-lagged model of PSMU and depression.

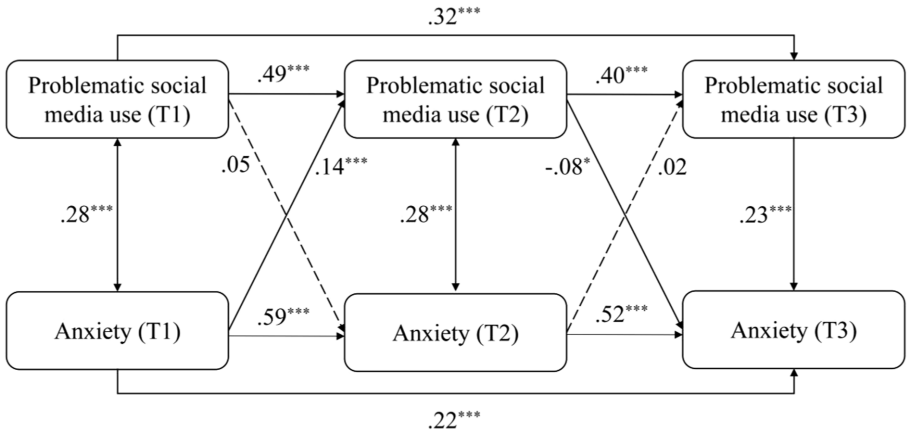

FIGURE 4
Model 3: the cross-lagged model of PSMU and anxiety.

loneliness (12, 33). The present study seems to prove that mental health risks were key risk factors for PSMU severity.

The relationship between PSMU severity and mental health risks was also reported as bi-directional in several previous longitudinal studies (18) and by the I-PACE model, which was not consistently identified in all models in the present study. Instead, PSMU severity measured at the same waves were stronger predictors of mental health risks, while the effects of earlier PSMU were weak. The longitudinal link between PSMU and mental health risks can be different between different intervals in this study. For example, depression significantly predicted PSMU severity from T1 to T2 but not vice versa, while this link was only significant from PSMU to depression from T2 to T3. The possible reason for this might be the different research context of the participants, for example, different term times or the changing university experiences. Thus, the bi-directional link between PSMU and mental health needs further investigation.

Besides, the model of the sum scores of mental health risks was different from the models for separate variables in the current study. Such difference is possibly caused by the difference between anxiety, depression, stress and loneliness, as they represent different aspects of mental health. Previous studies tested the links between PSMU and single mental health risks separately [e.g., (6, 33)] or overall psychological distress (using the sum scores or latent variables) [e.g., (35, 36)]. Chen et al. (36) used the sum scores of anxiety and depression to represent the overall psychological distress and found that initial PSMU predicted the growth of psychological distress. However, little is known about the different results between the sum scores of mental health risks and separated ones with PSMU. Studies testing the relationship between PSMU and separate mental health risks did not further explore such links using the sum scores [e.g., (6)]. Our findings indicate that it is not easy to simply conclude that social media is good or bad for people's general mental health or overall well-being. In other words, the association between PSMU and overall well-being or mental health conditions might not represent the potential specific mental health problems related to social media use. Future studies in this topic need to test different types of mental health risks separately and be aware of their differences.

The present study enhances our understanding of the prevalence of PSMU among first-year undergraduates in China. Previous studies found that Chinese first-year undergraduates were more likely to use

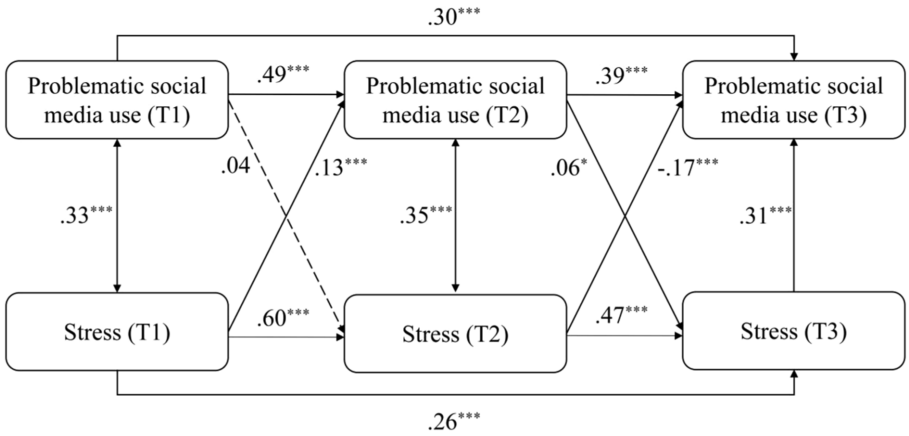

FIGURE 5
Model 4: the cross-lagged model of PSMU and stress.

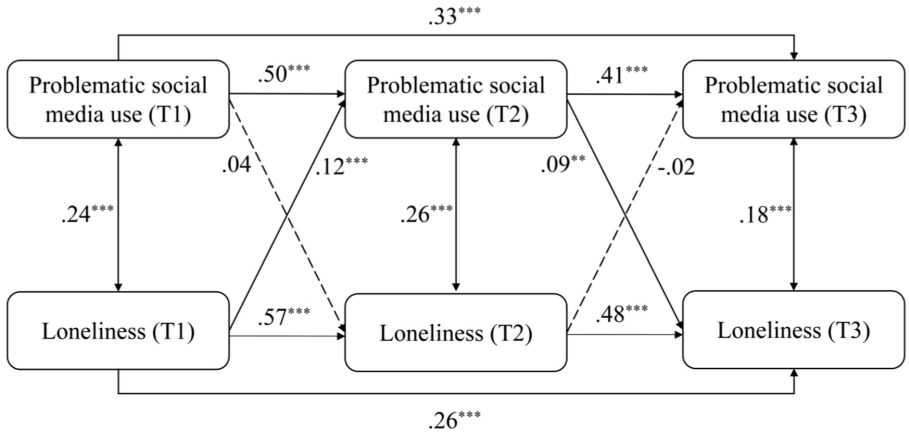

FIGURE 6
Model 5: the cross-lagged model of PSMU and loneliness.

smartphones and the internet problematically than students from other countries since they were not ready for a more relaxed university lifestyle compared with their strictly managed high school lives (19). However, without longitudinal studies, it cannot be confirmed whether the students' problematic internet use increase or decrease during their education transition, though they might have difficulty in adapting to a different learning and living environment. Previous longitudinal studies reported different results. Teng et al. (29) found that Chinese first-year undergraduates had increased levels of internet gaming disorder over the three waves of study. However, Wang et al. (12) reported that the junior (first and second-year) undergraduates' problematic smartphone use decreased over 18 months. Though, the mixed sample of first and second-year students might affect the results, the trend of problematic internet use remains unclear with limited research evidence. In this context, the present study observed an increased level of PSMU severity over the freshmen's first year at university. Using the same cut-off point, Luo et al. (40) reported that the 12 months prevalence of social media addiction among Chinese adolescents was 3.5%. The results of the present study were similar, the first-year university students who scored above the cut-off point were 2.5% (T1), 3.6% (T2), and 4.7% (T3). A clear trend of increased PSMU severity indicates that more attention should be paid to the first-year undergraduates' problems of dealing with online applications such as social media. Such finding also suggest that early interventions are necessary (in the first term of studies) to counteract PSMU and mental health issues. For example, programmes for managing social media usage and getting used to university life.

After 8 months' of adaption to university, the participants reported higher depression and stress but lower loneliness, which clearly shows that different types of mental health risks should be considered differently. The results from the cross-lagged models showed that the links between PSMU and different types of mental health issues were not the same. This is in line with previous studies which identified that the longitudinal effect of internet addiction on subsequent anxiety and depression were different (13). Similarly, a systematic review by Elhai et al. (53) concluded that depression was the most consistent and powerful psychopathological variable (consistent but with medium effect sizes), and correlated with problematic smartphone use compared with anxiety (consistent but with small effect sizes) and stress (less consistent with small to medium effect sizes). It is therefore important for future studies to focus on specific mental health issues when investigating problematic internet use and psychopathology.

Limitations and future directions

There are several limitations to the present study. The risk of providing socially desirable answers to survey questions is one limitation of this study, though all the scales obtained good reliabilities with Cronbach's alpha values larger than 0.70 in all three waves of the study. Furthermore, only self-perceived scores for PSMU and mental health risks were obtained which may not fully reflect the students' diverse mental health conditions. Qualitative data analysis or sentiment analysis for their narrative expressions are needed besides quantitative data analysis. The sample size of 685 were not representative enough compared with previous longitudinal studies, though the present study focused on a special and under-researched group of first-year undergraduates. Thus, the results might not be generalised to other senior undergraduate students who have already adapted to their university lives much better.

Future studies could adopt different designs such as mixed-methods studies and longitudinal qualitative studies. For example, future studies could investigate the first-year undergraduates' narrative descriptions or their social media posts to better understand mental health conditions. Furthermore, longitudinal studies with larger sample sizes or more waves of surveys can be implemented to explore the link between PSMU and mental health. Besides, systematic reviews are needed to investigate the relationships between PSMU and multiple mental health risks and to compare the effect sizes of PSMU on several different types of mental health issues. Future longitudinal studies could also adopt alternative data analysis methods such as growth modelling to explore the relationship between PSMU and mental health with particular focus on the growth of the variables.

Conclusion

The present study used a three-wave longitudinal design to investigate the relationship between PSMU severity and mental health risks among Chinese first-year university students. The results showed that PSMU was positively correlated with mental health risks, and the effect sizes were larger for this link in the same waves. Cross-lagged models revealed that earlier mental health risks positively predicted subsequent PSMU severity, and bi-directional associations were identified but not consistent in all models over all waves of studies. The presents study indicates that Chinese first-year undergraduates' levels of PSMU can increase during their adaptation year in university. The present study serves to highlight the importance of implementing longitudinal research designs to better understand PSMU. The findings can inform prevention and intervention programmes (e.g., behaviour focused and youth development programmes) to tackle PSMU among university students.

Data availability statement

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

Ethics statement

The studies involving humans were approved by Ethics Committee of School of Education at Soochow University. 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

WZ, ZYY, and ZHY: concept and design, acquisition, analysis, interpretation of data, and statistical analysis. ZYY, ZHY, WZ, and ZH: drafting of the manuscript and critical revision of the manuscript. 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.

Publisher's note

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Internet addiction and suicidal ideation among Chinese college students: the mediating role of psychotic-like experiences

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Background: Individuals with Internet addiction (IA) are at significant risk of suicide-related behaviors. This study aimed to investigate the relationships among IA, psychotic-like experiences (PLEs), and suicidal ideation (SI) among college students.

Methods: A total of 5,366 college students (34.4% male, mean age 20.02 years) were assessed using the self-compiled sociodemographic questionnaires, Revised Chinese Internet Addiction Scale (CIAS-R), 15-item Positive subscale of the Community Assessment of Psychic Experiences (CAPE-P15), Self-rating Idea of Suicide Scale (SIOSS), and 2-item Patient Health Questionnaire (PHQ-2).

Results: The prevalence of IA and SI were 9.3 and 12.1% among Chinese college students, respectively. There were direct effects of IA and PLEs on SI. The total effect of IA on SI was 0.18 ($p < 0.001$). PLEs mediated the relationship between IA and SI (Indirect effect = 0.07).

Conclusion: IA had both direct and indirect effects on SI. These findings enable us to elucidate the mechanism of how IA influences individual SI, which can provide vital information for developing and implementing targeted interventions and strategies to alleviate SI among Chinese college students.

KEYWORDS

Internet addiction, psychotic-like experiences, suicidal ideation, college students, mediating role

1. Introduction

Nowadays, the Internet has become an essential part of people's lives. As Internet use sharply increases, the problem of Internet addiction (IA) gradually emerges and becomes a hot-debated issue. IA refers to a problematic behavior related to excessive and uncontrollable Internet use (1). In a recent literature review, Pan and colleagues reported that the median prevalence of IA was 7.02% among the general population, and it increased over time (2). The Internet has gained tremendous popularity among college students. Compared with the general population, college students have easier Internet access and more substantial incentives for Internet use. However, college students lack monitoring and obtain more freedom of choice, making them more fragile and vulnerable to IA (3). Prior studies also supported that university life increased the risk of IA

(4, 5). Results from the recent meta-analysis indicated a high level of IA (31.51%) among Iranian college students (6). Joseph et al. summarized that the prevalence of IA among Indian college students was approximately 19.9% (7). In China, one meta-analysis including 26 studies documented that the pooled prevalence rate of IA was 11% among Chinese college students (8). Chi et al. have found that 15.2% of college students have IA (9), while a rate reported as 7.9% in Shen et al.'s study (10). It seems that IA prevalence varies due to culture, measures, cut-offs, and definitions of IA across previous studies.

Previous studies showed that IA was associated with academic failure (11), social isolation (12), psychological symptoms (e.g., depression and anxiety) (13), and risky behaviors (e.g., self-harm and suicidality) (14). Among these factors, suicidality has attracted particular attention due to its devastating consequences (15). Suicide is considered as the second leading cause of death among adolescence and young adulthood worldwide (16). While in China, suicide is the leading cause of death in persons aged 15–34 years (17), which accounts for 19% of all deaths (18). In a literature review, Mortier and colleagues reported a pooled prevalence of lifetime and 12-month suicidal attempts among college students were 3.2 and 1.2%, respectively (19). Notably, suicidal ideation (SI) is one of the strongest predictors of eventual suicidal behavior, and undoubtedly, investigation of SI could contribute to the early identification of adolescents who may be at risk for suicide (20). One large-scale cross-sectional survey ($N = 136{,}266$) has shown that adolescents with IA had a higher prevalence of SI than those without IA (21). However, the relationship between IA and SI (22–24) and the specific mechanism remain unknown.

PLEs are widely conceptualized as the subthreshold psychotic symptomatology among the general population and have also been interpreted as a resemblance of positive symptoms of psychosis in the absence of a full-blown psychotic disorder (25, 26). Based on the psychosis proneness-persistence-impairment model (27), PLEs are influenced by a combination of genetic factors and environmental risks. IA may be an environmental stressor in the etiology of PLEs. For instance, IA triggers a range of unhealthy lifestyles (e.g., staying up late (28)) that may increase the risk of PLEs (29). Few studies have demonstrated that IA was significantly associated with PLEs among adolescents and young adults (30, 31). Moreover, PLEs serve as a robust risk factor for SI. One survey of 8,096 Korean adolescents aged 14–19 years found that higher PLEs are associated with stronger SI (32). According to Yates et al.' report, individuals with PLEs may be twice as likely to report SI (33). These findings suggest that increased IA is associated with greater PLEs, and PLEs can predict SI. Thus, PLEs are regarded as an underlying mediator between IA and SI.

This study investigated the mediating role of PLEs on the IA-SI relationship. We hypothesized that (a) IA and PLEs have a positive effect SI among college students; (b) PLEs mediate the IA-SI relationship. Given that depression is strongly associated with IA (34), PLEs (35), and SI (36), consequently, the current study aimed to validate the above hypotheses after controlling for individual depression.

2. Materials and methods

2.1. Participants

Using a cross-sectional design, eight universities/colleges in China [Guangxi Province (Southern China: 2 universities/colleges), Hainan Province (Southern China: 1 university/college), Gansu Province (Northwestern China: 1 university/college), Shandong Province (Eastern China: 1 university/college), Hunan Province (Central China: 2 universities/colleges), and Guangdong Province (Southern China: 1 university/college)] were selected by convenience sampling method during July 2023. The study was conducted through the "Questionnaire Star" system. College students used their cell phones to scan the Quick Response (QR) code to access the questionnaire page and complete the survey. This survey is anonymous, and participants can stop or withdraw at any time if they feel uncomfortable during the survey. Finally, 5,824 college students participated in the web-based survey and provided complete data on all measures. In order to improve the quality of data, exclusion criteria for participation included: (a) time to complete the survey <5 min; (b) have current significant mental disorders that were identified by self-reported; (3) scores above 4 on the dishonesty subscale of the Self-rating Idea of Suicide Scale (SIOSS) (37, 38). Among these participants, 458 college students were subsequently removed, leaving 5,366 with valid data entry for further analyses.

2.2. Measures

2.2.1. Sociodemographic variables

The sociodemographic variables of the participants included age, sex, grade, ethnicity, single-child status, parental marital status, family income, and parents' educational level.

2.2.2. IA

The Revised Chinese Internet Addiction Scale (CIAS-R) was used to assess IA (39). It consists of 19 items, clustering into four dimensions: compulsive use of the Internet or withdrawal symptoms, tolerance symptoms, interpersonal and health-related problems, and time management problems. Each item was rated on a four-point Likert scale, from 1 ('complete inconformity') to 4 ('complete conformity'). The higher the total score, the greater the level of IA. According to previous studies (10, 40), the CIAS-R has satisfactory reliability and validity among Chinese college students, and a cut-off total score of 53 has been suggested to identify probable IA. In our study, Cronbach's α was 0.98.

2.2.3. PLEs

The 15-item Positive subscale of the Community Assessment of Psychic Experiences (CAPE = P15) was adopted to measure PLEs (41). The scale includes three dimensions, namely persecutory ideation, bizarre experiences, and perceptual abnormalities. Each item was rated within a time frame of the last month on a four-point Likert scale, from 1 ('never') to 4 ('nearly always'), with higher scores reflecting more frequent PLEs. The Chinese version of CAPE-P15 has demonstrated acceptable reliability and construct validity among college students (42). Participants were regarded to have genuine PLEs in the past month when they scored ≥ 1.57 on an average score of items in CAPE-P15 (43). In our study, Cronbach's α was 0.96.

2.2.4. SI

The Self-rating Idea of Suicide Scale (SIOSS) was utilized to assess SI (37). It comprises 26 items within four dimensions, which are despair, pessimism, sleep, and concealment. Each item was answered on a dichotomous scale from 0 (no) to 1 (yes). We added the first three

subscales (despair, pessimism, and sleep) to generate a total score of SI, with higher scores indicating stronger SI. Participants are considered to have SI when their score reaches or exceeds 12 (37). Meanwhile, the test is invalid, if the concealment factor is ≥4 (37). The SIOSS has satisfactory psychometric properties among Chinese college students (38, 44). In our study, Cronbach's α was 0.88.

2.2.5. Depression

The 2-item Patient Health Questionnaire (PHQ-2) was employed for screening depressive symptoms over the past 2 weeks (45). Each item was rated on a four-point Likert scale, from 0 ('not at all') to 3 ('nearly every day'), with higher total scores indicating more significant depressive symptoms. A total score ≥ 3 refers to the positive result of depression. The PHQ-2 is widely used among Chinese college students with good reliability and validity (46, 47). In our study, Cronbach's α was 0.80.

2.3. Ethics statement

The studies involving human participants were reviewed and approved by the Ethics Board of the South China Normal University, China (SCNU-PSY-2022-235). All participants who volunteered to participate were informed of the purpose, process, benefits, and risks.

2.4. Statistical analysis

Data were analyzed through IBM SPSS Statistics Version 23.0. The sociodemographic characteristics and variables were described with frequency (proportion) for categorical variables and mean (standard deviation, SD) for continuous variables. The χ^2 tests and Mann–Whitney U tests were used to compare differences in categorical and continuous variables between the IA and non-IA groups, respectively. The hierarchical multiple logistic regression was conducted to explore the associations between IA and SI. In step 1, the model was unadjusted by setting SI as the dependent variable and IA as the independent variable. In step 2, we made adjustments for all sociodemographic variables. In step 3, school PLEs was added, and depression was added in the last step. The results were demonstrated with odds ratios (ORs) and their 95% confidence intervals (CIs). Spearman correlation analysis examined the association among IA, PLEs, SI, and depressive symptoms. The mediating hypothesis was tested via PROCESS (48). Bootstrap analysis was conducted with 5,000 iterations yielding 95% confidence intervals estimating the size of each model's effects. The mediation effect (model 4) was tested: IA was entered as the predictor, PLEs as the mediator, and SI as the outcome. All sociodemographic variables and depression were included in the analyses as covariates. The same approach examined the mediating role of PLEs in males and females without controlling for sex. Tests of statistical significance were two-sided, and statistical significance was set at $\alpha = 0.05$.

3. Results

3.1. Sample characteristics

This study comprised 5,366 college students (mean age: 20.02 ± 1.38 years, 34.4% male). The majority of the students were Ethnicity Han (84.0%). More than half of the students are freshmen (52.1%). Further sample characteristics are presented in Table 1.

The prevalence of IA and SI were 9.3 and 12.1% among Chinese college students. The prevalence of IA among males and females were 8.2 and 9.9%, respectively, ($\chi^2 = 4.04$, $p = 0.048$). The prevalence of SI among the male and female were 12.4 and 12.0%, respectively ($\chi^2 = 0.15$, $p = 0.692$). 36.7% of college students with IA reported the presence of SI, which was significantly higher than the rate reported in those without IA (9.6%, $\chi^2 = 314.45$, $p < 0.001$). Students with IA also showed significantly higher severity of PLEs ($Z = -20.16$, $p < 0.001$) and depression ($Z = -21.06$, $p < 0.001$) than those without IA. Table 1 also compares sample characteristics and other study variables between IA and non-IA groups.

3.2. Hierarchical regression analyses

Table 2 illustrates the results of hierarchical regression analyses. Participants who reported having IA were more likely to have SI (OR = 5.48; 95% CI = 4.46–6.73). After controlling for all sociodemographic variables, IA was still significantly associated with increased odds of SI (OR = 5.59; 95% CI = 4.54–6.89). Furthermore, this association remained significant after adjusting for PLEs and depression [OR (95% CI) = 3.56 (2.84, 4.45) and 2.34 (1.84, 2.98) in Step 3 and Step 4, respectively].

3.3. The mediating role of PLEs

As shown in Table 3, IA is positively significantly associated with PLEs ($r = 0.54$, $p < 0.001$), SI ($r = 0.41$, $p < 0.001$), and depression ($r = 0.45$, $p < 0.001$).

Table 4 described the standardized regression results of mediation to test the effects of IA on SI through the mediator of PLEs. Sociodemographic variables and depression served as covariates in the presented models. The total effect of IA on SI was 0.18 ($p < 0.001$). As shown in Figure 1A, IA had a significant positive effect on both PLEs ($\beta = 0.36$, $p < 0.001$) and SI ($\beta = 0.11$, $p < 0.001$). PLEs also positively predicted SI ($\beta = 0.20$, $p < 0.001$). The bootstrap results with 5,000 resample revealed that IA exerted a significant indirect effect on SI, due to the mediating effect of PLEs (effect = 0.07, 95% CI = 0.06–0.09). Thus, PLEs partially mediated the relationship between IA and SI in the total sample.

As shown in Table 4, separate analyses showed that the indirect effects in males were 0.09 (95% CI: 0.06–0.11). The direct effect was not statistically significant (95% CI: −0.01–0.09) after accounting for the effect of confounders factors in males. In comparison, the direct and indirect effects in females were 0.15 (95% CI: 0.12–0.18) and 0.07 (95% CI: 0.05–0.08). Thus, PLEs fully mediated the association between IA and SI in males (Figure 1B), while partially mediating the IA-SI relationship in females (Figure 1C).

4. Discussion

This study deepened our understanding of how IA impacts SI through the mediating role of PLEs among Chinese college

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TABLE 1 Descriptive statistics of participants [*N* (%)].

Variables		Overall *N* = 5,366	Non-IA 4865 (90.7%)	IA[e] 501 (9.3%)	χ^2/Z	*p*
Age [year]	Mean(SD)	20.02 (1.38)	20.01 (1.37)	20.11 (1.47)	−0.99	0.321
Sex	Male	1846 (34.4)	1,694 (34.8)	152 (30.3)	4.04	0.048
	Female	3,520 (65.6)	3,171 (65.2)	349 (69.7)		
Grade	Freshman	2,796 (52.1)	2,569 (52.8)	227 (45.3)	18.39	<0.001
	Sophomore	1,484 (27.7)	1,315 (27.0)	169 (33.7)		
	Junior	907 (16.9)	828 (17.0)	79 (15.8)		
	Senior	179 (3.3)	153 (3.2)	26 (5.2)		
Ethnicity	Han[a]	4,507 (84.0)	4,106 (84.4)	401 (80.0)	6.42	0.013
	Others	859 (16.0)	759 (15.6)	100 (20.0)		
Single child status	Yes	898 (16.7)	834 (17.1)	64 (12.8)	6.22	0.012
	No	4,468 (83.3)	4,031 (82.9)	437 (87.2)		
Parental marital status	Married	4,733 (88.2)	4,303 (88.4)	430 (85.8)	3.00	0.094
	Not current married[b]	633 (11.8)	562 (11.6)	71 (14.2)		
Family income (monthly), RMB	<3,000	2,119 (39.5)	1917 (39.4)	202 (40.3)	0.35	0.840
	3,000 ~ 5,000	1742 (32.5)	1,578 (32.4)	164 (32.7)		
	>5,000	1,505 (28.0)	1,370 (28.2)	135 (26.9)		
Father's education	Junior high school or less	3,715 (69.2)	3,354 (68.9)	361 (72.1)	2.23	0.328
	Senior high school	1,053 (19.6)	966 (19.9)	87 (17.4)		
	College or more	598 (11.1)	545 (11.2)	53 (10.6)		
Mother's education	Junior high school or less	4,176 (77.8)	3,764 (77.4)	412 (82.2)	6.24	0.044
	Senior high school	728 (13.6)	674 (13.9)	54 (10.8)		
	College or more	462 (8.6)	427 (8.8)	35 (7.0)		
CAPE-P15 score	Mean(SD)	19.06 (6.56)	18.33 (5.48)	26.13 (10.67)	−20.16	<0.001
SIOSS score	Mean(SD)	5.25 (4.62)	4.79 (4.33)	9.74 (4.85)	−21.16	<0.001
PHQ-2 score	Mean(SD)	1.72 (1.30)	1.60 (1.23)	2.89 (1.35)	−21.06	<0.001
PLEs[c]	Yes	976 (18.2)	726 (14.9)	250 (49.9)	373.45	<0.001
SI[d]	Yes	650 (12.1)	466 (9.6)	184 (36.7)	314.45	<0.001

[a]Han is the major ethnic group in China.
[b]Not current married included separated, divorced and widowed.
[c]PLEs calculated using the CAPE-P15, with a clinical cut-off average score of 1.57.
[d]SI calculated using the SIOSS, with a clinical cut-off total score of 12.
[e]IA calculated using the CIAS-R, with a clinical cut-off total score of 53.CAPE-P15, 15-item Positive Subscale of the Community Assessment of Psychic Experiences; SIOSS, Self-rating Idea of Suicide Scale; PLEs, psychotic-like experiences; SI, suicidal ideation; IA, internet addiction.

students. Evidence shows that IA and PLEs were associated with SI, controlling for depression. Meanwhile, PLEs mediated the IA-SI relationship.

In our study, approximately 9.3% of college students reported IA. Shen et al. reported that the prevalence of IA between February to June 2019 was 7.7% among Chinese college students (N = 8,098) with the same scale and cut-off point (10). The increase in this rate can be explained by the COVID-19 pandemic of recent years. As a result of the pandemic lockdown, college students have much greater access to the Internet for entertainment, online courses, and connecting with friends, leading to an increased risk of IA (49). The prevalence rate of IA is slightly higher for female students compared with male students in our study. This is consistent with the results from Deb et al.'s study among 258 medical students in West Bengal (50) and Shen et al.'s study among 8,098 college students in China (40). Contrary findings have been obtained from one meta-analysis based on Chinese college students, indicating the prevalence of males in IA was found to be higher (8). This may be related to females' increased demand for online social interactions (e.g., WeChat) (51) and online shopping (e.g., Taobao) (52). Among these college students, the self-reported prevalence of SI was 12.1%, slightly lower than the results of a survey of medical students with migraines using the same measure (13.7%) (44). Meanwhile, the SI prevalence did not differ by sex, which aligns with a previous meta-analysis (53).

Compared with those without IA, students with IA had a higher prevalence of SI, which validated our hypothesis. Specifically, students with IA were 5.48 times more likely than other students to develop SI. Extensive works have proved the association between IA and SI (14). For example, Kuang et al. proposed that greater IA increased the likelihood of SI (21). One possible reason is that

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TABLE 2 Results of hierarchical regression analyses [OR (95%CI)].

Variables		Step 1	Step 2	Step 3	Step 4
Age	–		0.91 (0.83,0.98)*	0.92 (0.84,1.00)	0.94 (0.86,1.03)
Sex	Male		Ref.	Ref.	Ref.
	Female		0.87 (0.72,1.04)	0.99 (0.82,1.20)	0.97 (0.80,1.18)
Grade	Freshman		Ref.	Ref.	Ref.
	Sophomore		1.29 (1.04,1.60)*	1.28 (1.03,1.60)*	1.19 (0.94,1.50)
	Junior		1.40 (1.04,1.88)*	1.43 (1.05,1.94)*	1.33 (0.97,1.83)
	Senior		1.27 (0.74,2.18)	1.32 (0.77,2.32)	1.14 (0.64,2.04)
Ethnicity	Han[a]		Ref.	Ref.	Ref.
	Others		1.13 (0.90,1.42)	1.13 (0.90,1.43)	1.10 (0.86,1.40)
Single child status	Yes		Ref.	Ref.	Ref.
	No		0.88 (0.69,1.12)	0.82 (0.64,1.05)	0.82 (0.64,1.06)
Parental marital status	Married		Ref.	Ref.	Ref.
	Not current married[b]		1.33 (1.04,1.70)*	1.32 (1.03,1.70)*	1.21 (0.93,1.58)
Family income (monthly), RMB	<3,000		Ref.	Ref.	Ref.
	3,000 ~ 5,000		0.63 (0.50,0.80)***	0.70 (0.56,0.89)**	0.73 (0.57,0.93)*
	>5,000		0.62 (0.50,0.76)***	0.65 (0.52,0.80)***	0.67 (0.54,0.84)***
Father's education	Junior high school or less		Ref.	Ref.	Ref.
	Senior high school		0.82 (0.64,1.05)	0.82 (0.64,1.06)	0.87 (0.67,1.14)
	College or more		1.00 (0.71,1.40)	1.04 (0.74,1.48)	1.20 (0.84,1.73)
Mother's education	Junior high school or less		Ref.	Ref.	Ref.
	Senior high school		1.26 (0.96,1.67)	1.26 (0.95,1.67)	1.23 (0.92,1.65)
	College or more		1.33 (0.91,1.94)	1.26 (0.85,1.86)	1.09 (0.72,1.64)
Depression[a]	Yes				5.18 (4.28,6.27)***
PLEs[b]	Yes			4.27 (3.54,5.14)***	3.20 (2.63,3.90)***
IA[c]	Yes	5.48 (4.46,6.73)***	5.59 (4.54,6.89)***	3.56 (2.84,4.45)***	2.34 (1.84,2.98)***

[a]Depression calculated using the PHQ-2, with a clinical cut-off total score of 3.
[b]PLEs calculated using the CAPE-P15, with a clinical cut-off average score of 1.57.
[c]IA calculated using the CIAS-R, with a clinical cut-off total score of 53.PLEs, psychotic-like experiences; IA, internet addiction; OR, odds ratio; CI, confidence interval. Step 1: unadjusted. Step 2: adjusted for age, sex, grade, ethnicity, single child status, parental marital status, family income (monthly), and parents' education. Step 3: Model 2 variables + PLEs. Step 4: Model 3 variables + Depression. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

TABLE 3 Spearman's correlation coefficients between all study variables [*r*].

	IA	PLEs	SI	Depression
IA	1			
PLEs	0.54	1		
SI	0.41	0.41	1	
Depression	0.45	0.43	0.53	1

IA, internet addiction; PLEs, psychotic-like experiences; SI, suicidal ideation. All $p < 0.001$.

students may acquire harmful online information about suicide and hold a positive attitude toward suicide, which has been associated with an increased risk of SI (54). Further, in line with previous studies (32, 33), PLEs were significantly associated with higher endorsement of SI in the present study. Echoing Sun et al.'s study, this result indicated that PLEs can be considered as a promising predictor for SI independent of the other psychopathology during the pandemic lowdown (55).

Our observations confirmed our hypothesis, that the direct link between IA and SI is mediated by PLEs after adjusting for sociodemographic variables and depression. This result suggests that IA may increase susceptibility to PLEs. The possible reasons are that individuals who overuse the internet are more likely to develop poor habits that are detrimental to their mental health, such as lack of physical activity (56), irregular diet (57), and reduced sleep duration (29). Meanwhile, people with IA may further isolate others (12), neglect meaningful relationships, lack social support, and feel loneliness, which, in turn, may increase the risk of PLEs among vulnerable groups (58). The finding supports our hypothesized model, suggesting that IA may affect college students' SI by worsening PLEs. Moreover, our finding also indicated that PLEs fully mediate the association between IA and SI in males, while partially mediating the IA-SI relationship in females. This suggests that PLEs have a greater percentage of mediation for the IA-SI relationship in males. As for females, in addition to PLEs and negative emotions, other factors may influence the relationship between IA and SI, such as insomnia symptoms (24). Previous work also demonstrated that the

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TABLE 4 The mediating effect of PLEs on the relationship between IA and SI by sex.

Pathway	Effect	S.E.	95%CI
Total sample			
Total effect (c)	0.18	0.01	0.16, 0.21
Direct effect(c')	0.11	0.01	0.09, 1.14
Indirect effect (a × b)	0.07	0.01	0.06, 0.09
Males			
Total effect (c)	0.13	0.02	0.08, 0.17
Direct effect(c')	0.04	0.02	−0.01, 0.09
Indirect effect (a × b)	0.09	0.01	0.06, 0.11
Females			
Total effect (c)	0.22	0.02	0.19, 0.25
Direct effect(c')	0.15	0.02	0.12, 0.18
Indirect effect (a × b)	0.07	0.01	0.05, 0.08

All continuous variables were standardized before they were entered in the path model. All mediation models adjusted for age, sex, grade, ethnicity, single child status, parental marital status, family income (monthly), parents' education, and depression.

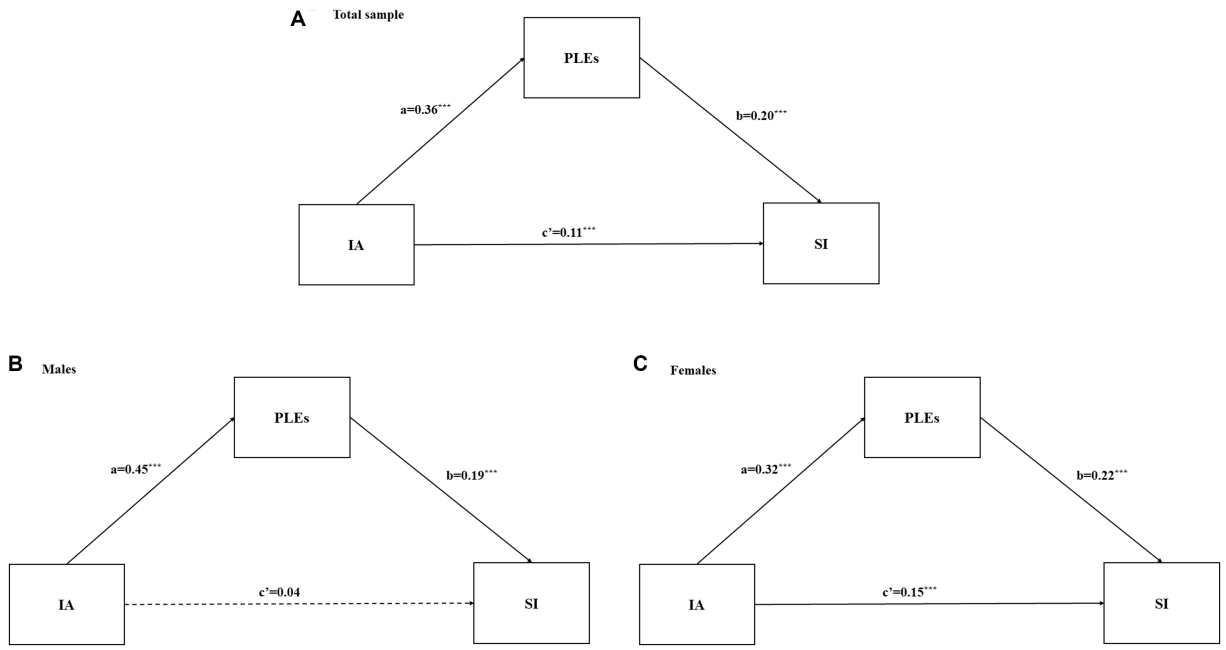

FIGURE 1
(A-C) Path model testing the mediation effect of PLEs in the association between IA and SI. IA, internet addiction; PLEs, psychotic-like experiences; SI, suicidal ideation. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

IA-insomnia symptoms link was greater in females than males (59). Thus, further research is necessary to explore sex differences in the mechanisms of the association between IA and SI.

To our knowledge, this study is the first to examine the specific mediating effect of PLEs in the association between IA and SI among a large sample of college students. These findings underscore that IA should be evaluated in future research and educational and clinical practice. Interventions for SI might benefit from promoting coping strategies to reduce IA. Psychological therapies, such as multi-family group therapy (60), and cognitive behavioral therapy (CBT) (61), have shown significant effectiveness in reducing IA. Moreover, PLEs should be assessed and intervened for college students who have IA, to reduce the risk of SI. Reduction in PLEs can be achieved by promoting psychological resilience (62) or improving sleep quality (63).

However, this study has several limitations that need to be clarified. Firstly, all study variables relied on self-report questionnaires rather than clinical diagnosis, which might cause potential reporting bias and potentially threaten the validity of the findings. Clinical interviews also should be conducted to determine

the severity of IA, PLEs, and SI in the future. Secondly, the cross-sectional design of this study also limits the ability to make causal inferences. Further longitudinal studies are therefore necessary to validate the current results. Thirdly, since suicide attempts and behaviors were not included in our study, extended research is expected to further clarify the association between IA and comprehensive suicide indexes. Finally, this study did not consider other critical potential confounders, such as insomnia and adverse life events. Our study also did not examine the majors of college students, although there is evidence that study field may be related to college students' SI (64). Therefore, examining the role of more extensive risk factors in this association is also warranted.

5. Conclusion

In conclusion, this study suggests that PLEs have a mediating effect on the association between IA and SI among Chinese college students. This indicates that college students with IA can be considered a high-risk group for SI, which requires early intervention. When intervening, the effects of PLEs on students' SI should be comprehensively considered.

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 studies involving humans were approved by Ethics Board of the South China Normal University. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

MK: Conceptualization, Writing – original draft. BX: Writing – review & editing, Conceptualization, Visualization. CC: Writing – review & editing, Conceptualization. DW: Conceptualization, Data curation, Formal analysis, Project administration, Writing – review & editing.

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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.

Publisher's note

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Association between daily use of social media and behavioral lifestyles in the Saudi community: a cross-sectional study

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Objective: This study aimed to investigate the association between nine social media platforms use and health-related behavior, including fruit and vegetable intake, physical activity, tobacco use, and risk factors including depression and obesity.

Methods: A cross-sectional study was conducted using secondary data from the Sharik Health Indicators Surveillance System (SHISS). Participants 18 years and older were recruited via phone-interviews. The nine social media platform use [Twitter-(X), Facebook, Instagram, WhatsApp, LinkedIn, Snapchat, TikTok, Telegram, and YouTube] were assessed using self-reported use. Health-related variables include behavioral factors including diet, physical activity, and tobacco use including (cigarettes, waterpipes, and e-cigarettes), risk of depression and obesity. Logistic regression analysis was performed to explore the association between social media use and health-related variables.

Results: The study indicated that daily Snapchat users had a lower healthy diet (fruit and vegetable intake), whereas daily LinkedIn and WhatsApp users were positively associated with a healthier diet, relative to those with infrequent social media use. Furthermore, daily interaction with Instagram, TikTok, Telegram, and YouTube was significantly associated with increased depression risk. Conversely, Snapchat and WhatsApp usage was significantly linked to a decreased depression risk. Tobacco-smoking behaviors were associated with specific social media platforms: cigarette smoking was associated with Snapchat, TikTok, and YouTube; e-cigarette with Facebook, LinkedIn, Snapchat, and TikTok; and waterpipe smoking with Facebook and TikTok. Interestingly, some platforms, such as Instagram, were associated with reduced cigarette smoking. The relationship between social media activity and health-related outcomes remained significant after adjusting for age and gender.

Conclusion: This study highlights the potential negative impact of particular daily social media use on health-related variables, including dietary habits, tobacco use, and depression. Nevertheless, particular daily social media use of some platforms was associated with a potential positive impact on the health-related variables. Social media platforms are tools that can be used to achieve both a positive and negative effect. By knowing which demographic segments have a greater presence on one platform, we are creating opportunities to understand the social phenomena and at the same time use it to reach those segments and communicate with them, because each social media platform has its unique way and framework of user communication.

KEYWORDS
social media, Saudi Arabia, behavior, lifestyle, mental health

1. Background

Over the last 20 years, social media has emerged from obscurity to become a fully integrated part of everyday life (1). The United States has one of the highest social network usage rates in the world (1). In 2020, over 223 million Americans were using social networks to send private messages, post pictures, or like or post comments on content posted by others (2). Facebook is the largest social media platform in the world, with over 2.9 billion users (3). Other social media platforms, including YouTube and WhatsApp, also have more than 2 billion users each (4). These numbers are huge, considering that there are 7.7 billion people in the world, at least 3.5 billion of whom have access to the internet. This means that social media platforms are now used by a third of the people in the world and by more than two-thirds of all internet users (4). In the United States, more females use social media than males (54 and 46%, respectively); males account for 54.4% of the average global population (5). Meanwhile, the number of social media users in Saudi Arabia is also on the rise (6). According to a report from the BBC, among Middle Eastern countries, Saudi Arabia has the largest social media user base (6). Due to the high rate of smartphone use in the country, 79.3% of the Saudi population are active social media users, and 27.66 million of them access it via mobile device (6). These users are most active on social media platforms such as Twitter, YouTube, and Facebook (7). In this regard, it is mainly religious, political, and cultural factors that shape the social media engagement of the country (8). These factors influence Saudi nationals to use social media platforms in different contexts (8). This offers them ways to interact and communicate, and also helps in promoting user engagement (9).

Research into the effects of social media on health and behavior in general has expanded rapidly in recent years (10). In addition, it been encouraged by controversial public debates and critical primary research, systematic reviews, and meta-analyses (10). These works focus on the usage of social media and its links to health and behavior, especially for young people (11). For instance, a cohort study of 6,595 teenagers aged 12–15 years in the United States found that teenagers who spend more than 3 h per day using social media might be at a higher risk for mental health problems compared with those who never use it (12).

In contrast, other research suggests that social media may even have health related and behavioral lifestyle benefits (13). Recent discourse around the implications of social media on health and behavioral lifestyles has predominantly spotlighted its potential drawbacks. Such apprehensions often concern issues related to mental health, privacy, and cyberbullying (14). However, an emerging body of research provides a counter-narrative, positing that social media, when used judiciously, can offer tangible benefits for both mental and physical well-being.

Specifically, studies have shown that social media platforms can serve as tools for disseminating health-related information, facilitating peer support, and even aiding in chronic disease management (15). For instance, online communities provide venues for patients to share their experiences, which often leads to better coping mechanisms and improved mental health outcomes (16). Furthermore, these platforms have also been employed in public health campaigns, with agencies leveraging their wide reach to spread awareness about diseases, vaccinations, and health-promoting behaviors (17).

Another facet where social media has demonstrated potential benefits is in the realm of behavioral lifestyles. Platforms such as Instagram and YouTube are full with fitness influencers and health educators who disseminate advice on exercise routines, balanced diets, and mindfulness practices (18). For many, these platforms serve as primary sources of inspiration and motivation for adopting healthier lifestyles (11).

Nonetheless, it is imperative to approach these findings with caution. The quality of information on social media platforms is heterogeneous, and users need to be discerning about their sources. Furthermore, while certain studies underscore the benefits of social media, it is crucial to balance this perspective with research highlighting its potential drawbacks, ensuring a comprehensive understanding of its overall impact on health and behavioral lifestyle (19).

These conflicting findings make it challenging to navigate the research investigating the effects of social media on mental health and how best to use social media. There is evidence that, in general, routine social media use is positively associated with health and social well-being. However, this is only the case if the user is not "emotionally invested" in the media; if they are, the outcomes are negative (12). Nevertheless, the degree to which social media harms health or behavior is debatable. Another recent study found that most studies investigating the link between social media and mental health demonstrate "weak" or "inconsistent" associations (12).

Thus, the objective of the this research project was to explore the association between the utilization of nine distinct social media platforms, namely Twitter (X), Facebook, Instagram, WhatsApp, LinkedIn, Snapchat, TikTok, Telegram, and YouTube, and health-related behaviors. These behaviors encompassed consumption patterns of fruits and vegetables, engagement in physical activities, usage of tobacco, and potential risk factors such as depression risk and obesity.

2. Methods

2.1. Design

This study comprises a secondary analysis of cross-sectional data from the Sharik Health Indicators Surveillance System (SHISS) (20). The SHISS consists of short phone interviews conducted from all 13 administrative regions of Saudi Arabia on a quarterly basis. Each interview lasts approximately 8–12 min and is conducted by a trained data collector. In SHISS, the ZdataCloud® system was used. It has integrated eligibility and sampling modules, which control the distribution of the sample and prevent human-related sampling bias

(21). All questions had to be answered for an individual questionnaire to be successfully submitted to the database. All data were coded, collected and stored through the ZdataCloud® system and database (21). The Sharik institutional review board granted approval for this project (approval no. 2021–2), in line with Saudi Arabia's research ethics standards and regulations.

2.2. Sampling and sample size

The SHISS achieves an equal distribution of participants, stratified by age and gender, within and across the 13 regions of Saudi Arabia, by using a proportional quota sampling. It employs two age groups, based on the Saudi Arabian median age of 36 years, which generates a quota of 52 for this study. Researchers calculated the sample size based on a medium effect size of nearly 0.3, with 80% power and a 95% confidence level, allowing for comparison between quotas based on region, age, and gender (16). Consequently, each quota necessitates at least 135 participants and total sample was 7,020 participants. The ZdataCloud® stops accepting participants with similar characteristics once the quota sample is reached. The data collection system, with no human interference, automatically controls the quota sampling process (15).

2.3. Participants and recruitment

The study focused on recruiting Arabic-speaking Saudi residents aged 18 or older. The Sharik Association for Research and Studies (formerly known as the Sharik Association for Health Research) provided a random list of mobile phone numbers to identify possible participants (17). The Sharik database contains individuals interested in taking part in future research projects, with over 170,000 users spread across Saudi Arabia's 13 regions and still expanding (17). Participants were called up to three times, and if there was no response, another individual with similar demographics was selected from the database. This process continued until the required number of participants was reached and the recruitment process was automatically closed. Consent was verbally acquired from participants during the interview sessions. Once consent was given, the interviewer evaluated the participant's eligibility, and if they met the criteria, the interview commenced.

2.4. Questionnaire design and validation

The SHISS dataset includes behavioral risk factors (diet, physical activity, and tobacco use, including cigarettes, waterpipes, and e-cigarettes), the risk of depression, which is measured using the Patient Health Questionnaire (PHQ-2) with a cut-off of 3 and above (22, 23), and obesity, measured as the body mass index (BMI) via height and weight. We calculated the participants' body mass indices (BMIs). We used the Center for Disease Control and Prevention's (CDC) BMI category status, which classifies a BMI of 30 or above as obese (24). By the end of 2021, the SHISS included a variable for collecting data related to the daily use of some social media applications, including Twitter (X), Facebook, Instagram, WhatsApp, LinkedIn, Snapchat, TikTok, Telegram, and YouTube.

This study also used the WHO's global recommendations of physical activity for adults (18–64 years old): (1) vigorous-intensity physical activity (VIPA) for 75 min per week, or (2) moderate-intensity physical activity (MIPA) for 150 min per week (25). Based on the participants' self-reported responses to the interview questionnaire (i.e., the weekly number of minutes, frequency, and intensity level of exercise), two categorical outcome variables were created that reflected whether or not the guidelines were met: an acceptable level of physical activity (ALPA; at least 150 min of MIPA per week and/or at least 75 min of VIPA per week) and a low level of physical activity (LLPA; less than 150 min of MIPA and/or less than 75 min of VIPA).

We asked the participants about their daily fruit and vegetable intake. If a participant's daily food intake included at least one portion of fruit and one portion of vegetables, they were categorized as having an acceptable level of fruit and vegetable intake (AFVI). If not, they were categorized as having a low level of fruit and vegetable intake (LFVI).

Sharik Health Indicators Surveillance System questions were linguistically validated to ensure that the participant understood the questions as intended and could provide accurate answers. The validation was preformed via focus group, asked to discuss and respond to the survey as one group. This process was repeated with the same people to test the survey's reliability. Afterwards, a new group was interviewed to ensure the clarity of the original meaning and to develop modified questions. The final version of the questionnaire was produced accordingly.

2.5. Statistical analysis

Data were transferred to the Statistical Package for Social Sciences (SPSS), version 25, which was used for data management and analyses. This study employed automated electronic data collection, there were no missing values; the ZdataCloud involves a data integrity check to prevent users from entering invalid data (e.g., the minimum age is 18) (21). Descriptive statistics were used to describe the variables. The quantitative variables are presented herein as the mean and SD if they have a normal distribution, or as the median and range, as appropriate. The categorical variables are presented as percentages. Logistic crude regression, adjusted for age and gender, was used to was used to explore the association between social media use and other health-related variables.

3. Results

In total, between July and December of 2021, 13,915 participants from the 13 administrative regions of Saudi Arabia completed the interview, with a response rate of 67.29%. Out of the total contacted potential participants, 49.9% were female. The mean age was 36.80 (SD: 13.68; minimum: 18; maximum: 99; range: 81). Table 1 shows the demographic distribution of participants according to their daily social media usage.

Table 2 shows a crosstabulation between daily social media platform use and health-related behaviors including obesity, physical activity, fruit and vegetable intake, smoking (traditional cigarettes, waterpipes, and e-cigarette), and the risk of depression.

TABLE 1 Demographic distribution of participants (n = 13,915) in the context of their daily social media usage.

	Twitter (X)	Facebook	Instagram	WhatsApp	LinkedIn	Snapchat	TikTok	Telegram	YouTube
	n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)
Sex									
Male	2,893 (41.5)	481 (6.9)	1839 (26.4)	4,861 (69.7)	216 (3.1)	3,895 (54.4)	1,699 (24.4)	819)11.7(	2,194 (31.5)
Female	2,283 (32.9)	265 (3.8)	2,563 (36.9)	4,695 (67.6)	124 (1.8)	4,410 (63.5)	1927 (27.8)	851)12.3(	1,611 (23.2)
Age									
≤19	288 (40.9)	23 (3.3)	378 (53.7)	422 (59.9)	9 (1.3)	501 (71.2)	302 (42.9)	122 (17.3)	269 (38.2)
20–29	2,160 (46.8)	176 (3.8)	2014 (43.6)	2,904 (62.9)	168 (3.6)	3,365 (72.9)	1,551 (33.6)	723 (15.7)	1,614 (35.0)
30–39	1,174 (41.4)	208 (7.3)	967 (34.1)	2040 (71.9)	85 (3.0)	1854 (65.4)	744 (26.2)	350 (12.3)	793 (28.0)
40–49	1,000 (33.2)	183 (6.1)	700 (23.3)	2,240 (74.5)	53 (1.8)	1,597 (53.1)	620 (20.6)	325 (10.8)	637 (21.2)
50–59	445 (24.3)	122 (6.7)	278 (15.2)	1,393 (76.0)	18 (1.0)	705 (38.4)	306 (16.7)	125 (6.8)	351 (19.1)
≥60	109 (11.9)	34 (3.7)	65 (1.5)	557 (60.9)	7 (0.8)	183 (20.0)	103 (11.3)	23 (2.5)	141 (15.4)
Level of education									
Lower than a bachelor's degree	2,079 (28.6)	348 (4.8)	2,064 (28.4)	4,851 (66.8)	74 (1.0)	4,023 (55.4)	1,995 (27.5)	687 (9.5)	1,926 (26.5)
Bachelor's degree and above	3,097 (46.5)	398 (6.0)	2,338 (35.1)	4,705 (70.7)	266 (4.0)	4,182 (62.8)	1,631 (24.5)	983 (14.8)	1,879 (28.2)
Region									
Asir	390 (36.0)	39 (3.6)	368 (34.0)	770 (71.2)	14 (1.3)	687 (63.5)	320 (29.6)	156 (10.2)	319 (29.5)
Baha	475 (43.9)	56 (5.2)	348 (32.1)	725 (66.9)	24 (2.2)	584 (53.9)	320 (29.6)	111 (10.2)	290 (32.3)
Eastern region	364 (33.7)	55 (5.1)	467 (43.2)	816 (75.5)	44 (4.1)	647 (59.9)	188 (17.4)	139 (12.9)	349 (32.3)
Hail	418 (38.6)	52 (5.1)	276 (25.5)	692 (64.0)	32 (3.0)	628 (58.8)	326 (30.1)	141 (13.0)	266 (24.6)
Jazan	262 (24.2)	65 (6.0)	273 (25.2)	750 (69.)	8 (0.7)	599 (55.3)	347 (32.0)	147 (13.6)	347 (32.0)
Al Jouf	406 (37.6)	38 (3.5)	284 (26.3)	772 (71.5)	10 (0.9)	676 (62.6)	282 (26.1)	97 (9.0)	214 (19.8)
Madinah	450 (41.4)	59 (5.4)	417 (38.3)	755 (69.4)	30 (2.8)	669 (61.5)	259 (23.8)	138 (12.7)	338 (31.1)
Makkah	328 (30.3)	106 (9.8)	378 (35.0)	779 (72.1)	48 (4.4)	628 (58.1)	258 (23.9)	121 (11.2)	350 (32.4)
Najran	250 (27.1)	27 (2.9)	169 (18.3)	506 (54.9)	4 (0.4)	390 (42.3)	117 (12.7)	36 (3.9)	124 (13.4)
Northern border	458 (42.4)	44 (4.1)	336 (31.1)	718 (66.4)	27 (2.5)	658 (60.9)	346 (32.0)	136 (12.6)	301 (27.8)
Qassim	468 (43.3)	76 (7.0)	324 (29.9)	762 (70.4)	34 (3.1)	706 (65.2)	275 (25.4)	142 (13.1)	282 (26.1)
Riyadh	464 (42.8)	74 (6.8)	392 (36.1)	767 (70.7)	48 (4.4)	661 (60.9)	279 (25.7)	141 (13.0)	313 (28.8)
Tabuk	443 (40.8)	55 (5.4)	370 (34.1)	744 (68.6)	17 (1.6)	672 (61.9)	292 (26.9)	165 (15.2)	312 (28.8)
Overall	5,176 (37.2)	746 (5.4)	4,402 (31.6)	9,556 (68.7)	340 (2.4)	8,205 (59.0)	3,626 (6.1)	1,670 (12.0)	3,805 (27.3)

Table 3 shows an association between the daily use of social media platforms and health-related behaviors including obesity, physical activity, fruit and vegetable intake, smoking (traditional cigarettes, waterpipes, and e-cigarettes), and the risk of depression, compared to those who do not use these platforms on a daily basis.

In terms of obesity, seven out of nine social media platforms show a significant association with obesity after adjusting for age and gender, including Twitter, Facebook, WhatsApp, LinkedIn, Snapchat, and TikTok. However, none of the social media platforms were associated with physical activity. Meanwhile, three platforms were

TABLE 2 Cross tabulation between daily use of social media platforms and health-related behaviors.

	Twitter (X)	Facebook	Instagram	WhatsApp	LinkedIn	Snapchat	TikTok	Telegram	YouTube
	n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)
Obesity									
Yes	921 (17.8)	201 (26.9)	820 (18.6)	2,273 (23.8)	61 (17.9)	1713 (20.9)	719 (19.8)	307 (18.4)	780 (20.5)
No	4,255 (25.2)	545 (22.2)	3,582 (19.6)	7,283 (67.5)	279 (22.6)	6,492 (24.8)	2,907 (23.4)	1,363 (23.0)	3,025 (23.2)
Physical activity									
MPA	1,082 (20.9)	146 (19.6)	876 (19.9)	1958 (20.5)	71 (20.9)	1,652 (20.1)	694 (19.1)	351 (21.0)	772 (20.3)
VPA	783 (15.1)	119 (16.0)	628 (14.3)	1,271 (13.3)	57 (16.8)	1,156 (14.1)	509 (14.0)	238 (14.3)	578 (15.2)
Combined	1,367 (26.4)	194 (26.0)	1,108 (25.2)	2,414 (25.3)	96 (28.2)	2075 (25.3)	889 (24.5)	440 (26.3)	989 (26.0)
Fruit and vegetable Intake									
ALF	582 (11.2)	106 (14.2)	488 (11.1)	1,261 (13.2)	54 (15.9)	900 (11.0)	405 (11.2)	210 (12.6)	437 (11.5)
ALV	612 (11.8)	115 (15.4)	512 (11.6)	1,330 (13.9)	57 (16.8)	990 (12.1)	450 (12.4)	220 (11.6)	462 (12.1)
Combined	290 (5.6)	57 (7.6)	226 (5.1)	632 (6.6)	31 (9.1)	416 (5.1)	193 (5.3)	99 (5.9)	220 (5.8)
Smoking									
Cigarettes	1,059 (20.5)	191 (25.6)	718 (16.3)	1,751 (18.3)	96 (28.2)	1,518 (18.5)	720 (19.9)	295 (11.7)	819 (21.5)
E-cigarettes	765 (14.8)	135 (18.1)	626 (14.2)	1,103 (11.5)	87 (25.6)	1,132 (13.8)	534 (14.7)	237 (14.2)	628 (16.5)
Waterpipes	907 (17.5)	188 (25.2)	716 (16.3)	1,451 (15.2)	88 (25.9)	1,358 (16.6)	627 (17.3)	264 (15.8)	710 (18.7)
Risk of depression (PHQ-2)									
At risk (cut-off 3 and above)	1,114 (21.5)	160 (21.4)	1,050 (23.9)	1,893 (19.8)	90 (26.5)	1,727 (21.0)	889 (24.5)	424 (25.4)	881 (23.2)
Not at risk	4,062 (78.5)	586 (78.6)	3,352 (76.1)	7,663 (80.3)	250 (73.5)	6,478 (79.0)	2,737 (24.7)	1,246 (74.6)	2,924 (76.8)

associated with a healthy diet: LinkedIn, WhatsApp (positive association), and Snapchat (negative association).

Regarding smoking behavior, three social media platforms were positively associated with cigarette smoking: Snapchat, TikTok, and YouTube. Four social media platforms were positively associated with e-cigarette smoking, namely, Facebook, LinkedIn, Snapchat, and TikTok. Meanwhile, two social media platforms were positively associated with waterpipe smoking (Facebook and TikTok).

Finally, three social media platforms, TikTok, Telegram, and YouTube, were positively associated with a risk of depression.

4. Discussion

The use of social media has become increasingly prevalent in recent years, with billions of people around the world using various platforms to connect with others, share information, and engage in a variety of activities. While social media has many potential benefits, including increased social connectedness and access to information, there are also concerns about the potential negative effects of social media use on health and behaviors. In this study, we aimed to explore the association between the daily use of social media and health and behavior in the Saudi population during in the second half of 2021.

Our results showed that there was a significant association between social media use and obesity, with seven out of nine social media platforms showing a significant association with obesity. This finding is consistent with previous research that has found a link between social media use and obesity (26). One possible explanation for this association is that social media use may lead to a sedentary lifestyle and unhealthy eating habits, which can contribute to weight gain and obesity (27).

Interestingly, we did not find any significant association between social media use and physical activity. This finding is somewhat surprising, as previous research has suggested that social media use may have a negative impact on physical activity levels (28). However, it is possible that the lack of association in our study is due to the fact that we only looked at daily social media use and did not take into account other factors that may influence physical activity levels, such as work or family obligations.

We also found that three social media platforms were associated with a healthy diet, namely, LinkedIn, WhatsApp (positively), and Snapchat (negatively). This finding is consistent with previous research that has found a link between social media use and dietary habits (29). One possible explanation for this association is that social media use may influence food choices and eating behaviors through exposure to food-related content and social norms (30).

TABLE 3 Logistic regression results of the association between daily use of social media platforms and health-related variables, compared to those who do not use these platforms on a daily basis.

Variable	Crude OR (95% CI) (*p* value)	Adjusted OR (95% CI) (*p* value)
Obesity		
Twitter (X)	0.68 (0.62–0.75) (<0.001)	0.80 (0.73–0.88) (<0.001)
Facebook	1.53 (0.1.29–1.82) (<0.001)	1.4 (1.16–1.66) (<0.001)
Instagram	0.79 (0.72–0.88) (<0.001)	0.900 (0.81–1.00) (0.050)
WhatsApp	1.400 (1.27–1.53) (<0.001)	1.26 (1.15–1.38) (<0.001)
LinkedIn	0.88 (0.66–1.17) (0.38)	0.96 (0.72–1.29) (<0.001)
Snapchat	0.91 (0.83–0.98) (0.027)	1.11 (1.01–1.22) (0.03)
TikTok	0.89 (0.83–0.98) (0.036)	0.96 (0.87–1.06) (<0.001)
Telegram	0.88 (0.76–1.01) (0.08)	0.90 (0.78–1.04) (0.16)
YouTube	0.98 (0.90–1.1) (0.74)	1.08 (0.97–1.19) (0.14)
Physical activity (combined)		
Twitter (X)	1.13 (1.04–1.23) (0.003)	1.07 (0.98–1.17) (0.095)
Facebook	1.02 (0.86–1.22) (0.747)	0.98 (0.83–1.17) (0.902)
Instagram	0.96 (0.88–1.06) (0.487)	1.01 (0.92–1.12) (0.696)
WhatsApp	1.08 (0.99–1.17) (0.075)	1.08 (0.99–1.17) (0.080)
LinkedIn	1.12 (0.87–1.43) (0.355)	1.06 (0.83–1.36) (0.600)
Snapchat	1.08 (0.97–1.15) (0.178)	1.07 (0.98–1.17) (0.090)
TikTok	0.93 (0.84–1.02) (0.147)	0.94 (0.85–1.03) (0.200)
Telegram	1.074 (0.96–1.21) (0.242)	1.03 (0.90–1.17) (0.620)
YouTube	1.08 (0.99–1.18) (0.069)	0.99 (0.90–1.09) (0.880)
Healthy diet (combined)		
Twitter (X)	0.89 (0.76–1.04) (0.174)	1.02(0.86–1.20) (0.805)
Facebook	1.26 (0.94–1.69) (0.109)	1.26 (0.84–1.50) (0.426)
Instagram	0.83 (0.70–0.99) (0.047)	0.98 (0.81–1.17) (0.835)
WhatsApp	1.31 (1.12–1.53) (<0.001)	1.20 (1.03–1.41) (0.020)
LinkedIn	1.26 (1.12–2.47) (0.010)	1.77 (1.19–2.63) (0.004)
Snapchat	0.63 (0.55–0.74) (<0.001)	0.77 (0.66–0.91) (0.002)
TikTok	0.91 (0.76–1.09) (0.333)	0.97 (0.81–1.17) (0.817)
Telegram	1.03 (0.81–1.30) (0.786)	1.06 (0.84–1.35) (0.583)
YouTube	0.99 (0.83–1.18) (0.979)	1.04 (0.87–1.24) (0.666)
Smoking cigarettes		
Twitter (X)	1.12 (0.99–1.25) (0.052)	0.898 (0.79–1.01) (0.083)
Facebook	1.40 (1.13–1.73) (0.002)	1.09 (0.87–1.37) (0.420)
Instagram	0.59 (0.52–0.68) (<0.001)	0.84 (0.73–0.98) (0.029)
WhatsApp	1.01 (0.90–1.14) (0.750)	0.92 (0.81–1.05) (0.234)
LinkedIn	1.31 (0.95–1.79) (0.092)	1.09 (0.79–1.51) (0.580)
Snapchat	1.03 (0.92–1.16) (0.582)	1.31 (1.15–1.49) (<0.001)
TikTok	1.15 (1.02–1.3) (0.023)	1.27 (1.11–1.45) (<0.001)
Telegram	0.88 (0.73–1.05) (0.162)	0.95 (0.79–1.15) (0.663)
YouTube	1.47 (1.30–1.67) (<0.001)	1.14 (1.00–1.30) (0.044)
Smoking e-cigarettes		
Twitter (X)	1.29 (1.10–1.51) (0.002)	1.09 (0.93–1.28) (0.266)
Facebook	1.66 (1.28–2.15) (<0.001)	1.50 (1.14–1.96) (0.003)

(Continued)

TABLE 3 (Continued)

Variable	Crude OR (95% CI) (*p* value)	Adjusted OR (95% CI) (*p* value)
Instagram	0.86 (0.72–1.03) (0.100)	1.03 (0.86–1.24) (0.680)
WhatsApp	0.76 (0.65–0.89) (0.001)	0.75 (0.64–0.89) (0.001)
LinkedIn	2.00 (1.42–2.82) (<0.001)	1.77 (1.25–2.51) (0.001)
Snapchat	1.20 (1.02–1.42) (0.026)	1.26 (1.06–1.49) (0.009)
TikTok	1.16 (1.42–2.82) (0.070)	1.24 (1.04–1.47) (0.014)
Telegram	0.91 (0.72–1.14) (0.422)	0.94 (0.74–1.19) (0.62)
YouTube	1.47 (1.24–1.74) (<0.001)	1.17 (0.99–1.40) (0.065)
Smoking waterpipes		
Twitter (X)	1.19 (1.01–1.40) (0.032)	1.01 (0.86–1.20) (0.830)
Facebook	2.11 (1.63–2.73) (<0.001)	1.75 (1.34–2.28) (<0.001)
Instagram	0.74 (0.61–0.89) (0.002)	0.99 (0.81–1.20) (0.949)
WhatsApp	0.83 (0.70–0.98) (0.027)	0.76 (0.64–0.90) (0.001)
LinkedIn	1.46 (0.97–2.18) (0.063)	1.29 (0.86–1.93) (0.217)
Snapchat	0.911 (0.77–1.074) (0.267)	1.08 (0.91–1.08) (0.342)
TikTok	1.21 (1.01–1.44) (0.034)	1.31 (1.10–1.57) (0.003)
Telegram	0.91 (0.71–1.16) (0.472)	0.97 (0.75–1.25) (0.834)
YouTube	1.35 (1.12–1.61) (0.001)	1.11 (0.92–1.33) (0.255)
At risk of depression (PHQ-2)		
Twitter (X)	0.98 (0.89–1.07) (0.687)	0.99 (0.90–1.08) (0.839)
Facebook	0.89 (0.74–1.07) (0.231)	0.98 (0.81–1.18) (0.842)
Instagram	1.24 (1.13–1.37) (<0.001)	1.12 (1.01–1.24) (0.025)
WhatsApp	0.81 (0.74–0.89) (<0.001)	0.85 (0.77–0.93) (<0.001)
LinkedIn	1.20 (0.93–1.55) (0.149)	1.24 (0.96–1.60) (0.092)
Snapchat	0.96 (0.87–1.05) (0.391)	0.88 (0.80–0.96) (0.009)
TikTok	1.30 (1.18–1.43) (<0.001)	1.25 (1.14–1.38) (<0.001)
Telegram	1.24 (1.08–1.41) (0.001)	1.21 (1.06–1.38) (0.004)
YouTube	1.11 (1.10–1.23) (0.034)	1.16 (1.04–1.28) (0.004)

In terms of tobacco-use behaviors, we found that three social media platforms were positively associated with cigarette smoking: Snapchat, TikTok, and YouTube. E-cigarette smoking was positively associated with four social media platforms, including Facebook, LinkedIn, Snapchat, and TikTok. Finally, two social media platforms were positively associated with waterpipe smoking (Facebook and TikTok). These findings are consistent with previous research that has found a link between social media use and tobacco use (31, 32). One possible explanation for this association is that social media use may expose individuals to pro-tobacco content and social norms that promote smoking (33).

Finally, we found that three social media platforms were positively associated with the risk of depression: TikTok, Telegram, and YouTube. This finding is consistent with previous research that has found a link between social media use and depression (34). One possible explanation for this association is that social media use may lead to social comparisons and feelings of inadequacy, which can contribute to the development of depression (35).

Overall, our study provides important insights into the association between social media use and health and behaviors in the Saudi population. While our findings are consistent with previous research, it is important to note that the relationship between social media use and health and behavior is complex and multifaceted. There are many factors that can influence the impact of social media use on health and behavior, including individual differences, social norms, and cultural factors (36).

However, via studying the social media distribution among demographic variables and health indicators, and by going deeper to explore the relationship between social media daily use and specific health indicators, we can confidently lean toward the logical argument that social media platforms are tools that can be used to achieve both a positive and negative effect.

Furthermore, the way the users use these tools influences the type of individuals they attract and the way those individuals are affected by them. This can be inferred by the way, social media platforms accumulate specific demographic segments with similar health indicators. These platforms are more likely not the cause of the existence or accumulation of these segments of the population, but the way the users use these tools can be associated with the segments they attract. By knowing which segments have a greater presence on one

platform, we are creating opportunities to understand the social phenomena and at the same time use it to reach those segments and communicate with them, because each social media platform has its unique way and framework of user communication.

One limitation of our study is that it is cross-sectional in nature, which means that we cannot establish causality between social media use and health and behaviors. Future research should use longitudinal designs to better understand the temporal relationship between social media use and health and behavior. Additionally, future research should explore the mechanisms underlying the association between social media use and health and behavior, including the role of social norms, social comparison, and exposure to pro-health or unhealthy content.

In conclusion, our study provides important insights into the association between social media use and health and behavior in the Saudi population. Our findings suggest that social media use is associated with a range of health and behavior outcomes, including obesity, dietary habits, tobacco use, and depression. These findings have important implications for public health interventions aimed at reducing the negative impact of social media use on health and behavior. By understanding the factors that influence the impact of social media on users' health and behavior, we can develop more effective interventions to promote healthy behaviors and prevent negative health outcomes.

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 studies involving humans were approved by Sharik institutional review board. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin because the study used phone interviews. Participant consent was obtained verbally during the interviews and recorded in the data collection system.

Author contributions

NB: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. NA: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. RA-D: Writing – review & editing. SA: Writing – review & editing. ZA: Writing – review & editing. AA: 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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Relapse prevention therapy for internet gaming disorder in Swedish child and adolescent psychiatric clinics: a randomized controlled trial

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Objectives: To evaluate the effectiveness of relapse prevention (RP) as a treatment for internet gaming disorder (IGD).

Design: Randomized controlled trial.

Setting: Three child and adolescent psychiatry (CAP) units in Region Skåne, Sweden.

Participants: Children aged 13–18 years, coming for their first visit to CAP during 2022, were screened for gaming behavior. Those who met the proposed DSM-5 criteria for IGD were offered participation in the trial, if they had the capacity to provide written informed consent and if they spoke Swedish. A total of 111 CAP patients agreed to participate. Out of those, 11 patients were excluded due to incorrect inclusion such as young age ($n = 1$), or due to the absence of responses to follow-up measures ($n = 9$). After exclusion, 102 participants remained (intervention = 47, control = 55).

Interventions: The intervention, RP, is based on cognitive behavioral treatment (CBT) and was provided individually, comprising of five to seven 45-min sessions over a period of 5 to 7 weeks versus treatment as usual.

Outcome measures: Participants were assessed with Game Addiction Scale for Adolescents pre-treatment (GASA) (baseline), post-treatment (treatment group only), and 3 months after baseline (follow-up).

Results: The repeated measures ANOVA showed a significant interaction effect between treatment and time. Both the control group and treatment group lowered their mean GASA score from baseline to follow-up significantly, but the improvement was greater in the treatment group (mean difference in control group −5.1, $p < 0.001$, 95% CI = – 3.390 to −6.755, mean difference in treatment group −9.9, $p < 0.001$, 95% CI = −11.746 to −8.105).

Conclusion: RP was found to be superior to treatment as usual in terms of reduction of IGD symptoms. Future research should address which aspects within a given treatment are effective, who benefits from treatment, in what aspects, and why.

Trial registration number: ClinicalTrials.gov, NCT05506384 https://clinicaltrials.gov/ct2/show/NCT05506384.

KEYWORDS

gaming, internet gaming disorder, CBT, GASA, relapse prevention

1. Introduction

Gaming is one of the most common leisure activities among children and adolescents and is nothing more than a source of entertainment, for the majority. However, some individuals engage in gaming in a way, and to such an extent, that negative consequences ensue (1–3). For some, gaming activity can become so extensive and severe that other activities and obligations, such as school, social relationships, and even physical needs, are neglected (2, 4). Most research agrees on the pathological potential of the behavior which has reached formal recognition with inclusion in both the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) and in the *International Classification of Diseases* (ICD-11). Gaming disorder (GD) has its own diagnostic code in ICD-11 while the DSM-5 mentions internet gaming disorder (IGD) as a tentative diagnosis requiring more clinical research (5, 6). The DSM-5 definition of IGD is similar to their definition of pathological gambling, and so is most of the numerous existing screening tools (6–8).

Despite the increasing amount of research on IGD, controversy remains regarding fundamentals such as the validity of the condition but also regarding terminology, measurement approach, and diagnostic cut-off (7–9). The greatly varying estimates of prevalence and comorbidity are likely influenced by the controversies and discord. The reported prevalence of IGD varies across studies but has globally been estimated as approximately 3%, with the highest numbers found in adolescent samples (8). Apart from age, male gender is an established risk factor, and commonly listed comorbidities are ADHD, anxiety, and depression (1, 10). IGD is further known to cause impairment in both school performances and sleep habits – causing great concern in child and adolescent psychiatry (CAP) and school healthcare (2, 11, 12).

There is no consensus on how to treat IGD, over the past years, a few treatment studies have been published (13). However, these studies have been criticized for poor design and methodological flaws such as lack of control groups (13–15). Cognitive behavioral treatment (CBT) is one of the few methods that have been explored in relation to IGD (13, 14) and is recommended as a first line of treatment (16).

Relapse prevention (RP) is a CBT-based treatment developed to treat alcohol problems in adults, but the method is also used to treat addiction to alcohol, drugs, tobacco, and gambling among both adults and adolescents (17). RP focuses on cognitive restructuring, control of, and recognition of triggers for a problem behavior and the method has been raised as a possible therapy for IGD (18). RP is a relatively short and low-cost treatment which is also an established and well-received treatment method within the clinics that are part of the current project. We developed a CBT-based manual derived from RP for treatment of child and adolescent IGD. Together with experienced clinical psychologists, the manual was adjusted to suit children and adolescents within the CAP context. The number of sessions was reduced, and a fictionalized person was incorporated in a series of vignettes when demonstrating a particular theme. In a pilot study, we evaluated RP as a treatment for IGD and gambling among children and adolescents, showing promising results (19).

While most youth engage in gaming to some extent, a minority need help to control their gaming or to reduce the negative consequences thereof. To this date, no specific treatment is offered to children and adolescents suffering from IGD. Given this, our aim was to evaluate the effectiveness of RP as a treatment for problematic gaming within a CAP setting.

2. Methods

2.1. Trial design and setting

The current study is a non-blinded randomized control trial, performed within three different child and adolescent psychiatric (CAP) units in Region Skåne, Sweden. Detailed methods are described in the trial protocol paper (20).

In our protocol, we specified that our aim in this trial was to determine the effectiveness of RP as a treatment of not only IGD but also problem gambling (20). The results regarding gambling will be published separately.

2.2. Ethics approval

The study was reviewed and approved by the Swedish Ethical Review Authority (Ref 2019-04797, December 13, 2019). Subsequent amendments have been approved (Ref 2021-05592-01, January 3, 2021; Ref 2022-01289-02, March 15, 2022).

2.3. Participants

This trial and recruitment were performed from 1 September 2021 to 30 December 2022. Due to administrative error the trial was not registered in the clinicaltrials.gov until August 2022. All patients, between the years 13–18, coming for their first visit to CAP, were supposed to be screened via an application called The Blue App, for gaming behavior. Those meeting the proposed DSM-5 criteria for IGD (6) were offered participation in the trial, if they had the capacity to provide written informed consent and if they spoke Swedish. Unfortunately, not every patient was screened digitally due to technical problems, thus some were provided the assessment on paper. Caregivers' consents were required for children younger than 15 years. Out of 2,630 new visits, we were able to register 622 (≈24%) patients assessed with GASA whereof 123 (≈20%) met the cut off for IGD. In

the study protocol for this trial, we present a power calculation estimating that approximately 40% in the intervention group and 20% in the control group would improve by follow-up. With these figures, we estimated that 160 (80 + 80) patients should be included in the trial for us to be able to demonstrate a significant difference with sufficient power (20). However, among the CAP patients meeting the criteria for IGD during the study's inclusion period, a total of 113 patients agreed to participate. One patient was excluded due to incorrect inclusion, being younger than 13 years old, and 10 patients were excluded because of not completing follow-up measures. The final sample consisted of 102 participants aged between 13 and 18 years old (M age = 14.42 years, SD = 1.367). For an overview of the inclusion, exclusion and randomization, see the flow diagram in Figure 1.

2.4. Randomization

Participants were randomized in a 1:1 ratio to either intervention or control. For randomization, we applied a random allocation sequence using the 'chit method' by preparing 160 chits of paper indicating either control or treatment (21). Each patient was distributed to a condition (control or treatment), and the chit was not replaced if the patient dropped out of the study. The control group received treatment as usual (TAU) at their home clinic. It was not possible to blind either participants, clinicians, or supervising researchers to randomization allocation.

2.5. Intervention

We collected pre-intervention (baseline) data from the participants before starting treatment. The treatment ran for 5 to 7 weeks for each participant. Post-intervention data were collected at weeks five to seven after completion of treatment. Follow-up data were collected 3 months after baseline date. The intervention ran for 14 months in total with final data collection and closure in month 16. We planned for the treatment to consist of seven to nine sessions over a period of 7 to 9 weeks. Based on experience from our pilot study (19), we decided to compress the treatment to facilitate participation. Consequently, the number of sessions differs from our protocol (20). The participants were considered dropouts if they completed less than five sessions.

2.5.1. Relapse prevention

Participants assigned to the treatment group were administered RP over the course of five to seven sessions, each session lasting

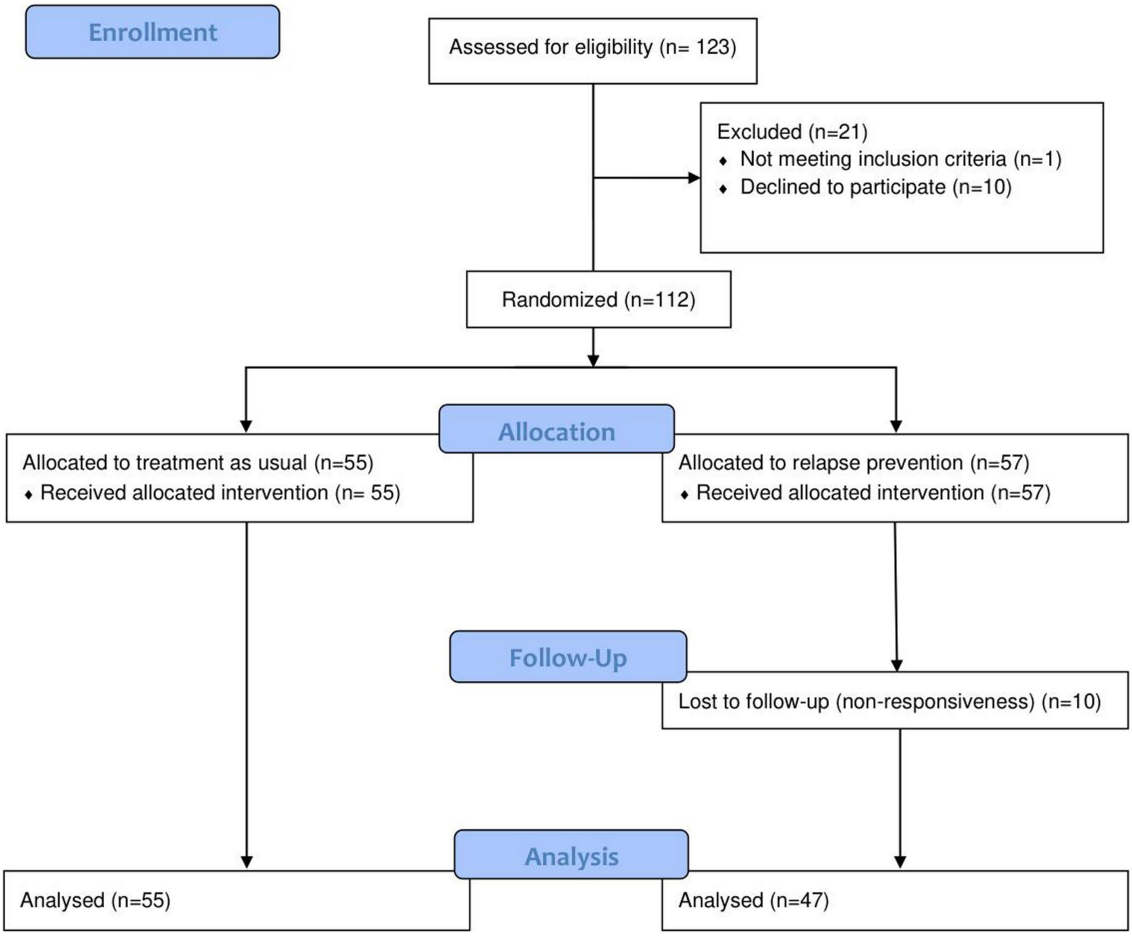

FIGURE 1
Flow diagram. Inclusion, exclusion, and randomization.

45 min. The intervention was provided individually at the respective CAP units or via video link and was led by a clinician. The clinicians implementing the treatment were four licensed psychologists, certified in accordance with the Swedish National Board of Health and Welfare, one social worker, and one psychiatrist; all of them had competence in CBT. The treatment consists of three parts: (1) setting goals, in which the clinician examines the patient's unwanted behavior, mapping his/her motivation for change and goals with treatment; (2) understanding and identifying high-risk situations and problem behaviors; and (3) identifying future high-risk behaviors and early warning signals and consolidating the new activity schedule. An important part of the treatment was theme- specific homework given at the end of each session to be discussed and evaluated at the next.

2.5.2. Treatment as usual

Neither CAP, school healthcare staff, nor social services currently provide any treatment to children and adolescents who need help to stop or regulate their gaming behavior. Consequently, participants in the control group who received TAU received different interventions according to existing practice. Treatments provided in the control group were counseling ($n = 21$), medication for ADHD (Methylphenidate $n = 22$, Dexamphetamine = 1), antidepressants (Sertraline $n = 1$), referral to other unit ($n = 1$), further psychiatric evaluation ($n = 1$). Some individuals ($n = 3$) were put on a waiting list and did not start treatment, and some ($n = 2$) were discharged from CAP during the study period.

2.6. Measures

In addition to assessment regarding gaming behavior, basic demographics routinely recorded in the journal, such as gender, age, housing situations, and diagnosis, were collected. The treatment group was assessed with GASA regarding gaming (22) at baseline (before treatment), after the treatment, and at follow-up (3 months after baseline assessment). The control group were assessed with GASA at baseline and at follow-up.

2.6.1. GASA

The 7-item GASA was used to screen for IGD (22). GASA is one of the most frequently used measures for IGD (22, 23). The instrument is based on the DSM criteria for problem gambling (salience, tolerance, mood modification, relapse, withdrawal, conflicts, and problems) and applies to gaming behavior during the past 6 months (22). The DSM suggests that half of the criteria should be met to qualify for a diagnosis. However, a ranking of the constituent items has been proposed. It has been argued that the 'core criteria' of relapse, withdrawal, conflicts, and problems relate more heavily to addiction than the criteria that concern salience, tolerance, and mood modification, which, according to some scholars, should be considered peripheral (16, 24, 25). Therefore, the 'core approach' applies a prioritization of the four core criterion, creating three categories of gamers: engaged gamers, problem gamers, and addicted gamers. This approach has been reported as clinically relevant as the created categories seem to relate to degrees of negative consequences as well as severity of addictive behavior (25, 26).

Responses were given on a 5-point scale from 1 = never, to 5 = very often. An item was considered endorsed when rated 3 or higher (22). The scale produces two outcome measures: firstly, a continuous GASA score with a minimum of seven points to a maximum of 35 and secondly, categories of gamers (engaged, problem, and addicted gamers) in accordance with the core approach (24).

2.7. Data preparation

Statistical analyses were performed in SPSS (IBM SPSS statistics version 27). Gender, housing situation, and diagnosis were recoded into binary variables (Yes = 1/No = 0). The least prevalent diagnoses were merged into a new variable labeled 'other diagnosis' (see Table 1). This variable included anxiety disorders (anxiety disorder, unspecified, 'mixed anxiety, and depressive disorder, generalized anxiety disorder), other symptoms and signs involving emotional state, obsessive compulsive disorder, adjustment disorder, pathological gambling, and diagnoses primarily used during the psychiatric evaluation phase (observation for suspected mental and behavioral disorders, general psychiatric examination, not elsewhere classified, examination and observation for unspecified reason, observation following alleged rape or seduction, examination and observation for unspecified reason).

The sum of GASA score at baseline, after treatment, and at follow-up composed separate continuous variables used as outcome measures for ANOVA analysis. The difference in score from baseline to follow up, labeled 'improvement', constituted another continuous outcome variable used in a linear regression analysis.

Individuals meeting every core criterion (16, 23–25) in GASA were categorized as 'addicted gamers'. The respondents that endorsed two to three of the core criteria were categorized as problem gamers, and those who endorsed all three of the peripheral criteria but not more than one of the core criteria were categorized as 'engaged gamers'. At follow-up, some participants did not meet the criteria for either of the gaming categories, and were labeled '<engaged gamers'.

2.8. Data analysis

The mean GASA score at baseline and at follow-up was used in a repeated measure ANOVA to compare the change in mean value between control group and treatment group. The treatment group was analyzed in a repeated measure ANOVA separately to compare the mean GASA score at baseline, after treatment, and at follow-up, against each other. The mean difference in GASA score between baseline and follow-up (improvement) was used in an independent sample *t*-test of the difference between treatment group and control group to unable an estimate of the effect size. The improvement in GASA score was also used as the dependent variable in a regression model to quantify the impact of treatment, with adjustment of baseline GASA score, demographics and comorbidity diagnosis.

McNemar's test was applied to compare the prevalence of gaming categories between baseline and follow-up, in control group and treatment group separately.

3. Results

Sample characteristics are shown in Table 1. Out of the 102 participants, 46% constituted the treatment group, and 6% were dropouts. One-quarter of the total sample was female and constituted 17% of the treatment group and 30% of the control group. A majority

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TABLE 1 Sample characteristics.

	Control		Treatment		Total	
	Frequency	%	Frequency	%	Frequency	%
Total sample	55	53.9	47	46.1	102	100
Dropouts	0	0	6	5.7	6	5.9
Gender						
Male	36	65.5	39	83.0	75	73.5
Female	19	34.5	8	17.0	27	26.5
Age, years						
13–15	43	78.2	38	80.9	81	79.4
16–18	12	21.8	9	19.1	21	20.6
Housing situation						
Cohabiting parents	33	60.0	23	48.9	56	54.9
Separated parents	22	40.0	24	51.1	46	45.1
Diagnosis						
ADHD	20	36.4	17	36.2	37	36.3
ADD	10	18.2	3	6.4	13	12.7
ASD	6	10.9	5	10.6	11	10.8
Depression	2	3.6	5	10.6	7	6.9
Other diagnosis	17	30.9	17	36.2	34	33.3

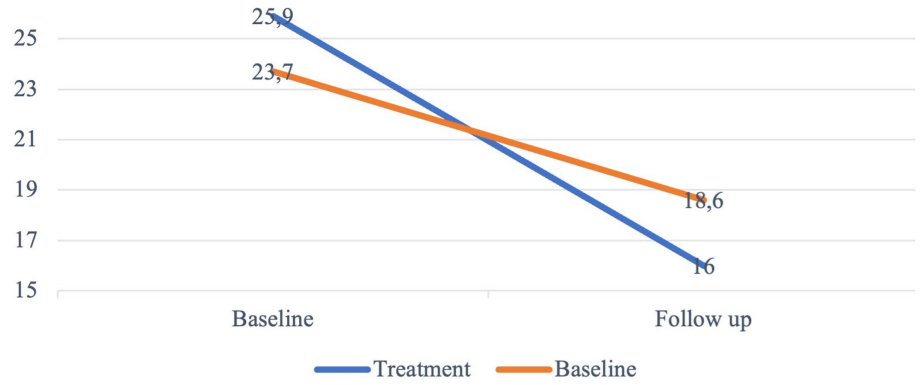

FIGURE 2
Mean GASA score. Changes in mean score from baseline to follow-up. $N = 102$.

were aged 13–15 years and the mean age was 14 years. The distribution of cohabiting and separated parents was relatively even. The most common diagnosis was ADHD followed by ADD, ASD, and depression.

At baseline, 11% met the cut off for engaged gaming in the control group and none in the treatment group. Problem gamers constituted 55 and 49% of the control and treatment group, respectively. Addicted gamers constituted 35 and 51% of the control and treatment group, respectively.

3.1. Reduction in mean GASA score

The following analyses were checked for assumptions of equal variance and normality, the assumptions were met.

As shown in Figure 2, both the control and treatment group lowered their GASA score over time. The repeated measures ANOVA test of within subject effects showed that there was a significant interaction effect between time and treatment ($p < 0.001$). The *post hoc* analysis of estimated marginal means (EMMEANS) showed that the mean GASA score differed significantly between control and treatment group, both at baseline (mean difference 2.2, $p = 0.008$, 95% CI = 0.578, 3.806) and at follow-up (mean difference −2.7, $p = 0.026$, 95% CI = −0.322, −4.999). Both the control group and treatment group lowered their mean GASA score from baseline to follow-up significantly (mean difference in control group −5.1, $p < 0.001$, 95% CI = − 3.390, −6.755, mean difference in treatment group −9.9, $p < 0.001$, 95% CI = −11.746, −8.105). The independent samples *t*-test showed a significant difference in the mean improvement in GASA

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scores between control group and treatment group ($t = -3.88$ (100), $p = <0.001$, CI = −7.331, −2.374). The effect size, as measured by Cohen's d, was $d = 0.77$, indicating a medium effect (27).

The linear regression model is reported in Table 2. The regression analysis showed that the treatment contributed significantly to a greater difference in GASA score from baseline to follow-up, meaning that the improvement among those who underwent treatment was significantly greater. Additionally, the mean GASA score at baseline contributed significantly to the model; a high baseline score was positively associated to a greater improvement. Demographics, such as age, gender and housing situation, did not contribute significantly to any change in GASA score and neither did any of the most common diagnosis.

The treatment group was further analyzed separately in a repeated measure ANOVA to unable incorporation of the GASA score collected immediately after treatment. The mean score from baseline, post treatment and follow-up are visualized in Figure 3. As the post-treatment GASA score was missing for five individuals, this analysis only included 43 participants. The mean difference in GASA score was significant, both between baseline and post-treatment (mean difference = 8.4, $p < 0.001$, 95% CI = −10.813 – −5.954), and from post-treatment to follow-up (mean difference = 2.0, $p = 0.007$, 95% CI = −3.612 – −0.481).

3.2. Reduction in gaming severity level

As shown in Table 3, McNemar's test showed that the proportion of both problem and addicted gamers was significantly lower at follow-up in comparison to baseline in the treatment group whereas no difference was seen in the control group.

TABLE 2 Hierarchical linear regression analysis.

	Coefficients		Model summary			
Predictor	β	Sig.	R^2	Δ R^2	ΔF	Sig. ΔF
Model 1			0.131	0.131	15.088	<0.001
Treatment	4.853	<0.001				
Model 2			0.277	0.146	19.995	<0.001
Treatment	3.472	0.004				
Baseline GASA score	0.630	<0.001				
Model 3			0.255	0.000	0.001	0.979
Treatment	3.468	0.005				
Baseline GASA score	0.629	<0.001				
Male gender	0.036	0.159				
Model 4			0.292	0.015	2.014	0.979
Treatment	3.514	0.004				
Baseline GASA score	0.639	<0.001				
Male gender	−0.050	0.970				
<Age 15	2.008	0.159				
Model 5			0.292	0.000	0.015	0.904
Treatment	3.501	0.005				
Baseline GASA score	0.637	<0.001				
Male gender	−0.038	0.978				
<Age 15	2.019	0.160				
Cohabiting parents	−0.142	0.904				
Model 6			0.292	0.025	0.832	0.508
Treatment	3.462	0.007				
Baseline GASA score	0.616	<0.001				
Male gender	0.080	0.953				
<Age 15	1.682	0.268				
Cohabiting parents	−0.003	0.998				
ADHD	1.348	0.355				
ADD	1.714	0.329				
ASD	1.999	0.111				
Depression	4.017	0.378				

Dependent variable GASA mean improvement.

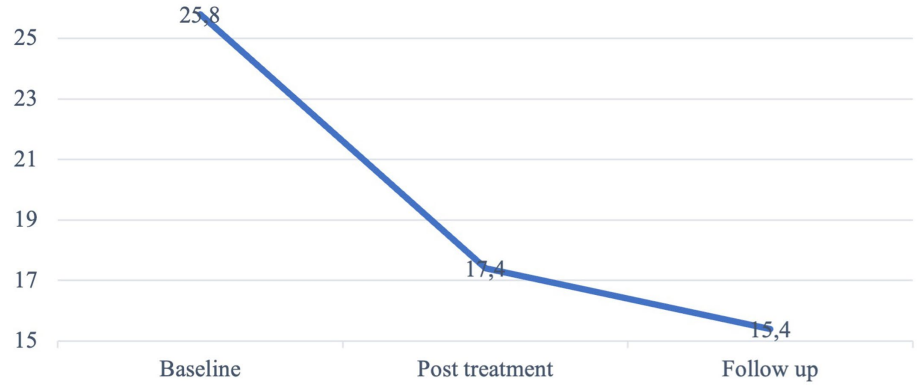

FIGURE 3
Mean GASA score at baseline, post-treatment, and at follow-up. Treatment group. *N* = 43.

TABLE 3 McNemar's test for X^2 -comparisons of the prevalence of gaming categories between baseline and follow-up, in control group and treatment group separately.

	Control			Treatment		
	Baseline N (%)	Follow-up N (%)	*p*-value	Baseline N (%)	Follow-up N (%)	*p*-value
<Engaged gamers	0 (0)	34.5 (19)	–	0 (0)	59.6 (28)	–
Engaged gamers	10.9 (6)	5.5 (3)	0.453	0 (0)	4.3 (2)	–
Problem gamers	54.5 (30)	41.8 (23)	0.167	48.9 (23)	25.5 (12)	0.043
Addicted gamers	34.5 (19)	18.2 (10)	0.064	51.1 (24)	10.6 (5)	<0.001

N = 102.

4. Discussion

Interest in the treatment of IGD has clearly increased in recent years, from a basically non-existent level to an ever-increasing number of published articles on the subject (13, 14). It seems reasonable to assume that the interest in the treatment of IGD represents a need, identified by parents, school healthcare providers, and other caregivers seeing problems they interpret as related to excessive gaming among children. However, existing research within this field is still sparse and marked by methodological flaws (13).

The present RCT evaluates RP as a treatment for IGD among children and adolescents ages 13–18, within the context of CAP in southern Sweden. The participants were assessed regarding symptoms of IGD at baseline and at follow-up, carried out 3 months after the initial screening. In addition, the treatment group was also assessed regarding symptoms of IGD immediately after the treatment had been completed. Both the treatment group and the control group improved regarding IGD symptomatology from baseline to follow-up. In the treatment group, however, children and adolescents exhibited significantly greater improvement in terms of their IGD. Further, the proportion of both addicted and problem gamers showed a significant decrease from baseline to follow-up in the treatment group, whereas no difference was seen in the control group.

Relapse prevention was developed in the 80s, originally as a response to the failed long-term effects of other therapies at the time (17, 28). The method has ever since been used for various substance use disorders but also for the treatment of behavioral addictions and it has been suggested as a treatment for IGD specifically (23, 28). The treatment model aims to identify and address triggers or high-risk situations/circumstances in order to prevent relapse, to preserve abstinence or to reduce harm, but also how to handle a relapse if occurred, such that further relapses can be prevented (17, 28). Possibly, the model is specifically beneficial when it comes to IGD as the confrontation with triggers is particularly frequent, considering young people's constant access to gaming via smart phones, tablets and computers.

Interestingly, both the control and the treatment group improved significantly regarding mean GASA score from baseline to follow-up. The findings on the natural course of IGD differ across studies (29). Gentile et al. showed that 84% of the pathological gamers, in a secondary school setting, were still pathological gamers 2 years later (30). Another study, also conducted on a sample of secondary school students, showed that 50% of the addicted gamers were still addicted 1 year later (31) while Krossbakken et al. reported on a three-year stability of 35%, among a representative sample of Norwegian 17-year-olds (3).

The fact that this trial also showed a significant improvement regarding IGD symptomatology in the control group could reflect the self-healing nature of the condition, but it could also be a consequence of the fact that the control group did receive some form of psychiatric care. Possibly, their improvement was a positive side effect of adequate care of another psychiatric comorbidity. It is evident that there is a reciprocal link between psychological distress and IGD (3) and it is

therefore possible that treatment of psychiatric problems had some positive spillover effect on IGD.

The treatment group in this trial improved to a higher degree relative to the control group. Additionally, the analyses of prevalence of gaming categories showed a significant decrease of problem and addicted gamers in the treatment group but not in the control group, which possibly should be considered more clinically relevant than the change in GASA score (24, 25). The prevalence of addicted gamers dropped by 79% in the treatment group, in comparison to a drop by 47% in the control group. Comparing this treatment efficacy with findings of previous research is not entirely straightforward as comparable studies are few and the outcome measures differ. Zajac et al. summarized the research field in a systematic review published in 2020, in which they identified only four previously published RCT evaluating CBT-based treatments of IGD. Among these trials, two did not find an advantage of CBT over control (13). One of the other two reported that a mindfulness-oriented group treatment was superior to a support group, in a sample of 30 students and university employees (32). The other successful trial showed that combined CBT and bupropion was an effective treatment of IGD in 65 male adolescents with major depressive disorder (33); thus, a study carried out in a very specific population. The less successful RCTs both provided therapeutically active treatments for the control group, and both had a relatively small sample size with 28 and 24 participants, respectively (34, 35). In summary, previous comparable research is barely existent, and the findings are not entirely clear-cut.

This trial contributes with further support for CBT-based treatments of IGD, specifically RP. RP has the advantages of being a relatively short, low cost and manual-based treatment that does not place higher demands on the practitioner than the basic psychotherapeutic competence. The treatment could thus be offered outside of psychiatry, such as through primary care or school healthcare. Knowledge gaps remain, such as how the family situation and parent–child relationships can affect and might be affected by IGD treatment (20). Also, future research should address which aspects within the given treatment are effective, who benefits from treatment, in what aspects, and why.

4.1. Strengths and limitations

The presented findings should be considered in the light of the study's limitations. One limitation is the fact that the treatment group showed a higher GASA score than the control group at baseline, which might impact the relative efficacy of treatment. One could argue that an individual with greater gaming problems would show a greater improvement than an individual with less pronounced problems, representing a ceiling effect (36). However, when the baseline score was controlled for, the effect of the treatment remained significant, which supports the main findings in the study.

One other potential limitation is the absence of blinding which entails a risk that the participants in the control group, and possibly also their parents, experienced disappointment when they were informed that they had been randomized to a group that would not receive gaming-specific treatment. Possibly this disappointment contributed to a reduction in improvement that might have been seen otherwise.

The fact that TAU could not be kept constant is another limitation. The interventions in the control group differed due to the diversity in the sample and TAU was not given for a particular diagnosis, but more non-specifically for each of the participants individual psychiatric problems. This is the naturalistic setting of CAP Skåne. As no specific treatment to date is provided targeting gaming behavior among adolescents within the Swedish CAP context, this methodological approach was the most reasonable for us.

One other possible limitation is the fact that GASA applies to experiences with games over the last 6 months whereas the DSM-5 criteria for IGD concern the last 12 months (6). However, GASA is developed for adolescents specifically (22) and our clinical understanding and experience of youth gaming is that 6 months of destructive gaming is enough to cause negative consequences and a need for help.

Also, measures other than GASA, and reflecting additional psychological health complaints used as secondary outcomes, would have contributed valuable information on the potential range of effects of the treatment provided.

One could argue that the fact that each of the participants was diagnosed with a psychiatric condition might affect the generalizability of the results. However, this specific circumstance could also be considered as strengthening the external validity since psychiatric comorbidity, not least ADHD, is a known feature of IGD (1). Our results show that the given treatment appears to be effective in an actual clinical setting, among individuals with psychiatric comorbidity who could be considered particularly difficult to treat.

Given the limitations mentioned, the current study is to our knowledge the largest RCT to evaluate a CBT treatment for IGD among children and adolescents, and the findings are promising.

4.2. Conclusion

Relapse prevention was found to be superior to TAU in terms of reduction of IGD symptoms among children and adolescents in CAP clinics. The present study adds to a research field still in its infancy with further evidence that CBT, and specifically RP can be an effective treatment for IGD among children and adolescents.

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 the Swedish Ethical Review Authority (Ref 2019-04797, December 13, 2019). Subsequent amendments was approved (Ref 2021-05592-01, January 3, 2021; Ref 2022-01289-02, March 15, 2022). The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/ next of kin. Written informed consent was obtained for every

participant and caregivers' consents were required for children younger than 15 years in concordance with Swedish regulations.

Author contributions

FA: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. SK: Conceptualization, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – review & editing. IE: Conceptualization, Methodology, Visualization, Writing – review & editing. ST: Conceptualization, Methodology, Visualization, Writing – review & editing. LF: Conceptualization, Methodology, Visualization, Writing – review & editing. AM: Conceptualization, Methodology, Visualization, Writing – review & editing. AH: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. EC-K: Conceptualization, Investigation, Methodology, Project administration, Resources, Software, Supervision, Visualization, Writing – review & editing.

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Conflict of interest

AH has an employment at Lund University, sponsored by the state-owned Swedish gambling operator Svenska Spel. AH also has research funding from the research council of the Swedish state monopoly for alcohol, Systembolaget AB. EC-K has funding from the research council of Svenska Spel. None of these bodies had any role in, or influence on, the present study. The authors alone are responsible for the content and writing of the paper.

The remaining 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.

Publisher's note

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The quality of information provided by the most popular dementia videos on TikTok

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Summary of background: Dementia is among the leading causes of death and disability worldwide, having a major impact not only on the affected person but also on all of society. The Internet is a popular and growing source of health-related information for patients, family members, carriers, and physicians. TikTok, one of the most popular social media platforms, is an important source for knowledge access and adoption. However, the quality of health information on TikTok has not been sufficiently studied.

Objective: To evaluate the quality of the information provided in the most popular videos on dementia shared on TikTok.

Study design: A cross-sectional study.

Methods: The top 100 most popular videos on TikTok obtained by searching the hashtag "dementia" were included in the study and grouped based on their source and content. The popularity of the videos was estimated based on the numbers of likes, comments, and shares. The quality of health-related information was evaluated using the DISCERN score and the Global Quality Score (GQS).

Results: Videos had a median duration of 33.29 s; the median number of likes was 635,100, with a total of 93,698,200 likes, 903,859 comments, and 5,310,912 shares. The source (uploader) of 65% of the videos was family members, while only 4% were uploaded by doctors. The content was lifestyle-related in 62% of the videos, while 12% of the videos were for fun. Videos had a median DISCERN score of 22.5 (IQR 20–27) and a median GQS of 2 (IQR 1–3). The videos uploaded by doctors had the highest quality scores and the lowest popularity.

Conclusion: The most popular dementia videos on TikTok are mostly shared by family members and are of poor quality. Given the major public health issues associated with dementia, experts must provide appropriate and active assistance to patients in interpreting the information identified.

KEYWORDS

dementia, online health information, video quality, social media, TikTok, credibility, reliability

1 Introduction

Dementia is among the leading causes of death and disability worldwide, having a major impact not only on the affected person but also on all of society. The burden of dementia, estimated by years lived with disability, is one of the highest among all non-communicable diseases (1). Since the population of older adults is growing and the prevalence of dementia increases with age, it is logical to assume that the number of dementia cases will also increase.

The World Health Organization (WHO) predicts that the prevalence of dementia will almost double every 20 years, resulting in a worldwide prevalence of 131.5 million by 2050 (2). It is anticipated that by 2030, the global cost of caring for people with dementia will have climbed to US$2 trillion, a figure that might impair global social and economic growth and overwhelm health and social services (3).

The worldwide action plan by the WHO regarding the public health response to dementia specifies the domain of public health as a priority action area, increasing dementia awareness and friendliness as well as support for dementia carers (2). Technological advancements may help to sustain cognitive function (4) or redefine effective aging at home for people with dementia by granting them continued autonomy and independence while also relieving relatives and caregivers (5). Social media platforms have the potential to make significant contributions to health communication and promotion as well as the potential to drive greater engagement with dementia research (6, 7).

The significant expansion of web-based medical information has drastically altered how consumers access health information. Before visiting a doctor, an increasing number of patients seek information online (8). With the rise in social networking platforms, people are increasingly using videos to gather medical information. However, the quality of health-related video clips on social media is unsatisfactory, and the rate of health misinformation is high (9, 10). Although health material has been widely investigated on video sites such as YouTube, studies examining online video platforms such as TikTok are rare (11).

TikTok is a short-form video hosting service that has gained global popularity since its launch, gathering over 1 billion monthly global users and growing its user base faster than any other social media platform (12). Therefore, TikTok has become another medium for sharing and seeking information globally (11). Previous studies have investigated the quality of TikTok videos regarding diabetes (13), COVID-19 (14), chronic obstructive pulmonary disease (15), and gallstone disease (16). However, the dementia material on TikTok has not yet been assessed.

With the growth of social media and Internet use, information can spread more rapidly. This can help users to acquire information more quickly but can also amplify dangerous messages. The term *infodemic* refers to a large increase in the volume of information associated with a specific topic, which can occur exponentially in a short period of time due to a specific incident, such as the COVID-19 pandemic. In this situation, misinformation and allegations appear on the scene, along with manipulation of information with uncertain intentions. This phenomenon is intensified through social networks, spreading rapidly and over long distances, like a virus (17). Accordingly, the WHO suggests risk- and evidence-based analysis and approaches to manage infodemics and reduce their impact on health behaviors (18).

On this basis, the aim of this study was to evaluate the quality of the most popular dementia videos on social media platforms, such as TikTok.

2 Methods

2.1 Data collection

We performed a cross-sectional analysis of TikTok dementia videos during June and July of 2023. This social media platform was investigated using an Android application (version 30.2.3) with a new research account. The authors independently engaged in data collection on the same day, with different mobile devices, using a single search with the hashtag "dementia". We examined all video categories with no time limit (all dates posted), and videos were sorted by like count. At the time of data collection, each video was given a unique ID (identifying its order in the rating) and linked to its associated data in a master database (MS Access), with a screenshot of the video for verification. The target sample size was set to the first 100 unique videos. Data were collected for 108 videos, while 8 videos were excluded from further analysis based on the exclusion criteria of non-English language ($n = 5$) or animal content ($n = 3$).

For each video analyzed, we collected generic data (username, title, upload date, days since upload, source (uploader), content, and video duration) and engagement metadata (number of likes, comments, and shares). During the process of data collection and analysis, the investigator did not engage in any interactions within the application (e.g., posting comments, likes, or reactions, or messaging).

2.2 Classification of videos

The method of classification of videos was drawn from previous analyses of health-related topics on TikTok (13–16). The content of videos was classified as follows: (1) therapy suggestion, (2) disease description, (3) lifestyle, (4) news, (5) fun, and (6) other (unclassified). Video sources were categorized as follows: (1) doctors, (2) patients, (3) family members, (4) other medical staff, (5) news agencies (e.g., network media, newspaper, TV station, or radio station), (6) organizations (e.g., hospitals, universities, research groups, and health authorities), and (7) other (unclassified).

2.3 Quality assessment

The quality of the information in videos was assessed using the DISCERN instrument and the Global Quality Score (GQS).

The overall quality was assessed using the GQS, a five-point scale ranging from 1 to 5. A score of 1 represents poor quality, 2 indicates generally poor quality, 3 signifies moderate quality, 4 denotes good quality, and a maximum score of 5 reflects excellent quality (19).

The DISCERN instrument was developed to judge the quality of health information on treatment choices (20). Treatment refers to a course of action taken to address a health problem or illness, which may include self-care. Treatment options relate to the various possibilities for dealing with a health problem and include both treatments and no treatment, i.e., not taking

any direct action or employing any type of treatment. The instrument is made up of 15 main questions and an overall quality assessment. Each of the 15 key questions reflects a distinct quality criterion, i.e., an important feature or standard that is a principal component of high-quality information. The overall DISCERN scores ranged from 16 to 80 and were labeled as very poor, poor, fair, good, or excellent, according to the number of points (21, 22).

The assessment and rating were performed by two reviewers independently. Reviewer 1 was a consultant neurologist, and reviewer 2 was a psychiatry resident. Potential differences between reviewers were resolved using the modified Quaker-based consensus model, which can be effectively applied in any consensus decision-making process (23). The uncertainties or disagreements most frequently raised related to the judgment of DISCERN tool items, which were originally designed for printed material. Final scores were determined by consensus.

2.4 Statistical analyses

Descriptive statistics are presented in the form median, interquartile range (IQR), or as a percentage, as appropriate. Differences between groups were tested using the Kruskal–Wallis test. Spearman's rank correlation coefficients, adjusted with the Bonferroni method to account for multiple comparisons, were employed to assess the relationships between variables. A significance threshold of $p = 0.05$ was applied to determine statistical significance. Statistical analysis was performed using STATA software package (StataCorp LP, USA).

2.5 Ethical considerations

This study used no clinical data, human specimens, or laboratory animals. All the data used in this study came from publicly available TikTok videos, and none of the data involved

TABLE 1 Features of the top 100 TikTok dementia videos by source.

Video source ($n = 100$)	Likes Median (IQR)	Comments Median (IQR)	Shares Median (IQR)	Days since upload Median (IQR)	Duration (seconds) Median (IQR)
Doctors ($n = 4$)	581,150 (432,950–656,450)	6,307.5 (3,584.5–7,955.5)	74,900 (36,985.5–97,650)	271.5 (158.5–279.5)	162 (122–175)
Patients ($n = 2$)	1,108,950 (417,900–1,800,000)	12,170.5 (9,241–15,100)	176,550 (141,600–211,500)	88 (60–116)	9.5 (6–13)
Family members ($n = 65$)	620,600 (416,800–963,200)	5,251 (1,942–10,500)	19,800 (6,285–40,900)	312 (131–351)	18.5 (15–40)
Other medical staff ($n = 14$)	840,900 (444,900–1,800,000)	2,530 (897–18,300)	13,450 (1,921–105,200)	208.9 (216.9)	37 (35.16)
News agency (portals) ($n = 3$)	772,100 (567,800–776,400)	3,145 (1,011–11,100)	34,900 (12,200–52,400)	97 (53–211)	46 (21–48)
Organizations ($n = 5$)	719,000 (449,200–782,900)	2,625 (2,285–3,079)	46,700 (40,100–54,800)	200 (172–341)	35 (22–45)
Other ($n = 7$)	630,500 (483,200–2,000,000)	4,361 (2,904–13,300)	50,900 (41,700–71,400)	114 (50–272)	21 (8–49)
Total	635,100 (433,400–1,039,950)	4,608.5 (1,849.5–10,600)	27,400 (6,453–6,453)	176 (101.5–284.5)	42 (18–78.5)

IQR, interquartile range.

TABLE 2 Features of the top 100 TikTok dementia videos by type of content.

Video content ($n = 100$)	Likes Median (IQR)	Comments Median (IQR)	Shares Median (IQR)	Days since upload Median (IQR)	Duration (seconds) Median (IQR)
Therapy suggestions ($n = 1$)	776,400	3,145	52,400	97	48
Disease description ($n = 12$)	708,550 (560,450–1,125,800)	5,131 (2,171–8,867.5)	35,650 (2,431–82,500)	236 (72–298)	51.5 (34–87.5)
Lifestyle ($n = 62$)	612,050 (407,400–963,200)	4,319.5 (1,819–10,500)	16,000 (5,499–46,000)	176 (129–272)	52.5 (21–83)
News ($n = 2$)	557,650 (547,500–567,800)	5,106.5 (1,011–9,202)	45,600 (12,200–79,000)	162.5 (53–272)	108 (46–170)
Fun ($n = 22$)	674,750 (483,200–1,800,000)	4,589.5 (1,942–11,100)	52,550 (25,600–123,700)	172.5 (96–313)	14.5 (8–26)
Other ($n = 1$)	654,700	11,100	22,000	67	164

IQR, interquartile range.

personal privacy concerns. In addition, the authors did not participate in any interaction, and therefore, no ethics approval was required.

3 Results

3.1 Features of dementia videos

The 100 TikTok dementia videos analyzed had a median duration of 42 s. They had received a total of 93,698,200 likes, 903,859 comments, and 5,310,912 shares. The median numbers were 635,100 likes, 4,608.5 comments, and 27,400 shares. The median number of days since upload was 176 (IQR: 101.5–284.5) at the time of data collection (Table 1).

Regarding video sources, 65% (65 of 100) of the videos were posted by family members, while only 4% (4 of 100) were posted by doctors. Other video sources were patients at 2% (2 of 100), other medical staff at 14% (14 of 100), news agencies at 3% (3 of 100), organizations at 5% (5 of 100), and other (unclassified) sources at 7% (7 of 100).

Regarding the content, lifestyle videos were the most dominant, accounting for 62% (62 of 100) of all the videos. The proportions of other types of content were 22% (22 of 100) for fun, 12% (12 of 100) for disease description, and 2% (2 of 10) for news, while therapy suggestions and other types content covered 1% (1 of 100) each (Table 2).

3.2 Video quality assessments

According to the DISCERN and GQS instruments, the quality of dementia-related videos on TikTok was very low. The median DISCERN and GQS scores for all 100 top videos were 22.5 (IQR 20–27) and 2 (IQR 1–3), respectively. Most videos were very poor or poor quality according to their DISCERN score and generally poor or moderate according to their GQS score (Table 3; Figure 1).

The quality of videos was found to be significantly related to video source and content. Only videos uploaded by doctors approached the reference line for "fair" quality according to DISCERN score and "good" quality on the GQS scale (Figure 2). The quality of doctors' videos as measured by as DISCERN score (median 39.5, IQR 34.5–40.5) was significantly better than that of other videos (Kruskal–Wallis test, chi-squared: 19.761, df = 6, $p < 0.01$). In addition, the quality of doctors' videos as measured by GQS (median 3.5, IQR 3–4) was significantly different from that of other videos (Kruskal–Wallis test, chi-squared: 19.578, df = 6, $p < 0.01$).

Regarding the video content, most videos were of poor or very poor quality. Videos with news content (median DISCERN score: 35.5, IQR 31–40; median GQS: 3.5, IQR 3–4) were of significantly higher quality in comparison to other videos (Kruskal–Wallis test, chi-squared: 26.352, df = 5, $p < 0.01$ for DISCERN; chi-squared: 24.342, df = 5, $p < 0.01$ for GQS) (Figure 3).

Although patients' videos received the most likes, comments, and shares, they were of very poor quality according to the instruments used.

TABLE 3 DISCERN and Global Quality Scores for the top 100 TikTok dementia videos.

Score	Percentage (%)
DISCERN	
16–26 (very poor)	70
27–38 (poor)	27
39–50 (fair)	3
51–62 (good)	/
63–80 (excellent)	/
GQS score	
1 (poor)	26
2 (generally poor)	36
3 (moderate)	36
4 (good)	2
5 (excellent)	/

GQS, Global Quality Score.

The correlation analysis revealed connections between the following parameters: likes and comments (rho = 0.48, $p < 0.01$); likes and shares (rho = 0.51, $p < 0.01$); comments and shares (rho = 0.54, $p < 0.01$); comments and duration (rho = −0.32, $p < 0.05$); and shares and days since upload (−0.3382, $p < 0.05$; Table 4).

With the exception of video duration, which showed positive correlations with DISCERN and GQS at rho = 0.3881 and rho = 0.4208, respectively ($p < 0.05$ for both), we observed no significant associations between video quality scores and the other video-related variables (Table 5).

4 Discussion

The main finding of this study is that the overall quality of the information in dementia-related videos on TikTok is very low and differs significantly depending on the source. The most popular dementia videos are mainly provided by family members and are of low quality. The infrequent videos uploaded by doctors had the highest quality scores and the lowest popularity.

We discovered positive correlations between likes, comments, and shares, showing that popular videos were more likely to gather comments and to be shared. The number of comments was also found to be positively associated with the number of shares, implying that videos with more comments are more likely to be shared. The number of days since upload was not correlated with number of likes and comments, but was negatively correlated with number of shares, showing that there was no time-dependent influence on popularity. It is notable that there was no link between video length and number of likes and shares. With the exception of a link between duration and quality, implying that longer videos were of higher quality, we discovered no associations between video parameters and quality scores.

Overall, this study found that the most popular videos about dementia on TikTok are of the lowest academic and educational quality. These findings suggest that TikTok users are unable

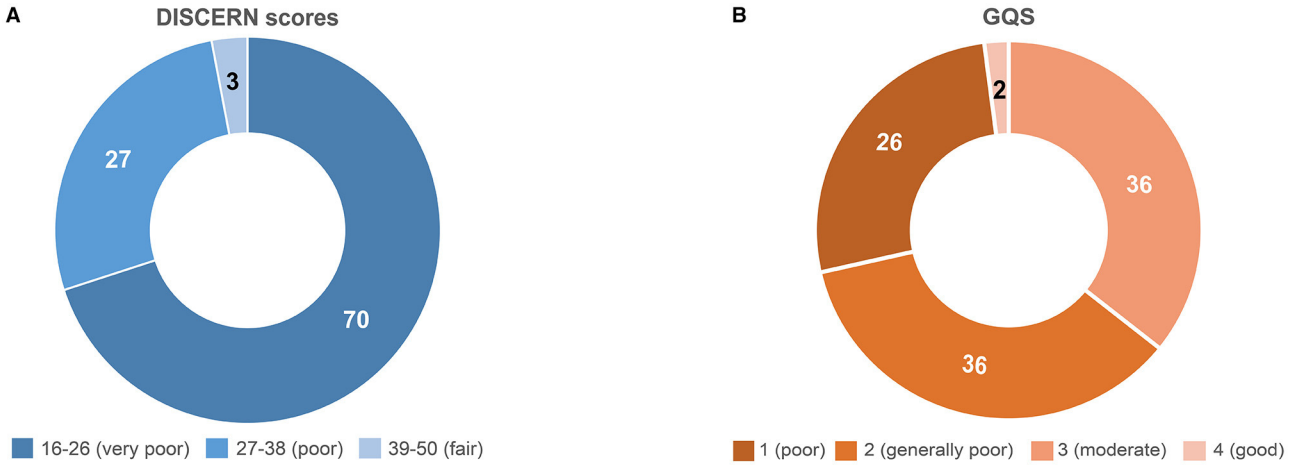

FIGURE 1
DISCERN and Global Quality Scores of the top 100 most popular dementia videos on TikTok. **(A)** DISCERN scores (5 levels); **(B)** Global Quality Scores (GQS). Colors represent the quality scores of videos; darker colors correspond to lower quality. The numbers in the figures represent the percentage of videos in each category.

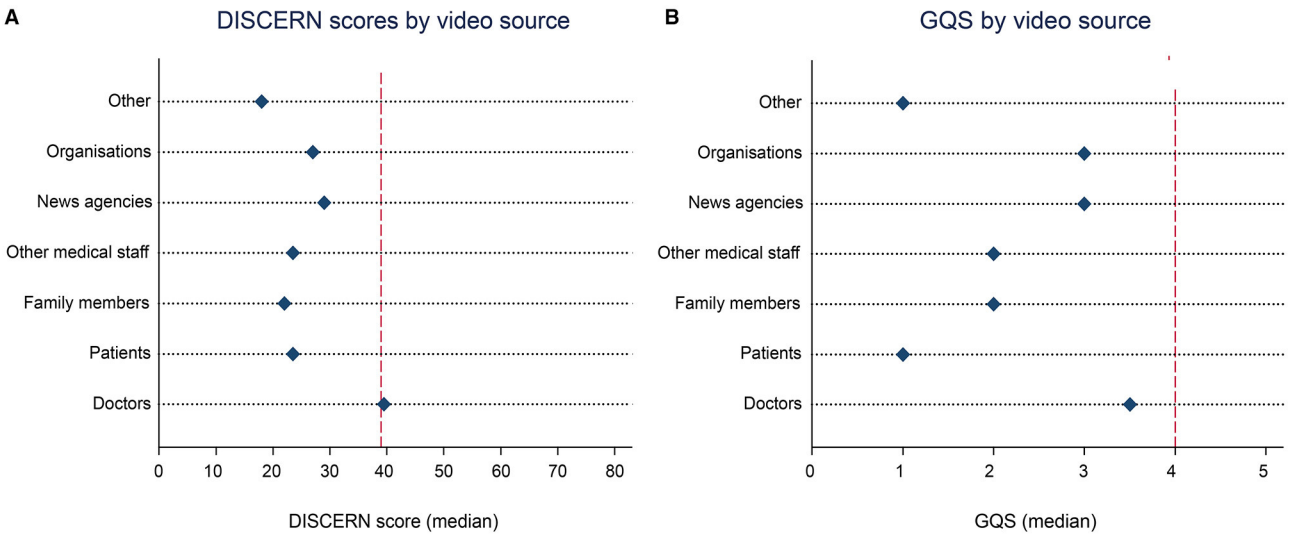

FIGURE 2
Quality assessments of the top 100 TikTok dementia videos by source. **(A)** Median DISCERN score by video source. Reference line: DISCERN score = 39 (lower limit for "fair" quality). **(B)** Median GQS by video source. Reference line: GQS = 4 (lower limit for "good" quality). GQS, Global Quality Score.

to distinguish between high-quality and low-quality videos. The results may be connected to the characteristics of TikTok users. Since TikTok is primarily a lifestyle activity platform, its users prefer entertaining videos, and videos with pleasant graphics are more attractive. Videos with better credibility are not popular, most likely because professional content is serious or even monotonous, making it difficult for such videos to gain popularity.

Some studies suggest that users may be more likely to seek out video information that differs from standard medical procedures (24). Content that is unconventional and differs from conventional medical recommendations may be more attractive to users and thus gain more views and likes. Educational videos may not be as exciting, which makes them less interesting to non-professionals.

The primary limitation of our study is that we analyzed only the first 100 videos obtained by searching the hashtag "dementia". Previous studies have found that most users do not read more than one or two pages of online search results (25), and that it is unlikely for users to read beyond the first 50 search engine results (26, 27). Therefore, we evaluated the top 100 videos obtained via this search.

Another possible limitation is that videos were sorted by number of likes. We chose this method because the primary goal of the study was to assess the quality of the most popular videos that may have the largest public impact. In addition, we used this method to reduce potential location effects, since the default settings of the application may differ depending on the user's Internet Protocol address or other unknown conditions.

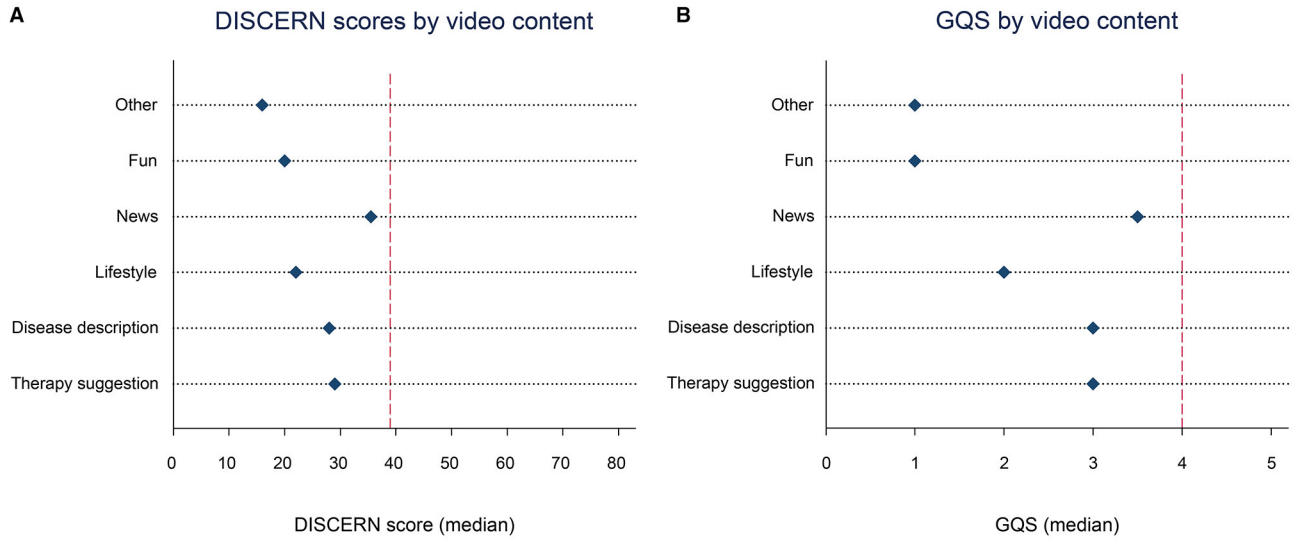

FIGURE 3
Quality assessments of the top 100 TikTok dementia videos by content. **(A)** Median DISCERN score by video content. Reference line: DISCERN score = 39 (lower limit for "fair" quality). **(B)** Median GQS by video content. Reference line: GQS = 4 (lower limit for "good" quality). GQS, Global Quality Score.

TABLE 4 **Results of the correlation analysis between video-related variables.**

	Likes	Comments	Shares	Days	Duration
Likes	-	-	-	-	-
Comments	0.4812**	-	-	-	-
Shares	0.5094**	0.5379**	-	-	-
Days	0.0087	−0.0202	−0.3382**	-	-
Duration	0.0087	0.3201*	0.1045	−0.0683	-

The results represent Spearman's rank correlation coefficients with Bonferroni adjustment for calculation of the significance level.
*$p < 0.05$.
**$p < 0.01$.

Similarly, the search was performed at a single timepoint without engagement in any interaction (e.g., likes, comments, reactions, or messages) to minimize adjustment or recommendations by social networking algorithms (28) and to enable better reproducibility of the results.

In addition, we did not analyze the characteristics of music the associated with the videos. Background music does not considerably improve the popularity of videos, according to a previous study (29). Therefore, the evaluation of the technical quality of the video image or the included music are beyond the scope of this study.

Furthermore, although we performed an analysis of engagement data (likes, comments, and shares), we did not conduct a deeper investigation into the content of the comments. Some viewers may make comments out of displeasure, and these unfavorable reviews may boost the number of comments. However, we identified strong positive correlations among the numbers of comments, likes, and shares, which corresponds to positive rather than negative popularity. Further studies should focus on analysis of the association between positive and negative comments and video quality.

Thus, despite potential limitations, we feel that this study established an objective framework for assessment of the quality of the most popular dementia videos on TikTok.

Several studies have been conducted on health-related content on TikTok, and these have used different instruments (13–16, 30–33). Some studies have evaluated videos only based on engagement data (14), using minimal tools (30, 31), or according to clinical guidelines (33). However, we have used the most comprehensive and most frequently employed instruments: DISCERN and the GQS (13, 15, 16, 32). In addition, previous studies have found that the JAMA benchmark criteria (34) could not accurately assess video information and were not precise enough (16). Regarding the topic, research exploring mental health content on TikTok is essentially absent from the published research literature (30). To the best of our knowledge, this is the first study to evaluate the quality and reliability of information regarding dementia on TikTok. We believe that this novel study will facilitate further investigation and serve as a reference comparator for research examining dementia content on this social media platform. The videos analyzed in our study had more than 93 million likes, suggesting that there is substantial interest in content providing

TABLE 5 Results of analysis of the correlation between video quality scores and video-related variables.

	DISCERN	GQS
Likes	0.1187	−0.0640
Comments	−0.0165	−0.0541
Shares	−0.0744	−0.1917
Days	0.0872	0.0452
Duration	0.3881**	0.4208**

The results represent Spearman's rank correlation coefficients with Bonferroni adjustment for calculation of the significance level.
**$p < 0.01$.
GQS, Global Quality Score.

information on dementia on TikTok. This indicates great public interest and is a potential avenue for promising interventions. Specifically, increasing the number of videos uploaded by doctors or academic groups and ensuring that content remains engaging while maintaining a professional standard could enhance audience engagement and contribute to the wider dissemination of accurate medical knowledge.

The clinical characteristics of dementia, reflected by changes in personality and mental capacity, frequently necessitate ongoing care, which can be extremely taxing physically and emotionally for the family members or professional caregivers who handle most of this care. Additionally, it is common for family members of dementia patients to not receive enough information or counsel on the disease, including information on the legal, financial, diagnostic, and treatment-related aspects of the disease (35). Furthermore, the stress of providing dementia care is linked to a wide range of physical and mental health conditions and negatively affects the quality of life of both care recipients and carers. Interventions for dementia carers have mostly concentrated on education and skill development with the aim of reducing feelings of stress and workload (36). Social media platforms have the potential to significantly contribute to health communication and to improve public health outcomes by increasing dementia awareness through a public campaign to promote a dementia-inclusive society (2).

5 Conclusion

This study shows that less accurate and less reliable dementia videos are more favored by TikTok users. However, due to the growing popularity of this platform and the major burden imposed by dementia, the potential of public health promotion via this platform cannot be overlooked. More videos created by health professionals and refined via a serious review process may increase health knowledge and public awareness of dementia, as well as support for dementia caregivers.

Data availability statement

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

Author contributions

SL: Conceptualization, Formal analysis, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. JP: Data curation, Methodology, Writing – original draft, Writing – review & editing.

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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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Latent profile analysis of psychological needs thwarting in Chinese school teachers: longitudinal associations with problematic smartphone use, psychological distress, and perceived administrative support

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Introduction: In light of the significant impact that teachers have on education quality and student growth, their mental health warrants special attention. With the increasing popularity of Information and Communication Technology (ICT) and the rise of online teaching during the pandemic, teachers have become a group prone to developing problematic smartphone use (PSU). Psychological need thwarting (PNT) has been shown to be closely related to PSU, psychological distress, and perceived administrative support. However, most previous studies have adopted a variable-centered approach, which may overlook the possibility that the three basic needs are not closely associated and could form distinct profiles. Therefore, this study aims to apply latent profile analysis to identify different PNT profiles and their associations with PSU, psychological distress, and perceived administrative support.

Methods: A longitudinal survey was conducted using convenience and purposive sampling methods. The survey involved 1,642 primary and middle school teachers working in China over a two-month interval, with the first assessment in November 2021 (Time 1) and the second in January 2022 (Time 2).

Results: The results indicate that a three-profile model, intricately based on the PNT data gathered at Time 1, is most optimal: Class 1 is labeled as 'High autonomy-High competence and Moderate relatedness thwarting', Class 2 as 'High autonomy-High competence and High relatedness thwarting', and Class 3 as 'Low psychological needs thwarting'. Distinct associations were observed among the three profiles concerning PSU, psychological distress, and perceived administrative support. Specifically, in terms of PSU, the score of Class 2 was higher than Class 1, with that of Class 3 being the lowest at Time 1, while at Time 2 no significant difference was found between any two of these three groups; in terms of distress, the scores of the three profiles were arranged from high to low as Class 2, 1, and 3 at both time points; and in terms of perceived administrative support, the order was just the opposite, with 3, 1, and 2 from high to low at both Time 1 and Time 2.

Conclusion: Notably, the consistent ranking of the three classes in terms of psychological distress and administrative support suggests a lasting influence of PNT. Future studies should explore this enduring impact further by employing

additional longitudinal data sets and examining potential mediators or moderators beyond the current study's scope.

KEYWORDS

psychological needs thwarting, problematic smartphone use, psychological distress, perceived administrative support, latent profile analysis

1 Introduction

The psychological well-being of teachers holds significant importance in the educational system. Compromised health can impact not only their ability to deliver quality instruction and address students' needs but also increase the workload for other staff (1). In this context, studies like those by Chen et al. (2) have highlighted how teachers' negative moods, such as fear, can influence their students. A related and growing concern is the rise of Problematic Smartphone Use (PSU) among teachers, particularly due to the increased reliance on Information and Communication Technology (ICT) in education (3, 4). This issue has become more pronounced during the pandemic, where the abrupt shift to online teaching has necessitated that teachers spend extensive time on smartphones, leading to PSU (5–7). This excessive smartphone use, while a direct consequence of the pandemic-induced changes, also feeds into a cycle of psychological distress among teachers (8, 9).

To address these interconnected issues, this study employs the concept of Psychological Need Thwarting (PNT) (10), recognized both as a marker of psychological distress (11, 12) and as a risk factor for PSU (13, 14). The study uses PNT as a framework to explore the intricate relationship between PSU, psychological distress, under the topic of mental health of teachers. Crucially, we also delve into the role of administrative support during the pandemic's transition to online teaching. This period highlighted the importance of administrative support, not only as a critical resource for teachers (15) but also as a potential source of PNT (16). Inadequate support can lead to increased PNT (17), exacerbating the challenges of PSU (18) and psychological distress (19). In the following sections of the manuscript, we commence with a detailed discussion of PNT. This establishes a foundational understanding, which is essential for later examining its connection with PSU and psychological distress among teachers. Simultaneously, the study explores how varying levels of administrative support during the emergency transition to online teaching either exacerbated or alleviated these challenges, a topic intrinsically linked to PNT. By including PSU, psychological distress, and administrative support in our analysis, we aim to provide a more comprehensive understanding of the factors affecting teachers' mental health in the digital age, particularly under the unique strains introduced by the pandemic.

1.1 Psychological need thwarting and related studies

Rooted in Self-Determination Theory (SDT), PNT is characterized by the perception that basic psychological needs are actively undermined by various obstacles and damages (10). According to SDT, needs define innate psychological nutrients necessary to maintain psychological integrity, growth, and well-being, in which three basic psychological needs are identified: autonomy, competence, and relatedness (20–22). Autonomy reflects a willingness to be responsible for one's experiences and behaviors, aiming for an integrated and authentic self. Competence pertains to a sense of effectiveness and the ability to interact with one's environment and fulfill responsibilities. Relatedness involves feeling connected to others and being valued by them (22). Also, this theory holds that engaging in interesting activities, exercising capacities, and establishing connections with others are essential parts of the human adaptive design (22). Satisfying these psychological needs is crucial for motivation and well-being (23, 24).

Conversely, thwarting these needs leads to experiences of PNT (11) and has a more negative consequences on affect than psychological need satisfaction (20, 25, 26). Yet, PNT has been less explored than psychological need satisfaction (27). Studies have linked PNT to student disengagement (28), depression in weight management contexts (12), and negative outcomes in sports (10). Gunnell et al. (29) also found that PNT predicted ill-being in physical activity contexts.

However, research of PNT focusing on teachers in social professions, is limited. Most studies have centered on physical education teachers (1, 30). Bartholomew et al. (1) found that each need thwarting was positively associated with burnout and job pressure. Another study linked burnout with teachers' perceptions of need thwarting (30). Some research has also explored teachers' PNT in online teaching contexts (11, 20). However, most studies have used variable-centered models, like structural equation modeling, with few adopting a person-centered approach.

Empirical evidence suggests that the three basic needs are not highly correlated (17). For instance, the correlation coefficients between relatedness thwarting and autonomy thwarting, and between relatedness thwarting and competence thwarting, are below 0.5 (17). This indicates potential for distinct profiles. Given this, our primary aim is to determine if distinct teacher groups emerge based on PNT using Latent Profile Analysis (LPA). If yes, how many groups will be divided into?

1.2 The association of psychological need thwarting with PSU, psychological distress, and administrative support among teachers

As an emerging construct in teacher health research, PNT offers insights into how the thwarting of these three basic needs impacts an individual's mental health and behaviors (8). PNT has been linked to several factors, including PSU (31), psychological distress (10, 12), and

administrative support (11). PSU has been identified as one factor associated with PNT. With their convenience and portability, smartphones have become integral to daily life, facilitating interpersonal communication, socialization, and knowledge acquisition. However, excessive and uncontrolled smartphone use, termed PSU, can have detrimental effects on users' physical and mental health (32, 33). Existing research has discussed the impact of PSU on teachers and students. Adopting a mixed method, Varanasi et al. (4) found that though smartphones were helpful for teaching, problematic use of them also significantly predicted teachers' burnout. Butt and Arshad studied the basic psychological needs of university students with PSU and found that those with PSU experienced higher levels of need thwarting, often using smartphones to fulfill their relatedness needs in social environments (31). In addition, PSU was proved to exert an indirect positive impact on teachers' psychological distress with PNT being a mediator in online teaching contexts (8). Unmet psychological needs have been identified as significant predisposing factors for adolescents' PSU (33, 34). Besides, the phenomenon that people with negative feelings such as PNT, depression are easy to subject to PSU can be explained by the Compensatory Internet Use Theory (CIUT), which denotes that when faced with negative life circumstances, people may resort to excessive smartphone use to relieve their negative feelings (35).

In addition to PSU, previous studies have also highlighted the negative effects of PNT on psychological distress, such as depression (10, 12), stress, and anxiety (1). Vansteenkiste et al. (21) noted a direct association between PNT and students' symptoms of ill-being and distress. Similarly, Nishimura and Suzuki (36) found that the thwarting of each need predicted symptoms of ill-being, specifically, depressed affect. Gilbert et al. (37) also reported a strong predictive relationship between need thwarting and students' psychological distress. Besides focusing on students, Chen et al. (20) evaluated the persistent and long-term impact of PNT of online teaching on teachers' distress.

Another focal factor of this study is perceived administrative support. The term was defined by Borman and Dowling (38) as assistance provided by the school administrators for teachers in the fields of teaching methods innovation, student management, teaching environment improvement, and so on. This support has been highlighted as a strong predictor of teachers' job satisfaction and retention willingness (16, 39). Using a cross-lagged panel model and hierarchical linear modeling, Chen et al. (11) demonstrated that increased administrative support significantly alleviated teachers' PNT during online teaching. Conversely, when teachers feel pressured rather than supported by administrators, they experience thwarted basic needs, leading to increased exhaustion and negative interactions with students (40).

While the associations between PNT, PSU, psychological distress, and perceived administrative support have been individually studied, few investigations have addressed these factors collectively. Integrating these factors with PNT in a single study focusing on teachers can enhance our understanding of their mental health, paving the way for more effective administrative support. This research adopts a longitudinal approach, allowing for between-group mean comparison. This methodology offers an advantage over previous cross-sectional studies (41, 42) by enabling the observation of trends in the effects of PNT on teachers' psychological distress, PSU, and perceived administrative support across different groups. Through detailed analysis of teachers' PNT status as well as its association with the three mentioned factors, the present study can provide valuable guidance for developing interventions for each PNT profile to enhance the well-being of Chinese primary and middle school teachers.

Consequently, the primary research questions for the current study are:

i. How many distinct teacher profiles can be identified based on PNT using LPA?
ii. Do these distinct teacher groups exhibit differences in problematic smartphone use, psychological distress, and perceived administrative support at different time points?

2 Method

2.1 Procedure and participants

In a provincial city in central China, we conducted a longitudinal study to investigate factors associated with primary and middle school teachers. The study included two observation points: Time 1, which took place from November 19 to November 21, 2021, and Time 2, which occurred from January 5 to January 16, 2022. The duration of the follow-up period was approximately 2 months. At the outset, during Time 1, an outbreak of COVID-19 necessitated the closure of all primary and middle schools within the city, prompting an immediate shift to online teaching. By Time 2, schools had recommenced in-person instruction, having been operational for approximately 2 weeks.

We employed a combination of convenience and purposive sampling methodologies to select participants. The inclusion and exclusion criteria, along with the participant screening procedure, are detailed in Figure 1. Specifically, we collaborated with the city's Education Bureau to distribute an online questionnaire to primary and middle school principals, who then forwarded it to their teaching staff. Participation in the survey was entirely voluntary. The questionnaire included a query about teachers' willingness to participate in a follow-up survey 2 months later, asking them to provide their email addresses if they were agreeable. Out of the initial 9,554 respondents, 2,098 teachers provided their email addresses and were subsequently sent the follow-up survey at Time 2. The inclusion criteria for our analysis required participants to provide a valid email address and complete the second survey. Of the teachers contacted for the follow-up, 1,642 responded, resulting in an attrition rate of 21.7%. We further confirmed that there was no obvious attrition bias, as evidenced by the non-significant differences between the datasets of 2,098 and 1,642 participants ($t = 1.85$, $p = 0.06$ for age; $\chi^2 = 0.43$, 1.72, and 0.15, $p = 0.51$, 0.19, and 0.70 for sex, school level, and school type, respectively). Notably, since the survey was conducted using the Questionnaire Star platform, comprehensive data collection was ensured with no missing data.

Participant demographic details are elucidated in Table 1. A substantial 96.3% of the teachers ($n = 1{,}581$) are associated with public educational institutions, with 70.6% ($n = 1{,}159$) engaged in primary education. The cohort predominantly comprises females, accounting for 79% ($n = 1{,}305$). Geographically, the majority of these teachers are based in counties (37.1%) and villages (55.7%). In terms of teaching

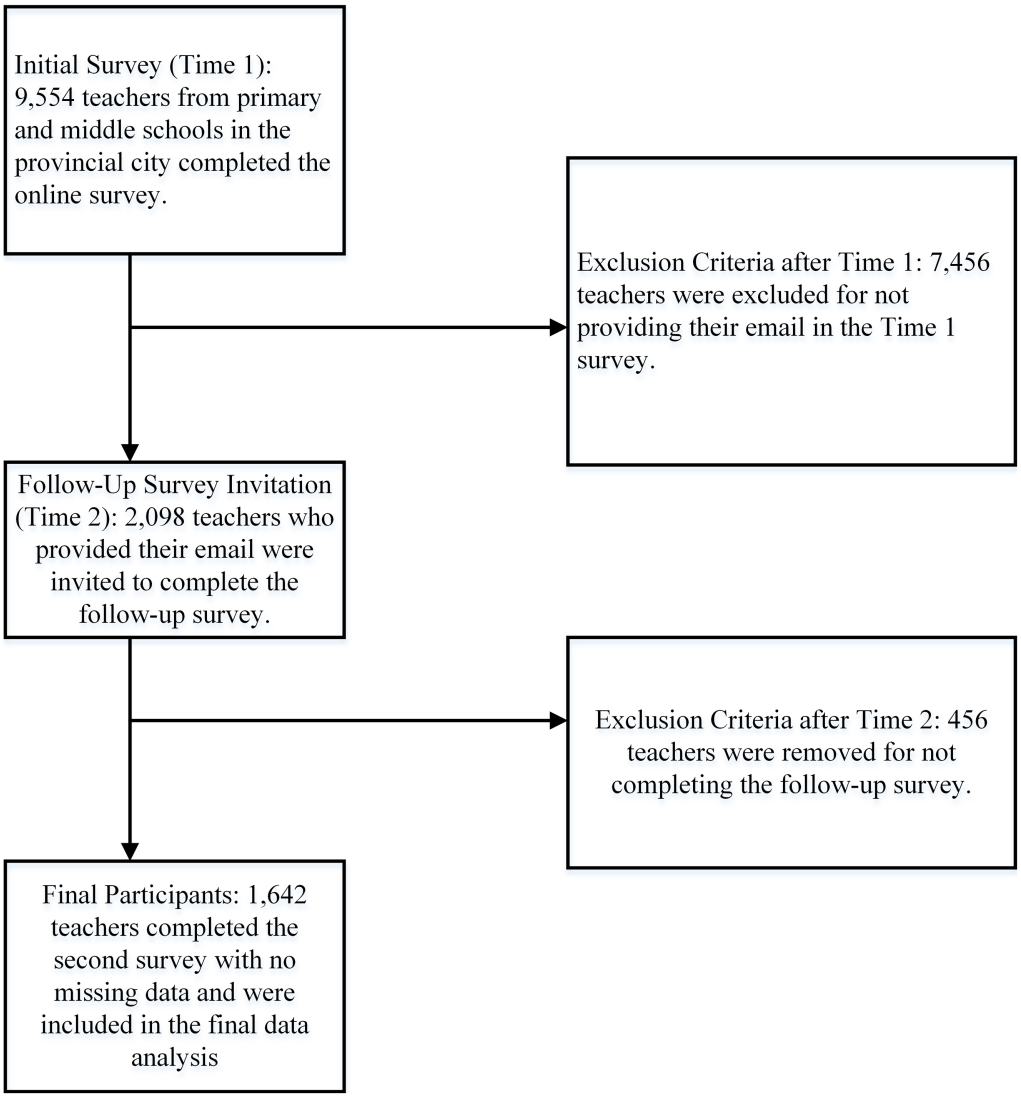

FIGURE 1
Flowchart depicting the sampling procedure and inclusion/exclusion criteria.

tenure, there's a discernible decline in the 16–20 years range, but other experience intervals exhibit a relatively even distribution. Compared to the demographic characteristics of the overall population of middle and primary school teachers in China (43), the participants in our study were, on average, approximately 3 years younger ($t = -15.45$, Cohen's $d = 0.38$, indicating a small effect). The proportion of female teachers in our sample was higher ($\chi^2 = 70.21$, Cohen's $W = 0.21$, representing a small effect), and there was a greater representation of primary school teachers ($\chi^2 = 30.90$, Cohen's $W = 0.14$, also a small effect). Additionally, our sample included a higher percentage of public school teachers ($\chi^2 = 5.71$, Cohen's $W = 0.06$, a trivial effect). Despite these statistically significant differences when compared with the population, the effect sizes were small to trivial. Therefore, it can be concluded that our study does not exhibit substantial sample bias in terms of sample composition.

Prior to the survey, participants were presented with an electronic informed consent form detailing the study's objectives. This research secured ethical clearance from the Jiangxi Psychological Consultant Association (IRB ref.: JXSXL-2020-J013).

2.2 Instruments

In this study, we measured variables such as teachers' PNT, problematic smartphone use, psychological distress, and perceived administrative support using the instruments described below. Both the Chinese and English versions of each instrument can be found in Supplementary Table S1. We also collected background information, including school level, type, location, years of employment, and gender. Although PNT was also measured in the follow-up survey, this study exclusively utilized the Time 1 data. The Time 2 data, gathered for measurement invariance in a different study (20), were not relevant or used in the present research. All other variables were assessed at both times. Details regarding the individual validity and reliability of

TABLE 1 Participant characteristics (n = 1,642).

	n (%)
School type	
Public school	1,581 (96.3)
Private school	61 (3.7)
Level	
Middle school	483 (29.4)
Primary school	1,159 (70.6)
School location	
City	119 (7.2)
County	609 (37.1)
Village	914 (55.7)
Sex	
Male	337 (20.5)
Female	1,305 (79.5%)
Working years	
Under 5 years	465 (28.3)
6 years to 10	375 (22.8)
11 years to 15 years	275 (16.7)
16 years to 20 years	160 (9.7)
Over 21 years	367 (22.4)

each measure employed in this study will be presented later. The discussion of the overall validity, considering all instruments collectively, will be specifically addressed in the results section.

2.2.1 Psychological need thwarting scale of online teaching

We used the Psychological Need Thwarting Scale of Online Teaching (PNTSOT) to measure the extent to which teachers' psychological needs were thwarted (8). Designed based on SDT, the PNTSOT assesses three core psychological needs: autonomy, competence, and relatedness. The scale comprises three subscales, each having seven items. Teachers were instructed to reflect on the situation when emergency online teaching was initiated. Examples include: "I feel compelled to follow a predetermined online teaching method during the pandemic" (for autonomy thwarting), "Online teaching during the pandemic occasionally makes me feel inadequate" (for competence thwarting), and "While teaching online during the pandemic, I often feel disconnected from my colleagues and supervisors" (for relatedness thwarting). Respondents rated these items on a seven-point Likert scale, with higher scores indicating a stronger perception of their psychological needs being thwarted in an online teaching context. The PNTSOT's three-factor structure was validated by previous studies (8, 11). In our research, we conducted an evaluation of the higher-order factor structure of the scale, incorporating three distinct types of PNT as first-order factors. The confirmatory factor analysis (CFA) yielded results that affirm the factorial validity of the scale. The analysis demonstrated a chi-square (χ^2) value of 509.885 with 50 degrees of freedom. The Comparative Fit Index (CFI) was recorded at 0.968, and the Non-Normed Fit Index (NNFI) stood at 0.958, both indices indicating a robust model fit. The Root Mean Square Error of Approximation (RMSEA) was observed at 0.075, while the Standardized Root Mean Square Residual (SRMR) was calculated to be 0.066. These values collectively suggest a satisfactory fit of the model. Furthermore, the internal consistency of the PNTSOT was found to be commendable, with ordinal McDonald's ω values for the three subscales being 0.84, 0.88, and 0.95, respectively, indicating a high level of reliability.

2.2.2 Smartphone application-based addiction scale

To evaluate teachers' problematic smartphone use, we employed the Smartphone Application-Based Addiction Scale (SABAS) (44). The SABAS consists of six items, each representing a criterion from the addiction components model. This scale identifies the risk of addiction to smartphone applications. Items are rated on a six-point Likert scale, from 1 (strongly disagree) to 6 (strongly agree). Higher scores indicate a higher risk of addiction. The scale was translated into simplified Chinese and demonstrated strong factorial validity and impressive internal consistency with a coefficient of 0.81 (45). SABAS also remained consistent over a three-month period (45). In our study, the SABAS demonstrated a unidimensional structure. CFA indicated that the structure had a satisfactory model fit. At Time 1, the χ^2 value was 51.275 with 9 degrees of freedom, the CFI was 0.991, the NNFI was 0.985, the RMSEA was 0.054, and the SRMR was 0.037. At Time 2, the chi-square (χ^2) value was 47.607 with 9 degrees of freedom, the CFI was 0.994, the NNFI was 0.990, the RMSEA was 0.051, and the SRMR was 0.037. The internal consistency of the SABAS was commendable, with ordinal McDonald's ω values of 0.91 at Time 1 and 0.93 at Time 2, respectively. At Time 1, participants were prompted to reflect on their smartphone usage during the onset of emergency online teaching. Later, they were asked to describe their phone use from the recent months.

2.2.3 The depression, anxiety, and stress Scale-21 version

In our current study, we employed the Depression, Anxiety, and Stress Scale-21 Version (DASS-21) (46) to assess psychological distress among teachers. This scale, comprising 21 items evenly distributed across three subscales—depression, anxiety, and stress—is extensively used for evaluating distinct negative emotional states. However, recent research (47, 48) suggests that it primarily measures overall psychological distress. We interpreted the mean scores of the DASS-21 subscales as indicators of teachers' psychological distress. Participants rated their feelings on a four-point Likert scale, from 0 (never) to 3 (almost always), with higher scores indicating greater distress. At Time 1, participants were asked to reflect on their experiences during the initiation of emergency online teaching, while at Time 2, they recalled their feelings from the previous 2 weeks.

Building upon our previous study (49), we found that the DASS-21 demonstrated acceptable factorial validity in its original three-factor structure. The CFA from our earlier research yielded χ^2 (df) values of 1373.082 (186) and 1226.004 (186), CFI values of 0.992 and 0.994, NNFI values of 0.991 and 0.994, RMSEA values of 0.062 and 0.058, and SRMR values of 0.044 and 0.038 at Time 1 and Time 2, respectively. Furthermore, our prior research confirmed the DASS-21's acceptable internal and test–retest reliability among Chinese teachers, with all three subscales exhibiting Cronbach's α values exceeding 0.85 and intraclass correlation coefficients above 0.70. The time-invariance feature of the DASS-21 was also established in our

earlier work. In the current study, the McDonald's ω for the depression, anxiety, and stress subscales were 0.892, 0.866, and 0.865 at Time 1, and 0.916, 0.890, and 0.901 at Time 2, respectively.

2.2.4 Teachers' perception of administrators' support scale

In this study, we utilized the Teachers' Perception of Administrators' Support Scale (TASS), developed by Chen et al. (11), to evaluate teachers' perceptions of administrative support during the shift to emergency online teaching amid the COVID-19 pandemic. The TASS, an adaptation of the Scale of Technology Users' Beliefs, measures expectations of key stakeholders in the context of technology use (50). At Time 1, participants were asked to reflect on the immediate context of emergency online teaching, whereas at Time 2, they were prompted to recall their experiences from 2 months prior, marking the onset of emergency online teaching. The TASS comprises four items, with examples including: 'Administrators expect teachers to transition smoothly to online teaching during the outbreak' and 'School administrators have provided the majority of essential resources to support teachers' shift to online instruction during the pandemic'. Responses were elicited on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). In our study, we tested its factorial validity within a one-factor structure. The CFA results showed χ^2 (df) values of 12.552 (2) and 3.127 (2), CFI values of 0.993 and 0.999, NNFI values of 0.980 and 0.991, RMSEA values of 0.057 and 0.019, and SRMR values of 0.034 and 0.018 at Time 1 and Time 2, respectively. The ordinal McDonald's ω coefficient for TASS was 0.92 at Time 1 and 0.93 at Time 2, indicating high internal consistency.

2.3 Data analysis

To analyze the temporal trends in teachers' psychological distress, perceived administrative support, and PSU over two distinct time points, ensuring the temporal reliability of the instruments used is essential. This verification is key to effectively identifying potential measurement bias in the longitudinal framework. For a comprehensive assessment of this test–retest reliability, the Intraclass Correlation Coefficient (ICC) was employed. This robust statistical method assesses the consistency of continuous measurements across time by evaluating both correlation and agreement between two measurement sets. The ICC, ranging from 0 (no reliability) to 1 (perfect reliability), compares the variability of scores between subjects against the total variation across all measurements and subjects. We will adopt a two-way mixed-effects model, suitable for repeated measurements on the same subjects, to calculate the ICC, thereby accounting for both systematic and random errors. An ICC value above 0.70, as recommended by Thompson et al. (51), is considered indicative of good reliability.

Subsequently, we conducted confirmatory factor analyzes (CFA) on our data collected at Time 1 and Time 2 to establish the construct validity of our metrics, focusing on both factorial and convergent validity. For evaluating factorial validity, we utilized several specific fit indices in our CFA. We determined that both the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), should exceed the threshold of 0.90 to indicate a good model fit. Additionally, we aimed for the Root Mean Square Error of Approximation (RMSEA) to be below 0.06 and the Standardized Root Mean Square Residual (SRMR) to be under 0.08, as these values are indicative of an acceptable model fit according to the standards set by Hu and Bentler (52). Furthermore, to assess convergent validity through our CFA, we calculated the Composite Construct Reliability (CCR) and the Average Variance Extracted (AVE) for each construct. These metrics are crucial for determining the extent to which a set of items represents a single latent construct. We adhered to the guidelines provided by Fornell & Larcker (53) and Hair et al. (54), confirming convergent validity when the CCR exceeds 0.70 and the AVE is above 0.50 for each construct. These thresholds ensure that our constructs are reliable and that a significant portion of the variance in the observed variables is accounted for by the latent construct.

After validating the integrity and quality of our measurement instruments, we began a preliminary examination. This initial phase involved analyzing descriptive statistics, paired *t*-tests, and zero-order correlations of the observed variables, using their raw scores without any transformations.

Subsequently, employing the tidyLPA package in R, we conducted Latent Profile Analysis (LPA). This methodological approach was specifically applied to identify the number of latent profiles within the three dimensions of online teaching PNT, based on the 12-item PNTSOT scale. LPA, as emphasized by Tein et al. (55), is a statistical technique used to identify distinct subgroups within a heterogeneous dataset based on observed variables. LPA classifies individuals into mutually exclusive groups, or 'profiles', based on their response patterns. This method is particularly useful in uncovering hidden structures within complex data, allowing for a more nuanced understanding of the underlying patterns and relationships. By applying LPA in our study, we aimed to discern and characterize consistent latent groups, thereby enhancing the depth and precision of our data analysis. To determine the optimal number of profiles, we considered metrics such as Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), the Sample-Adjusted BIC (SABIC), Integrated Complete-data Likelihood (ICL), Entropy, and the Bootstrap Likelihood Ratio Test (BLRT). A better model fit is typically indicated by lower values of AIC, BIC, and SABIC, along with higher values of ICL and entropy, the latter ideally being higher than 0.90 (56). The BLRT (Bootstrap Likelihood Ratio Test) comparisons were also integral to our analysis, aiding in the evaluation of model structures with 'K' and 'K-1' classes. Consistent with the principle of model parsimony, a model with 'K' classes is considered redundant if the BLRT does not demonstrate significant improvements over the 'K-1' class model. This lack of significant improvement implies that the additional category in the 'K' class model fails to provide substantial new information. Moreover, in light of the larger sample size of our study, we adopted the 'elbow-criterion' as described by Morin and Wang (57). This method entails selecting a profile solution at the juncture where the curve begins to plateau, thereby indicating an optimal balance between model complexity and explanatory power.

In this study, after identifying potential latent profiles, our primary aim was to explore how these profiles differ in their perceptions of administrative support, psychological distress, and patterns of PSU across two survey time points. To achieve this,

Structural Equation Modeling (SEM) was utilized. This technique was instrumental in assessing the varying impacts that distinct latent classes had on their corresponding latent variables: administrative support, psychological distress, and PSU, both at the initial survey (Time 1) and the follow-up (Time 2). The indicators used for these variables were items from the TASS for administrative support, the SABAS for PSU, and the mean scores of the three emotional disorder subscales of the DASS-21. In the SEM framework, we accounted for sex, age, and autoregressive effects by linking each latent variable at time 1 with its corresponding variable at time 2, thereby improving the precision of our estimations. This approach also allowed for the simultaneous estimation of the effects of latent classes on the latent variables, a strategy that helped in mitigating the risk of inflating the Type I error rate. It's crucial to note that our analysis did not incorporate cross-lagged effects, as the study's scope did not include investigating the causal relationships among administrative support, psychological distress, and PSU. In the SEM section, we first evaluated the overall model fit using the criteria established in the CFA mentioned previously. Following this, the path coefficients were rigorously examined and duly reported.

Before presenting our results, we conducted a thorough examination of the underlying assumptions necessary for conducting LPA and SEM, with a particular focus on the normality distribution of the indicators for the latent classes or variables (56, 58). For each item of the selected scale, we observed that skewness ranged between −0.69 and 1.06, while kurtosis varied between −1.05 and 1.26. Regarding the mean score of the subscale of the DASS-21, which serves as an indicator for psychological distress, skewness values ranged from 1.12 to 1.89, and kurtosis values were between 1.05 and 4.38. These values align with Kline's criteria (58), which state that absolute skewness higher than 3.0 and absolute kurtosis above 8 are indicative of severe skewness and kurtosis, respectively. Furthermore, we employed the Intraclass Correlation Coefficient (ICC) to test the assumption of independence, specifically using 12 items of PNTSOT. We found that small ICC values, with the highest being 0.022, suggest a negligible nested effect. This finding allows us to consider the participants as independently sampled, which is also a critical assumption for Latent Profile Analysis (LPA) (59).

3 Results

3.1 Test–retest reliability and construct validity

In an evaluation of test–retest reliability, ICCs were initially utilized to compare observed means across two distinct time points. The findings revealed that two of the three instruments exhibited commendable reliability over time, with both psychological distress and PSU yielding an ICC of 0.74. However, TASS displayed a slightly lower ICC of 0.62.

Subsequent CFA for the measurement models at both time points further substantiated acceptable construct validity. Model fit indices presented in Table 2 endorsed the factorial validity of the instruments. Factor loadings for each item, illustrated in Figures 2, 3, consistently exceeded the threshold of 0.50. Based on these loadings, the Average Variance Extracted (AVE) and Composite Reliability (CR) were computed for each latent variable. For Time 1, the AVE and CR values were as follows: PSU (0.49, 0.85), psychological distress (0.85, 0.94), autonomy thwarting (0.50, 0.80), competence thwarting (0.57, 0.84), relatedness thwarting (0.66, 0.88), and perceived administrative support (0.57, 0.84). For Time 2, the AVE and CR for PSU were 0.56 and 0.88 respectively, with psychological distress at 0.88 and 0.96, and perceived administrative support at 0.65 and 0.88. Taken collectively, the aforementioned results substantiate that the observed scores derived from this study exhibit consistent temporal reliability and demonstrate commendable construct validity, indicating no obvious longitudinal measurement bias.

TABLE 2 Model fit for measurement models for all variables in time 1 and time 2.

	χ^2 (df)	CFI	NNFI	RMSEA	SRMR
Time 1	1207.98 (142)	0.953	0.944	0.068	0.068
Time 2	259.22 (62)	0.984	0.980	0.044	0.043

CFI, comparative fit index; NNFI, non-normed fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.

3.2 Preliminary analysis

Table 3 displays the mean observed scores (with standard deviations) for the study's variables and their associations. Notably, among the three types of need thwarting, autonomy and competence thwarting were more prominent, both exceeding relatedness thwarting. Additionally, the scores for PSU, psychological distress, and perceived administrative support at Time 2 were all lower than at Time 1. Paired *t*-tests were further conducted, revealing that PSU and perceived administrative support were significantly lower at Time 2 compared with Time 1 (PSU: $t = 7.81$, $p < 0.01$; perceived administrative support: $t = 5.81$, $p < 0.01$), while there was no significant difference in psychological distress between the two time points.

In terms of variable correlations, we observed significant positive correlations among the three types of psychological needs thwarting: autonomy, competence, and relatedness. The correlation coefficients for these variables were as follows: between autonomy and competence, $r = 0.62$ ($p < 0.01$), between autonomy and relatedness, $r = 0.36$ ($p < 0.01$), and between competence and relatedness, $r = 0.44$ ($p < 0.01$). These coefficients indicate a moderate to strong positive relationship among these types of needs thwarting, suggesting that they often occur concurrently within our sample.

Furthermore, we found a negative correlation between psychological needs thwarting and perceived administrative support at both measured time points. The coefficients ranged from −0.13 to −0.44 (all $p < 0.01$) at Time 1 and from −0.13 to −0.31 (all $p < 0.01$) at Time 2, indicating a consistent moderate negative relationship. This suggests that higher levels of psychological needs thwarting are associated with lower levels of perceived administrative support.

Lastly, positive correlations were observed between psychological needs thwarting and both psychological distress and problematic smartphone use. The correlation with psychological distress ranged from 0.17 to 0.34 (all $p < 0.01$), and with problematic smartphone use, it ranged from 0.17 to 0.30 (all $p < 0.01$) across two

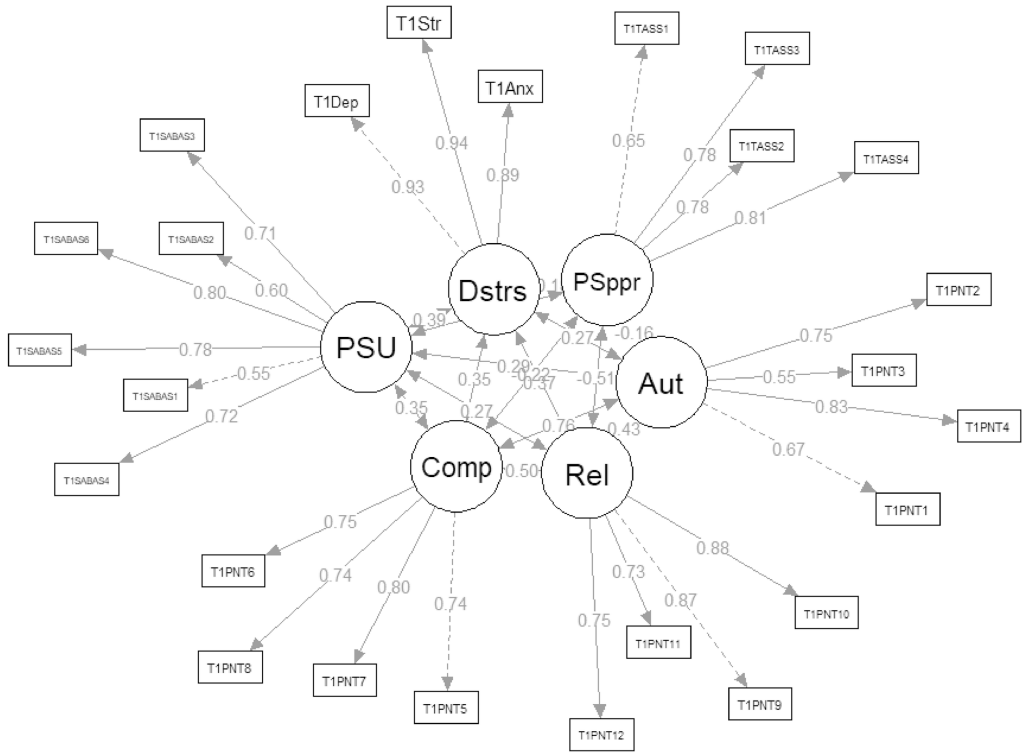

FIGURE 2
Measurement model at time 1. PSU: problematic smartphone use; Dstrs: psychological distress; PSppr: perceived administrative support; Comp: competence thwarting; Aut: autonomy thwarting; Rel: relatedness thwarting.

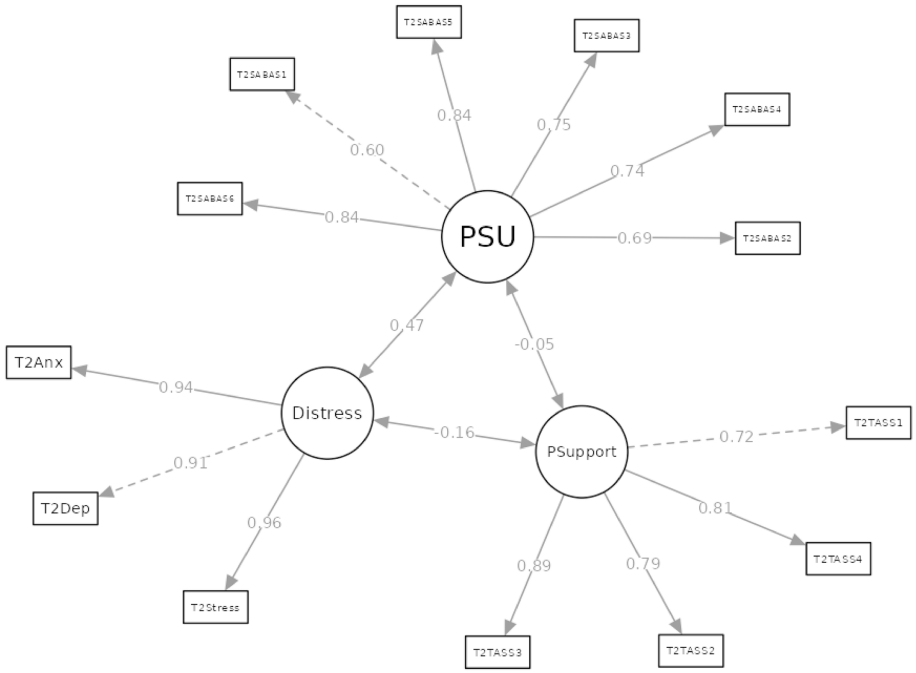

FIGURE 3
Measurement model at time 2. PSU: problematic smartphone use; Distress: psychological distress; PSupport: perceived administrative support.

time points. These moderate positive correlations suggest a notable relationship between the thwarting of psychological needs and increased levels of psychological distress and problematic smartphone use. It's worth noting that the correlations between the PNTs at Time 1 and other Time 1 variables were stronger than those with Time 2 variables.

TABLE 3 Descriptive statistics and Pearson correlations among internet activities, three kinds of psychological needs thwarting, perceived administrative support, distress, and problematic smartphone use.

	M (SD)	1	2	3	4	5	6	7	8
1. Autonomy thwarting	15.69 (4.77)	1							
2. Competence thwarting	15.73 (5.12)	0.62**	1						
3. Relatedness thwarting	9.57 (4.29)	0.36**	0.44**	1					
4. Perceived administrative support_Time 1	15.19 (2.65)	−0.13**	−0.18**	−0.44**	1				
5. Perceived administrative support_Time 2	14.78 (2.77)	−0.13**	−0.14**	−0.31**	0.45**	1			
6. Distress _Time 1	9.81 (10.10)	0.23**	0.31**	0.34**	−0.16**	−0.12**	1		
7. Distress _Time 2	9.56 (10.89)	0.17**	0.22**	0.26**	−0.15**	−0.14**	0.58**	1	
8. Problematic smartphone use_Time 1	17.52 (5.93)	0.24**	0.30**	0.23**	−0.08**	-0.07**	0.35**	0.31**	1
9. Problematic smartphone use_Time 2	16.46 (6.15)	0.17**	0.22**	0.17**	−0.09**	−0.03	0.29**	0.43**	0.59**

**$p < 0.01$.

TABLE 4 Summary of the model selection for the latent profiles based on three kinds of psychological needs thwarting.

Class	LogLik	AIC	Δ AIC	BIC	ΔBIC	SABIC	Δ SABIC	ICL	Δ ICL	BLRT(*p*)	Entropy
1-Profile	−34853.18	69754.36		69884.05		69807.80		−69884.05			1.00
2-Profile	−32460.97	64995.94	−4758.42	65195.87	−4688.17	65078.33	−4729.47	−65325.97	4558.07	0.010	0.89
3-Profile	−31057.89	62215.77	−2780.17	62485.96	−2709.92	62327.11	−2751.22	−62639.36	2686.62	0.010	0.91
4-Profile	−30637.28	61400.57	−815.20	61741.00	−744.96	61540.86	−786.26	−61966.12	673.24	0.010	0.90
5-Profile	−30289.88	60731.75	−668.82	61142.43	−598.57	60900.99	−639.87	−61438.16	527.97	0.010	0.88
6-Profile	−29909.31	59996.62	−735.13	60477.55	−664.88	60194.81	−706.18	−60798.19	639.97	0.010	0.89
7-Profile	−29625.48	59454.95	−541.67	60006.13	−471.42	59682.09	−512.72	−60391.43	406.76	0.009	0.88
8-Profile	−29454.88	59139.76	−315.19	59761.18	−244.95	59395.85	−286.24	−60143.66	247.76	0.01	0.88
9-Profile	−29340.20	58936.40	−203.36	59628.07	−133.11	59221.44	−174.41	−60034.03	109.64	0.010	0.88
10-Profile	−29137.78	58557.56	−378.85	59319.48	−308.60	58871.54	−349.90	−59724.00	310.02	0.010	0.88

LogLik refers to the model's log-likelihood, Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), the Sample-Adjusted BIC (SABIC), Integrated Complete-data Likelihood (ICL), and the Bootstrap Likelihood Ratio Test (BLRT). The model marked in bold is the most optimized, selected based on its statistical analysis and clarity in interpretation.

3.3 Latent profile analysis

LPA was conducted to identify distinct latent profiles within our sample. The fit information for 10 potential profiles is presented in Table 4. Based on indicators such as AIC, BIC, SABIC, and ICL, we observed that as the number of classes increased, these values continuously decreased (except for ICL, which increased), and the *value of p*s of the BLRT was significant for each profile. A significant BLRT result indicates that the model with more profiles represents the data better than the model with fewer profiles. Given the complexity of determining the optimal number of categories based solely on these indicators, we employed a strategy focusing on the disparity in AIC, BIC, SABIC, and ICL values among successive profiles. Our objective was to identify significant changes in value within these nested models. This analysis highlighted that the 3-profile model exhibited the most substantial variation in ΔAIC, ΔBIC, ΔSABIC, and ΔICL values compared to the preceding profile. An examination of Figure 4, which illustrates the 'elbow' in the plot, further supports the distinctiveness of the 3-profile model. Consequently, the three-profile solution was deemed optimal, balancing model performance and simplicity. Notably, the 3-profile model was the only one with a value exceeding 0.90.

Next, we took a closer look at the characteristics of these three profiles. Specifically, each of the identified profiles is characterized by distinct mean scores across three types of psychological needs thwarting, as detailed in Table 5. Figure 5 provides a graphical representation of the individual item scores within the PNTSOT. Our findings indicate significant differences in mean scores for autonomy, competence, and relatedness thwarting across the groups, with *F*-values ranging from 436.88 to 1784.43 (all $p < 0.01$) and large effect sizes (η^2 of 0.35, 0.61, and 0.69, respectively). In exploring autonomy and competence thwarting, the Games-Howell post-hoc test revealed that Class 1 and Class 2 exhibited significantly higher levels than Class 3. For relatedness thwarting, the groups were ranked from highest to lowest as follows: Class 2, Class 1, and Class 3.

Based on the unique characteristics of each class, we labeled these and reported their prevalence within our sample. Class 1, labeled as 'High Autonomy-High Competence and Moderate Relatedness Thwarting,' comprises the largest group at 46.1% (757 participants). This indicates a substantial segment with high thwarting in both autonomy and competence (evidenced by scores above the median in these subscales) and moderate levels of relatedness thwarting, positioned between Class 2 and Class 3. Class 2, 'High Autonomy-High Competence and High Relatedness Thwarting,' encompasses

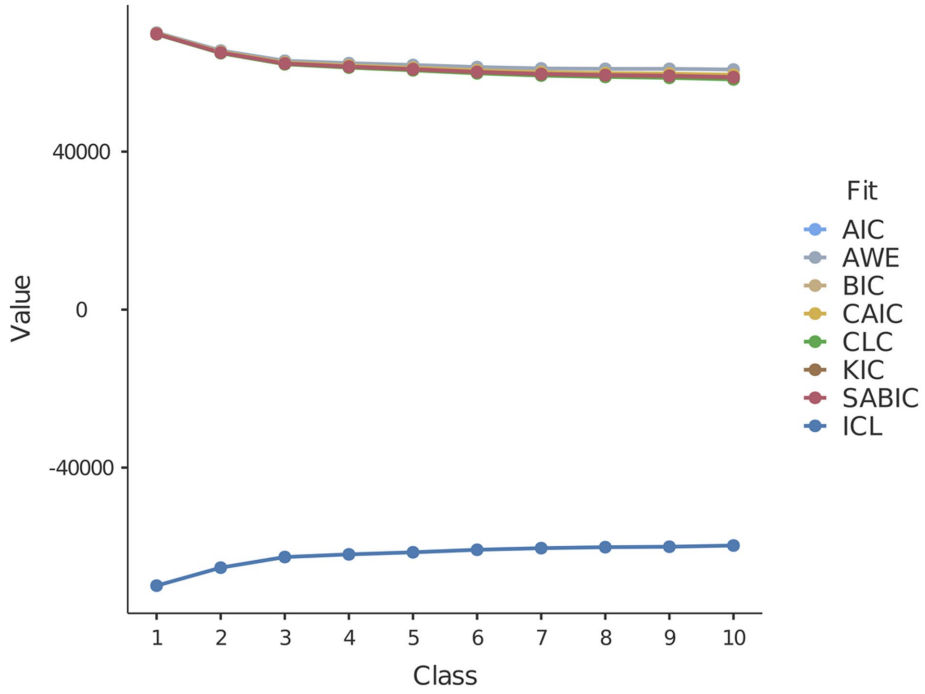

FIGURE 4
Elbow plot illustrating information criteria values for all latent profiles. Take note that a 3-class profile was selected.

TABLE 5 The comparisons between three -profiles in terms of three kinds of psychological needs thwarting.

	Class 1 (*n* = 757, 46.1%)	Class 2 (*n* = 452, 27.5%)	Class 3 (*n* = 433, 26.4%)	*F*-test (*value of p*)	*Post-hoc*
Variable: Mean (SD)					
1. Autonomy thwarting	17.29 (3.93)	17.53 (3.37)	10.99 (4.19)	436.88 (<0.01)	C1 > C3; C2 > C3
2. Competence thwarting	18.17 (3.09)	18.04 (3.50)	9.06 (3.09)	1273.26 (<0.01)	C1 > C3; C2 > C3
3. Relatedness thwarting	8.05 (2.48)	15.21 (2.48)	6.33 (2.17)	1784.43 (<0.01)	C2 > C1 > C3
4. Perceived administrative support_Time 1	15.57 (2.28)	13.62 (2.14)	16.18 (3.01)	136.31 (<0.001)	C3 > C1 > C2
5. Perceived administrative support_Time 2	14.93 (2.55)	13.74 (2.49)	15.62 (3.08)	56.48 (<0.001)	C3 > C1 > C2
6. Psychological distress _Time 1	9.61 (8.86)	13.96 (12.03)	5.84 (8.10)	78.60 (<0.01)	C2 > C1 > C3
7. Psychological distress _Time 2	9.34 (9.90)	13.09 (12.83)	6.27 (9.10)	46.14 (<0.01)	C2 > C1 > C3
8. Problematic smartphone use_Time 1	18.22 (5.63)	18.71 (5.80)	15.07 (5.90)	54.31 (<0.01)	C1 > C3; C2 > C3
9. Problematic smartphone use_Time 2	16.99 (5.95)	17.39 (6.14)	14.57 (6.12)	29.39 (<0.01)	C1 > C3; C2 > C3

Post hoc comparisons were performed using the Games-Howell test, which is appropriate for datasets with unequal variances and different sample sizes.

27.5% of the sample (452 individuals) and mirrors Class 1 in autonomy and competence but exhibits markedly higher relatedness thwarting. Finally, Class 3, 'Low Psychological Needs Thwarting,' accounts for 26.4% of the sample (433 participants) and is characterized by consistently scoring below the median across all PNTSOT dimensions. This class's lower level of needs thwarting across all areas highlights a contrastingly positive psychological experience compared to the other two classes. The distribution of these classes underscores the diversity of psychological needs thwarting experiences, with each class reflecting a distinct interplay of autonomy, competence, and relatedness thwarting in our sample.

Furthermore, in addressing potential sources of bias in our LPA, we considered factors such as sample representativeness, measurement accuracy, and model selection criteria. The composition of the sample was carefully examined to ensure a broad representation of the population of interest (for more details, please refer to the Procedure and Participants' section). To enhance measurement accuracy, we utilized validated scales, specifically the PNTSOT, and took measures to ensure data quality. The construct validity of the PNTSOT, as mentioned earlier, was also verified (for further information, please see the Test–Retest Reliability and Construct Validity section). Our model selection process was guided not only by statistical fit indices

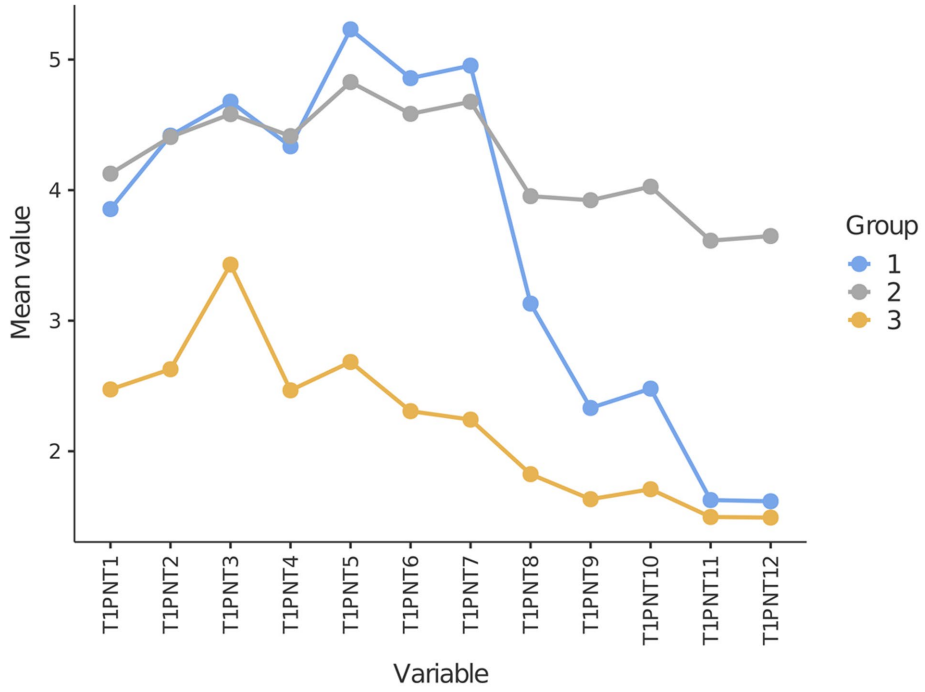

FIGURE 5
Line graph depicting profile comparisons for psychological needs thwarting.

but also by the theoretical coherence and interpretability of the profiles. These measures were implemented to mitigate potential biases and thus enhance the reliability of our findings.

3.4 Structural equation modeling: delineating the differences across distinct latent classes

Using Maximum Likelihood (ML) estimation and controlling for sex and age, the model's fit was confirmed, as evidenced by the following metrics: χ^2 (df) = 2853.54 (370), Comparative Fit Index (CFI) = 0.917, Non-Normed Fit Index (NNFI) = 0.903, Root Mean Square Error of Approximation (RMSEA) = 0.065, and Standardized Root Mean Square Residual (SRMR) = 0.049. The path coefficients for the two dummy variables were then scrutinized, with Class 3 serving as the reference, as illustrated in Figure 6. At the initial assessment (time 1), Classes 1 and 2, compared to Class 3, were found to have significantly lower levels of perceived administrative support (Dummy 1: Class 1 vs. Class 3, $\beta = -0.10$, $t = -3.40$, $p < 0.01$; Dummy 2: Class 2 vs. Class 3, $\beta = -0.45$, $t = -14.08$, $p < 0.01$) and increased distress (Dummy 1: Class 1 vs. Class 3, $\beta = 0.18$, $t = 6.00$, $p < 0.01$; Dummy 2: Class 2 vs. Class 3, $\beta = 0.36$, $t = 12.04$, $p < 0.01$), along with elevated PSU (Dummy 1: Class 1 vs. Class 3, $\beta = 0.28$, $t = 8.28$, $p < 0.01$; Dummy 2: Class 2 vs. Class 3, $\beta = 0.29$, $t = 8.66$, $p < 0.01$).

At the subsequent time point (time 2), although the differences between Class 3 and the other classes were reduced compared to the initial time frame, Class 3 still maintained significantly higher support (Dummy 1: Class 1 vs. Class 3, $\beta = -0.09$, $t = -2.96$, $p < 0.01$; Dummy 2: Class 2 vs. Class 3, $\beta = -0.11$, $t = -3.52$, $p < 0.01$) and lower distress compared to Class 2 ($\beta = 0.08$, $t = 2.86$, $p < 0.01$). Nonetheless, the variations in PSU between Class 3 and the other classes did not reach statistical significance.

Furthermore, the analysis was replicated with a shift in the reference category from Class 3 to Class 1 to enable a more direct comparison between Classes 1 and 2. The model's fit indices indicated an excellent fit, with both the CFI and the NNFI surpassing the threshold of 0.90, and the RMSEA and the SRMR registering below 0.07. The path coefficient outcomes revealed that Class 1 reported higher levels of administrative support than Class 2 across the two measured time points (Time 1: $\beta = -0.40$, $t = -14.40$, $p < 0.01$; time 2: $\beta = -0.06$, $t = -2.27$, $p = 0.02$). Moreover, Class 2 exhibited higher levels of psychological distress than Class 1 at both Time 1 and Time 2 (Time 1: $\beta = 0.26$, $t = 10.02$, $p < 0.01$; Time 2: $\beta = 0.06$, $t = 2.64$, $p < 0.01$). In terms of PSU, Class 2's scores were significantly greater than those of Class 1 at Time 1. ($\beta = 0.13$, $t = 4.55$, $p < 0.01$).

4 Discussion

Empirically, the three basic needs of thwarting have been shown to correlate, albeit not strongly. Moreover, individuals can experience varied PNT when faced with identical challenges. This variability gives rise to potential profiles. Consequently, this study primarily seeks to determine the number of unique groups that arise from teachers based on PNT. By adopting a person-centered approach – LPA, and comparing 10 latent profiles, it was determined that the 3-profile model is the most optimal, as evidenced by variations in AIC, BIC, SABIC, and ICL values. Given the close relationship between PNT and PSU, psychological distress, and perceived administrative support, this study also aims to examine the differences in their associations across the three distinct PNT profiles at two time points (Time 1 and Time

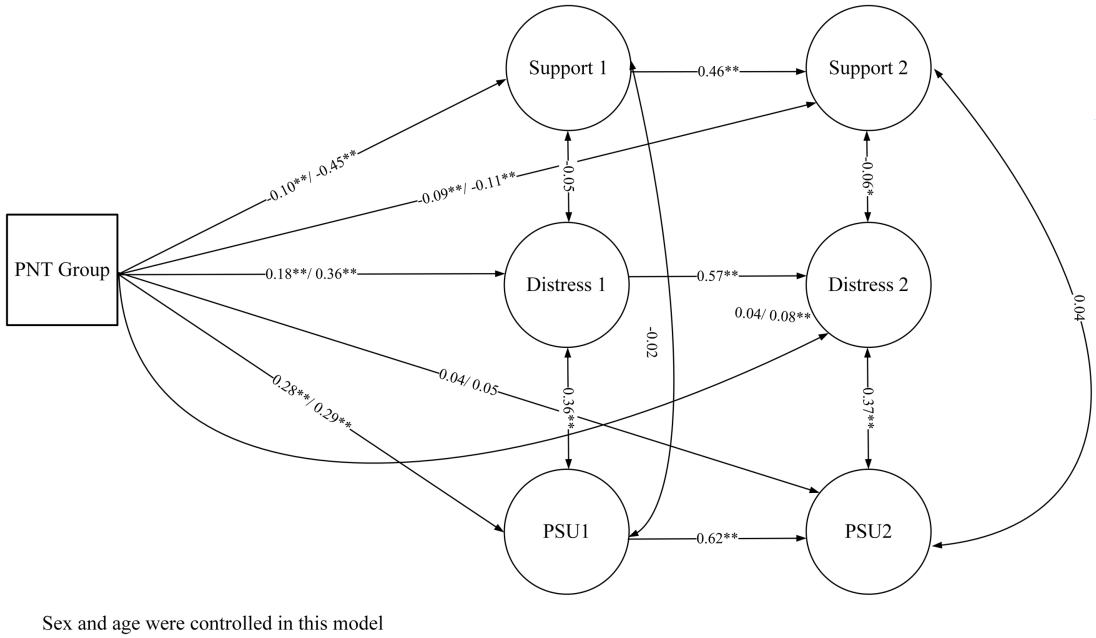

FIGURE 6
Structural equation modeling analysis of latent variables in distinct PNT groups over time. PNT Group: Psychological need thwarting latent classes; Support 1 and Support 2 represent administrative support at Time 1 and Time 2, respectively. Distress 1 and Distress 2 denote psychological distress at Time 1 and Time 2, respectively. PSU 1 and PSU 2 indicate problematic smartphone use at Time 1 and Time 2, respectively. ** $p < 0.01$, * $p < 0.05$. The figure presented above utilizes Class 3 as the reference group. To maintain brevity and clarity of presentation, results using Class 1 as the reference group are not depicted separately within the figure.

2). Detailed interpretations of these findings will be presented in the subsequent sections.

4.1 Psychological need thwarting profiles

In line with prior research (17), this study confirms that while the three PNT types are positively correlated, they exhibit unique characteristics. This distinction justified the use of LPA to segment the sample into different groups. Unlike the variable-centered approach, LPA enables researchers to determine if there are potential subgroups within a sample that share common characteristics (26). This method offers insights that complement the traditional variable-centered approach (60). As anticipated, distinct PNT profiles were identified among the teacher population. Upon comparison, only the 3-profile model was deemed optimal. Notable differences in the mean scores for the three PNT types were observed across these profiles. The first profile, Class 1, constitutes the majority (46.1%) of the sample and is characterized as "High autonomy, High competence, and Moderate relatedness thwarting." Both autonomy and competence thwarting scores in this class exceed the median, while the relatedness score is relatively lower but still higher than that of Class 3. Class 2, representing 27.5% of the sample, is labeled "High autonomy, High competence, and High relatedness thwarting," with no thwarting type scores falling below the median. In contrast, Class 3, which makes up 26.4% of the sample, is described as "Low psychological needs thwarting," with all scores below the median.

The PNT profiles identified in this study enhance our understanding from previous research on psychological need satisfaction (PNS) and psychological need frustration (PNF) profiles (61–63). It's important to note that within the context of Self-Determination Theory, PNT and PNF are distinct yet interrelated constructs (64). PNF typically relates to situations where one's basic psychological needs remain unfulfilled (65). Continuous experiences of need frustration can result in feelings of ineffectiveness and a perceived loss of control, prompting individuals to adopt specific behaviors to regain autonomy and competence (66). Conversely, PNT is viewed as an active hindrance or disruption to one's basic psychological needs. Therefore, this study augments, rather than replicates, existing PNF research.

4.2 Association of PNT with PSU, psychological distress, and perceived administrative support

In examining variable correlations, this study determines that, overall, the three PNTs are negatively correlated with perceived administrative support and positively with psychological distress and PSU at both time points. This is consistent with prior research (37, 67, 68). For example, Schultz et al. (67) found that reduced managerial support actively thwarts employees' basic psychological needs.

Regarding PSU, SEM results reveal that at Time 1, Class 2's score was higher than that of Class 1, followed by Class 3. This pattern indicates significant differences in PSU levels among teachers with varying degrees of PNT during the pandemic, with those having high PNT facing the highest risk. This finding is consistent with the Compensatory Internet Use Theory (CIUT), which suggests that people turn to smartphones to compensate for dysphoria and avoid real-life problems (35). It also aligns with prior studies (13, 14)

showing that engaging in online social networks on smartphones helps individuals with PNT connect with others, providing a sense of relatedness and autonomy. Playing online games on smartphones fulfills the needs for social interaction (relatedness), achievement (competence), and decision-making (autonomy). Therefore, the higher the PNT level, the greater the likelihood of developing PSU. This explains the descending order of PSU severity among the three classes, ranked as 2, 1, and 3. However, at Time 2, no significant differences were observed between these groups, suggesting that the impact of PNT on PSU was most pronounced during the pandemic and lessened as the pandemic eased and negative emotions decreased.

Concerning psychological distress, the three profiles rank as follows at both time points: Class 2 > Class 1 > Class 3. This ranking reaffirms previous findings (1, 10, 12) that PNTs correlate positively with psychological distress. Past research has shown that thwarting of the three basic psychological needs can exacerbate negative outcomes such as burnout (1) and depression (10, 12). In terms of perceived administrative support, given that the profiles rank as C3 > C1 > C2 at both time points and considering the previously identified negative relationship between PNT and perceived administrative support, it can be concluded that relatedness thwarting plays a pivotal role in this domain, especially when considering the differences between Class 1 and 2. This study diverges from earlier findings (40), highlighting the significant impact of relatedness thwarting, as opposed to competence and autonomy thwarting. The analysis confirms a negative correlation between PNT and perceived administrative support, and a positive correlation with both psychological distress and PSU. Importantly, it identifies relatedness thwarting as a key factor negatively impacting perceived administrative support and positively affecting psychological distress, emphasizing its critical role in the framework of basic psychological needs.

4.3 Analysis of changes and influence of PNT through longitudinal study

The present longitudinal study shows a decrease in PSU and perceived support scores from Time 1 to Time 2, with the pandemic's alleviation being a key predictor of this change. Echoing previous studies (6, 69), teachers faced high demands, overload, physical isolation, and scant administrative support during the pandemic, leading to increased reliance on PSU as a coping mechanism. With the pandemic's easing and school reopening, there was a shift in focus toward teaching improvement and student attainment, reducing the need for compensatory smartphone use and lessening the demand for administrative support, hence the lower scores at Time 2. However, it's important to recognize that reopening schools did not restore the pre-pandemic environment (70). New challenges, such as the necessity for ICT skills and resource imbalances, continued to contribute to teachers' psychological distress. Interestingly, unlike previous reports of heightened psychological distress in teachers post-reopening, this study observed no significant difference in psychological distress levels at Time 2.

Regarding perceived administrative support, this study determined that based on the scores, the three groups were ranked as Class 3, Class 1, and then Class 2 at both time points. This suggests that both Class 3 and Class 1 perceived greater administrative support than Class 2. Likewise, in terms of psychological distress, the scores of the three groups are ordered as Class 2, Class 1 and Class 3 from high to low at both time points. It's important to highlight that for Class 2, which exhibited high thwarting in autonomy, competence, and relatedness, perceived administrative support consistently remained low across both time points. In contrast, the psychological distress scores of this class occupies the highest position at Time 1 as well as Time 2. This suggests that high PNT has a sustained, longitudinal influence on these two variables. The observation presents a novel insight when contrasted with existing cross-sectional research on PNT (41, 42).

5 Limitations, future directions and conclusion

5.1 Limitations

The present study, while providing valuable insights, acknowledges key limitations including potential observer, recall, and time-related biases. The involvement of the city's Education Bureau in our sampling process may limit the representativeness of our sample and introduce observer bias, as teachers' responses could be influenced by the perceived authority of the data collectors. Additionally, our reliance on retrospective recall for the second measurement is susceptible to recall bias, potentially skewing the data due to teachers' current circumstances influencing their recollections. A significant time-related bias arises from the study's two distinct phases: mandatory online learning (Time 1) and offline teaching (Time 2). This shift in teaching modes could affect the comparability of data across these periods, introducing inconsistencies. Furthermore, the unique conditions of our study, particularly during the pandemic, may not accurately represent traditional educational settings, posing another limitation in terms of the generalizability of our findings. Moreover, although according to the aforementioned data provided by the Ministry of Education, there are more female teachers among primary and secondary school teachers, the overrepresentation of female teachers in this study is indeed a research limitation. Lastly, we did not explore some variables serving as mediators or moderators within our conceptual model (i.e., Figure 6) which is also a limitation of the present study.

5.2 Future directions

The limitations identified in our study pave the way for future research to validate our findings within more traditional educational settings, ensuring a balanced gender ratio to comprehensively evaluate their applicability and generalizability. Future sampling methods should aim to minimize the influence of authority to reduce potential data bias. Moreover, our study did not encompass the exploration of mediators or moderators. Therefore, future research could beneficially incorporate variables such as 'anti-mattering' into our testing model, as illustrated in Figure 6. Anti-mattering, the perception of being insignificant to others, often leads individuals to feel alienated and can increase susceptibility to mental health issues. Those exhibiting high levels of anti-mattering are more likely to rely on smartphones for interaction rather than engaging directly with others. Additionally, when individuals perceive themselves as irrelevant to others, they may

overlook or fail to recognize the care and support available to them. Therefore, examining the mediating effects of anti-mattering could provide insightful contributions to our understanding of its impact in educational and social contexts.

5.3 Conclusion

To conclude, our present study is the first to apply a person-centered approach rather than a variable-centered model to investigate PNT. Three profiles are identified, and different associations are found between them and psychological distress, PSU, and perceived administrative support. A detailed understanding of teachers' PNT status fosters the development of more targeted intervention measures, then to lessen teachers' psychological distress, PSU, and increase perceived administrative support. Moreover, through longitudinal data, the present study demonstrates that PNT exerts a lasting influence, which complements findings from cross-sectional studies and highlights the importance of focusing on teachers' basic psychological needs.

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 Jiangxi Psychological Consultant Association (IRB ref.: JXSXL-2020-J013). 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

X-LL: Conceptualization, Investigation, Writing – original draft. C-HC: Conceptualization, Writing – original draft, Writing – review & editing. JG: Writing – review & editing. L-LL: Data curation, Writing – review & editing. X-YJ: Data curation, Writing – review & editing. C-XB: Data curation, Funding acquisition, Writing – review & editing. I-HC: Formal analysis, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing.

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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.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2023.1299929/full#supplementary-material

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Physical exercise/sports ameliorate the internet addiction from college students during the pandemic of COVID-19 in China

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The rapid advancement of modern technology has significantly driven progress in various IT-related activities, resulting in a substantial increase in internet penetration rates, particularly among college students. The utilization of the internet has become one of the most essential tools in our modern society. However, internet addiction (IA) has emerged as a serious concern, particularly among college students, adversely affecting academic performance and having significant psychological and psychiatric implications. The aim of the current study was to determine the impact of physical exercise, gender and academic year on IA among college students. In the present study, we investigated internet usage, engagement in sports activities, and academic performance among college students from Western, Middle, and Eastern regions of Chinese universities. It's noteworthy that most of the respondents were freshmen. Our findings indicate that freshmen students were more susceptible to experiencing IA. Approximately 75% of students engaged in leisure sports activities, revealing an inverse correlation between sports activity and IA. This correlation aligns with the level of sports involvement, emphasizing the potential benefits of physical activity in mitigating IA. However, our study did not uncover any correlation between geographic location and the occurrence of IA, nor did it find differences between medical and non-medical students. Furthermore, our study revealed no significant variations in IA among students from different ethnic backgrounds. The underlying mechanism of IA is being currently determined. Our data suggest that physical exercise, gender, and academic year have a significant impact on IA among college students.

KEYWORDS

internet addiction, college students, physical excise, disciplines, China

Introduction

The rapid advancement of modern technology has greatly propelled the progress of various IT-related activities in recent decades. This advancement can be attributed to the increasing affordability and accessibility of the internet, bringing substantial benefits to society, including cashless shopping, online registration, and ticketing. According to the 51st Statistical Report from the China Internet Network Information Centre (CNNIC), the number of internet users in China had reached 1.067 billion by December 2022, marking an increase of 35.49 million compared to December 2021, resulting in an internet penetration rate of 75.6% (1). Notably, a significant portion of these internet users, particularly among college students, accounted for 21.0% (1). Consequently, the utilization of the internet has emerged as one of the most essential tools in our modern society.

While the responsible use of the internet can enhance people's lives in terms of enjoyment and reliability, some individuals fall into the trap of internet addiction (IA) (2, 3). This not only hampers academic performance but also gives rise to profound psychological and psychiatric issues among the students (2) As a result, the consequences of IA extend well beyond the surface, causing significant harm.

The simultaneous emergence of COVID-19 outbreaks, resulting from the infection of the SARS-CoV-2 virus, was initially identified in Wuhan in December 2019 (4). In an effort to contain and eradicate the transmission of the SARS-CoV-2 virus, authorities declared a state of emergency on January 25, 2020. This declaration led to the implementation of measures such as maintaining social distance, locking down non-essential facilities (4, 5), and mandating the wearing of facial masks.

As a response, Chinese authorities adopted a zero-tolerance policy, followed by a dynamic zero policy (6), in confronting one of the most perilous challenges of the millennium. Subsequently, the Minister of Education in China recommended suspending in-person classes but not suspending lessons altogether, transforming traditional face-to-face teaching into digital online instruction. This directive encouraged individuals to stay at home and engage in remote work, which, in turn, became an additional contributing factor to the rise in IA. Reports indicate that over 35% of the general population in China experienced IA during the COVID-19 lockdown [3]. Furthermore, it has been observed that complete lockdowns have had significant psychological and psychiatric impacts on the general population (7), notably increasing the risk of IA during the COVID-19 pandemic in China (3).

In light of the pandemic outbreak, universities transitioned from in-person to online teaching methods, resulting in a heightened frequency and prolonged duration of college students' online activities. Research has demonstrated a substantial increase in anxiety, stress, and depression among both the community and healthcare professionals in Wuhan during the complete lockdown (8).

Surprisingly, our earlier research findings indicate that the academic performance of first-year medical students (9) and nursing students (10) has not only declined but also shown improvements at certain levels in online teaching during the lockdown. Admittedly we did not explore any psychological issues from these two studies.

Furthermore, the COVID-19 lockdown and the shift to online teaching prompted many students to engage in IT-related activities, potentially making them susceptible to IA or exacerbating the problem for those already addicted to IT. To address IA, it has been proposed that physical exercise can play a significant role in alleviating mild-to-moderate depression and anxiety in individuals (11). Additionally, it may also enhance mental activity to some extent. However, the connection between IA, physical exercise, and subsequent academic performance among college students, especially during the COVID-19 lockdown period, warrants further investigation.

However, there is a need for clarification regarding IA among college students in the past 1–3 years. Consequently, we conducted a recent survey to assess the preventive impact of engaging in sports exercise and the intensity of exercise on IA. The aim of the current study was to determine the impact of physical exercise, gender and academic year on IA among college students.

Methods

Sample size of research participants

In this study, we employed a convenience sampling technique and conducted a cross-sectional survey. The sample comprised 1,087 undergraduate students drawn from over ten universities, including but not limited to Chengdu University, Qinghai University, Chengdu Medical College, Chongqing University, Sichuan University, Sichuan Normal University, Southwest Medical University, North Sichuan Medical College, Guilin Medical University, Hubei University, Nanchang University, Tsinghua University, Zhejiang University, Xiamen University, Fudan University, and Shanghai Jiao Tong University, among others, representing diverse regions of China. We utilized PASS 2021 software for the analysis. To account for potential inefficiencies, a minimum of 1,145 students should have been included, assuming a 5% margin of error. This study has been approved by the Human Ethic Committee, The Second Affiliated Hospital, Guilin Medical University, Guilin, China.

Data collection

This research was carried out during March and April 2023, in the midst of a significant COVID-19 pandemic outbreak in China. We distributed an online questionnaire survey to undergraduates using the Questionnaire Star platform.[1] A total of 2,115 questionnaire sheets were distributed, and we received 2,108 valid responses, yielding an impressive effective response rate of 99.7%. Only seven questionnaires were excluded from the analysis due to incorrect or unclear answers.

Questionnaire

The questionnaire utilized in this study was developed through a comprehensive review of relevant literature and encompassed both Independent Variables (IV) and Dependent Variables (DV). The Independent Variables (IVs) encompassed various sociodemographic characteristics of the students, including age, gender, ethnicity,

1 https://www.wjx.cn/

discipline, grade, geographic location of the university (East, Middle, or West of China), Double 1st-Class status, as well as aspects related to physical exercise, such as participation in exercise and physical activity levels. The Dependent Variable (DV) centered on Internet Addiction.

Scales for questionnaire

Physical activity rating scale

The assessment of physical exercise levels was conducted using the Physical Activity Rating Scale (PARS-3), originally developed by Kimio Hashimoto, a psychologist at Kyushu University in Japan. It was subsequently adapted into a revised Chinese version by Liang (12). The PARS-3 comprises three items, which include exercise intensity, duration time, and exercise frequency during the past month. Each item is rated using a 5-point Likert scale. Specifically, the exercise intensity and exercise frequency items are assigned scores ranging from 1 to 5, while the duration time item is scored from 0 to 4.

The total physical exercise score was computed using the formula: total physical exercise score = exercise intensity × duration time × exercise frequency, resulting in a total score ranging from 0 to 100 points (13, 14). Higher scores indicate a higher level of physical exercise (15). Additionally, the physical activity level was categorized into three levels based on Liang's (12) classification: low level (≤ 19 points), moderate level (20–42 points), and high level (≥ 43 points). The Cronbach's α coefficient for the PARS-3 scale in this study was 0.633.

Internet addiction scale

All participating students in the study completed the Internet Addiction Test (IAT) to gauge the severity of compulsive internet surfing. The IAT, developed by Young (16), is widely recognized in international research and has exhibited strong validity and reliability in prior investigations (3, 17). The IAT comprises 20 items, each rated on a 5-point Likert scale (1 = rarely, 2 = occasionally, 3 = frequently, 4 = often, and 5 = always). The total score spans from 20 to 100 points (18), with scores categorized into two primary groups: average users (< 40 points) and problematic users (≥ 40 points) (19). Furthermore, the severity of IA can be classified as normal (20–39 points), mild (40–59 points), moderate (60–79 points), and severe (80–100 points) (18). The scale exhibited excellent reliability in the present sample, with a Cronbach's α coefficient of 0.928, signifying a high level of internal consistency among the items.

Statistical analysis

Since the measurement data did not conform to a normal distribution, it was presented as the median and interquartile range (IQR) [M (P25, P75)]. To assess the relationships between the two data groups, the Mann–Whitney U test was employed. Categorical data was expressed in terms of frequency (n) and percentage (%), and differences between two or multiple groups were detected using the chi-square test or Fisher's exact test.

To investigate the association between exercise participation and Internet Addiction (IA), we conducted Modified Poisson regression analysis (20, 21). This analysis allowed us to examine the relative risk (RR) and 95% confidence interval (CI) of the dependent variable (DV) in relation to the independent variables (IV) (22). We adjusted for age, gender, ethnicity, grade, geographic location of the university, and Double 1st-Class status as part of the analysis. All statistical analyses were carried out using IBM SPSS Statistics 26.0, and a value of p less than 0.05 (two-sided) was considered statistically significant.

Results

Participant characteristics

We received a total of 2,108 valid responses from college students. Table 1 offers a comprehensive summary of the demographic characteristics of these students. The ages of the college students ranged from 18 to 20 years, with a median age of 19 years. The proportion of females was 1.2 times higher than that of males. Furthermore, the percentage of Han ethnicity was significantly higher, with a 146.3-fold difference compared to the proportion of minority ethnicities. Additionally, the ratio of Non-Double 1st-class universities was 8.0 times higher than that of Double 1st-class universities.

TABLE 1 Overall descriptive statistics for variables (n = 2,108).

Variables		Median (n)	IQR (P25, P75) (%)
Age		19.0	(18.0, 20.0)
Sex	Men	957	45.4
	Women	1,151	54.6
Ethnic	Han	1973	93.6
	Minority	135	6.4
Double 1st -class	Non	1875	88.9
	Yes	233	11.1
University location	East	219	10.4
	Middle	150	7.1
	West	1739	82.5
Discipline	Medicine	977	46.3
	STEM	598	28.4
	Others	533	25.3
Grade	1st	1,551	73.6
	2nd	297	14.1
	3rd	133	6.3
	4th	105	5.0
	5th	22	1.0
Leisure sports participation	No	353	16.7
	Yes	1755	83.3
Exercise intensity	Low (≤19)	1,346	63.9
	Moderate (20–42)	459	21.8
	High (≥43)	303	14.4

STEM: Science, Technology, Engineering and Math.

Regarding the geographical distribution of universities, the West of China had the highest representation, whereas the Middle of China had the lowest proportion. Among the various disciplines, Medicine had the highest representation, accounting for 46.3% of the participants, followed by STEM (Science, Technology, Engineering, and Math) at 28.4%, with other disciplines making up 25.3%. Grade 1 undergraduates constituted most respondents, comprising 73.6% of the total, in comparison to students from other grade levels.

Regarding other factors, a substantial proportion of students (83.3%) indicated their participation in leisure sports, a figure approximately 5 times higher than those who did not engage in such activities. Furthermore, 63.9% of students were categorized as having a low level of exercise intensity, which was roughly 2.9 times more prevalent than those classified with a moderate level and 4.4 times more prevalent than those with a high level of exercise intensity.

TABLE 2 Internet addiction among college students (n = 2,108).

Types		Median / n	IQR (P25, P75)/(%)
IAT Scores		41.0	(32.0, 51.0)
NIA (<40)		931	44.2
IA (≥40)	Mild (40–59)	937	44.4
	Moderate (60–79)	224	10.6
	Severe (80–100)	16	0.8
Total		2,108	100.0

NIA: Non-Internet Addiction, IA: Internet Addiction.

Overall situation of internet addiction

The Internet Addiction Test (IAT) scores for all participants had a median value of 41.0, with a range spanning from 32.0 to 51.0. This score distribution indicated that the severity of IA was generally classified as mild. Based on the IAT scores, 55.8% of the participants were identified as suffering from IA, which was approximately 1.3 times more prevalent than the proportion of Non-Internet Addiction (NIA) cases. Among the IA participants, 44.4% were categorized as having a mild level of addiction, a significantly higher percentage than those classified with moderate or severe addiction levels (Table 2).

Prevention effect of exercise participation on internet addiction

The Chi-square test revealed that participation in leisure sports, exercise intensity, gender, and grade had a significant impact on Internet Addiction (IA) ($p < 0.05$) (Table 3). Furthermore, there were notable associations between IA and engagement in leisure sports (unadjusted RR = 0.930, 95% CI = 0.900–0.962, $p < 0.001$), exercise intensity (unadjusted RR = 0.957, 95% CI = 0.939–0.976, p < 0.001),

TABLE 3 Comparison between participants with NIA and IA for category variables (n = 2,108).

Variables	Group	Total	NIA (n = 931)	IA (n = 1,177)	Mann Whitney test /chi square test	
					Z Value/χ^2 Value	P Value
Leisure Sports Participation (n) (%)	No	353	122 (34.6)	231 (65.4)	15.860	<0.001
	Yes	1755	809 (46.1)	946 (53.9)		
Exercise intensity (n) (%)	Low	1,346	552 (41.0)	794 (59.0)	20.927	<0.001
	Moderate	459	212 (46.2)	247 (53.8)		
	High	303	167 (55.1)	136 (44.9)		
Sex (n) (%)	Male	957	471 (49.2)	486 (50.8)	18.135	<0.001
	Female	1,151	460 (40.0)	691 (60.0)		
Double 1st-class Univ (n) (%)	Non	1875	837 (44.6)	1,038 (55.4)	1.552	0.213
	Yes	233	94 (40.3)	139 (59.7)		
University Location (n) (%)	East	219	97 (44.3)	122 (55.7)	2.501	0.286
	Middle	150	57 (38.0)	93 (62.0)		
	West	1739	777 (44.7)	962 (55.3)		
Discipline (n) (%)	Medicine	977	423 (43.3)	554 (56.7)	0.725	0.696
	STEM	598	272 (45.5)	326 (54.5)		
	Others	533	236 (44.3)	297 (55.7)		
Ethnic (n) (%)	Han	1973	864 (43.8)	1,109 (56.2)	1.747	0.186
	Minority	135	67 (49.6)	68 (50.4)		
Grade (n) (%)	1st	1,551	698 (45.0)	853 (55.0)	9.911	0.042
	2nd	297	117 (39.4)	180 (60.6)		
	3rd	133	49 (36.8)	84 (63.2)		
	4th	105	55 (52.4)	50 (47.6)		
	5th	22	12 (54.5)	10 (45.5)		
Age M (P_{25}, P_{75})		2,108	19 (18, 20)	19 (18, 20)	−0.224	0.823

STEM: Science, Technology, Engineering and Math.

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TABLE 4 Modified poisson regression.

Variables		Adjusted			Unadjusted		
		RR Value	*RR* 95% CI	*P* Value	*RR* Value	*RR* 95% CI	*P* Value
Leisure sports participation	No*						
	Yes	0.950	0.917–0.983	0.004	0.930	0.900–0.962	<0.001
Exercise intensity		0.971	0.951–0.991	0.005	0.957	0.939–0.976	<0.001
Sex	Male*						
	Female	1.042	1.012–1.073	0.005	1.061	1.033–1.091	<0.001
Double 1st-class	Non*						
	Yes	1.032	0.986–1.080	0.171	1.028	0.985–1.072	0.203
Univ location	East*						
	Middle	1.028	0.964–1.096	0.405	1.040	0.976–1.109	0.224
	West	0.997	0.951–1.045	0.904	0.998	0.954–1.043	0.913
Discipline	Medicine*						
	STEM	0.989	0.956–1.023	0.509	0.986	0.954–1.019	0.397
	Others	0.987	0.953–1.022	0.454	0.994	0.961–1.028	0.714
Ethnic	Han*						
	Minority	0.959	0.907–1.015	0.150	0.963	0.909–1.020	0.197
Grade		0.991	0.968–1.014	0.434	0.999	0.984–1.015	0.947
Age		1.003	0.988–1.018	0.705	0.998	0.989–1.008	0.765

*Referent; RR = Risk Ratio; 95% CI = 95% Confidence Interval; STEM: Science, Technology, Engineering and Math.

and being female (unadjusted RR = 1.061, 95% CI = 1.033–1.091, $p < 0.001$) (Table 4).

Moreover, a noteworthy association was found between IA and engagement in leisure sports (adjusted RR = 0.950, 95% CI = 0.917–0.983, $p = 0.004$), exercise intensity (adjusted RR = 0.971, 95% CI = 0.951–0.991, $p = 0.005$), and gender (adjusted RR = 1.042, 95% CI = 1.012–1.073, p = 0.005), even after controlling for other covariates. However, no significant associations were observed between IA and variables such as Double 1st-class University status, university location, discipline, ethnicity, grade, or age, independent of other covariates (Table 4).

Discussion

In this prospective study, we recruited approximately 2000 undergraduate students from diverse universities located across China, including institutions from the Eastern, Middle, and Western regions. This sampling approach was carefully structured to provide a reasonable representation of the broader population of Chinese undergraduate students.

First and foremost, we noted no substantial gender disparities among the participants, signifying the absence of any selection bias. The average age of the participants, at 19 years, falls within the typical age range for undergraduate students. More specifically, among these universities, incoming freshmen typically range in age from 17 to 19 years. In relation to ethnicity, the ratio of Han Chinese participants to those from other ethnic backgrounds closely mirrored the demographic composition of the general population in China.

The universities in our study were divided into two groups: those designated as double-first class and those classified as non-double-first class institutions, based on their comprehensive assessment scores, which encompassed both teaching and research performance, including research funding. As a result, we had approximately 10% of the universities falling into the double-first class category, while the remaining 90% belonged to the non-double-first class category. This observation aligns with our finding that there were nine times as many students from non-double-first class universities as there were from double-first class universities.

While we endeavoured to recruit students evenly from various regions within the universities, we observed a higher proportion of students hailing from the Western region in comparison to the Middle and Eastern regions. This disparity can be partially attributed to the researchers' location, as they were situated in Sichuan and Guangxi, situated in the Western or Southern part of China.

Moreover, we sought to explore potential differences between medical and non-medical students in our study, as prior research has indicated that medical students may exhibit a higher susceptibility to internet addiction (23). To mitigate selection bias, we took care to recruit a comparable number of both medical and non-medical students.

Although students from all academic years were invited to participate, it's noteworthy that most respondents were in their first year, with the number gradually decreasing in the subsequent years. This trend can be attributed to the mounting academic demands that students encounter as they advance in their studies.

It's worth noting that approximately 75% of students reported their participation in leisure sports activities. This notably high participation rate can be attributed to effective educational initiatives undertaken by the universities. These initiatives emphasize the crucial role of physical exercise in enhancing academic performance. The primary explanation for this

improvement lies in exercise's ability to enhance oxygen flow to the brain, leading to an increased production of brain neurotransmitters (24).

This assertion is further substantiated by other studies indicating that exercise appears to mitigate internet addiction by modulating the neurobiology of the central and autonomic nervous systems. For instance, exercise can elevate the levels of neurotrophic factors, cortisol, and neurotransmitters (18). As a result, critical brain functions such as focus, concentration, learning, memory, and stress management are notably improved (25). Our research findings are also consistent with Kim's report, underscoring the impact of personalized individual characteristics, encompassing personal psychological and emotional factors, on internet addiction (26). However, it's important to acknowledge that most students engaged in leisure sports activities at a moderate level, which is understandable given their academic commitments.

As anticipated, there was an inverse correlation between IA and sports activity, with this correlation linked to varying levels of sports participation. It is noteworthy that over 56% of the participating undergraduate students exhibited different levels of IA. It is reassuring to observe that most IA students fell into the moderate level category, with less than 0.8% classified as experiencing severe IA. From a statistical perspective, the data derived from the Chi-square test confirmed the presence of an inverse correlation between participation in leisure sports and IA, consistent with its connection to the intensity of sports involvement.

We noted that women exhibited a higher susceptibility to IA in comparison to men, which could be attributed to their relatively lower levels of physical exercise. This observation aligns with the earlier finding of an inverse correlation between sports participation and IA. When considering academic performance and university status, we found no significant difference in IA prevalence between students from double-first-class and non-double-first-class universities. This suggests that IA is not directly associated with academic performance or the status of the universities.

Furthermore, we discovered no correlation between geographic location and the occurrence of IA. While there might be variations in internet coverage between regions, such as rural mountainous areas compared to metropolitan areas, it's important to note that internet access is nearly universally comprehensive across all universities. Consequently, the availability of internet access does not seem to be a significant contributing factor to the development of IA among students across different geographic locations.

No significant difference in IA was observed between medical and non-medical students, implying that IA is not linked to the specific academic discipline's students pursue. This finding suggests that, despite potential variations in academic-related stressors, the campus environments appear to be similar and do not substantially contribute to the development of IA. Furthermore, our study revealed no significant disparity in IA among students from different ethnic backgrounds. This can be attributed to the modernization of societies and the widespread accessibility of modern technologies. In China, almost every student can access the internet at a relatively low cost, which diminishes the influence of ethnicity on IA. This is supported by the report demonstrating that Chinese education is gradually shifting towards online teaching among college students, making internet access more affordable (27).

It's also noted that freshmen students were more prone to experiencing IA. This tendency may be attributed to the culmination of their long-term preparations for university entrance, combined with the stress arising from family expectations. Upon entering the university, they often find themselves in a more independent and unsupervised environment. However, as students' progress through their academic journey, they gradually mature and assume more responsibilities, which tends to result in a decline in IA. This observation aligns with the previously mentioned inverse correlation between age and IA, especially during adolescence (28), some of which may be associated with structural changes in the brain (29).

While the data collected was from March 2023, it is important to note that the students' performance occurred during the COVID-19 lockdown period, spanning from 2020 to 2022. We did not compare the outcomes before and after the COVID-19 lockdown, which is a consideration for future research. In summary, our data suggests that physical exercise, gender, and academic year have a significant impact on IA.

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 The Second Hospital, Guilin Medical University. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

PC: Data curation, Funding acquisition, Methodology, Writing – original draft. JW: Data curation, Methodology, Writing – review & editing. PY: Data curation, Methodology, Writing – review & editing. XF: Methodology, Investigation, Writing – review & editing. GY: Methodology, Data curation, Writing – original draft. CH: Methodology, Data curation, Writing – review & editing. XC: Data curation, Investigation, Writing – original draft. BH: Writing – review & editing. SB: Writing – review & editing, Supervision. SL: Conceptualization, Writing – review & editing, Funding acquisition, Project administration.

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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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Associations of mobile phone addiction with suicide ideation and suicide attempt: findings from six universities in China

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Background: Mobile phones are becoming indispensable for life and have changed various aspects of people's lives. The psychological impacts of excessive mobile phone use have emerged as an impressive problem among college students. However, little is known about the associations of mobile phone addiction with suicide ideation and suicide attempt.

Methods: A cross-sectional study was conducted with students from six universities in 2022. We collected the socio-demographic characteristics, suicide ideation, suicide attempt, psychosocial factors (depressive symptoms, social support, sleep quality), and health-related characteristics (smoking, drinking, body mass index). Mobile phone addiction was ascertained by the Mobile Phone Addiction Tendency Scale (MPATS). The associations of mobile phone addiction with suicide ideation and suicide attempt were estimated using binary logistic regression and restricted cubic splines regression.

Results: A total of 18,723 college students [6,531 males (34.9%) and 12,192 females (65.1%)] were included in the final analysis. Eleven percent of participants had a history of suicide ideation, and 1.8% of participants had engaged in suicide attempt. A total of 5,553 students (29.7%) met the criteria of mobile phone addiction (MPATS score $\geq$48), and the average score on the MPATS was 39.5 $\pm$ 13.0. After adjustment for potential covariates, mobile phone addiction was significantly associated with increased odds of suicide ideation (OR, 1.70; 95% CI, 1.53–1.88) and suicide attempt (OR, 1.48; 95% CI, 1.18–1.86). Gender did not affect the associations of mobile phone addiction with suicide ideation and suicide attempt (*P for interaction* $>$ 0.05). The restricted cubic splines regression displayed a nonlinear dose-response association between MPATS score and risk of suicide ideation (*P for non-linearity* $<$ 0.001), while a monotonically increasing risk of suicide attempt was found to be associated with an increasing MPATS score (*P for non-linearity* $=$ 0.420).

Conclusions: Mobile phone addiction is associated with suicide ideation and suicide attempt among college students. The findings indicate that early examination, prevention, and intervention for mobile phone addiction may benefit the prevent and control of suicide.

KEYWORDS

mobile phone addiction, suicide ideation, suicide attempt, epidemiology, college students

1 Introduction

Approximately one million people around the world died by suicide every year (1). In both China and Japan, suicide is the leading cause of death among youth aged 15–34, resulting in substantial loss of life (2). Suicide was regarded as a continuous process, which usually involves suicide ideation, suicide plan, suicide attempt, and completed suicide (3). Recent global surveys indicated that 10%−20% of adolescents report having had suicide ideation or suicide attempt during the last year (4). More specifically, approximately 25 attempts occur for every suicide death, and an even greater number of people consider suicide (5, 6). Over the past two decades, there has been a considerable increase in a variety of studies on suicide among youth (7), but limited progress has been made in reducing suicide rates (8, 9). Suicide among youth remains a heavy burden on the state and society. Therefore, further exploring the influencing factors of suicide is essential for decreasing the incidence of suicide behavior and, ultimately, reducing suicidal death.

There is an increasing interest in revealing the adverse health effects of excessive mobile phones use among youth, especially for the generation born after 1995, who were tagged as iGens by Twenge (10). The iGens have spent their entire adolescence in the era of mobile phones, their social interactions and mental health might be shaped by the combined influence of mobile phones and social media. For the above reasons and circumstances, mobile phone addiction has become the major problem among the iGens, which is similar to the internet addiction with the characteristics of withdrawal symptoms, tolerance, loss of control, and adverse effects (11). Many previous epidemiological surveys found a high rate of mobile phone addiction among college students. For example, Zhang et al. (12) found that the prevalence of problematic mobile phone use among Chinese university students was as high as 26.1%. As a systematic review reported, China was at the highest incidence of mobile phone addiction (13). Furthermore, the COVID-19 outbreak has brought many impacts on people's lives, particularly on current college students who are the first generation of iGens. The quarantine measures for COVID-19 forced college students to take online classes at home or in dormitories, which increased their use of mobile phones and resulted in an increased risk of mobile phone addiction (14, 15). Several studies indicated that individuals who engage in mobile phone addiction may suffer many adverse consequences, such as bodily and headache pain, dry eyes, depression, anxiety, sleep disorders, and poor academic performance (16–20). Among the various health effects, the psychological impacts of mobile phone addiction are of the greatest concern, but the relationship between mobile phone addiction and suicide is still unclear.

Given the amount of time spent on mobile phones, iGens with mobile phone addiction or prolonged use of mobile phones will increase the risk of exposure to suicide pictures, videos, texts, and cases. What's more, mobile phones also provide an important way for iGens to find and join suicide peers, where they can share their experiences of suicide and even be encouraged (21). In addition, studies have shown that over-indulgence in various apps on mobile phones can decrease the interest in face-to-face relationships (22), resulting in non-adaptation to real life, may causing a series of problems (e.g., depression, anxiety, sleep quality) (18), which will lead to suicide in turn. Mobile phone use has also been linked to structural and functional abnormalities in brain areas related to cognitive control and emotional regulation. Zou et al. (23) found that decreased integrity of brain white matter is associated with mobile phone addiction, and lower white matter integrity is believed to be associated with suicide in adolescents (24). Therefore, it is natural to hypothesize that mobile phone addiction is likely to increase the risk of suicide.

To date, a few studies have revealed the relationships of mobile phone addiction with suicide ideation and suicide attempt. However, the findings from these studies are not consistent. Shinetsetseg et al. (25) conducted a web-based survey of 54,948 middle and high school students in Korea, suggested that mobile phone addiction leads to significant higher risk of suicide ideation and suicide attempt. Similarly, findings from 1,609 senior high school students in China also indicated a significant relationship between mobile phone addiction and suicide ideation or suicide attempt (26). In addition to high school students, there were several studies on college students. Wan Ismail et al. (27) showed that mobile phone addiction was positively related to suicide in 525 college students from six public universities in Malaysian. Recently, Hu et al. (28) also found significant association of mobile phone addiction with suicide ideation among 1,042 college students at a Chinese university. However, a recent study of 439 college students found no relationship between suicide ideation and mobile phone addiction (29). While, most previous studies on the association between mobile phone addiction and suicide among college students have been conducted at only one university, from specific majors, or only from public universities, and all with a small sample size. Adding to the limited relevant studies at present, further research is required.

Therefore, this study aims to examine the associations of mobile phone addiction with suicide ideation and suicide attempt using a large sample of college students from six universities.

2 Methods

2.1 Study design and participants

This cross-sectional survey was conducted among undergraduates across six representative universities in Shaanxi Province, which is located in northwest China, from October to November 2022. In short, we used multi-stage random cluster sampling to choose participants. First, with assistance from the educational bureaus, we sampled six of 57 universities in Shaanxi province, including four of 34 public universities and two of 23 private universities. Then, we randomly selected two to four classes from all faculties and grades at each sampled university, inviting a total of 20,165 undergraduates from 559 selected classes to join the study. We excluded students refused to participate, submitted in a short time (<500 s), and those invalid questionnaire assessed by logic questions. In the end, 18,723 students were included in the final analysis, leading to a response rate of 95.4% (18,723/20,165).

Trained investigators conducted the survey and they were available to explain to students any questions they may have about

the structured questionnaire. Before the survey, we conducted a two-stage training to inform students of the purpose and procedures in detail. First, two class officers from each selected class were assembled for a 27 min standardized training with the participation of school leaders. Subsequently, the class officers conducted another training to all students in each selected classes, and instructed other classmates to complete the questionnaire. All participants finished the questionnaire with an average time of 27 min. Ethics approval was obtained from The Second Affiliated Hospital of Xi'an Jiaotong University (Approval number: 2022-248).

2.2 Measures

2.2.1 Socio-demographic characteristics

Socio-demographic information, including gender, grade, race, registered permanent residence (rural, urban), siblings (yes, no), and parental educational attainment (middle school or under, high school, college or above), were collected.

2.2.2 Mobile phone addiction

Mobile Phone Addiction Tendency Scale (MPATS) developed by Xiong et al. (30) for Chinese college students was used to measure mobile phone addiction. It included 16 items with four dimensions, including salience, withdrawal symptoms, social comfort, and mood changes. The items were rated from 1 (very inconsistent) to 5 (very consistent), with a total score ranging from 16 to 80. A higher total score indicates a higher level of mobile phone addiction. A score of 48 or more is considered to be mobile phone addiction. In this study, Cronbach α coefficient was 0.94.

2.2.3 Suicide ideation and suicide attempt

Suicide ideation was assessed by the question "During the last week, what was your level of desire to actively attempt suicide." "During the last week, to what extent do you want external forces to end your life." A "weak" or "moderate to strong" response to the preceding two questions implies the presence of suicide ideation (31). Suicide attempt was measured by "During the last year, did you ever attempt suicide?" An affirmative answer to this question was defined as suicide attempt. In the present study, the Cronbach α coefficient was 0.83.

2.2.4 Depression symptoms

Depression symptoms were measured by using the Self-Rating Depression Scale (SDS), which is developed by Zung (32). It included 20 questions that evaluates 10 positive symptoms and 10 negative symptoms for nearly 1 week. All items were scored from 1 (no or little time) to 4 (majority or all of the time). A higher score indicates more severe depression symptoms. The presence of depression symptoms was defined as a standard score higher than 50. The Cronbach α was 0.88 in this study.

2.2.5 Social support

Adolescent Social Support Scale was used to assess social support (33). It consists of 16 items with three dimensions (subjective support, objective support and support utilization). The items were scored from 1 (inconsistent) to 5 (consistent), with higher scores indicating greater level of perceived social support. The Cronbach α was 0.98 in this study.

2.2.6 Sleep disorders

Pittsburgh Sleep Quality Index (PSQI) developed by Buysse (34) was used to measure sleep disorders. It contains 19 items to evaluates the sleep quality during the last month. The total score of seven domains produced a global PSQI score ranging from 0 to 21, with a score of 8 or more defined as sleep disorders. The Cronbach α was 0.85 in this study.

2.2.7 Health-related characteristics

We also asked health-related characteristics information include smoking, drinking, height, and weight. Current smokers were participants who have smoked one or more cigarettes in the past 30 days. Current alcohol drinkers were defined as those who had consumed at least one glass of wine during the past 30 days. Body mass index (BMI) was calculated by dividing body weight (kg) by the square of height (m).

2.3 Statistical analysis

Continuous and categorical variables were presented as mean (SD) and frequencies, respectively. χ^2 test or *t*-test was performed to compare the distributions of the different characteristics.

Four sets of binary logistic regression were constructed to estimate the odds ratios (ORs) and 95% confidence interval (CIs) of mobile phone addiction with suicide ideation and suicide attempt separately, with adjustment for potential confounders ascertained based on prior publications (28, 29). Model 1 is a crude model, unadjusted for other factors. In model 2, we adjusted for gender, grade, and race. In model 3, we also adjusted for siblings, registered permanent residence, parental educational attainment, smoking, drinking, and BMI. In model 4, we additionally adjusted for depressive symptoms, social support, and sleep disorders.

Given that the gender-specific differences in the prevalence of suicidal behaviors were reported in previous study (35). We additionally performed subgroup analyses to examine any gender differences in the associations of mobile phone addiction with suicide ideation and suicide attempt. We inserted gender × mobile phone addition as an interaction term in the regression models to obtain *P* value for interaction. In addition, restricted cubic splines regression with three knots at 10th, 50th, and 90th percentiles of MPATS score were used to estimate the dose-response relationship of the MPATS score with the odds of suicide ideation and suicide attempt.

R 4.0.2 software (https://www.r-project.org/) was used for all data analyses.

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TABLE 1 Characteristics of participants.

Characteristics	Suicide ideation		*P*-value	Suicide attempt		*P*-value
	Never	Ever		Never	Ever	
Gender, *n* (%)						
Male	5,862 (35.1)	669 (33.1)	0.083	6,415 (34.9)	116 (32)	0.276
Female	10,841 (64.9)	1,351 (66.9)		11,946 (65.1)	246 (68)	
Grade, *n* (%)						
1st	4,884 (29.2)	569 (28.2)	<0.001	5,336 (29.1)	117 (32.3)	0.068
2nd	3,950 (23.6)	518 (25.6)		4,371 (23.8)	97 (26.8)	
3rd	3,872 (23.2)	527 (26.1)		4,317 (23.5)	82 (22.7)	
4th+	3,997 (23.9)	406 (20.1)		4,337 (23.6)	66 (18.2)	
Race, *n* (%)						
Han	16,214 (97.1)	1,956 (96.8)	0.593	17,820 (97.1)	350 (96.7)	0.800
Others	489 (2.9)	64 (3.2)		541 (2.9)	12 (3.3)	
Registered permanent residence, *n* (%)						
Rural	9,061 (54.2)	1,056 (52.3)	0.098	9,954 (54.2)	163 (45)	<0.001
Urben	7,642 (45.8)	964 (47.7)		8,407 (45.8)	199 (55)	
Siblings, *n* (%)						
No	4,897 (29.3)	632 (31.3)	0.071	5,411 (29.5)	118 (32.6)	0.217
Yes	11,806 (70.7)	1,388 (68.7)		12,950 (70.5)	244 (67.4)	
Maternal educational attainment, *n* (%)						
Middle school or under	4,999 (29.9)	604 (29.9)	0.195	5,499 (29.9)	104 (28.7)	0.063
High school	5,784 (34.6)	653 (32.3)		6,322 (34.4)	115 (31.8)	
College or above	5,920 (35.4)	763 (37.8)		6,540 (35.6)	143 (39.5)	
Parental educational attainment, *n* (%)						
Middle school or under	3,451 (20.7)	446 (22.1)	0.037	3,814 (20.8)	83 (22.9)	<0.001
High school	5,730 (34.3)	605 (30)		6,238 (34)	97 (26.8)	
College or above	7,522 (45)	969 (48)		8,309 (45.3)	182 (50.3)	
BMI, *n* (%)						
Normal weight	13,125 (78.8)	1,534 (76.3)	0.009	14,375 (78.6)	284 (78.5)	1.000
Overweight or obesity	3,521 (21.2)	477 (23.7)		3,920 (21.4)	78 (21.5)	
Smoking, *n* (%)						
No	14,776 (88.5)	1,685 (83.4)	<0.001	16,177 (88.1)	284 (78.5)	<0.001
Yes	1,927 (11.5)	335 (16.6)		2,184 (11.9)	78 (21.5)	
Drinking, *n* (%)						
No	13,656 (81.8)	1,500 (74.3)	<0.001	14,917 (81.2)	239 (66)	<0.001
Yes	3,047 (18.2)	520 (25.7)		3,444 (18.8)	123 (34)	
Sleep disorders, *n* (%)						
No	14,319 (85.7)	1,339 (66.3)	<0.001	15,476 (84.3)	182 (50.3)	<0.001
Yes	2,384 (14.3)	681 (33.7)		2,885 (15.7)	180 (49.7)	
Depression symptoms, *n* (%)						
No	15,895 (95.2)	1,579 (78.2)	<0.001	17,233 (93.9)	241 (66.6)	<0.001
Yes	808 (4.8)	441 (21.8)		1,128 (6.1)	121 (33.4)	

(Continued)

TABLE 1 (Continued)

Characteristics	Suicide ideation		*P*-value	Suicide attempt		*P*-value
	Never	Ever		Never	Ever	
Social support score, mean (SD)	67.9 (14.9)	59.9 (15.6)	<0.001	67.3 (15.1)	56.9 (15.7)	<0.001
MPATS- salience, mean (SD)	15.8 (5.3)	18 (5.7)	<0.001	16 (5.3)	18.8 (5.8)	<0.001
MPATS-withdrawal symptoms, mean (SD)	8.5 (3.3)	10.2 (3.8)	<0.001	8.6 (3.3)	10.6 (4)	<0.001
MPATS-social comfort, mean (SD)	7.4 (2.9)	8.8 (3.2)	<0.001	7.5 (3)	9.4 (3.2)	<0.001
MPATS-mood changes, mean (SD)	7 (2.8)	8.3 (3)	<0.001	7.1 (2.8)	8.9 (2.9)	<0.001
MPATS score, mean (SD)	38.8 (12.7)	45.3 (14)	<0.001	39.3 (13)	47.7 (14.2)	<0.001
Mobile phone addiction, *n* (%)						
No	12,134 (72.6)	1,036 (51.3)	<0.001	13,003 (70.8)	167 (46.1)	<0.001
Yes	4,569 (27.4)	984 (48.7)		5,358 (29.2)	195 (53.9)	

3 Results

Table 1 presents the baseline characteristics of the participants. Among 18,723 participants, the majority were Han nationality (97.0%), 65.9% were females, 29.5% were from one-child families, and 54.0% were rural residents. Overall, 2020 participants (10.8%) had a history of suicide ideation, and 362 participants (1.9%) had engaged in suicide attempt. We also observed that 5,553 participants (29.7%) met the criteria of mobile phone addiction (MPATS score ≥48), and the average MPATS score of all participants was 39.5 ± 13.0. The average scores for the four dimensions of withdrawal symptoms, salience, social comfort, and mood changes were 16.0 ± 5.4, 8.7 ± 3.4, 7.6 ± 3.0, and 7.1 ± 2.8, respectively.

The associations of mobile phone addiction with suicide ideation and suicide attempt are shown in Table 2. Among participants with mobile phone addiction, the rates of suicide ideation and suicide attempt were 17.7% and 3.5%, respectively. Mobile phone addiction was positively correlated with an increased risk of suicide ideation and suicide attempt. After adjusting for gender, grade, and race (Table 2, Model 2), mobile phone addiction was significantly related to increased odds of suicide ideation (OR, 2.51; 95% CI, 2.28–2.75) and suicide attempt (OR, 2.81; 95% CI, 2.28–3.47). Further adjusting for siblings, registered permanent residence, parental educational attainment, and health-related characteristics (smoking, drinking, BMI) (Table 2, Model 3), the ORs were reduced slightly. In fully adjusted model further adjusted for depressive symptoms, social support, and sleep disturbances (Table 2, Model 4), mobile phone addiction remained positively associated with suicidal ideation (OR, 1.70; 95% CI, 1.53–1.88) and suicide attempt (OR, 1.48; 95% CI, 1.18–1.86), despite a substantial decrease in ORs. Each five points increase in MPATS score was significantly associated with the higher odds of suicide ideation (OR, 1.12; 95% CI, 1.09–1.14) and suicide attempt (OR, 1.11; 95% CI, 1.06–1.15). Similar significant results were observed for each dimension of MPATS (Table 2).

Table 3 displays the findings of the gender-stratified analysis. In male participants, mobile phone addiction was associated with suicide ideation (OR, 1.70; 95% CI, 1.42–2.03), but was not statistically significant in relation to suicide attempt (OR, 1.29; 95% CI, 0.86–1.95). For female participants, mobile phone addiction was found positive correlated with risk of suicide ideation (OR, 1.69; 95% CI, 1.49–1.91) and suicide attempt (OR, 1.59; 95% CI, 1.21–2.1). The current study found no significant gender-specific differences in the relationships of mobile phone addiction with suicide ideation and suicide attempt were found in the present study (*P for interaction* > *0.05*). Moreover, the restricted cubic splines regression revealed a non-linear association between MPATS score and suicide ideation (*P for non-linearity* < 0.001; Figure 1), whereas a monotonically increasing risk of suicide attempt was found to be associated with increasing MPATS score (*P for non-linearity* = 0.420; Figure 2).

4 Discussion

The present study was conducted to investigate the associations of mobile phone addiction with suicide ideation and suicide attempt. Compared with college students without mobile phone addiction, those who engage in mobile phone addiction had significant increased odds of suicide ideation and suicide attempt.

4.1 Comparison with other studies

Mobile phone ownership has been increasing over the past decade, and the problematic mobile phone use has raised concerns about mobile phone addiction. A review across 24 countries identified that the prevalence of mobile phone addiction is increasing around the world from 2014 to 2020, and differs considerably by country (13). Prior studies (18, 36–38) have reported varied prevalence of mobile phone addiction from 14% to 48% among college students across different countries. In China, several studies have shown a comparatively high prevalence of mobile phone addiction among youths (13, 39). The present study conducted among six universities in Shannxi Province of China showed a 29.7% prevalence of mobile phone addiction, which was comparable to the majority of previous studies (39–42). For example, a survey from Anhui Province of China (43), reported a 29.8% rate of mobile phone addiction among college students.

TABLE 2 Associations of mobile phone addiction with suicide ideation and suicide attempt.

Models	OR (95% CI)	
	Suicide ideation	Suicide attempt
Mobile phone addiction		
Model 1	2.52 (2.30–2.77)	2.83 (2.30–3.50)
Model 2	2.51 (2.28–2.75)	2.81 (2.28–3.47)
Model 3	2.44 (2.22–2.68)	2.62 (2.13–3.24)
Model 4	1.70 (1.53–1.88)	1.48 (1.18–1.86)
MPATS score, per 5-unit increases		
Model 1	1.21 (1.19–1.23)	1.27 (1.22–1.32)
Model 2	1.21 (1.19–1.23)	1.27(1.22–1.32)
Model 3	1.20 (1.18–1.22)	1.25 (1.20–1.30)
Model 4	1.12 (1.09–1.14)	1.11 (1.06–1.15)
Withdrawal symptoms, per unit increases		
Model 1	1.08 (1.07–1.09)	1.10 (1.08–1.13)
Model 2	1.08 (1.07–1.09)	1.10 (1.08–1.13)
Model 3	1.08 (1.07–1.08)	1.09 (1.07–1.11)
Model 4	1.04 (1.03–1.05)	1.04 (1.01–1.06)
Salience, per unit increases		
Model 1	1.15 (1.13–1.16)	1.17 (1.13–1.20)
Model 2	1.15 (1.13–1.16)	1.17 (1.13–1.20)
Model 3	1.14 (1.13–1.16)	1.16 (1.12–1.19)
Model 4	1.08 (1.07–1.10)	1.06 (1.02–1.09)
Social comfort, per unit increases		
Model 1	1.16 (1.15–1.18)	1.21 (1.17–1.25)
Model 2	1.16 (1.15–1.18)	1.21 (1.17–1.25)
Model 3	1.16 (1.14–1.18)	1.20 (1.16–1.24)
Model 4	1.10 (1.08–1.12)	1.10 (1.06–1.14)
Mood changes, per unit increases		
Model 1	1.17 (1.15–1.19)	1.24 (1.19–1.28)
Model 2	1.17 (1.15–1.19)	1.23 (1.19–1.28)
Model 3	1.16 (1.14–1.18)	1.22 (1.17–1.26)
Model 4	1.09 (1.07–1.11)	1.10 (1.06–1.14)

Model 1, crude model.
Model 2, adjustment for gender, grade, and race.
Model 3, adjustment for gender, grade, race, registered permanent residence, siblings, maternal educational attainment, paternal educational attainment, BMI, smoking, and drinking.
Model 4, adjustment for gender, grade, race, registered permanent residence, siblings, maternal educational attainment, paternal educational attainment, BMI, smoking, drinking, sleep disorders, depressive symptoms, and social support.

Geng et al. (44) also presented a 23.5% prevalence of mobile phone addiction in medical college students in China. However, it is lower than the study from Lei et al. (16), which showed a 40.6% prevalence of mobile phone addiction among 574 medical students in a public medical university. The variation in the prevalence of mobile phone addiction among different studies could be related to the study population, the assessment tool, and the location of the survey. In this study, the population was comprised of students from six universities, covering different majors and grades, and it may have overcome the limitations of the representative sample population in prior studies performed at only one university or only from specific majors. As relevant research is limited at present, there is a need for further research in a nationally representative population.

Given the comparatively high prevalence of mobile phone addiction among students, it is necessary to know about the impact of mobile phone addiction on suicide of current college students, especially among iGens who grow up with the surroundings of mobile phones. To our best knowledge, only five studies have examined the associations of mobile phone addiction with suicide, but conclusions are not entirely consistent. Four studies indicated a positive association between mobile phone addiction and suicide ideation or suicide attempt (25–28), while one study found no relationship of mobile phone addiction and suicide (29). Some other studies suggest that the length of mobile phone use is linked to suicide. For example, Zhang et al. (45) found that longer duration of mobile phone use predicted suicide behaviors in Chinese adolescents. Huang et al. (29) also reported that students with suicide ideation may have longer mobile phone use time. The findings in our survey were consistent with majority of previous studies, which suggested that students with mobile phone addiction had significant higher prevalence of suicide, extending the limited available evidence on the association between mobile phone addiction and increased odds of suicide in iGens. Thus, our study is important for considering the significant role of mobile phone addiction when developing suicide prevention programs for college students.

To our knowledge, no study has examined gender differences in the association between mobile phone addiction and suicide. While most previous studies have suggested that women may demonstrate distinct patterns when confronting mental health issues, this study did not uncover substantial gender disparities in the prevalence of suicide ideation and suicide attempt. Furthermore, there was no significant gender-smartphone interaction on the likelihood of suicide ideation and suicide attempt identified in this study. These findings indirectly reflect the importance of giving equal consideration to different genders in future interventions related to mobile phone usage. Moreover, our study may be the first study to evaluate the dose-response relationship of mobile phone addiction with suicide ideation and suicide attempt. We found a non-linear association between mobile phone addiction score and suicide ideation, and a monotonically increasing relationship between mobile phone addiction score and suicide attempt. However, because the related study is still limited so far, further longitudinal investigations or intervention studies on the association between mobile phone addiction and suicide ideation/attempt are warranted.

4.2 Possible explanations of the association

Suicide is a complex social phenomenon, which is generated by the interaction of biological, psychological, and social perspectives factors. The exact mechanism underlying its association with mobile phone addiction is complex and unclear. The Integrated Motivation-Volition Model of Suicidal Behavior (IMV) proposed that suicide develops through pre-motivational phase (the

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TABLE 3 Associations of mobile phone addiction with suicide ideation and suicide attempt, stratified by gender.

Mobile phone addiction	Suicide ideation		*P* for interaction	Suicide attempt		*P* for interaction
	Male	Female		Male	Female	
Mobile phone addiction	1.70 (1.42–2.03)	1.69 (1.49–1.91)	0.841	1.29 (0.86–1.95)	1.59 (1.21–2.10)	0.441
MPATS score, per 5-unit increases	1.11 (1.07–1.14)	1.12 (1.09–1.15)	0.563	1.08 (1.00–1.16)	1.12 (1.06–1.18)	0.485
Salience, per unit increases	1.04 (1.02–1.05)	1.04 (1.03–1.06)	0.472	1.02 (0.99–1.06)	1.04 (1.02–1.07)	0.524
Withdrawal symptoms, per unit increases	1.08 (1.05–1.11)	1.08 (1.06–1.10)	0.976	1.05 (0.99–1.11)	1.06 (1.02–1.10)	0.768
Social comfort, per unit increases	1.11 (1.08–1.14)	1.09 (1.07–1.12)	0.512	1.09 (1.02–1.16)	1.11 (1.06–1.16)	0.562
Mood changes, per unit increases	1.09 (1.06–1.12)	1.09 (1.07–1.11)	0.910	1.09 (1.02–1.17)	1.11 (1.06–1.16)	0.801

Adjusted for gender, grade, race, registered permanent residence, siblings, maternal educational attainment, paternal educational attainment, BMI, smoking, drinking, sleep disorders, depressive symptoms, and social support.

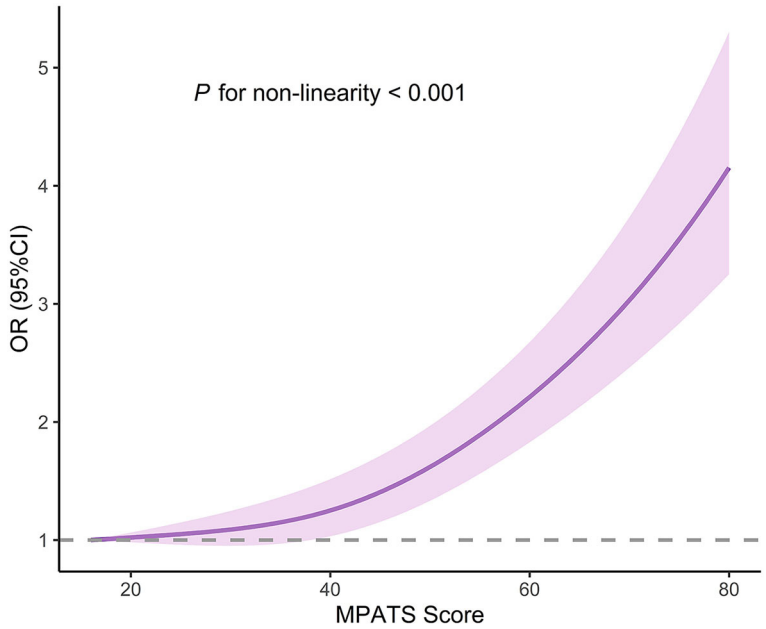

FIGURE 1
Restricted cubic splines regression analysis of MPATS score with suicide ideation risk. OR, odds ratio; CI, confidence interval. The analysis was adjusted for gender, grade, race, registered permanent residence, siblings, parental educational attainment, BMI, smoking, drinking, sleep disorder, depressive symptoms, and social support.

transitions from the defeat/humiliation stage to entrapment), the motivational phase (from entrapment to ideation/intent), and the volitional phase (from ideation/intent to behavior) (22). Whether an individual will act on their suicidal ideation/intent is determined by a range of factors, labeled volitional moderators. Impulsivity, having the capability to attempt suicide, knowing others who engage in suicide, and having access to the means of suicide are examples of volitional moderators. According to IMV, on the one hand, students who are addicted to mobile phones may be more likely to access suicide-related information and learn about suicide tactics, and thus more likely to imitate and commit suicide. On the other hand, mobile phone addiction can lead to depersonalization, affecting the normal social functioning of adolescents and reducing emotions such as alertness and fear. Ultimately, it tends to produce impulse inhibition disorder, which can increase the risk of suicide. Furthermore, previous studies have identified depression and sleep as mediating variables between mobile phone addiction and suicide. For example, Zhang et al. (45) found the link between mobile phone use and suicide was partially mediated by depressive symptoms. In the present study, we also found that students with suicide ideation or attempt had more depression and bad sleep quality. Nevertheless, the associations of mobile phone addiction with suicide ideation and suicide attempt were still significant after additional adjustments for depression and sleep quality, indicating the independent effect of mobile phone addiction on the risk of suicide.

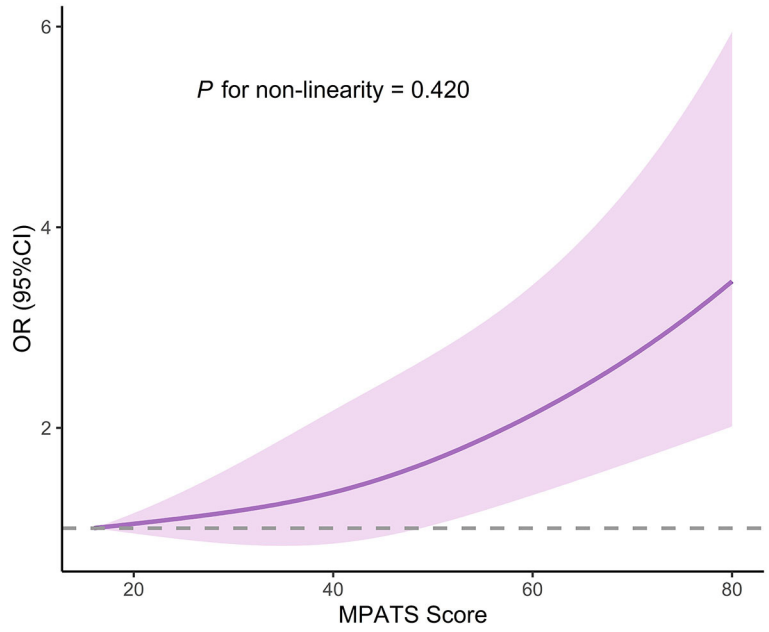

FIGURE 2
Restricted cubic splines regression analysis of MPATS score with suicide attempt risk. OR, odds ratio; CI, confidence interval. The analysis was adjusted for gender, grade, race, registered permanent residence, siblings, parental educational attainment, BMI, smoking, drinking, sleep disorder, depressive symptoms, and social support.

Internet addiction and mobile phone addiction are both technology addiction, which refers to behavior addictions that associated with the excessive and uncontrolled use of technology, with similar characteristics and formation mechanisms (46). Previous research on internet addiction may provide evidence of the link between mobile phone addiction and suicide. First, it is widely accepted that the hypothalamic-pituitary-adrenal (HPA) axis dysregulation is the important pathophysiology mechanism for suicide. 5-HT is a key neurotransmitter of HPA (47), and its reduction is believed to be associated with suicide. Cerniglia et al. (48) have shown that the decrease of 5-HT is also related to the dysfunction of the prefrontal cortex caused by internet addiction. Hence, 5-HT may also be responsible for the association between mobile phone addiction and suicide. Second, changes in brain structure and function may be the neurobiological mechanisms between mobile phone addiction and suicide. Research have showed that people with internet addiction are prone to abnormal changes in the structure as well as function of the gray and white matter in the prefrontal lobe of the brain (49, 50). In addition, several studies have highlighted that the prefrontal lobe also plays an important role in suicide (51, 52), which may indirectly confirm the results of this study. However, to understand the detailed mechanisms underlying the relationship of mobile phone addiction with suicide ideation and suicide attempt, more cohort or intervention studies are needed.

4.3 Limitations

This study has some limitations. First, the collection of suicide ideation, suicide attempt, and mobile phone addiction information through a self-report questionnaire may result in recall bias. Second, although most of the available important covariates were included in this study, some residual or unmeasured confounding parameters may had an impact on the results. Last, the cross-sectional study design limits the causal inferences of this study.

5 Conclusions

The findings of our study suggest that mobile phone addiction is associated with increased risk of suicide ideation and suicide attempt. Mobile phone addiction should thus be considered in intervention programs for the aim of reducing the rate of suicide, especially among iGens.

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 the Second Affiliated Hospital of Xi'an Jiaotong University. 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. Written informed consent was obtained from the individual(s), and minor(s)' legal guardian/next of kin, for the publication of any potentially identifiable images or data included in this article.

Author contributions

WW: Data curation, Formal analysis, Investigation, Project administration, Writing – original draft, Writing – review & editing. MW: Writing – original draft, Writing – review & editing. ZZ: Methodology, Project administration, Supervision, Validation, Writing – review & editing. LM: Writing-review & editing, Methodology, Supervision, Validation, and Visualization. LZ: Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing, Conceptualization. HL: Methodology, Supervision, Writing – review & editing, Conceptualization, Project administration, Validation, Visualization.

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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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Mobile phone addiction and insomnia among college students in China during the COVID-19 pandemic: a moderated mediation model

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Background: Nowadays, it is widely acknowledged that mobile phone addiction is a risky factor for insomnia symptoms, but to date, people know little about the underlying relationship between them among undergraduates during the COVID-19 pandemic. The purpose of the present study was to examine the potential association between mobile phone addiction and insomnia, as well as the mediating role of social anxiety and the moderating role of physical activity.

Methods: Using the Mobile Phone Addiction Tendency Scale, Social Phobia Inventory, Physical Activity Rating Scale and Insomnia Severity Index, 301 eligible college students in China were investigated. For data analysis, descriptive analysis, correlation analysis, moderating effect test, moderating effect test were carried out in turn.

Results: The findings revealed a favorable correlation between mobile phone addiction, social anxiety and insomnia, as well as between social anxiety and insomnia. But physical activity was negatively correlated with social anxiety and mobile phone addiction, and social anxiety partially mediated the relationship between mobile phone addiction and insomnia. Additionally, physical activity played a significant moderating effect between mobile phone addiction and social anxiety.

Conclusion: This study advances the knowledge of how mobile phone addiction raises the likelihood of experiencing insomnia symptoms, and also implies that upping physical activity level could lessen the harmful impacts from mobile phone addiction.

KEYWORDS

mobile phone addiction, insomnia, social anxiety, physical activity, moderated mediation model, college students, the COVID-19 pandemic

Introduction

Except for posing a serious threat to individual lives and respiratory function, the outbreak of novel coronavirus pneumonia (COVID-19) in late December 2019, has been also strongly linked to psychological and behavioral issues, such as depression, anxiety, and suicidal thoughts (1–3). Given that, the Chinese government implemented emergent measures to stop

the spread of the COVID-19 pandemic due to the acute and contagious nature of this outbreak, including early isolation of confirmed or suspected cases, closure of schools and public transportation (4). While these emergent public health measures are highly necessary for reducing interpersonal transmission of COVID-19, there are still some possible reasons for concern as they may further lead to social isolation and other negative healthy outcomes (5). Researchers believe that there is a large number of potentials for using social media (e.g., mobile phones) during an epidemic lockdown, and that digital technology could be an effective way to alleviate public health needs and also provide social support (6), since it may be used online to communicate, access, learn, and receive the most lately information about the outbreak instead of face-to-face conversation (7).

Despite these latent benefits, it should be also kept in mind that excessive mobile phone use could produce lots of undesirable effects, especially the mobile phone addiction. As well all know, insomnia symptoms have been regarded as one of the main adverse outcomes generated by mobile phone addiction, with a series of cross-sectional studies showing that insomnia would be largely deteriorated with the escalation of mobile phone usage frequency (8–10). The longitudinal study has also demonstrated that problematic mobile phone use at baseline was a risky factor for adverse effects on students' sleep and mental health, such as insomnia and depression during an 8 months follow-up survey (11).

However, at present, the key issue cannot be ignored by us would be that the underlying association between mobile phone addiction and insomnia among college students in the context of this emerging coronary pneumonia pandemic is poorly understood, because prior studies have mostly focused on the impact of mobile phone addiction on adolescents' mental health. What's worse, up till now, the probable mechanism in the relationship between mobile phone addiction and insomnia are still unknown for us. Given that, the current study attempts to built a moderated mediation model to evaluate the mediating role of social anxiety between mobile phone addiction and insomnia, and the moderating role of physical activity between mobile phone addiction and social anxiety among Chinese college students, so as to provide objective and persuasive answers for these concerns.

The mediating role of social anxiety

Social anxiety refers to strong feelings of worry, unease, or fear in response to certain interpersonal situations (12), and numerous research has documented that social anxiety predicts depression and perceived stress in a positive way (13, 14). In turn, depression and stress perception would cause serious insomnia symptoms (15, 16). In addition, a study conducted by Buckner et al. found that social anxiety was significantly and unfavorably correlated with scores on measures of sleep-related dysfunction in American undergraduate students (17).

It can be obviously seen that social anxiety could be obviously influenced by mobile phone addiction. According to Clark and Wells' cognitive model of social anxiety, persons with poor cognition and low self-esteem will be more prone to produce social anxiety (18). However, it has been discovered that mobile phone addiction may be strongly linked to cognitive dysfunction (19), and long-term and continuous exposure to electromagnetic radiation could also lower individuals' working memory capacity and impair their attentional control, which in turn raises the risk of cognitive impairment (20). These findings suggest that using mobile phones excessively may not only result in cognitive impairment, but also evidently increase social anxiety. Therefore, based on the theoretical and empirical findings mentioned above, it is plausible to assume that mobile phone addiction could affect social anxiety. Given that, mobile phone addiction may lead to social anxiety, which then produces insomnia symptoms. Thus, the present study reasonably assumes that (H1): social anxiety possibly mediates the relationship between mobile phone addiction and insomnia.

The moderating effect of physical activity

Actually, not all college students may be similarly impacted by mobile phone addiction, despite the fact that it could easily cause social anxiety and insomnia. However, it is also crucial to examine that whether other factors acting as a moderator influence the relationship between mobile phone addiction and insomnia which is mediated by the effect of social anxiety. Given that, the current study investigated whether a person's amount of physical activity could affect the direct impact of mobile phone addiction on social anxiety. No doubt, physical activity has been widely defined as a variety of physical exercise forms that are planned and structured by the individuals, contracted by skeletal muscles, and usually caused manifest energy loss, with a strong subjective and directional nature (21). The previous work has shown that physical activity could improve levels of self-esteem associated with fear of negative evaluation (a core feature of social anxiety) (22, 23). Furthermore, social anxiety can be effectively improved by participating in an 8-week moderate-intensity aerobic exercise program, and this positive and desirable effect is more likely to happen to those guys with high levels of social anxiety (24). And several studies have also demonstrated that actively engaging in physical activity might lessen the detrimental consequences from addictive behaviors on people's physical and mental health. For instance, Tao et al. (25) discovered that physical activity could mediate the association between mobile phone addiction and sadness, with the association being higher for individuals with lower physical activity.

Therefore, in accordance with those persuasive and reliable evidence, it can be naturally inferred that physical activity would potentially contribute to the relationship between mobile phone addiction and its negative effects by mitigating risk (e.g., social anxiety). That is, physical activity could influence the link between mobile phone addiction and social anxiety in a large degree. Given that, the present study assumes that (H2): physical activity may play a moderating role in the relationship between mobile phone addiction and social anxiety.

The moderated mediation model

In summary, in the light of those analyses mentioned above, the purpose of this study was to testify the latent mechanism that underlies the correlation between mobile phone addiction and insomnia among college students. In other words, the current work developed a moderated mediation model to address two issues: (a) social anxiety could or not mediate the association between mobile phone addiction and insomnia, and (b) whether physical activity

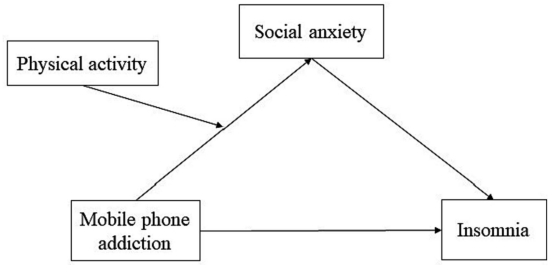

FIGURE 1
The hypothesized model between mobile phone addiction and insomnia.

could moderate the relationship between mobile phone addiction and social anxiety. The below moderated mediation model in this study (Figure 1) can be used to properly explain how mobile phone addiction affects insomnia, and how to moderate the relationship between mobile phone addiction and social anxiety by physical activity.

Methods

Procedures and participants

Given the emergence of a new crown epidemic at that hard time and the drawbacks from interpersonal social interaction, this cross-sectional study with an online questionnaire was finally completed by us in the middle of January 2022; and then, a convenient sampling was conducted in Shandong University, a comprehensive university affiliated with the Ministry of the Education in China, which has 55 colleges covering thirteen broad disciplines, including philosophy, economics, law, education, literature, history, science, engineering, agriculture, medicine, management, military science, and art. At last, 301 eligible college students with the mean age of 20.47 (SD = 4.99) were luckily chosen and then successfully filled out their online questionnaires. Before completing that, they were also informed and highlighted that this online survey was totally anonymous and voluntary, and they need to sign the informed consent first. To confirm the accuracy and validity of the data, the researchers seriously and carefully checked each questionnaire's completed data after it had been filled out for internal logic and consistency.

The present work involving human participants was carried out in accordance with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards, and also reviewed and approved by the research ethics committee at South China University of Technology. And all participants had provided their online informed consent before formally engaging in this survey.

Measures

Study design

This cross-sectional study aimed to explore the relationships among mobile phone addiction, social anxiety, insomnia, and physical activity among college students during the COVID-19 pandemic.

Mobile phone addiction

The degree of mobile phone addiction among college students was assessed using the Chinese version of the Mobile Phone Addiction Tendency Scale (MPATS), originally developed by Xiong et al. (26). The scale has 16 items in four dimensions. College students rated each item on a 5-point-Likert scale, ranging from 1 (very non-compliant) to 5 (very compliant). There were no reverse scoring items, and the total score was determined by adding up the scores from the 16 items. Higher score would indicate a higher likelihood of mobile phone addiction. This measure has been widely used in Chinese university populations and has shown good reliability and validity (27). For the current study, the test showed good reliability (Cronbach's $\alpha = 0.884$).

Social anxiety

Social anxiety among college students was assessed using the Chinese version of the Social Phobia Inventory (SPIN) (28). The scale has 17 items in three aspects. Participants rated each item on a 5-point-Likert scale ranging from 0 (not at all) to 4 (extremely), with higher score indicating more severe social anxiety symptoms. This measure has been widely used in Chinese university populations and has shown good reliability and validity (29). The Cronbach's alpha coefficient of this scale displayed good reliability in the current study (Cronbach's $\alpha = 0.934$).

Physical activity

Physical activity levels were assessed using the Physical Activity Rating Scale (PARS-3) (30). This scale has 3 items (intensity, time, and frequency), and the amount of physical activity was calculated by the following formula: "exercise intensity × (exercise duration − 1) × exercise frequency." The total scores of physical activity amount were from 0 to 100. This measure has been widely used in the Chinese university populations and has shown good reliability and validity (31, 32). The internal consistency of the PARS-3 in this study was generally satisfactory, with the Cronbach's alpha coefficient of 0.702.

Insomnia

Insomnia symptoms were assessed by the Insomnia Severity Index (ISI) (33), a scale that has been validated in Chinese youth populations and totally meets psychometric requirements (34). Each item of the ISI was rated on a 5-point-Likert scale (0 = none, 4 = very severe), and responses to the seven items were summed to obtain the total score of ISI, with higher scores indicating higher levels of insomnia symptoms. In the present study, the Cronbach's alpha coefficient for ISI was 0.715.

Demographic variables

Except the four main variables mentioned above, the current study also investigated several demographic indicators about the participants, including age, gender, grade, place of residence,

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TABLE 1 General characteristics of participants.

Variables	Categories	*n*	%
Gender	Male	174	57.8
	Female	127	42.2
Grade	Freshman	38	12.6
	Sophomore	69	22.9
	Junior	90	29.9
	Senior	85	28.2
	Postgraduate	19	6.4
Place of residence	Rural	73	24.3
	Urban	228	75.7
Self-evaluation of academic performance	Poor	39	13.0
	Average	180	57.8
	Good	82	27.2
Daily sleep time	≤6 h	25	8.3
	6–8 h	239	79.4
	≥8 h	37	12.3

self-evaluation of academic performance, and daily sleep time by using a standard form.

Statistical analysis

All statistical analyses were performed using SPSS 26.0 software. Continuous variables were presented as mean and standard deviation (M ± SD), and categorical variables displayed as frequency (*n*) and percentage (%). If the continuous variable does not conform to the normal distribution, the normality transformation would be adopted by processing the root number. In this study, we first analyzed the general characteristics of participants. Secondly, preliminary analyses were performed to explore the potential correlation between mobile phone addiction, social anxiety, physical activity, and insomnia. The third step was to examine the mediating role of social anxiety between mobile phone addiction and insomnia through the SPSS macro-PROCESS model 4, and likewise, SPSS macro-PROCESS model 7 was utilized to assess the moderating role of physical activity between mobile phone addiction and social anxiety. In this work, 5,000 bootstrapped samples were drawn from the data, and 95% bootstrap upper and lower confidence intervals (CI) were also calculated. Before testing the mediating and moderating effect, the four main variables were all centralized in advance, and as the control variable, gender and grade was all put into the measurement model. The significance level in the present study was set at alpha = 0.05.

Results

Common method bias

Due to the use of self-report scales for all variables in this study, there is a potential for common method bias. To examine whether such bias exists, the data underwent a Harman's single-factor test for homogeneity of variances. The first factor, without rotation, contributed 34.98% to the total loading, which is below the 40% threshold. This suggests that there is no significant common method bias in this study.

Demographic variables

As shown in Table 1, the sample for this study consisted of 301 college students, which comprises 174 male (57.8%) students and 127 female (42.2%) students. Of them, 73 students (24.3%) were from rural areas and 228 students (75.7%) from urban areas, and they were also distributed in five grades, namely freshmen (12.6%), sophomore (22.9%), junior (29.9%), senior (28.2%), and postgraduate (6.4%). In terms of academic performance, 39 students (13.0%) considered their academic performance poor, 180 students (57.8%) considered their academic performance average, and 82 students (27.2%) considered their academic performance good. About daily sleep time, 25 students (8.3%) were less than 6 h per day, 239 students (79.4%) were from 6 to 8 h per day, and 37 students (12.3%) were more than 8 h per day.

Preliminary analyses

Descriptive statistics and correlation analysis for mobile phone addiction, social anxiety, physical activity, and insomnia are shown in Table 2. Due to the variable of physical activity was not satisfactory with normal distribution, so the corresponding normality transformation had been firstly performed on it. The results showed that mobile phone addiction was positively correlated with social anxiety ($p < 0.01$) and insomnia ($p < 0.01$), and social anxiety was positively correlated with insomnia ($p < 0.01$). Physical activity was negatively correlated with social anxiety ($p < 0.05$) and mobile phone addiction ($p < 0.05$), and there was no statistically significance between physical activity and insomnia ($p > 0.05$).

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TABLE 2 Descriptive statistics and correlation analysis for main variables.

Variables	M	SD	1	2	3	4
1. Mobile phone addiction	48.15	10.86	–			
2. Social anxiety	40.07	12.89	0.32**	–		
3. Physical activity	3.47	1.40	−0.12*	−0.12*	–	
4. Insomnia	18.91	5.32	0.25**	0.21**	−0.03	–

M, mean; SD, standard deviation. *$p < 0.05$ and **$p < 0.01$.

TABLE 3 Testing the mediating effect of social anxiety between mobile phone addiction and insomnia.

Outcome variable	Predictors	R^2	F	β	LLCI	ULCI	t
Insomnia	Gender	0.07	7.71***	−0.06	−0.21	0.06	−1.11
	Grade			−0.05	−0.08	0.02	−1.01
	Mobile phone addiction			0.25	0.11	0.29	4.59***
Social Anxiety	Gender	0.12	13.88***	−0.10	−0.44	−0.00	−2.00
	Grade			0.03	−0.05	0.12	0.72
	Mobile phone addiction			0.32	0.28	0.55	5.98***
Insomnia	Gender	0.09	7.46***	−0.04	0.04	−0.08	−0.82
	Grade			−0.06	−0.08	0.02	−1.12
	Mobile phone addiction			0.20	0.07	0.25	3.55***
	Social Anxiety			0.14	0.01	0.16	2.51**

β, standardized regression coefficient; LLCI, lower level CI; ULCI, upper level CI. **$p < 0.01$ and ***$p < 0.001$.

TABLE 4 Testing the moderating effect of physical activity between mobile phone addiction and social anxiety.

Outcome variable	Predictors	R^2	F	β	LLCI	ULCI	t
Social anxiety	Gender	0.15	10.51***	−0.28	−0.05	−0.06	−2.55*
	Grade			0.01	−0.07	0.10	0.04
	Mobile phone addiction			0.41	0.27	0.55	5.94***
	Physical activity			−0.05	−0.09	−0.00	−2.21*
	Mobile phone addiction × physical activity			−0.05	−0.10	−0.01	−2.38*
				β	Boot SE	Boot LLCI	Boot ULCI
Conditional direct effect analysis at three kinds of moderator values = M ± 1SD							
M − 1SD (1.07)				0.55***	0.09	0.36	0.73
M (3.47)				0.41***	0.07	0.27	0.55
M + 1SD (5.87)				0.27***	0.08	0.10	0.44

M, mean; SD, standard deviation; β, standardized regression coefficient; LLCI, lower level CI; ULCI, upper level CI. *$p < 0.05$ and ***$p < 0.001$.

Mediating effect test

As shown in Table 3, after controlling for gender and grade, mobile phone addiction was positively correlated with social anxiety ($\beta = 0.32$, $p < 0.001$), and social anxiety was also positively associated with insomnia ($\beta = 0.14$, $p < 0.01$). The total effect between mobile phone addiction and insomnia was significant ($\beta = 0.25$, $p < 0.001$), and meanwhile, the indirect effect between them was also remarkably significant (indirect effect = 0.03, SE = 0.01, 95% Boot CI = 0.01–0.06), suggesting that social anxiety could partially mediate the correlation between mobile phone addiction and insomnia. Thus, it can be clearly seen that social anxiety played a mediating role in the relationship of mobile phone addiction on insomnia.

Moderating effect test

As shown in Table 4, a significant direct effect of mobile phone addiction on social anxiety was observed after controlling for gender and grade ($\beta = 0.41$, $p < 0.001$), and this effect was obviously moderated by physical activity ($\beta = -0.05$, $p < 0.05$). The results of the conditional direct effects analyses were depicted in Figure 2, which shows the

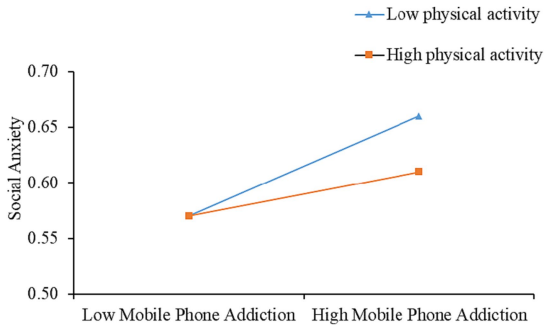

FIGURE 2
Physical activity as a moderator between mobile phone addiction and social anxiety.

relationship between mobile phone addiction and social anxiety at low and high levels of physical activity, namely the mean below 1SD or above 1SD, respectively. Likewise, a simple slope test also displayed that physical activity had a moderating effect on the impact of mobile phone addiction on social anxiety, and compared to the high physical activity, that was evidently stronger for college students with low levels of physical activity.

Discussion

The present study focused on the potential correlation between mobile phone addiction and insomnia, and the mediating effect of social anxiety and the moderating effect of physical activity possibly between them among college students in China. The final results demonstrated that mobile phone addiction was positively associated with insomnia, which is consistent with preceding research (9, 10). Additionally, social anxiety was also positively correlated with mobile phone addiction and insomnia, respectively, and meanwhile, social anxiety could mediate the relationship between them. Therefore, the hypothesis 1 (H1) of the current work has been fairly proved. This finding can be explained via the cognitive-behavioral model of social anxiety, which points out that individuals' early traumatic experiences would result in the development of unfavorable irrational beliefs and self-perceptions, as well as additional unfavorable cognitive processing biases, which might easily lead to emotional (such as anxiety) and behavioral (such as daytime sleepiness) issues (35). The cognitive model of insomnia maintenance also proposes that anxiety situations induce people to selectively pay attention to and monitor internal and external threat cues closely correlated with sleep, which would largely exacerbate the insomnia symptoms (36). But it is worth noting that social anxiety could only partially account for the relationship between mobile phone addiction and insomnia; thus other key latent indicators, such as interpersonal distress, should also considered when examining the mediation role between them afterwards.

Apart from the overall analyses, no doubt, the two essential processes of this mediating effect between mobile phone addiction and insomnia have been also equally noteworthy. On the one hand, in the first stage of this mediation, it can be easily found that college students with higher degree of mobile phone addiction also had more awfully social anxiety, which is in line with previous research findings (37, 38) and suggests that mobile phone addiction is an important risky factor for social anxiety. The previous research has also indicated that those severely addicted to mobile phones had poor interpersonal relationship and social communication skills in general, which might worsen their social anxiety and then cause an obvious decline in their interpersonal communicating skills in the real world, as well as eventually resulting in social anxiety (39). On the other hand, for the second stage of the mediation, it was not hard to find that college students with higher level of social anxiety would be more prone to produce insomnia, which is consistent with prior studies (40, 41). One possible explanation might be that higher level of social anxiety can lead to emotional distress and impairments in various functional domains (17), including depression and negative peer relationships (35, 42). Likewise, the previous research has also shown that depression and poor interpersonal relationships are important factors to predict insomnia (42, 43). Consequently, individuals with higher level of social anxiety may have significant symptoms of insomnia. Undoubtedly, all these evidence from the previous work persuasively support the mediating role of social anxiety played in the relationship between mobile phone addiction and insomnia.

At the same time, this research has also found that physical activity was inversely correlated with mobile phone addiction and social anxiety, respectively, and meanwhile, physical activity could significantly moderate the relation between them. Thus, the hypothesis 2 (H2) of the present study has been fairly proved, too. According to this finding, it can be properly inferred that mobile phone addiction does not always result in the same degree of behavioral issues, such as social anxiety, and that some healthy habits or lifestyles including the active participation with physical activity, may help persons to effectively lessen the negative impacts from mobile phone addiction. The following factors, in particular, could be utilized to interpret how does physical activity moderate the association between mobile phone addiction and social anxiety.

Firstly, engaging in physical activity could help people manage their negative emotions, such as loneliness and stress, and also enhance their psychological capital in terms of their mental health (44, 45). However, emotional issues, such as the symptoms of loneliness and stress, might contribute to generate recurrent social anxiety (46, 47). That is, compared to addictive individuals with low and even no physical activity level, those frequently engaging in physical activity and acquiring the higher level of physical activity, would be more likely to possess desirable mental health and great psychological capital, and as a result, the harmful impacts from mobile phone addiction might be considerably decreased for them. Secondly, actively participating in physical activity helps the person build "intrinsic assets" and "extrinsic resources," such as self-efficacy, self-esteem, parental support, and the good peer relationships (48, 49); and actually, these advantages have all been demonstrated to form defense mechanisms against mobile phone addiction (50, 51). According to the protective model of resilience (52), people can lessen or minimize the impact of risky exposure on adverse outcomes by increasing their assets (e.g., self-esteem) and resources (e.g., parental support); accurately speaking, when individuals are exposed to risky settings or conditions, they may still have the ability to show positive performance against these

adverse situations. It is no denying that physical activity would be a feasible and reliable means to help human beings obtain this so-called resilience. Therefore, as for those addicted to mobile phones, acquiring the higher level of physical activity may be the most likely to prevent, resist or avoid the passive effects from mobile phone addiction.

Limitations and future directions

It is crucial to underscore several limitations inherent in the present study, which need to be taken into account in coming days. Firstly, the utilization of a cross-sectional design employed in our study precludes the establishment of causal relationships. Therefore, to enhance the robustness of our findings, a longitudinal design and experimental protocols could be implemented. Secondly, the data for this study had to be collected online due to social restrictions during the COVID-19 period, leading to the exclusion of college students without internet access. Therefore, the experimental study could be conducted to objectively acquire relevant data in coming days, such as physical activity, and mobile phone addiction (53). Thirdly, relying on self-reported data introduces the potential for recall bias. To mitigate this limitation, future research could gain advantages from incorporating objective and effective instruments. For example, utilizing tools such as 3D-sensor pedometers, ActiGraph GT3X + accelerometers, and artificial sport bracelets could improve the accuracy and reliability of data, especially in the measurement of physical activity. Fourthly, the exclusive concentration on college students during a specific period of the new coronavirus pandemic raises concerns regarding the generalizability of our results to other populations or normal conditions. This necessitates additional external validation to confirm the external validity of the current study. Additionally, employing convenient sampling led to a moderate sample size. To enhance the methodological rigor of the study, future research should consider adopting probability sampling methods and larger sample sizes. Lastly, while our study centered on social anxiety, future researchers may explore analogous latent variables related to mobile phone addiction and insomnia as potential mediators. This approach would contribute to a more thorough understanding of the underlying mechanisms between these variables.

Implications

Regardless of those drawbacks mentioned above, the current study has also made some original contributions and a number of significant practicable implications. To our knowledge, this work is the first one to examine how social anxiety mediates the relationship of mobile phone addiction and insomnia, and the moderating effect of physical activity between mobile phone addiction and social anxiety, which has largely expanded the previous research. According to the analyses regarding the moderated mediation model, the potential mechanism, namely how mobile phone addiction affects insomnia among college students, has been perfectly disclosed and clearly told us that how does mobile phone addiction cause insomnia symptoms, and the feasible way to lessen the connection between mobile phone addiction and social anxiety. More important, based on these important findings, several essential practicable meanings of this study can be naturally concluded. First and foremost, aiming to make college students aware of the detrimental effects of mobile phone addiction on insomnia symptoms, parents and teachers should emphasize the latent correlation between mobile phone addiction and insomnia. Furthermore, given that social anxiety plays a pivotal mediating role between mobile phone addiction and insomnia, parents and teachers should employ practical approaches to assist students in acquiring effective strategies for managing their social anxiety in daily life. This may include engaging in communication dialogues, providing emotional support, and implementing dynamic cognitive-behavioral psychotherapy (54). Lastly, considering that physical activity has the potential to alleviate the adverse impact of mobile phone addiction on social anxiety, and higher levels of physical activity may be more beneficial in moderating social anxiety. Hence, college students should proactively engage in various exercise programs on campus. Simultaneously, they should strive to enhance their physical activity levels by increasing exercise intensity or frequency. Additionally, consistent with prior research, it is advisable to integrate additional motivational learning tasks into routine physical education content. This approach can effectively boost college students' motivation to embrace healthy behaviors (55), thereby enhancing their physical activity levels and alleviating the negative repercussions of mobile phone addiction.

Conclusion

The current study reveals the mechanism of association between smartphone addiction and insomnia. Our research found that smartphone addiction among college students is significantly positively correlated with social anxiety and insomnia, and significantly negatively correlated with physical activity. Social anxiety plays a mediating role to some extent in the relationship between smartphone addiction and insomnia. Furthermore, physical exercise plays a significant moderating role between smartphone addiction, social anxiety, and insomnia. In summary, our research results indicate that increasing physical activity and reducing social anxiety can improve insomnia symptoms among college students. To prevent future problematic behaviors among college students, it is necessary to adopt proactive health behaviors, such as engaging in physical activity, to counteract or avoid subsequent passive impacts.

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 authors.

Ethics statement

The studies involving humans were approved by South China University of Technology. 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

JW: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. XX: Conceptualization, Methodology, Writing – review & editing. LZ: Investigation, Writing – review & editing. HW: Conceptualization, Data curation, Writing – review & editing. GY: Conceptualization, Methodology, Supervision, Writing – review & editing.

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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.

Publisher's note

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The relationship between fear of missing out and mobile phone addiction among college students: the mediating role of depression and the moderating role of loneliness

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Background: Mobile phone addiction has adverse influences on the physical and mental health of college students. However, few studies shed light on the effect of fear of missing out on mobile phone addiction and the underlying mechanisms among college students.

Methods: To explore their associations, the present study used the Fear of Missing Out Scales (FoMOS), Loneliness Scale (USL-8), Mobile Phone Addiction Index Scale (MPAI), and Depression-Anxiety-Stress Questionnaire (DASS-21) to investigate 750 college students.

Results: The results suggested that fear of missing out significantly positively predicted mobile phone addiction. This direct effect could be mediated by depression, and the indirect effect of fear of missing out on mobile phone addiction could be moderated by loneliness. Specifically, the indirect effect was stronger for students with high levels of loneliness.

Conclusion: This study provides a theoretical basis for developing future interventions for mobile phone addiction in higher education students.

KEYWORDS

fear of missing out, depression, loneliness, mobile phone addiction, college students

1 Introduction

In the era of information explosion, the mobile Internet has dramatically changed the public's habits of mind, affected individual behaviors and psychosocial resilience. Meanwhile, smartphones have become a significant media tool for reshaping human existence and interpersonal interactions. As of June 2023, the number of Chinese Internet users reached 1.079 billion, and the percent of Internet penetration was 76.4%. The proportion of consumers using mobile phones to access the Internet reached 99.8% (1). Although smartphone is conducive to communicating online, shopping online, looking for entertainment, studying, and so on, which brings great convenience to their studies and lives, excessive use of mobile phones may affect the physical and mental health of individuals. Numbers of students perceive it tough to control the frequency and time of mobile phone use, which invisibly triggers a psychological disease called mobile phone addiction to some extent (2). Mobile phone addiction is also thought as mobile phone dependence, mobile phone abuse, problematic

mobile phone use, or mobile phone syndrome. Bianchi and Phillips consider mobile phone addiction to be a behavioral addiction, manifested by the presence of craving symptoms, withdrawal symptoms, tolerance, escape from other problems, and negative life consequences (3). Lapierre believes that mobile phone addiction is an inability to autonomously control and excessive use of mobile phones, which adversely affects individuals' daily life (4). A meta-analysis showed that the detection rate of mobile phone addiction was 23.0% in the college student population (5).

Previous studies have shown that college students with mobile phone addiction suffer from problems such as poor sleep quality, interpersonal tension, and decreased efficiency in both study and work (5–7). Excessive immersion in mobile phone use would also further affect their stress coping and self-control ability (8–10). In addition, inattention plays a negative role in concentrating on the lessons, which leads to weakening the initiative and continuity of learning, increasing the psychological risk of anorexia, and even bringing passive emotions such as anxiety and depression among college students (11). In conclusion, mobile phone addiction has become a primary public health problem among college students, it also has been thought as a hot issue in the related research field. At the same time, college students prove a vital reserve for social development, not only is the level of physical and mental health closely associated with their own and family circumstances but also with the future development of the whole country's society. Therefore, this study chooses college students as the research object to better analyze the mechanism and influencing factors of college students' mobile phone addiction.

1.1 The relationship between fear of missing out and mobile phone addiction

Fear of Missing Out (FoMO), is defined as a diffuse anxiety that occurs when individuals worry about missing out on wonderful experiences of others or something else (12–14). People with high levels of fear of missing out are more likely to use social media, which makes them more likely to develop mobile phone addiction (15–17). A study by the China Psychological Information Network (CPIN) reported (18) that more than 15% of social media users have experienced a severe fear of missing out; nearly 33% of users check Weibo frequently to avoid missing the latest topics; and 60% of users feel psychologically uneasy if they do not have a smartphone or their smartphone loses power. Individuals undergoing high levels of fear of missing out tend to display updates about themselves or track the lives of others through social media, thus creating irrational expectations about the social features of smartphones and investing more time and energy in smartphone use. Previous researches also demonstrated that individuals who experienced fear of missing out may attempt to reduce their anxiety by keeping on checking information about others through social media (19, 20). These behaviors immensely affect the daily life and study of college students. According to the Self-Determination Theory (SDT), the root cause of individuals' fear of missing out is the absence of basic psychological needs (21–23). The individual with fear of missing out will be bound to seek specific channels or platforms to meet their basic psychological demands, and the accessibility, as well as convenience of smartphones, make them an ideal social interaction tool. Studies have confirmed that the higher level of an individual's fear of missing out, the more obvious the behavior of mobile phone addiction (24, 25). Therefore, this study proposes hypothesis 1: Fear of missing out positively predicts mobile phone addiction.

1.2 Depression as a mediator

Depression is a kind of morbid psychology defined as a mood disorder by the World Health Organization, whose typical symptoms are primarily being down in spirits, lack of interest, losing the sense of pleasure, feeling exhausted throughout the day, decreasing energy, and so on. Previous studies suggested that individuals with a high degree of fear of missing out experience chronic anxiety because they worry about missing the exciting experiences of others or fail to receive and process the news in time, which can lead to negative emotions such as depression (26, 27). This is consistent with Wortham's view that fear of missing out is a risk factor for passive emotions such as depression (28). Depression Cognitive Theory (DCT) (29) refers to a portion of individuals who suffer from stressful events, that is, the individual experiencing fear of missing out develops negative cognitive biases so that prevent them from processing information correctly, and these cognitive biases recur as well as are not easily controlled, ultimately resulting in depressive moods. There are plenty of researches on the related influencing factors of depression at home and abroad. However, the potential pathway relationship between fear of missing out and depression among college students still needs to be further explored. In addition, studies have shown that higher levels of depression are associated with mobile phone addiction (30). The Affective Processing Model of Negative Reinforcement (APMNR) also argues for the analysis of motivations for addictive and problematic behaviors from an emotional processing perspective (31). The theory holds that avoidance of negative emotions is the motivation for addictive behaviors, as well as an intrinsic mechanism for the formation, maintenance, and relapse of addictions. When an individual is depressed, one will want to satisfy basic psychological needs by pleasing oneself through online channels, such as the joy of winning a game, or the inner support from the number of views and likes on WeChat or Weibo, and so on. The smartphone is known as a convenient mobile device by the public, which builds a bridge to eliminate negative emotions. Based on the above analysis, this study proposes hypothesis 2: depression mediates the relationship between fear of missing out and mobile phone addiction.

1.3 Loneliness as a moderator

DeJong thinks that (32) loneliness is a state of subjective social isolation accompanied by painful feelings of not being accepted due to personal isolation or lack of interactions with others. It has been shown that persistent and greater loneliness is a predisposing factor for depression (33–36). Fear of missing out is associated with mobile phone addiction among college students, but different individuals are not necessarily affected by fear of missing out to the same degree. College students are in a critical period of life development. Since individual development depends on the joint actions of individual and environmental factors (37), they are eager to maintain good interpersonal relationships while learning professional knowledge. However, due to personality, cognition, and other reasons, they have not yet achieved the expected goal, and the accompanying depression as well as frustration

make loneliness arise. The Risk Enhancement Model (REM) (38) suggests that one risk factor can enhance the risk of another, so the effect of fear of missing out on mobile phone addiction among college students may be moderated by loneliness.

The impact of loneliness on the physical and mental health of the human body can be divided into the following points: First, from the view of physiological mechanism analysis, the theory of excessive serotonin in autism believes that autism arises from excessive exposure of individuals to serotonin in the early stage, which reduces the serotonin receptors, in turn, low serotonin content will lead to depression, emotional impulse, and other negative emotions (39, 40). Secondly, loneliness can also mediate the addictive behavior of individuals. A large number of studies have proved that loneliness is the primary risk of mobile phone addiction, and college students with loneliness are more likely to develop mobile phone addiction (41, 42). For example, to relieve negative emotions and feel the joy brought by social support and interpersonal communication, some individuals may be inclined to choose network social platforms, resulting in their addiction to mobile phone use, which may further develop into mobile phone addiction. Individuals who suffer from fear of missing out are more likely to think that they are not fully integrated into social groups and worry about being unable to take part in social activities timely. In this case, with the participation of loneliness, they may be more inclined to choose the negative coping style, which is to immerse in the immediate pleasure of mobile phone use. In conclusion, this study proposes hypothesis 3: loneliness moderates the relationship between fear of missing out, depression, and mobile phone addiction. By constructing a moderated mediation model (Figure 1), the present study explored the influence of fear of missing out on college students' mobile phone addiction. At the same time, to verify the mediating role of depression as well as the moderating role of loneliness to provide a theoretical basis and objective empirical evidence for improving college students' mobile phone addiction.

2 Materials and methods

2.1 Participants

A convenience sampling method was used to test students at a university in Jilin Province, China, on an online questionnaire platform to obtain a representative sample of college students with mobile phone addiction. According to Kendall's sample estimation principle, the number of observed samples was 10–20 times the number of items, at the same time, given the possible invalidity of the questionnaire, the planned sample size was increased by 10%. Therefore, the required sample size was at least 715. We distributed 750 questionnaires in electronic forms to the students at our request, and 720 valid questionnaires were obtained (the effective rate of the questionnaires was 96.00%). The ages of the subjects ranged from 17 to 29 years old ($M = 21.72$ years old, SD = 2.43), including 252 (35.0%) were male and 468 (65.0%) were female, 498 (69.2%) were undergraduate students and 222 (31.8%) were graduate students.

2.2 Mobile phone addiction

The mobile phone addiction index scale developed by Leung (43) was used to measure the tendency of mobile phone addiction among college students. The scale consists of 17 items, using a 5-point Likert-type scale (from 1 = "never" to 5 = "always"), and the responses are summed up, with a total score ranging from 17 to 85, 17–33 is classified as having no mobile phone addiction, 34–50 is defined as having mild mobile phone addiction, 51–67 suggests moderate mobile phone addiction and the range of 68–85 is regarded as severe mobile phone addiction, and the higher the score, the higher the degree of mobile phone addiction. This scale has shown good reliability and validity among Chinese college students (44–46). In this study, Cronbach's α coefficient for this scale was 0.937.

2.3 Fear of missing out

The fear of missing out scale was designed by Przybylski and translated by Li et al. (12, 47). The applicability test was carried out with a sample of Chinese college students. It was divided into two dimensions: fear of missing information and fear of missing situations. It included 8 items (for example, "I am afraid that other people have more wonderful experiences and gains than me," etc.), and adopted a 5-point Likert-type scale scoring method (from 1 = "strongly disagree" to 5 = "strongly agree"). The total score is the sum of the scores for each

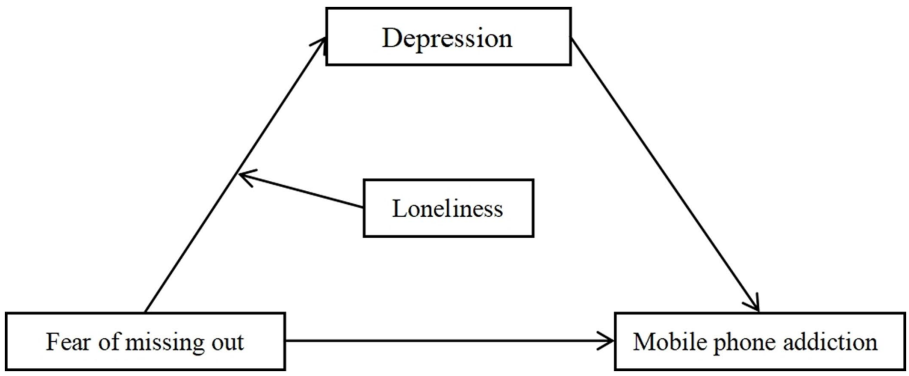

FIGURE 1
Hypothetical model for this study.

TABLE 1 Descriptive statistics and correlations among some of the observed variables.

Variables	*M*	SD	1	2	3	4
1 Fear of missing out	23.87	6.39	1			
2 Depression	11.13	9.18	0.374**	1		
3 Loneliness	17.75	4.52	0.412**	0.529**	1	
4 Mobile phone addiction	47.32	14.36	0.411**	0.490**	0.363**	1

**$p < 0.01$.

item ranging 8 to 40. Higher scores indicate a higher degree of fear of missing out. The overall reliability and validity index of the scale has proved good among Chinese college students (48). The Cronbach's α coefficient of this scale was 0.880.

2.4 Depression

The depression questionnaire in the Chinese depression-Anxiety-Stress scale (Depression-Anxiety-Stress Scale) revised by Gong et al. (49). was used to measure and evaluate the depression of the subjects. Using the 4-point Likert-type scale, the depression scale score is the sum of the seven items scored multiplied by 2, and ranges from 0 to 42 points, 0–9 proves normal, 10–13 is mild depression, 14–20 is moderate depression, 21–27 is as severe depression, and 28–42 is defined as extremely severe which suggests that the individual is in a negative emotional state, with higher scores indicating higher levels of depression. In this study, Cronbach's α coefficient of this subscale was 0.902.

2.5 Loneliness

This study adopts the USL-8 loneliness scale revised by Hays et al. to measure the extent of individuals' loneliness (50), which consists of 8 items. In this scale, the 3rd and 6th items were scored in reverse. And the level of loneliness was rated using a 4-point Likert-type scale (1 = "never," 4 = "always"), with higher total scores indicating higher levels of loneliness. Yan Liu introduced the ULS-8 into China and administered it to college students with good reliability and validity (51). The Cronbach's α coefficient of the loneliness scale in the present study was 0.817.

2.6 Data analysis

In the present study, SPSS and Hayes' SPSS macro program PROCESS were used for statistical analysis of the data. Descriptive statistical analysis was used to describe the basic sociodemographic characteristics of participants and their scores on study variables. Harman single factor test was used to determine the effect of common method variance on the study results (52). Pearson correlation analysis was used to explore the correlation between fear of missing out, depression, loneliness, and mobile phone addiction. The mediating effects of depression were analyzed using PROSCESS model 4, and then whether the direct effects and mediating effects were moderated was analyzed using PROSCESS model 7 (53).

3 Results

3.1 Descriptive statistics and the correlation among the studied variables

Table 1 presents the descriptive statistics and Pearson correlation analysis for studied variables, including the mean value, standard deviation, and correlation strength. The results showed that the correlation coefficients among all studied variables ranged from 0.363 to 0.529, and $p < 0.01$ significance level for them. In addition, fear of missing out, depression, loneliness, and mobile phone addiction were positively correlated with each other.

3.2 Testing for the mediating effect of depression

Model 4 in the SPSS macro program compiled by Hayes was used to analyze the mediating role of depression in the influence of fear of missing out on mobile phone addiction. The difference analysis of demographic variables in this study showed that gender and grade had significant effects on mobile phone addiction ($t = 3.71$, $p < 0.001$; $t = 2.24$, $p < 0.05$). Therefore, gender and grade were included in the subsequent analysis as control variables. Table 2 shows the results of this study: First, the fear of missing out significantly positively predicted mobile phone addiction ($\beta = 0.92$, $p < 0.001$); Secondly, the fear of missing out had a significant positive predictive effect on depression ($\beta = 0.54$, $p < 0.001$). Finally, when both fear of missing out and depression predicted mobile phone addiction, depression significantly positively predicted mobile phone addiction ($\beta = 0.64$, $p < 0.001$), and the positive prediction effect of fear of missing out on mobile phone addiction was still significant ($\beta = 0.57$, $p < 0.001$). However, it indicated that the predictive value of fear of missing out on mobile phone addiction decreased from 0.92 to 0.57, suggesting that depression played a partial mediating role in the influence of fear of missing out on mobile phone addiction. The mediating effect is 0.35, and its 95% Bootstrap confidence interval is [0.26, 0.44], excluding 0. The mediating effect accounts for 37.91% of the total effect. Therefore, the mediating effect of depression between fear of missing out and mobile phone addiction is established.

3.3 Testing for the moderated effect of loneliness

The SPSS macro PROCESS (model 7) was used to verify the moderated mediation model. As can be seen in Table 3, when loneliness was included as a moderator in the regression equation, the

TABLE 2 Regression results for the mediating effect of depression (mediation model).

Model						
		Fitting index			Coefficient and significance	
		R	R^2	*F*	*β*	*t*
Model 1: total effect model						
Outcome variables	Predictor variables					
Mobile phone addiction	Constant	0.433	0.188	55.122	25.350***	12.707
	Gender				−2.540*	−2.471
	Grade				3.056**	2.887
	Fear of missing out				0.918***	12.039
Model 2: mediator variable model						
Depression	Constant	0.388	0.150	42.279	−1.747	−1.328
	Gender				1.198	1.783
	Grade				−1.434*	−2.071
	Fear of missing out				0.540***	10.830
Model 3: dependent variable model						
Mobile phone addiction	Constant	0.576	0.332	88.710	26.475***	14.478
	Gender				−3.311***	−3.542
	Grade				3.980***	4.129
	Fear of missing out				0.570***	7.638
	Depression				0.644***	12.414
			β	**Boot SE**	**BootLLCI**	**BootULCI**
Total effect of fear of missing out on mobile phone addiction			0.918	0.076	0.769	1.068
Direct effect of fear of missing out on mobile phone addiction			0.571	0.075	0.424	0.717
Indirect effect of depression			0.348	0.047	0.259	0.444

*p< 0.05, **p < 0.01, ***p < 0.001. LL; low limit, CI; confidence interval, UL; upper limit.

TABLE 3 Regression results for the conditional indirect effects (moderated mediation).

Model						
		Fitting index			Coefficient and significance	
		R	R^2	*F*	*β*	*t*
Model 1: mediator variable model						
Outcome variables	Predictor variables					
Depression	Constant	0.567	0.322	67.741	10.846***	25.486
	Gender				0.793	1.318
	Grade				−1.004	−1.616
	Fear of missing out				0.300***	6.047
	Loneliness				0.902***	13.083
	Fear of missing out × Loneliness				0.026**	2.845
Conditional direct effect analysis at values of Loneliness (M ± SD)						
			β	**Boot SE**	**BootLLCI**	**BootULCI**
M − 1 SD (−4.747)			0.113	0.040	0.037	0.192
M (0.253)			0.198	0.041	0.121	0.283
M + 1 SD (4.253)			0.265	0.061	0.156	0.392

*p < 0.05, **p < 0.01, ***p < 0.001. LL; low limit, CI; confidence interval, UL; upper limit.

interaction term of fear of missing out and loneliness had a significant predictive effect on depression ($\beta = 0.03$, $p < 0.01$). It suggested that loneliness played a moderating role in the influence of fear of missing out on depression.

Besides, on this basis, we developed a simple slope analysis to decompose this significant interaction effect (54). The results of a simple slope analysis were shown in Figure 2. As can be seen from Figure 2, the impact of the fear of missing out on depression was

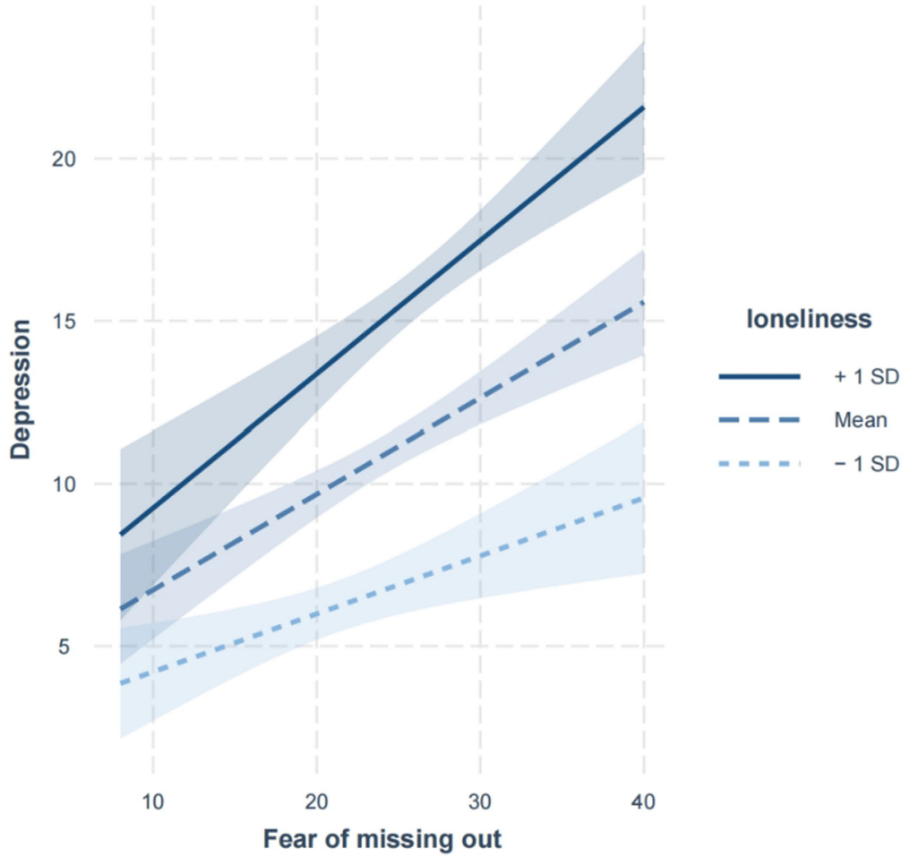

FIGURE 2
Loneliness moderates the relationship between fear of missing out and depression.

positive and significant regardless of their level of loneliness. The difference was that the influence of fear of missing out on depression performed stronger among college students with high levels of loneliness (simple slope = 0.412, $t = 6.030$, $p < 0.01$) than that of college students with low levels of loneliness (simple slope = 0.176, $t = 2.910$, $p < 0.01$).

4 Discussion

This study explored the influence of fear of missing out on mobile phone addiction, as well as the mediating role of depression and the moderating role of loneliness, and constructed a moderated mediation model based on previous researches and related theories. Studies indicated that fear of missing out was significantly positively associated with mobile phone addiction, and hypothesis 1 was supported. The higher the level of individuals' fear of missing out, the higher the degree of mobile phone addiction. Depression partially mediates the relationship between fear of missing out and mobile phone addiction, and hypothesis 2 was supported. In addition, the indirect effect of the fear of missing out on mobile phone addiction was exacerbated when the public experienced more loneliness in their daily lives, and hypothesis 3 was supported. These findings not only helped to identify risk factors of mobile phone addiction behavior, explored the path relationship between mobile phone addiction behavior and related factors, but also guided college students to form a correct attitude and cognitive system of using mobile phones. More important is to improve their physical and mental health, and to provide a theoretical basis for future intervention measures for college students' mobile phone addiction behavior.

4.1 Fear of missing out and mobile phone addiction

The present study found that fear of missing out significantly positively predicted mobile phone addiction, indicating that fear of missing out was a risk factor for mobile phone addiction. Consistent with previous research results (55), the fear of missing out could have an impact on individual behavior and was an important influencing factor for behaviors such as mobile phone addiction. The higher the degree of individuals' fear of missing out, the more possibly they tend to develop mobile phone addiction. That may be because individuals who are in a state of fear of missing out will consume their self-control and have a stronger desire for the pleasure brought by mobile phones, resulting in individuals being unable to withdraw from the state of using mobile phones promptly (56). At the same time, the fear of missing out due to the lack of timely access to information may stimulate non-adaptive cognition, and individuals believe that the network

environment can better meet their needs than reality (57), which makes individuals more addicted to mobile phones. Most previous studies mainly paid more attention to the role of fear of missing out as an intermediary factor in the relationship between mobile phone addiction (58, 59), but this study directly analyzed it as an independent variable to study the direct impact of fear of missing out as an emotional cognition on mobile phone addiction and the related factors affecting the direct path of the both.

4.2 Depression as a mediator

The results of the mediation effect test showed that the fear of missing out could not only predict mobile phone addiction through the direct path but also affect mobile phone addiction through the indirect path of depression. Studies have found that fear of missing out can enhance depression, possibly because individuals with a high level of fear of missing out are more afraid of missing external dynamics and social information, thus falling into anxiety, depression, and other negative emotions (26, 27). To change their negative emotional states, individuals often look for external stimuli (such as mobile phones) to release negative emotions or transfer emotional attention. That is consistent with previous research results, that is, users' Emotional cognitive experience is a direct influencing factor for individuals' excessive use of mobile phones (12, 60–62), which is also consistent with the idea of the Emotional enhancement Effect (30). A large number of empirical studies (63–65) have shown that depressed individuals are more likely to become dependent on the Internet than other individuals, leading to indulging in mobile phones. To sum up, the fear of missing out can cause depression among college students and further result in the formation of mobile phone addiction.

4.3 Loneliness as a moderator

The fear of missing out is related to mobile phone addiction among college students. Still, the indirect predictive effect of fear of missing out on mobile phone addiction is associated with the level of loneliness. To put this into a specific context, the mediating effects of depression in fear of missing out and mobile phone addiction are more obvious in individuals with high levels of loneliness. That may be because loneliness, as a negative emotion or coping style, enhances the direct effect of the fear of missing out on depression and the indirect effect of mobile phone addiction, which is also supported by the risk enhancement model (38).

Loneliness and fear of missing out are both passive emotions and risk factors for depression (34, 41, 42), which can strengthen the effect of fear of missing out on depression. College students, who face the pressure of heavy schoolwork, worry about being disconnected from society, fall into the confusion of interpersonal relationships and the sadness of being separated from their families, feel a high level of loneliness, and may look for online social support through social media to enrich their hearts. The smartphone, a convenient and portable mobile device, has become the best media tool for them to obtain their inner satisfaction and needs through immersion in the pleasure of using mobile phones. This is consistent with the idea of the emotional enhancement effect (30), that is, an individual in a negative mood is more inclined to relieve and suppress it through entertainment and leisure activities. Therefore, people with a high degree of loneliness and fear of missing out have a higher risk of depression and are more likely to develop mobile phone addiction behaviors.

5 Limitations and implications

This study provides a theoretical framework for preventing mobile phone addiction among college students. First of all, the application of self-determination theory proves that fear of missing out can significantly positively predict mobile phone addiction. Therefore, to alleviate the fear of missing out among college students, schools can establish a fast information channel and actively organize activities to break the information gap of students, reducing their fear of missing out. Secondly, this study uses the cognitive theory of depression and the negative reinforcement emotion processing model to provide theoretical support for the research on the mediating role of depression between fear of missing out and mobile phone addiction. Fear of missing out can not only directly affect mobile phone addiction, but also indirectly predict through the bridge of depression. Therefore, universities should pay attention to students' mental health and reduce the risk of depression. Finally, the risk enhancement model is applied to verify the moderating effect of loneliness. Students with high loneliness have a higher level of depression than students with low loneliness, which virtually increases the risk of mobile phone addiction.

Although the present study introduced the mechanism of the influence of fear of missing out on mobile phone addiction and enriched the contents of previous studies on the risk factors of mobile phone addiction, this study also has some limitations. Firstly, the current cross-sectional study was unable to draw rigorous and expected causal relationships. Longitudinal or experimental studies should be conducted to determine the causal direction between fear of missing out, depression, and loneliness. Future studies should also use ingenious intervention design to examine the moderating effect of loneliness by comparing the change in the influence of fear of missing out on depression before and after the intervention. Secondly, because this study was conducted on a group of college students at a university in Jilin Province, the universality of the research results was affected, and the conclusions of this study could not be extended to other social groups, such as teenagers, the older adult, and other populations from different cultures.

6 Conclusion

Through a questionnaire survey, this study found that there was a significant positive correlation between the fear of missing out and mobile phone addiction, and depression was a vital medium for the fear of missing out to contribute to mobile phone addiction among college students. At the same time, loneliness is the catalyst of depression induced by fear of missing out, and the indirect influence of fear of missing out on mobile phone addiction was mediated by loneliness. To prevent the mobile phone addiction behavior of college

students, we need to pay more attention to improving their mental health and enhancing their emotional regulation ability.

Data availability statement

The datasets presented in this article are not readily available because this data is only applicable to this research group. Requests to access the datasets should be directed to NL, L19981224525@163.com.

Ethics statement

The studies involving humans were approved by School of Public Health of Jilin University. 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

NL: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. SZ: Writing – review & editing, Supervision, Software, Methodology, Investigation, Data curation, Conceptualization. WZ: Writing – review & editing, Supervision, Methodology, Data curation. YS: Writing – review & editing, Supervision, Methodology, Data curation. XZ: Writing – review & editing, Conceptualization.

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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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Role of self-control, financial attitude, depression, anxiety, and stress in predicting consumers' online shopping addiction

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Online shopping addiction is a behavior that creates serious problems and has become increasingly prevalent in modern society. When addressing online shopping addiction, the direct or indirect causes of individuals' shopping actions must be taken into consideration. The present study aims to examine the effects of self-control, financial attitude, depression, anxiety, and stress on online shopping addiction by determining online shopping addiction, self-control, and financial attitude levels of consumers. The sample of this study consists of 694 voluntarily participating consumers selected through convenience sampling methods from a city in Türkiye. Data were collected through Google Forms and uploaded to the SPSS 25.0 package program. During the research process, the relationship patterns between self-control, financial attitude, depression, anxiety, and stress on online shopping addiction were examined by using structural equation modeling. It was determined in this study that consumers have moderate levels of financial attitude and self-control, and low levels of online shopping addiction. Given the results related to the relationships and hypotheses between variables, anxiety, depression, and financial attitude were found to have statistically significant effects on online shopping addiction, whereas stress and self-control were found to not have a significant effect. Within the scope of this study, it was identified that anxiety and depression positively affect online shopping addiction, whereas financial attitude has a negative effect.

KEYWORDS

online shopping addiction, financial attitude, depression, anxiety, stress

1 Introduction

With the rapid development of e-commerce in recent times, the usage rate of online shopping has also increased. According to the 2022 e-commerce bulletin in Türkiye, the e-commerce volume reached 800.7 billion TL with a 109% increase in comparison to the previous year. The number of orders in 2022 increased by 43% from the previous year, rising from 3.347 billion to 4.787 billion. Retail e-commerce volume in 2022 reached 458 billion TL (1, 2). As reported in the "Digital Türkiye February 2022" report prepared by the Global social media agency in collaboration with We Are Social and Hootsuite, the number of online shopping users in Türkiye increased by 3.6 million people in the last year, reaching 40.84 million, a 64% preference among internet users for purchasing goods or services through

virtual stores (3). The emergence of online shopping opportunities with the advancements in internet-based data technologies led to a shift in consumption habits and the development of new types of addiction (4), with online shopping addiction being one of them.

Recent studies indicated that individuals spend approximately half of their waking hours struggling with desires and conflicting wishes (5). Even though not all desires that individuals experience are problematic, many can be problematic on an individual or even societal level. Managing problematic and conflicting desires requires constant effort from individuals. Success in navigating the constant flow of desires is associated with an individual's ability to exercise self-control. Therefore, a variable in this study is self-control. The ability to regulate one's emotions, thoughts, and behaviors is referred to as self-control. As stated by Baumeister (6), self-control is the capacity of an individual to alter their responses to the situation they find themselves in or to stimuli in their environment. Studies carried out on self-control showed that it is effective in every aspect of life (7). In the present context, online shopping addiction (OSA) is expressed as the inability of an individual to control their online shopping activities. According to Kraepelin (1909), shopping addiction arises from an individual's lack of self-control. Individuals may decide to engage in shopping almost every day, and they often act unconsciously and cannot maintain self-control due to impulsive actions during the purchasing moment (8). Low self-control was associated with compulsive buying (9, 10) and behavioral addictions (11, 12). A study carried out by Rose and Dhandayudham (13) indicates that potential predictors of OSA include low self-esteem, low self-control, negative emotional state, depression, anxiety, and stress.

One of the variables in this study is depression-anxiety and stress. As stated in previous studies, factors such as entertainment, happiness, pleasure, boredom, depression, and stress are among the causes of online shopping addiction (14). Individuals are observed to engage in shopping, sometimes without the actual need, to alleviate stress, even occasionally without using the purchased products (15).

Depression, which is one of the most commonly observed mood disorders in individuals with online shopping addiction, is a condition that results in negative consequences both physically and emotionally after a prolonged period of sadness and unhappiness and has become increasingly prevalent recently (16). Anxiety is another frequent condition in individuals with online shopping addiction, typically characterized by fear and threat perception when facing a negative situation, often involving concerns about the future (17). Stress, defined as a continuous feeling of tension, arises when an individual does not feel sufficiently successful (16). Anxiety, depression, and stress are general emotional problems. During these problematic processes, individuals experience isolation, excessive restlessness, and tension, leading them to turn to online shopping, thereby increasing addiction tendencies (18). Many studies also indicated that online shopping is a method used to reduce tension in situations such as anxiety, depression, and stress (19).

Another variable examined in the present study is financial attitude. Considering Sen's (20) capability theory, it is assumed that financial abilities can be a significant determinant in online purchasing. Financial attitudes in individuals' lives affect their current and future behaviors (21). Financial attitude of an individual is a process that shapes emotions, thoughts, beliefs, and behaviors related to financial matters (22, 23). Individuals with poor financial attitude skills may make unhealthy decisions regarding online purchases, influencing their buying behavior. As reported in a study carried out by Ahmetoğulları (24), consumers' financial attitudes affect their online shopping behavior.

Factors determining the novelty of this study include, firstly, the limited number of studies in the literature that concurrently investigate online shopping addiction with numerous factors, filling a gap in the literature on this subject. Secondly, due to the limited knowledge about the relationship between shopping addiction and its potential determinants, characterizing the patterns of online shopping addiction is challenging. The results of this study facilitate a better understanding of online shopping addiction and provide significant insights for practitioners.

Due to the limited number of studies in this field and since the present study aims to investigate which factors affect online shopping addiction, this study focuses on examining the effects of self-control, anxiety, depression, stress, and financial attitude variables on online shopping addiction. In this context, the final model was determined as "Consumers' self-control, depression, anxiety, stress, and financial attitude significantly affect online shopping addiction."

To achieve the objectives of the study, the following hypotheses were tested;

> *H1*: DASS has a significant impact on online shopping addiction.
>
> *H1a*: Anxiety has a significant effect on shopping addiction.
>
> *H1b*: Depression has a significant effect on online shopping addiction.
>
> *H1c*: Stress has a significant effect on online shopping addiction.
>
> *H2*: Self-control has a significant effect on shopping addiction.
>
> *H3*: Financial attitude has a significant effect on online shopping addiction.

2 Material and method

2.1 Data collection instruments

2.1.1 Personal information form

The form includes 5 items related to the demographic and other personal characteristics of the consumers participating in this study. These questions were formulated by the researchers and they address the consumers' genders, ages, marital statuses, and income levels, as well as the items related to the amounts spent on online purchases.

2.1.2 Online shopping addiction scale

To measure consumers' online shopping addiction, the Online Shopping Addiction Scale developed by Zhao et al. (25) and adapted into the Turkish language by Yılmaz et al. (26) was used in this study. The scale consists of five sub-dimensions: "Salience-Tolerance," "Mood Change," "Recurrence," "Conflict," and "Deprivation," comprising 18

items in a 5-point Likert scale (26). In this study, the overall Cronbach's Alpha value of the scale was found to be 0.958. The reliability levels of the overall scale and its sub-dimensions were determined to be high (Cronbach's Alpha >0.70).

With established validity and reliability, this scale is a reliable and theory-based tool for measuring online shopping addiction. Moreover, the scale can be used by psychiatrists and psychologists working in the field of addiction for preliminary and final evaluations, as well as in cyberpsychology to examine the relationship between technology and human behaviors. The scale, consisting of 18 items, was preferred in the present study due to its effectiveness, as the response time is not long.

2.1.3 Short self-control scale

The 13-item Short Self-Control Scale, developed by Tangney et al. (27) and adapted into Turkish by Nebioğlu et al. (28), was utilized to measure consumers' self-control. The Short Self-Control Scale used in this study consists of a total of 13 items prepared in a 5-point Likert-type format with options ranging from "completely disagree" to "completely agree." There are 4 positive and 9 negative items in the scale, and scoring is done in reverse for the negative items. The lowest score that can be obtained from the scale is 13, and the highest one is 65. A high score on the scale indicates a high level of self-control. The scale consists of 2 subscales: self-discipline and impulsivity. The overall Cronbach's Alpha value for the scale in this study was determined to be 0.944. The reliability levels of the overall scale and its sub-dimensions were found to be high (Cronbach's Alpha >0.70).

2.1.4 Depression, anxiety, stress scale (DASS 21)

The Depression, Anxiety, Stress Scale (DASS 21) developed by Henry and Crawford (29) and Mahmoud et al. (30) was used to determine consumers' levels of depression, anxiety, and stress. The adaptation of the scale into Turkish was carried out by Yılmaz et al. (16). The scale comprises three sub-dimensions: "Depression," "Anxiety," and "Stress," with a total of 21 items in a 4-point Likert scale (16). In this scale, responses are coded as follows: 0 for "not suitable to me," 1 for "partially suitable to me," 2 for "mostly suitable to me," and 3 for "completely suitable to me." Subscale scores range from 0 to 28, with higher scores indicating higher levels of depression, anxiety, and stress. Since reliability levels were found to be higher than 0.70 for anxiety, depression, and stress measurements, it was determined that the reliability is at a high level (Cronbach's Alpha; Anxiety: 0.90; Depression: 0.88; Stress: 0.85).

2.1.5 Financial attitude scale

The Financial Attitude Scale developed by Onur and Nazik (21) was used to analyze consumers' financial attitudes. This scale is unidimensional and consists of 24 items measured on a 5-point Likert scale. In this multiple-choice test with a statement format, each statement is rated on a scale of 1–5 and ranked as follows: "5 = Strongly Agree, 4 = Agree, 3 = Partially Agree, 2 = Disagree, and 1 = Strongly Disagree." A single total score can be obtained from the scale, with the lowest score being 24 and the highest score being 120. A high score indicates a positive attitude toward individual finances. The reliability of the Financial Attitude Scale was calculated based on the alpha value using Cronbach's Alpha coefficient, and the scale's original internal consistency coefficient is 0.97. In this study, the overall Cronbach's Alpha value for the scale was determined to be 0.979. Given that the reliability level of the scale exceeds 0.70, it was established that the reliability is at a high level.

2.2 Procedure

In parallel with the purpose, this study was designed using a relational survey model. Accordingly, participants were provided with necessary explanations regarding the purpose of the study, the anonymous utilization of the obtained data, and the voluntary participation principle in this study in order to collect data. The sample of the research consists of 694 volunteer consumers selected through convenience sampling, one of the non-probabilistic sampling methods, from a city in Turkey. The link (insert link) containing the data collection instruments was disseminated to the target population through national associations, unions, and civil society organizations. During this process, online forms were sent to members of these institutions via applications such as WhatsApp, and the data collection process was completed in approximately 3 months."

2.3 Data analysis

This study was designed using the relational survey model. The data collection was performed online in a city in Türkiye in 2023 by using Google Forms. The analysis of the data obtained in the present study was conducted by making use of the LISREL 8.7 and SPSS 25.0 software packages. Significance levels were set at $p = 0.05$ and $p = 0.01$, and the reliabilities and validities of the scales used in the research were initially examined.

The reliability levels of the scales used in this study were calculated using the Internal Consistency method and the Cronbach Alpha reliability criterion. Confirmatory factor analyses were conducted to test the validity of the scales. Various fit indices were used to determine the adequacy of the model in confirmatory factor analysis. In addition to the Chi-square goodness-of-fit index, fit criteria such as IFI, CFI, RMSEA, GFI, and RMR were also considered in this study (31). Structural equation models were used to examine the results related to the research hypotheses. Normal distribution analyses and measures of central tendency were used to examine the distribution of data obtained in the research, and participants' levels of participation in each measurement were examined using mean and standard deviation values. Frequency and percentage analyses were conducted to examine the participants' demographic characteristics.

3 Results

3.1 Participants

The demographic characteristics of participants are shown in Table 1.

In the context of this study, a total of 694 participants were contacted, with the majority being female ($n = 374$, 53.90%), aged between 29 and 39 years ($n = 242$, 34.90%), married ($n = 461$, 66.40%), having an income range of 11,000–20,000 ($n = 321$, 46.30%), and monthly online shopping expenditures ranging between 500 and 1,500 ($n = 492$, 70.90%).

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TABLE 1 Demographic characteristics of participants.

Variables	Group	*n*	%
Gender	Female	374	53.90
	Male	320	46.10
Age	18–28	167	24.10
	29–39	242	34.90
	40–50	211	30.40
	51–60	74	10.70
Marital status	Single	233	33.60
	Married	461	66.40
Income level	1,000–4,000 TL	118	17.00
	5,000–10,000 TL	162	23.30
	11,000–20,000 TL	321	46.30
	21,000–30,000 TL	63	9.10
	31,000 TL and higher	30	4.30
Monthly amount of online purchases	500–1,500 TL	492	70.90
	1,600–3,000 TL	128	18.40
	3,100–5,000 TL	29	4.20
	5,100–7,500 TL	21	3.00
	7,500 TL and higher	24	3.50
Total		694	100

3.2 Data distribution and descriptive results

In this section, findings related to the descriptive results and the distribution of data obtained in the present study are presented (Table 2).

Given the results of the normal distribution analysis, it was determined that the data obtained, due to the proximity of the measures of central tendency, namely mean and median, and the kurtosis and skewness being within ±2, originated from a normal distribution (32). Additionally, given the sufficient number of participants included in the study ($n >= 30$), parametric methods, which are statistically more robust according to the central limit theorem, were employed (33) (Table 3).

The scores obtained from the DASS scale, designed in the Likert format, were used to calculate the levels of participants' responses with a point range of 15.75. In this case, the initial score of 0 points on the Likert scale is augmented by a 15.75-point interval, resulting in the calculation of intervals corresponding to each measurement level. Therefore, the range of 0–15.75 represents "Strongly Disagree," 15.75–31.50 represents "Disagree Somewhat," 31.50–47.25 represents "Agree Somewhat," and 47.25–63 represents "Strongly Agree." When examining the average and standard deviations of participants' anxiety dimension (7.54 ± 5.47), depression dimension (6.45 ± 5.04), and stress dimension (7.22 ± 4.77), it was determined that they did not strongly agree with these dimensions.

For scales created in the Likert format, a point interval of 0.8 (4/5 = 0.80) was used to calculate the levels of participants' responses based on the scores obtained. In this case, the Likert scale's starting point of 1 point is augmented by a 0.8-point interval, resulting in the calculation of intervals corresponding to each measurement level. Thus, the range of 1–1.80 represents "very low," 1.81–2.6 represents "low," 2.61–3.4 represents "medium," 3.41–4.2 represents "high," and 4.21–5.0 represents "very high." If the scale is calculated with the total score, then these intervals need to be multiplied by the number of items (34).

TABLE 2 Data distribution.

Measurements	Central tendency		Kurtosis-Skewness	
	Mean	Median	Kurtosis	Skewness
Anxiety	7.54	5.50	−0.551	0.859
Depression	6.45	5.00	−0.665	0.646
Stress	7.22	6.00	−0.598	0.697
Financial attitude	79.72	94.00	−1.099	−0.859
Self-discipline	11.07	10.00	−1.377	0.128
Impulsivity	12.70	9.00	−1.581	0.388
Self-Control	23.77	19.00	−1.611	0.321
Significance – Tolerance	17.31	14.00	−1.546	0.326
Mood change	7.13	6.00	−0.682	0.819
Deprivation	6.36	5.00	0.121	1.152
Recurrence	6.55	5.00	−0.210	1.011
Conflict	6.25	5.00	0.107	1.122
Shopping addiction	43.61	37.00	0.158	1.172

TABLE 3 Descriptive results.

Measurements	Mean	SD
Anxiety	7.54	5.47
Depression	6.45	5.04
Stress	7.22	4.77
Financial attitude	79.72	26.00
Self-discipline	11.07	4.63
Impulsivity	12.70	6.14
Self-control	23.77	10.31
Significance – Tolerance	17.31	7.34
Mood change	7.13	3.52
Deprivation	6.36	3.39
Recurrence	6.55	3.39
Conflict	6.25	3.52
Shopping addiction	43.61	17.57

The participants' level of financial attitude was determined to be moderate, with a mean of 79.72 ± 26.00.

Examining the participants' self-control levels, it was found to be at a moderate level with a mean of 23.77 ± 10.31. Exploring the sub-dimensions of self-control, the sub-dimension of self-discipline was found to be at a moderate level with a mean value of 11.07 ± 4.63, whereas impulsivity was at a low level with a mean of 12.70 ± 6.14.

The participants' level of online shopping addiction was identified as low, with a mean of 43.61 ± 17.57. Analyzing the sub-dimensions of shopping addiction, the dimension of clarity was found to be at a moderate level with a mean of 17.31 ± 7.34. The dimension of mood

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alteration was low with a mean of 7.13 ± 3.52, deprivation was low with a mean of 6.36 ± 3.39, recurrence was low with a mean of 6.55 ± 3.39, and conflict was low with a mean of 6.25 ± 3.52.

3.3 Relationships between variables and results for hypotheses

In this section, hypotheses established in accordance with the objective of this study were tested using Pearson's correlation analysis.

As seen in Table 4, when examining the results of the correlation analysis, a statistically significant, strong, and negative relationship ($r = -0.728$; $p < 0.01$) was found between participants' financial attitudes and the anxiety dimension, a sub-dimension of the Depression, Anxiety, and Stress (DASS) scale. This finding suggests that participants' financial attitudes will decrease significantly as their anxiety dimensions increase. Moreover, there was a moderately significant and negative relationship between the levels of financial attitudes and the depression dimension ($r = -0.410$; $p < 0.01$), as well as the stress dimension ($r = -0.446$; $p < 0.01$).

Furthermore, a positive and moderately significant relationship was found between participants' self-control levels and the anxiety dimension ($r = 0.521$; $p < 0.01$), as well as the stress dimension ($r = 0.412$; $p < 0.01$), both being sub-dimensions of the DASS scale. This result suggests that participants' self-control levels will also significantly improve when they improve their anxiety and stress dimensions. Additionally, a low-level positive relationship was determined between self-control levels and the depression sub-dimension ($r = 0.307$; $p < 0.01$).

Moreover, a moderately significant and negative relationship ($r = -0.508$; $p < 0.01$) was found between participants' self-control levels and their levels of financial attitudes. This result suggests that, as participants increase their financial attitudes, their self-control levels will decrease moderately.

In terms of participants' levels of online shopping addiction and the anxiety dimension ($r = 0.576$; $p < 0.01$), a positive moderately significant relationship was determined. This finding indicates that as participants improve their anxiety dimension, their levels of online shopping addiction will moderately improve. Additionally, a low-level positive relationship was identified between levels of online shopping addiction and the depression sub-dimension ($r = 0.362$; $p < 0.01$), as well as the stress dimension (r = 0.400; $p < 0.01$).

The level of online shopping addiction among participants was found to have a significantly high negative correlation with their financial attitude levels ($r = -0.716$; $^*p < 0.01$). This result indicates that as participants enhance their financial attitudes, the levels of shopping addiction are expected to decrease significantly.

Additionally, a positively moderate significant relationship was identified between participants' levels of online shopping addiction and their self-control levels ($r = 0.447$; $^*p < 0.01$). This finding suggests that as participants improve their self-control levels, there is a moderate improvement expected in their levels of online shopping addiction.

TABLE 4 Analyses of the relationships between variables.

Variables		1	2	3	4	5	6
Anxiety	r	1	0.462*	0.542*	0.728*	0.521*	0.576*
Depression	r		1	0.607*	0.410*	0.307*	0.362*
Stress	r			1	0.446*	0.412*	0.400*
Financial attitude	r				1	0.508*	0.716*
Self-control	r					1	0.447*
Shopping addiction	r						1

*$p < 0.01$; Pearson's correlation.

3.4 Study model and hypotheses

In this section of the study, the results of the model, which was constructed in accordance with the objectives of the research and the hypotheses related to the model, are presented (Figure 1).

3.5 Results related to study hypotheses and model

Examining the study model and hypotheses, the path diagram of Structural Equation Modeling (SEM) is presented in Figure 2, with statistical values corresponding to the analysis results provided in Table 5.

The Chi-Square value (χ^2) related to the model in Figure 3 was found to be $\chi^2 = 2340.62$, df = 1,259, $p = 0.000$, indicating significance at the 0.05 level. Examining the ratio of chi-square to degrees of freedom ($\chi^2/df = 1.859$), it was determined that it is lower than the acceptable threshold of 3, indicating an acceptable fit. Examination of the goodness-of-fit indices for the structural model yielded values of RMSEA = 0.030, RMR = 0.057, SRMR = 0.054, GFI = 0.91, AGFI = 0.91, CFI = 0.99, NFI = 0.99, and NNFI = 0.99. These values indicate that the structural model established here exhibits acceptable and excellent fit. The adequacy of the fit indices allows for the interpretation of path coefficients, and the results regarding the study hypotheses are presented in Table 5.

Uyum Kriterleri	Mükemmel Uyum	Kabul Edilebilir Uyum
$\chi 2/sd$	≤3	≤5
RMSEA	0 < RMSEA<0.05	0.05 ≤ RMSEA ≤ 0.10
RMR	0 ≤ SRMR<0.05	0.05 ≤ SRMR ≤ 0.10
SRMR	0 ≤ SRMR<0.05	0.05 ≤ SRMR ≤ 0.10
NFI	0.95 ≤ NFI ≤ 1	0.90 ≤NFI ≤ 0.95
NNFI	0.95 ≤ NNFI ≤ 1	0.90 ≤NNFI ≤ 0.95
CFI	0.95 ≤ CFI ≤ 1	0.90 ≤CFI ≤ 0.95
GFI	0.95 ≤ GFI ≤ 1	0.90 ≤GFI ≤ 0.95
AGFI	0.90 ≤ AGFI ≤ 1	0.85 ≤ AGFI ≤ 0.90

FIGURE 1
Fit criteria ranges used in this study. Source: Schermelleh-Engel and Moosbrugger (31).

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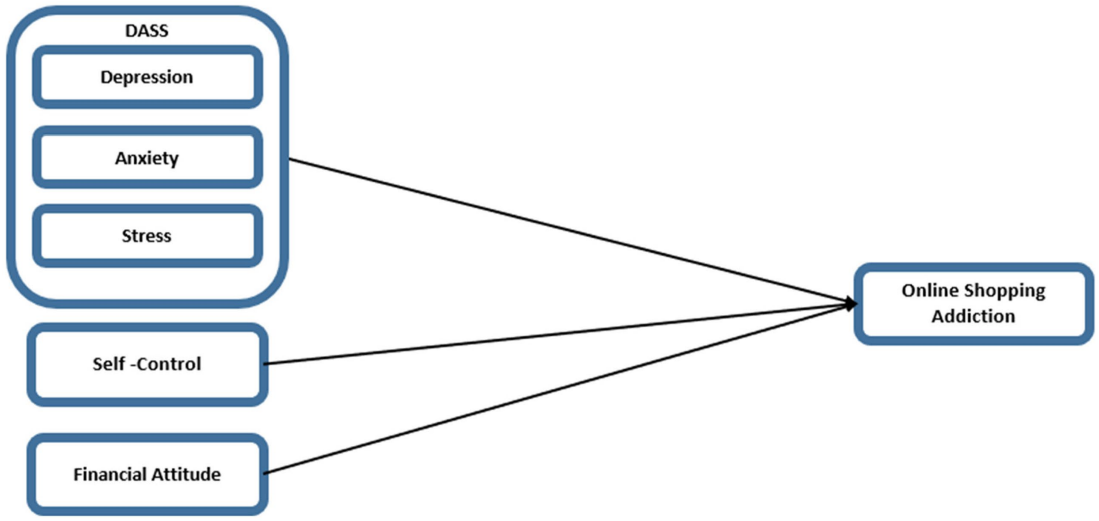

FIGURE 2
Study model.

TABLE 5 Results of the SEM for the research hypotheses.

Hypotheses	Paths	S.P.D	*t*	Result
H_{1a}: Anxiety has a significant effect on shopping addiction	(Anxiety)➔(OSA)	0.16	2.09*	Accepted
H_{1b}: Depression has a significant effect on online shopping addiction	(Depressi)➔(OSA)	0.18	2.29*	Accepted
H_{1c}: Stress has a significant effect on online shopping addiction	(Stress)➔(OSA)	0.13	0.88	Rejected
H_2: Self-control has a significant effect on shopping addiction	(Self_Con)➔(OSA)	0.14	0.99	Rejected
H_3: Financial attitude has a significant effect on online shopping addiction	(Finan_At)➔(OSA)	-0.46	−9.11**	Accepted

** $p < 0.01$; * $p < 0.05$.

Examining the results related to the hypotheses of the study in Table 5.

It was determined that anxiety has a positively significant effect on online shopping addiction (β: 0.16, t: 2.09, $p < 0.05$). This result suggests that there will be a 0.16 increase in online shopping tendencies when there is a one-unit increase in participants' anxiety levels.

It was determined that depression has a positively significant effect on online shopping addiction (β: 0.18, t: 2.29, $p < 0.05$). This result suggests that there will be a 0.18 increase in online shopping tendencies when there is a one-unit increase in participants' depression levels.

It was determined that stress does not have a significant effect on online shopping addiction (β: 0.13, t: 0.88, $p > 0.05$).

The effect of self-control on online shopping addiction was found to be statistically nonsignificant (β: 0.14, t: 0.99, $p > 0.05$).

On the other hand, financial attitude was found to have a significant and negative effect on online shopping addiction (β: −0.46, t: −9.11, $p < 0.01$). This result suggests that, for every unit increase in participants' financial attitude levels, there will be a decrease of 0.46 in online shopping tendencies.

4 Discussion

The results achieved in this study aiming to determine the predictive relationships between online shopping addiction and self-control, anxiety, depression, stress, and financial attitude variables are discussed in line with relevant literature. The literature review revealed a limited number of studies examining the predictability of online shopping addiction with self-control, anxiety, depression, stress, and financial attitude variables. Therefore, the findings of the research have also been discussed in comparison with the closest research findings.

In this study, it was determined that consumers exhibit moderate levels of financial attitude and self-control, with low levels of online shopping addiction.

In a study carried out by Müller et al. (35), approximately one-third of the participants were determined to be addicted to online shopping. Tang and Koh (36) found in their study that online shopping addiction is prevalent among university students.

The results achieved in a study carried out by Alkaya and Yağlı (37) indicated that the majority of students exhibit positive financial attitudes (37). In the study carried out by Yılmaz and Sevim (38), students' financial behaviors were reported to be at a good level, with moderate levels of financial attitudes. Dayı and Esmer (39) determined in their study that academics are conscious of and exhibit balanced financial attitudes and behaviors.

In this study, it was determined that there is no significant relationship between participants' levels of shopping addiction and their levels of self-control. In their study, Jiang et al. (40) reported that there is a negative relationship between self-control and online shopping addiction. Sümer and Büttner (41) identified self-control as

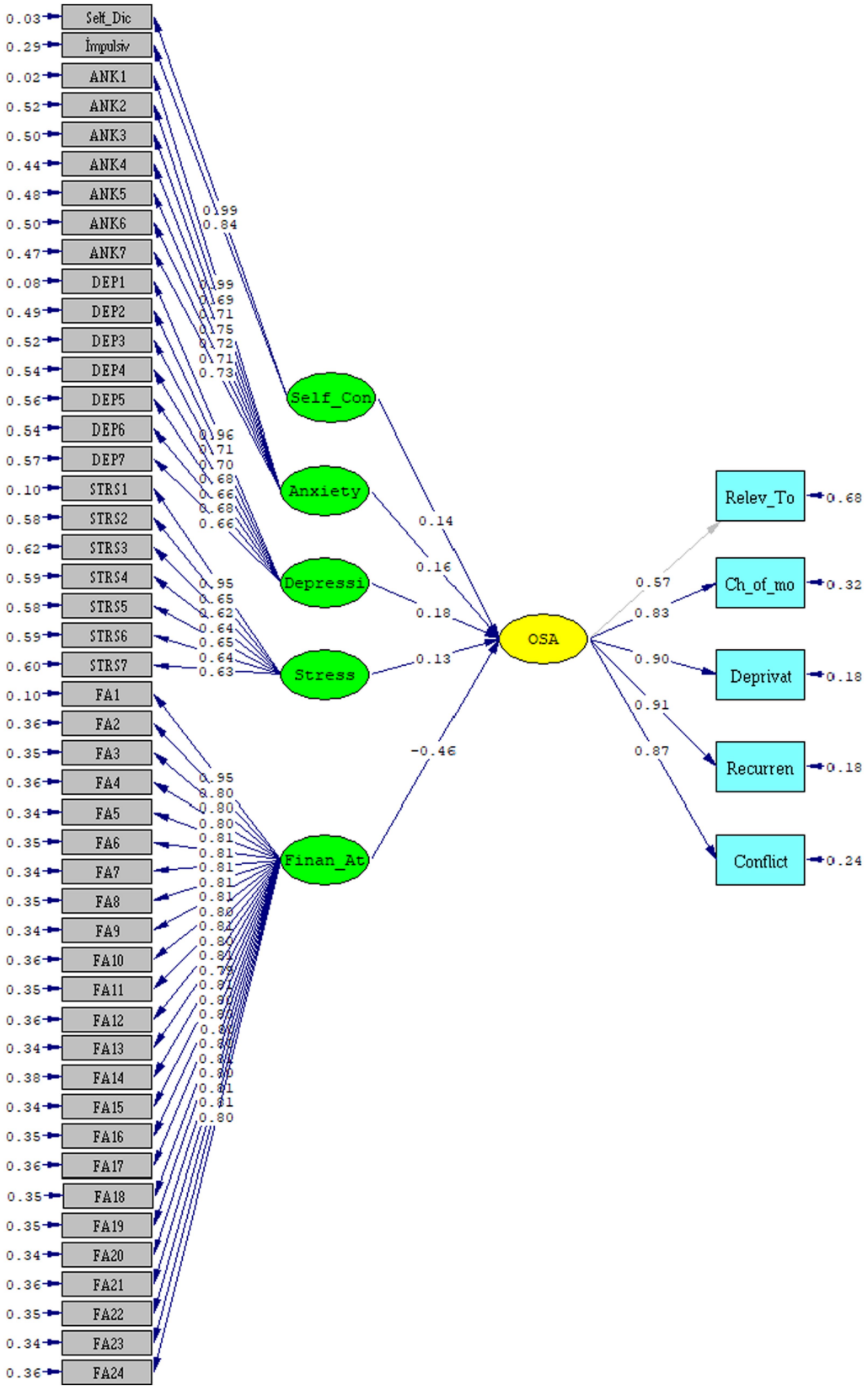

FIGURE 3
Results of the SEM for the research model. χ^2 = 2340.62, df = 1,259, p = 0.000, RMSEA = 0.030.

a significant predictor of online shopping addiction in their study. Trotzke et al. (42) stated in their study that decreased self-control is a determining factor in shopping addiction. In a study carried out by Duong and Liaw (43), it was determined that internet experience has a significant negative impact on online shopping addiction, and the time spent on daily internet shopping and the frequency of daily

internet shopping have a significant effect on online shopping addiction. In a study carried out by Ekşi et al. (44), it was found that self-control has a direct and high impact on social media addiction. Individuals with weak self-control tend to exhibit general procrastination behavior, leading to the development of social media addiction (44). The results reported in a study carried out by Korkman (45) indicated that self-control has a significant effect on anger, impulsivity, and risky behaviors. Nyrhinen (46) found in his study that low self-control facilitates online shopping addiction, leading to dissatisfaction with personal money management through indebtedness. Duroy et al. (47) expressed in their research that control and motivation loss are effective in online shopping addiction. Reviewing the literature, it was determined that there are studies with similar and different results in comparison to the present study. Different results are thought to originate from sample and cultural differences. The lack of a significant relationship between self-control and online shopping addiction levels in our study, attributed to the low levels of online shopping addiction among participants, suggests that different results may emerge with higher addiction levels and self-control. Additionally, the online nature of shopping may lead to differences compared to real-life shopping. In real-life shopping, individuals can notice how much they have bought, how much money is left in their wallet, how long they have been shopping, and whether they are tired, leading them to conclude their shopping. Similar external stoppers are absent in online shopping. Since individuals make purchases from the comfort of their seats, they may not realize the number of items purchased, the amount spent using a credit card, or the duration of time dedicated to shopping. In the absence of these factors, individuals may focus more on the pleasure of online shopping, potentially leading to increased shopping behavior. Therefore, the awareness levels of individuals in online shopping addiction should be considered.

Examining the results achieved in this study, it was determined that anxiety and depression have a positively significant impact on online shopping addiction, while stress does not have a significant effect on online shopping addiction. According to the research by Ayazoğlu et al. (17), some individuals experience changes in emotions during or after online shopping, such as regret, stress, anxiety, negative feelings, and excitement, as well as positive emotions like relaxation and distraction. In the same study, addictive factors were identified as impulses such as pleasure, relaxation, happiness, entertainment, affordable products, variety, comparison, and promotions; technological factors such as ease of use and usability; and psychological factors such as stress and boredom. In a study carried out by Aydın (48), a significant relationship was found between psychological symptoms such as anxiety and depression and shopping addiction. In the study carried out by Keskin and Günüç (15) aiming to examine why adults prefer online shopping and the factors leading to online shopping, the authors determined that usability, pleasure, stress, and depression affect online shopping addiction. According to the study carried out by Cojocariu et al. (49), there are seven variables thought to influence the potential development of online shopping addiction, and among them are negative emotions such as anxiety and stress. A study carried out by Müller et al. (35) demonstrated a significant relationship between anxiety, depression, and online shopping addiction. Given the results achieved in this study and those reported in the literature, it can be suggested that the levels of online shopping addiction will moderately improve when participants' levels of anxiety and depression are ameliorated. As for the dimension of stress, the absence of a significant relationship between online shopping addiction in this study can be attributed to online factors influencing online consumer behaviors based on the structure of different regions and the variability of stress perception among individuals in different regions.

Given the results achieved in the present study, it was observed that financial attitude has a significant negative impact on online shopping addiction. In the study carried out by Ahmetoğulları (24), the use of digital banking, financial attitude, smartphone usage, social media usage, and pandemic anxiety was found to have a positive effect on online purchasing. Given the results reported by Kirezli (50), financial attitude also has an effect on online shopping. In this context, it can be argued that as participants' levels of financial attitude improve, the levels of online shopping addiction will also decrease significantly.

5 Conclusion

Examining the content of the present study, it was observed that there is a lack of studies that collectively investigate the relationship between online shopping addiction, depression, anxiety, stress, and self-control and the financial attitude of consumers. The contribution of this study is that it fills a gap in the literature by identifying potential predictors of online shopping addiction. In this study, firstly, it was determined that consumers have moderate levels of financial attitude and self-control, and low levels of online shopping addiction. Secondly, based on the results of relationships and hypotheses among variables, it was found that anxiety, depression, and financial attitude are significant predictors of online shopping addiction, whereas stress and self-control do not significantly predict online shopping addiction. As a result, anxiety and depression were determined to positively influence online shopping addiction, whereas financial attitude was found to have a negative effect. To determine the reasons for online shopping addiction, it is recommended to conduct larger and more comprehensive studies with heterogeneous sample groups, take necessary precautions, increase awareness through education on online shopping addiction, and specifically focus on reducing individuals' online shopping dependencies.

5.1 Ethical aspect of the research

The data collection process started with the submission of an ethical approval request to the Atatürk University's Board of Social and Humanities Sciences Ethics Committee. The request was reviewed and approved (Session Nr. 21, Decree Nr. 321). Participants were provided with explanations regarding the purpose of the study, assurance of anonymous use of obtained data, and the voluntary nature of participation.

5.2 Limitations, future directions and implications

The strength of this study lies in the simultaneous examination of six variables, namely online shopping addiction, depression, anxiety,

stress, self-control, and financial attitude, while other studies examined the effects of one or two variables. There are various limitations that need to be addressed in future studies. The results reported in this study indicate that participants have a low level of online shopping addiction. Future studies should investigate these effects on a sample consisting of individuals with moderate and high levels of online shopping to enhance the level of generalizability. Despite efforts to create a homogeneous sample, it should be noted that there are limitations in terms of generalizability. Moreover, the measurement of online shopping addiction, depression, anxiety, stress, self-control, and financial attitude variables is based on subjective judgments, and this limitation should be considered since participants may have provided biased responses. The fact that the survey instruments, including measurement tools, were administered online is also a limitation. It is thought that measurement errors could be minimized if surveys were conducted face-to-face.

This study, relying on a cross-sectional design, provides evidence of the relationship between variables. Longitudinal studies could be useful in determining the dynamics of the research model over time. The results reported in this study reinforce the understanding of online shopping addiction and provide important implications for practitioners. Future studies may include multiple-method assessments to comprehensively understand online shopping addiction. Moreover, in future studies, other variables not included in this study could be incorporated into the research process to identify variances that the models in this study could not explain.

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

YE: Conceptualization, Data curation, Methodology, Resources, Validation, Writing – original draft, Writing – review & editing. GA: Investigation, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. BÇ: Data curation, Formal analysis, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. HT: Funding acquisition, Investigation, Software, Supervision, Writing – original draft, Writing – review & editing.

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Epidemiological characteristics and behaviors of online broadcast suicidality in China: implications for targeted prevention strategies

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Objectives: Suicide is a global health concern, exacerbated by stigma around mental illnesses. Online platforms like Twitter and Sina Weibo have seen a rise in "online broadcast suicide," where individuals share suicidal thoughts and actions. However, there is limited understanding of the epidemiological characteristics, particularly in China. This study aims to analyze the demographics and behaviors of individuals engaging in online broadcast suicide in China to inform targeted prevention strategies.

Methods: A total of 525 incidents were identified through systematic retrieval of relevant news reports from online sources. Subsequently, a content analysis was performed on these reports to extract detailed information on the characteristics of each individual incident.

Results: Among the incidents analyzed, the male-to-female ratio was 1:1.6, with an average age of 23.1 ± 5.9 years. Approximately 71.9% took place in Southern China. Unemployment was reported in 15.0% of incidents. Relationship breakup (62.3%) was cited as the leading cause of suicide. Wrist cutting (58.2%) emerged as the predominant suicide method, and home (36.2%) was the most common location for these tragic events. Instant messaging apps were the primary platforms (54.7%) for conveying suicidal thoughts and actions. Additionally, among the 525 incidents examined, 12.0% disclosed having a mental disorder, and 7.6% had a history of prior suicide attempts. Significant variations were observed across age, gender, region, and occupation categories.

Conclusion: This study emphasizes the importance of developing suicide prevention programs for internet users. Besides, interventions should be customized to meet the specific needs of various populations.

KEYWORDS

China, internet users, suicide, suicide attempt, suicide broadcast

1 Introduction

According to recent estimates by the World Health Organization (WHO), suicide continues to be a major global cause of mortality (1). Timely intervention has the potential to significantly reduce suicide-related deaths (2). Unfortunately, mental illnesses, including suicidal behaviors, often carry a stigma that undermines their seriousness and is sometimes

dismissed as mere attention-seeking (3). This stigma further hampers individuals from seeking proper treatment, resulting in an elevated risk of suicide and reduced chances of receiving timely assistance (4).

In the present day, the Internet has become an integral component of many people's everyday lives. Online platforms such as Twitter and Sina Weibo have provided users with interactive spaces where they feel more comfortable disclosing personal information (5). Consequently, individuals with suicidal tendencies may be motivated to share and communicate their thoughts and behaviors related to suicide online (6). This includes cases of livestreamed suicides, wherein individuals use various media formats (e.g., pictures, text messages, and videos) to broadcast their intentions and actions before taking their own lives, often referred to as "online broadcast suicidality" (5). The term "suicidality" encompasses all thoughts and actions related to suicide, including ideation, attempts, and completed suicides (7). As an increasing number of individuals with suicidal tendencies engage online, there is an amplified potential for interventions, prevention efforts, and crisis responses (6). Real-time notifications can alert other internet users when someone broadcasts their suicidality. By appropriately responding and offering support in these situations, there is a higher likelihood of mitigating the risk of fatal outcomes (6).

In order to enhance public responses to online broadcasts of suicidality, past research has primarily focused on examining public knowledge and beliefs regarding such broadcasts (5, 8). Nevertheless, it is equally crucial to comprehend the attributes of individuals who employ the internet for reasons related to suicide. Despite existing studies in this domain (9, 10), there remains a lack of comprehensive research concerning the epidemiological characteristics of individuals who engage in broadcasting their suicidal tendencies online. Consequently, the aim of this study is to conduct a systematic analysis of the epidemiological characteristics associated with online broadcasts of suicidality specifically within the context of China.

2 Methods

The research procedure entailed three sequential steps: (1) data acquisition, (2) data preprocessing, and (3) data analysis. Figure 1 illustrates the procedures involved in data collection and preprocessing.

2.1 Data collection

To establish a comprehensive dataset, an extensive collection of news reports was conducted on February 5, 2023. This involved searching six prominent Chinese news websites: Baidu,[1] 360 Search,[2] Sina news,[3] Sohu news,[4] Tencent news,[5] and 163 news.[6] The search criteria encompassed keywords related to the topic, including "suicide show" ("自杀秀," "自杀展示"), "live broadcasts of suicide" ("直播自杀," "自杀直播"), and "self-presentation of suicide" ("晒自杀," "秀自杀"). The determination of these key search terms was based on the following two steps. First, in order to maximize the relevant information related to online broadcast suicide, we conducted exploratory searches on the aforementioned six news websites to identify a list of relevant search terms. Second, we extensively reviewed literature on the subject to document existing effective keywords. Subsequently, after comprehensive review and consideration by our research team, we finalized these search keywords. Consequently, a total of 21,508 news reports accompanied by the aforementioned keywords were acquired as a result of the search.

2.2 Data preprocessing

Following the completion of data collection, preprocessing procedures were implemented to prepare the raw data for subsequent analysis. To eliminate irrelevant news reports, a manual examination of the collected data was carried out. This study defined irrelevant reports as those falling under the following categories: (1) reports pertaining to users engaging in non-suicidal activities or making jokes about suicide while broadcasting online; (2) reports focusing on topics unrelated to online broadcasts of suicidality, such as movie or real-world instances of suicidality; (3) reports discussing users whose suicidal messages were shared posthumously; (4) reports centering on suicides in non-human animals, like cats; (5) reports lacking the necessary context or relying solely on keywords, which hindered accurate coding; and (6) reports discussing incidents occurring outside of China. The assessment of all 21,508 news reports was conducted by two independent coders. Any report that both coders agreed to exclude was subsequently eliminated from consideration. In cases where discrepancies arose between the two coders, a third researcher was consulted to make a final decision. Following the removal of 18,794 irrelevant reports, a total of 2,714 reports remained for further analysis. To eliminate duplicate records, integration procedures were implemented, resulting in the removal of 2,189 redundant news reports. Ultimately, a collection of relevant news reports comprising 525 incidents was obtained.

2.3 Data analysis

Following data preprocessing, an in-depth content analysis was conducted by two independent coders on the relevant reports to extract information regarding the characteristics of each individual incident. The extracted information comprises two major components: demographic characteristics, including gender, age, geographical location, and employment status, as well as detailed aspects of the incidents, such as the time of occurrence, location of suicide, method used, reasons behind the act, internet platforms broadcasting suicidality, mental health status, history of suicide, and level of suicidality. The extent of interrater agreement between the coders was assessed using Cohen's kappa coefficient, with values equal to or exceeding 0.6 considered indicative of acceptable reliability. The final Kappa scores ranged from 0.8 to 1.0, reflecting substantial to perfect agreement. Any discrepancies that arose during the analysis were resolved through rigorous team discussions to attain consensus.

For data analysis in this study, we employed the IBM SPSS Statistics 22.0 and XLSTAT 2020 software. To explore the dataset's characteristics, descriptive analyses and Mann-Kendall trend tests were performed. A battery of statistical tests was conducted to examine age, gender, regional, and occupational differences across the various categories. These tests included chi-squared tests for categorical variables,

1 https://www.baidu.com/
2 https://www.so.com/
3 http://news.sina.com.cn/
4 http://news.sohu.com/
5 http://news.qq.com/
6 http://news.163.com/

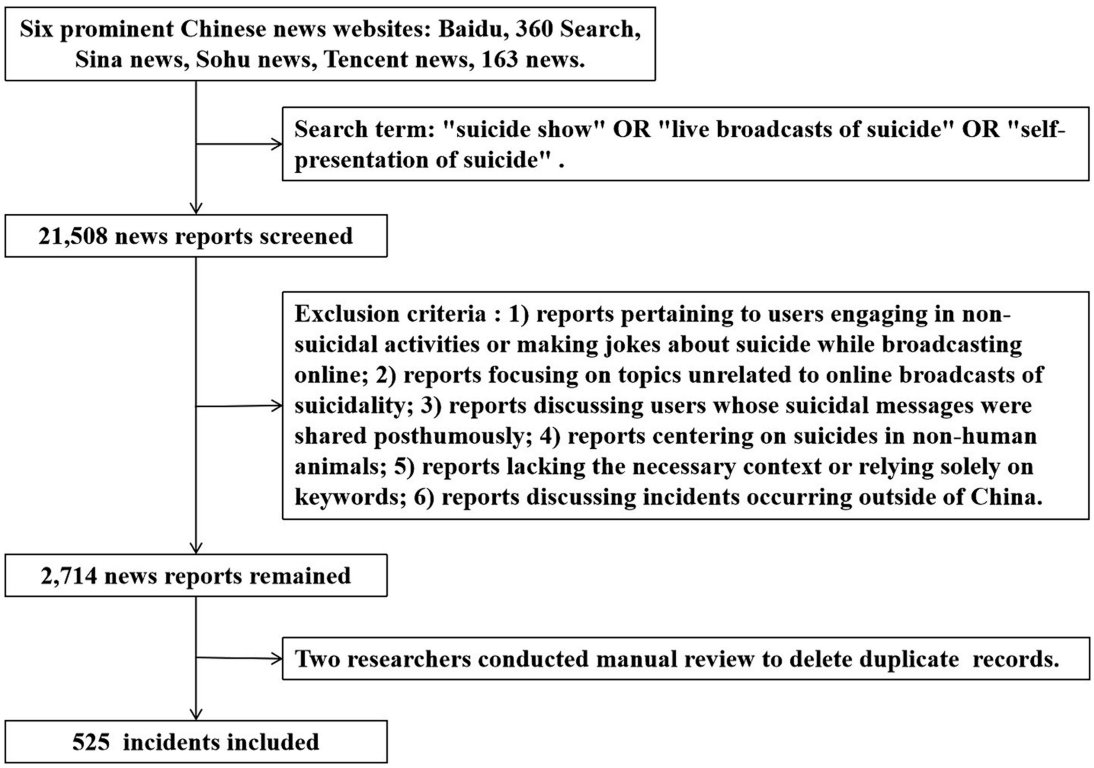

FIGURE 1
Flow chart of news report collection.

independent-sample *t*-tests for continuous variables, and 1-way ANOVA (followed by post-hoc Scheffe's tests) for multiple group comparisons. All statistical analyses were performed using two-tailed tests, and a significance level of 0.05 was set. Given that a few incidents may have multiple values within a single category, independent sample comparisons are not feasible. Thus, these incidents were excluded from the corresponding analysis for each category.

3 Results

3.1 Basic demographic characteristics

The final analysis comprised a total of 525 incidents, each involving a distinct individual. Table 1 presents the demographic characteristics of the sample. Of the 525 incidents, 516 reported their gender, resulting in a male to female ratio of 1:1.6. Age information was available for 308 incidents, with an average age of 23.1 ± 5.9 years (females, 22.4 ± 5.0 years; males, 24.3 ± 6.8 years). The age range varied from 15 to 53 years, with no significant gender differences observed. Regarding location, 501 incidents provided information on their occurrence. Among these, 44.1% ($n = 221$) were located in Eastern China, while 71.9% ($n = 360$) were concentrated in Southern China when considering the broader geographical regions. No significant age or gender disparities were found. Furthermore, 226 individuals disclosed their employment status. Among them, 34 incidents (15.0%) involved unemployed individuals. No significant age, gender, or regional distinctions were evident in this regard.

3.2 Time of occurrence

Based on the Mann-Kendall trend test ($S = 154$, $Z = 4.99$, $p < 0.001$), a significant increase in the frequency of incidents was observed from 2003 to 2022 (Figure 2). This increasing trend was consistent across gender, age, region, and occupation groups, with the exception of residents from Northeast China ($p > 0.05$), and students ($p > 0.05$). Regarding the monthly distribution, May had the highest frequency of incidents, accounting for 67 cases (12.8%). No significant variations were found when comparing different genders, age groups, regions, and occupations. Analyzing the hourly patterns, incidents were most frequently recorded between 18:00 and 00:00, with 207 cases (39.4%) occurring during this period. Again, no noteworthy disparities emerged across gender, age, region, or occupation.

3.3 Suicide locations

In this study, 345 incidents were found to have identifiable suicide locations (refer to Table 2). Among these incidents, the overwhelming majority ($n = 340$; 98.6%) were associated with a single location, while only 5 incidents (1.4%) were linked to two distinct locations. The most frequently reported suicide location was at home, which accounted for 36.2% ($n = 125$) of the total cases. In our analysis, significant gender differences in suicide locations were observed (Fisher exact test: $p < 0.01$). Specifically, females exhibited a higher likelihood of choosing rental places as the site for suicide compared to males ($\chi^2 = 7.6$, $p < 0.01$). There are no significant differences in age, region or occupation.

TABLE 1 Demographic information ($n = 525$).

Category	*n*	%
Gender (*n* = 516)		
Female	314	60.9
Male	202	39.1
Age (years, *n* = 308)		
15 ~ 19	50	16.2
20 ~ 24	135	43.8
25 ~ 29	68	22.1
30 ~ 34	36	11.7
35 ~ 39	14	4.6
≥ 40	5	1.6
Employment status (*n* = 226)		
Employed	162	71.7
Unemployed	34	15.0
Student	30	13.3
Province (*n* = 501)		
Jiangsu	55	11.0
Guangdong	53	10.6
Sichuan	47	9.4
Shandong	47	9.4
Fujian	40	8.0
Zhejiang	34	6.8
Hubei	32	6.3
Anhui	26	5.1
Shaanxi	21	4.2
Henan	16	3.2
Province (*n* = 501)		
Hebei	16	3.2
Shanghai	16	3.2
Beijing	15	3.0
Chongqing	14	2.8
Hunan	12	2.4
Hong Kong	7	1.4
Guangxi	7	1.4
Liaoning	7	1.4
Taiwan	5	1.0
Guizhou	5	1.0
Tianjin	4	0.8
Jiangxi	3	0.6
Shanxi	3	0.6
Heilongjiang	3	0.6
Jilin	2	0.4
Yunnan	2	0.4
Gansu	2	0.4
Hainan	2	0.4
Ningxia	1	0.2
Qinghai	1	0.2
Tibet	1	0.2
Xinjiang	1	0.2
Inner Mongolia	1	0.2

FIGURE 2
The number of incidents between 2003 and 2022.

3.4 Suicide methods

Among the 525 incidents analyzed, suicide methods were identifiable in 490 cases (Table 2). Out of these, 433 incidents (88.4%) were associated with a single method, while 57 incidents (13.2%) involved two different methods. The most frequently employed suicide method was wrist cutting, accounting for 58.2% ($n = 285$) of the total cases. Our analysis revealed significant age ($F = 3.9$, $p < 0.01$) differences in suicide methods. More specifically, individuals who committed suicide by hanging tended to be older compared to those who used medications or poisons ($p < 0.01$, post-hoc Scheffe's test), slit their wrists ($p < 0.01$, post-hoc Scheffe's test), or jumped from a high place ($p < 0.05$, post-hoc Scheffe's test). There are no significant differences in gender, region and occupation.

3.5 Reasons for suicide

In our study, suicide causes were identified in 478 cases (Table 2). Among these cases, 386 incidents (80.8%) were linked to a single cause, while 69 incidents (14.4%) and 23 incidents (4.8%) involved two and three distinct causes, respectively. The primary cause reported was relationship breakup, accounting for 62.3% ($n = 298$) of the total cases. Our analysis revealed significant gender differences in suicide causes ($p < 0.001$, Fisher exact test). More specifically, males were found to have a higher likelihood of committing suicide as a result of financial difficulties compared to females ($p < 0.001$, Fisher exact test). There are no significant differences in age, region or occupation.

3.6 Internet platforms

Out of the 525 incidents examined, 497 cases (94.7%) involved specific types of internet platforms through which suicidality was broadcasted (Table 2). Among these cases, 482 incidents (97.0%) were associated with the use of a single platform type, while 15 incidents (3.0%) involved the use of two different types of platforms. The most commonly utilized platform for broadcasting suicidality was instant messaging apps, accounting for 54.7% ($n = 272$) of the total cases.

Our analysis uncovered significant gender ($p < 0.001$, Fisher exact test), regional ($p < 0.01$, Fisher exact test), and occupational ($p < 0.01$, Fisher exact test) disparities in the usage of internet platforms for broadcasting suicidality. More specifically, males were more likely than females to employ online bulletin boards for this purpose ($\chi^2 = 12.5$, $p < 0.001$). Individuals from Southern China demonstrated a greater preference for instant messaging apps compared to those from Northern China ($\chi^2 = 4.8$, $p < 0.05$). Moreover, employed individuals were more inclined to using instant messaging apps, as opposed to students ($\chi^2 = 5.1$, $p < 0.05$). No significant variations were found when comparing different ages.

3.7 Mental health status and suicidal history

In this study, 63 cases documented the presence of mental disorders. Out of these cases, 92.1% ($n = 58$) were associated with a single type of mental disorder, whereas only 5 incidents (7.9%) involved two distinct types of mental disorders. Specifically, 57 individuals (90.5%) reported suffering from depressive disorder, 5 individuals (7.9%) reported anxiety disorders, and 3 individuals (4.8%) reported personality disorders. There were 3 cases where a specific type of mental disorder was not reported. There are no significant differences in age, gender, region or occupation. Furthermore, 7.6% of the incidents (40/525) disclosed a history of previous suicide attempts. No significant disparities emerged across age, gender, region, or occupation.

TABLE 2 Suicide methods, reasons, locations, and types of internet platforms used for broadcasting suicidality.

Category	*n*	%
Suicide methods (*n* = 490)[a]		
Slitting wrists	285	58.2
Taking medications or poisons	164	33.5
Jumping from a height	43	8.8
Charcoal burning	23	4.7
Drowning	12	2.4
Exposure to gas	10	2.0
Hanging	9	1.8
Exposure to poisonous animals	4	0.8
Motor vehicle collision	3	0.6
Setting fire	2	0.4
Reasons for suicide (*n* = 478)[b]		
Relationship breakup	298	62.3
Family conflicts	100	20.9
Job-related stress	55	11.5
Mental disorder	48	10.0
Financial difficulties	38	7.9
Physical illness	13	2.7
Encountering discrimination and bullying	11	2.3
Academic pressure	10	2.1
loss of close relationships	4	0.8
Type of platform (*n* = 497)[c]		
Instant messaging apps	272	54.7
Social networking websites	159	32.0
Online bulletin boards	86	17.3
Online chat rooms	7	1.4
Video-sharing websites	3	0.6
Suicide locations (*n* = 345)[d]		
Home[e]	125	36.2
Rental place	84	24.3
Hotel	66	19.1
Dormitory	13	3.8
Internet café	12	3.5
Others	51	14.8

[a]Occurrences involving multiple suicide methods were tabulated separately within their respective subcategories.
[b]Occurrences involving multiple suicide causes were tabulated separately within their respective subcategories.
[c]Occurrences involving multiple types of internet platforms were tabulated separately within their respective subcategories.
[d]Occurrences involving multiple suicide locations were tabulated separately within their respective subcategories.
[e]Home denotes an individual's permanent place of residence.

3.8 Levels of suicidality

In this study, 491 incidents revealed varying degrees of suicidal tendencies. Among them, 420 incidents (85.5%) were classified as suicide attempts, followed by suicidal ideation ($n = 39$; 8.0%) and suicide ($n = 32$; 6.5%). Significant disparities in levels of suicidality were observed across different occupations ($p < 0.05$, Fisher exact test). Employed individuals were found to have a higher likelihood of being associated with suicide attempts compared to those who were students ($p < 0.05$, Fisher exact test) and unemployed ($p < 0.05$, Fisher exact test). There are no significant differences in age, gender, or region.

4 Discussion

Lyu et al. (11) used official suicide mortality data provided by the Chinese Center for Disease Control and Prevention to examine the patterns of suicide across 33 provincial-level regions in China

based on gender and age. Their results indicated that over the past 30 years, the overall suicide rate in China has gradually declined, attributed to the rapid development of society, economy, and education (11). However, fast-paced lifestyles and high levels of internal migration may exacerbate other new sources of stress (12). Of concern is that online suicide attempts and completion rates appear to be increasing, showcasing the individual's internal struggles encompassing feelings of dissatisfaction, insecurity, isolation, and negative self-perception (5, 13, 14). Our study systematically examined the epidemiological characteristics of online broadcasts of suicidality in China, providing valuable evidence and insights for the development of future public awareness campaigns. By analyzing accounts of these incidents, our findings shed light on a deeper understanding of individuals with suicidal tendencies and, perhaps more importantly, how suicide can be prevented within an online environment.

To begin with, it is noteworthy to mention the demographic characteristics associated with online broadcasts of suicidality. In our study, a higher number of incidents were observed among females, aligning with previous findings suggesting an increased risk of suicide among females in China (15, 16). However, in offline suicide studies, the male-to-female ratio of suicide rates has been steadily increasing, reaching 1.56 in 2017 (11). The decrease in female suicide rates offline is related to the establishment of social networks, improvement in social and family status for women (11). One possible explanation for the different trends in online and offline suicide is the presence of gender-specific coping mechanisms and social support structures that differ between online and offline environments. Moreover, the majority of incidents (82.1%) occurred within the age group of 15 to 29 years, reflecting a persistently high prevalence of suicide risk within this specific age cohort of the Chinese population (17, 18). In terms of regional distribution, we found that a considerable portion of incidents took place in Eastern China (44.1%) and Southern China (71.9%). These figures are consistent with the proportions of internet users in each respective region (19). This correlation implies that the level of internet accessibility may play a role in influencing the distribution of online broadcasts of suicidality among different populations.

Second, regarding incident details, we found that a significant proportion (39.4%) of incidents occurred during the time frame of 18:00 to 00:00, which can be considered a high-risk period for suicide attempts (20). Notably, our study reports wrist cutting as the most prevalent method used, deviating from previous research findings (21, 22). Several factors could be speculated as potential explanations for this discrepancy. It is essential to consider that cultural norms and societal attitudes toward suicide can vary across regions and countries, leading to variations in the choice of methods employed (21). Variability in data collection techniques, such as reliance on self-reporting or medical records, could also contribute to divergent findings. Furthermore, public awareness campaigns, prevention efforts, or changes in access to lethal means can influence the popularity of certain suicide methods over time. Differences in the timing of data collection across studies might account for the observed inconsistencies (22). In terms of suicide location, the majority of incidents took place at home, highlighting the significance of personal surroundings in suicidal behaviors. Relationship breakup emerged as the leading cause of suicide, underscoring the impact of interpersonal relationships on individuals' mental well-being in this context (23). Instant messaging apps were identified as the primary medium for broadcasting suicidal thoughts and actions, shedding light on the role of modern communication technologies in facilitating such behaviors (24). Only a minority (12.0%) of incidents reported a history of psychiatric disorders, which is remarkable given prior studies indicating a higher prevalence (32.3%) of psychiatric comorbidities among suicide attempters (25). This discrepancy might be attributed to inadequate awareness and understanding of mental health issues among the Chinese population, resulting in an underestimation of psychiatric disorder rates (26). Further research is warranted to grasp the complex interplay between sociocultural factors, mental health literacy, and suicidal behaviors in this particular context.

Third, in China, there is limited availability of professional mental health services and suicide prevention training (27). Online suicide prevention has shown promise in previous studies (5, 28), as compassionate individuals within the online community have demonstrated a willingness to take positive actions. However, their knowledge and understanding of effective responses may be inadequate (5). Expanding the use of social media for suicide prevention training could be a cost-effective approach, considering its effectiveness and wide reach (29). To maximize the impact, it is important to make best-practice materials more accessible in multiple languages and distribute them across various social media platforms, not solely targeting professional organizations (30). Leveraging popular platforms such as search engine sites, Weibo, and other easily accessible websites can ensure widespread dissemination of this information within the social media environment (6). Furthermore, social media platforms can serve as a valuable avenue for skilled individuals to provide online support to those in need (31, 32). It is also crucial for emergency services to establish clear protocols for gathering information and responding to life-threatening crises (5).

5 Limitations

This study has several limitations that need to be acknowledged. First, given the way the research was done, there are certain limitations in terms of diversity and incompleteness of the data, as news services do not always include same information, and conceal some due to ethics and space limitations. Second, social media users cannot be representative of the entire population in China, which means the results might not be applicable to nonusers. Third, online suicide incidents could potentially vary across different online platforms due to variations in user environments, communication dynamics, and other contextual factors. Finally, within the scope of this study, there were a mere 58 incidents with complete data, precluding the possibility of conducting the necessary multivariate analysis. In future research, it would be beneficial to make a correlation of the observed variables, in order to better understand the relevant internal and external factors that increase the risk of this kind of behavior.

6 Conclusion

This study emphasizes the importance of developing suicide prevention programs for internet users. To effectively address the heterogeneity in characteristics and demographics observed in online

broadcasts of suicidality, interventions should be customized to meet the specific needs of various populations.

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

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

C-yL: Data curation, Writing – original draft. YX: Data curation, Investigation, Writing – review & editing. T-tC: Investigation, Writing – review & editing. S-yZ: Investigation, Writing – review & editing.

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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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Using machine learning algorithms and techniques for defining the impact of affective temperament types, content search and activities on the internet on the development of problematic internet use in adolescents' population

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Background: By using algorithms and Machine Learning – ML techniques, the aim of this research was to determine the impact of the following factors on the development of Problematic Internet Use (PIU): sociodemographic factors, the intensity of using the Internet, different contents accessed on the Internet by adolescents, adolescents' online activities, life habits and different affective temperament types.

Methods: Sample included 2,113 adolescents. The following instruments were used: questionnaire about: socio-demographic characteristics, intensity of the Internet use, content categories and online activities on the Internet; Facebook (FB) usage and life habits; The Internet Use Disorder Scale (IUDS). Based on their scores on the scale, subjects were divided into two groups – with or without PIU; Temperament Evaluation of Memphis, Pisa, Paris, and San Diego scale for adolescents (A-TEMPS-A).

Results: Various ML classification models on our data set were trained. Binary classification models were created (class-label attribute was PIU value). Models hyperparameters were optimized using grid search method and models were validated using k-fold cross-validation technique. Random forest was the model with the best overall results and the time spent on FB and the cyclothymic temperament were variables of highest importance for these model. We also applied the ML techniques Lasso and ElasticNet. The three most important variables for the development of PIU with both techniques were: cyclothymic temperament, the longer use of the Internet and the desire to use the Internet more than at present time. Group of variables having a protective effect (regarding the prevention of the development of PIU) was found with both techniques.

The three most important were: achievement, search for contents related to art and culture and hyperthymic temperament. Next, 34 important variables that explain 0.76% of variance were detected using the genetic algorithms. Finally, the binary classification model (with or without PIU) with the best characteristics was trained using artificial neural network.

Conclusion: Variables related to the temporal determinants of Internet usage, cyclothymic temperament, the desire for increased Internet usage, anxious and irritable temperament, on line gaming, pornography, and some variables related to FB usage consistently appear as important variables for the development of PIU.

KEYWORDS

machine learning, problematic internet use, A-TEMPS-A, adolescents, internet use

1 Introduction

Technical and technological progress at the end of the 20th century has lead to the wide-spread Internet use as a means of communication and a way to access desired information, which is one of the characteristics of humans as social beings. In a bigger sense and in an easier and faster way, the Internet provides individuals with a sense of belonging to a community regardless of gender, age, race, or other characteristics. In 1995, the term Internet Addiction Disorder was firstly used by Goldberg (1). Since then, almost 30 years later, controversies and criticisms of this disorder still exist and they mostly relate to the reality of its pathology. Researchers particularly point to the issue of pathologizing internet use (2). Despite many reservations, it is evident that in practice, there are many individuals seeking professional help due to losing control over Internet use, along with all the negative consequences that accompany it (3). The terms "Internet addiction" and "problematic Internet use- PIU" are used to describe a manner of Internet usage marked by excessive behavior, a lack of control, disregard for other significant activities, and persistent engagement despite experiencing negative consequences such as distress and functional impairment (4). Theoretical considerations, supported by some clinical studies (with small sample sizes), suggest that the symptoms of problematic internet use resemble those of other behavioral or psychological disorders: obsessive-compulsiveness, depression, hostility, anxiety, and emotional sensitivity (5). Based on these claims, we can conclude that the dimensions of PIU symptoms overlap with the symptoms of the disorders that most commonly lead to excessive internet use. It often happens that individuals with some problems (e.g., depression, anxiety) turn to the Internet in search of relief, which, on one hand, exacerbates their initial symptoms, and, on the other hand, intersects with new symptoms resulting from excessive internet use. This leads to a new complex of symptoms that cannot simply be equated with the initial psychological problems. The Internet is constantly evolving, and due to its capabilities, we may never be ahead of its development and fully predict all the directions in which problems and disorders related to its use can evolve (5).

Adolescents and young adults are a particularly sensitive population and they are increasingly facing very real and sometimes very serious consequences in their everyday lives arising from inadequate Internet use (6). By viewing the overall morbidity, school and student youth represent the healthiest part of the society, still, their specific characteristics make them sensitive to various negative influences coming from the living and social environment, which certainly include PIU along with all the negative risks it carries (7, 8). Besides the fact that the young people are a significant part of the population of Internet users, they also represent the largest portion of the general population with the highest risk of developing PIU (9–12). Adolescents are, also, considered the most exposed population: they are especially sensitive to the development of all types of addictions and they are the population that uses the Internet the most (13, 14). The importance of the need to protect the health of adolescents is also highlighted by the current WHO campaign titled "Global Strategy for Women's, Children's and Adolescents' Health (2016–2030)" (15). There is inconsistency in the data regarding prevalence of PIU in the adolescent population. By following the analogy with other addictions, the assumption is that boys develop PIU more often. Moreover, it is expected that adolescents with better academic performance and a better socio-economic status are less likely to develop PIU.

As an "umbrella concept," problematic Internet use encompasses a variety of problematic online behaviors (16). Until now, only problematic online gaming has entered official classifications and received its classification parameters. In the ICD-11, there is a category "disorders due to addictive behaviors," which officially acknowledges gambling disorder and gaming disorder as the two behavioral addictions falling within this classification (17). However, research has shown that those who meet the diagnostic criteria for this addiction do indeed use the Internet for following other content and engaging in other activities (2). Let us note that there has been some genetic basis for the development PIU (18). Moreover, temperament as a biological basis of inherited personality (19) together with certain lifestyle habits that can reduce the time spent using the Internet can have a significant factor in the analysis of this complex issue. The assumption that specific activities and content on the Internet can lead to a reduced reduce but also increase risk of developing PIU is particularly interesting. So, monitoring the development of PIU through the analysis of the impact of various online activities of adolescents, the content they follow, as well as their habits in everyday life and the possible influence of temperament truly represents a challenge. Forming a nationally representative sample of adolescents was one way to address this challenge. The other way was to select analytical methods through which this kind of extensive database could be analyzed (both in terms of breadth and depth). In addition

to data collection, conventional approaches to data analysis sometimes lack the capacity of variables extraction and selection. On the other hand, application of machine learning- ML methods would allow overcoming these shortcomings and enable better identification of target groups for interventions (20). ML encompasses a diverse array of methods and techniques designed to address a wide spectrum of issues. Tasks like identifying individuals with substance use disorders (21), finding patterns in neuro images, comprehending prognostic factors related to addictions and their correlations, and unraveling the genetic foundations of addiction are included. Over the past decade, various biomedical research domains, including addiction, have effectively applied machine learning in the last decade. In their review paper, Cresta Morgado et al. (22) stated that, through a PubMed database search, they discovered fewer than 200 articles pertaining to machine learning and addiction. While the number of these articles has been on the rise, articles using machine learning still constitute only 0.25% of the overall articles on addiction. Moreover, a small subset of these articles focuses specifically on behavioral addictions.

1.1 Machine learning techniques

Traditional data processing methods involve the use of mathematical and statistical methods to discover knowledge within a data set. They are usually based on predefined hypotheses, assumptions and mathematical models for data analysis. However, although they represent well-established methods, a problem arises when using high-dimensional and complex data sets. ML can be successfully used to solve these problems.

The ML algorithms have revolutionized the field of data processing by enabling the automatic extraction of patterns, connections and insights from complex data sets. ML can be broadly defined as computational methods which use experience to improve performance or to make accurate predictions (23). They analyze various forms of collected data. The quality and size of this data are crucial for the successful predictions made by the learner.

To successfully employ machine learning techniques for addressing various problem types, it is necessary to precisely define the problem and choose suitable ML algorithms. Different ML techniques exist based on how models are trained. Classifiers, which are classification models, predict categorical (discrete, unordered) class labels (24). The classification process unfolds in two key steps: the learning phase (creating a classification model) and the subsequent classification phase (this model is used to predict class labels for provided data points).

During the learning phase, a classification model is created by defining a predetermined set of classes or concepts (24). This constitutes the learning step during which the classification algorithm builds a model through the analysis or "learning from" a training dataset consisting of data points and their corresponding class labels. A data point, denoted as X, is represented by an n-dimensional attribute vector, $X = (x1, x2,.., xn)$, describing the data point through n measurements on attributes A1, A2,..., An. Each data point, X, is assigned to a predefined class determined by a specific attribute known as the class label attribute. This attribute is represented by an unordered discrete value, where each of its possible values signifies a distinct class or category. The individual data points of the training dataset, called training data points, are randomly selected from the database.

Since the class label is known for each training data point, this step is often called supervised learning (classifier learning is supervised because each training data point is explicitly assigned to a specific class) (24). The first step of classification can be viewed as the process of learning a mapping function, $y = f(X)$, capable of predicting the class label y for a provided data point X. In this sense, we want a mapping function that divides the data according to the class they belong to.

In the second phase, the created model is applied for classification (24). Initially, the classifier's predictive accuracy is evaluated using a test set consisting of test data points and their corresponding class labels. These test data points are independent from the training data points and they were not utilized in the creation of the classifier. The accuracy of the classifier on the provided test dataset is calculated as the percentage of correctly classified test data points. The class label assigned to each data point is compared to the classifier's prediction for that specific data point. If the classifier's accuracy meets acceptable standards, it can then be employed to predict future data points where the class label is entirely unknown.

Naive Bayes is a classifier based on Bayes' theorem. The term "naive" originates from the fact that the classifier assumes strong independence between attributes (24, 25). It is assumed that the value of a specific attribute is entirely independent of the value of any other attribute, given the assigned class label. Despite this simplifying assumption, the Naive Bayes classifier is recognized as a successful solution for practical problems related to text classification, healthcare, and similar applications.

Nearest-Neighbor classifiers use an analogy-based learning technique by comparing a given test data point with training data points that share similarities (24). Each data point, denoted as X, is represented as a point in an n-dimensional space. In the case of an unknown data point, the k-nearest-neighbor classifier explores the space to identify the k closest data points. These k training data points constitute the k "nearest neighbors" of the unknown data point. Closeness, or similarity, is usually defined in the context of a chosen distance metric (e.g., Euclidean distance).

Decision trees are a tree-like structure where each internal node represents a test on an attribute, each branch denotes the test result, and each leaf node (terminal node) represents a class label (24, 26). The attributes of a given data point, X, for which the class label is unknown, are tested using the decision tree. The path from the root node to the terminal node signifies the class prediction for the given data point.

Decision tree induction is the process of creating a decision tree based on a set of training data points with associated class labels. The induction process does not require domain knowledge or parameter tuning, making decision trees suitable for exploratory knowledge discovery (24). Decision trees generally exhibit a high level of accuracy.

Random forests, or random decision forests, are an ensemble machine learning technique that operates by constructing a multitude of decision trees during training (24). In classification, the output of the random forest is determined by the class selected by most trees.

Gradient boosting is a machine learning technique that generates a classification model in the form of an ensemble of weak classification models, typically decision trees (24). When a decision tree serves as

the weak model, the resulting classification model is referred to as gradient-boosted trees.

The neural networks field was originally kindled by psychologists and neurobiologists who sought to develop and test computational analogs of neurons (27). Artificial Neural Network consists of interconnected input/output units, where each connection is assigned a weight (24). During the learning phase, the network adapts by adjusting these weights to accurately predict the class label of input tuples. Neural networks require prolonged training times, making them more suitable for applications where such durations are feasible. Determining parameters such as network topology or "structure" typically requires empirical process. Artificial neural networks offer advantages, including a high tolerance for noisy data and the capability to classify patterns on which they have not been trained. They are a valuable solution when dealing with limited knowledge of relationships between attributes and classes (24, 28).

Deep learning networks are gaining importance due to their ability to discover complex representations of raw data. Deep learning networks are composed of multiple layers of interconnected neurons that learn hierarchically more complex attributes. These models have shown impressive results in various fields, including image and object recognition, natural language processing, speech recognition, and more. The main asset of the deep learning model is the automatic extraction of the most important attributes from the data, thus achieving a more precise and finer analysis of the data.

Feature selection – "The curse of dimensionality" occurs when data sets have many attributes. High-dimensional data is a barrier to use in several fields, such as data processing, statistical analysis, and machine learning. The problems are reflected in the increased complexity of calculations, the increased demand for resources in the form of memory and processing time, and, therefore, the increased time required for training and using the model. Many attributes also increase the chance of false correlations or dependencies between attributes. As a result, models are obtained whose accuracy is lower than expected or desired, while the model itself is much more difficult to understand (29, 30).

The evolution of machine learning has led to the development of algorithms and tools that effectively reduce dimensionality due to their ability to learn complex patterns and structures within the data. These algorithms aim to learn the underlying meaning of the data and thereby discover the most informative attributes and those that most determine the difference between samples. In this way, problems caused by high-dimensional data are successfully eliminated and more efficient data analysis is promoted.

Feature selection methods have mainly three categories (29, 30):

- Filter methods – Filter methods use the general characteristics of data itself and work separately from the ML algorithm. The filter methods use the statistical correlation between a set of attributes and the target class attribute. The amount of correlation between a specific attribute and the target class attribute determines the importance of that attribute. Filter based approaches are not dependent on classifiers and are usually faster and more scalable. Also, they have low computational complexity.
- Wrapper methods – These methods use the target ML algorithm as a black box to find the best subset of attributes. Selected attributes are highly dependent on the performance of the target ML algorithm.
- Embedded methods – Feature selection occurs naturally as part of the ML algorithm. Specifically, during the classification model training process, the ML algorithm itself decides which attributes to use and which to ignore. These methods imply the dependence of the selected attributes on the specific model used during training, but it also means that no tool for external selection of attributes is necessary.

Correlation-Based Feature Selection (CFS) is a simple filter algorithm that assesses and ranks attribute subsets using a correlation-based heuristic evaluation function (31). The evaluation function selects attributes highly correlated with the class label attribute while uncorrelated among themselves. The rationale is to ignore irrelevant attributes with low correlation to the class label attribute. Additionally, redundant attributes, which are highly correlated with one or more remaining attributes, are filtered out. CFS is usually based on Pearson correlation, where all attributes are standardized for consistency.

Decision trees, including individual decision trees in different ensemble methods, can be created using different algorithms (24). Differences in algorithms for decision tree induction include how the attributes are selected in creating the tree and the mechanisms used for pruning. An attribute selection measure serves as a heuristic for determining the optimal splitting criterion that effectively separates the given training data points. The aim of these algorithms is to identify the best predictor and split point, enhancing homogeneity within each new partition (29). Therefore, if a predictor remains unused in any split, it is functionally independent of the prediction function and is excluded from the model. Ensembles of trees share this property, although certain algorithms, such as random forest, intentionally introduce splits on irrelevant predictors during the tree induction leading to an over-selection of predictors.

LASSO is primarily serving two purposes: regularization and feature selection (32). In the LASSO method, a constraint is imposed on the sum of the absolute values of the model parameters, ensuring the sum has to be less than a fixed value (upper bound). The method uses a shrinking (L1 regularization) penalizing the coefficients of the regression variables, shrinking some of them to zero. During the features selection process the variables that still have a non-zero coefficient after the shrinking process are selected to be a part of the model. The objective of this process is to minimize prediction errors. In practice, the tuning parameter λ, that controls the strength of the penalty, assumes important importance. When λ is sufficiently large. Coefficients are forced to be exactly zero, effectively reducing dimensionality. The larger the parameter λ, the more coefficients are undergoing shrinkage to zero. On the other hand, if $\lambda = 0$, an OLS (Ordinary Least Square) regression occurs.

ElasticNET (also called ELNET) regression is a statistical hybrid method that combines two of the most often used regularized linear regression techniques, LASSO, and RIDGE, to deal with multicollinearity issues when they arise between predictor variables (33). They are regularization aids in solving the overfitting issues with the models.

It is also used for regularizing and choosing the essential predictor variables that important impact the response variable (33). Ridge uses an L2 penalty, while LASSO employs an L1 penalty. Since the ElasticNET utilizes both the L2 and the L1 models, the question of choosing between either one does not arise.

A genetic algorithm (GA) is an optimization tool based on principles of evolution from population biology. To effectively identify optimal solutions, the algorithm imitates the evolutionary process of a population. It generates a candidate set of solutions, allowing them to reproduce and create new solutions. The algorithm promotes competition, providing optimal solutions with the best chance to survive solutions and populate the subsequent generation (natural selection). This iterative process enables GAs to accumulate and refine good solutions over time, improving their quality and converging to an optimization plateau.

The challenge of identifying an optimal feature subset can be treated as a complex optimization problem. Therefore, if the feature selection problem is conceptualized in terms of evolutionary biology, the GA algorithm can be applied to search for optimal feature subsets (29).

Permutation Feature Importance (34) is an approach that measures the impact on the prediction error when the values of a feature are permuted, disrupting the relationship between the feature and the actual outcome. A feature is considered as "important" if shuffling its values increases the model error, indicating the model's reliance on that feature for prediction. On the opposite side, a feature is considered "unimportant" if shuffling its values leaves the model error unchanged, signifying the model's disregard for that feature in prediction. This model is very popular for ML models that are commonly labeled as "black-box" models, such as artificial neural networks. Nonetheless, there are instances where neural network models can provide explanatory insights using the permutation feature importance approach. The permutation feature importance metric was initially introduced for random forests in (35, 36) and subsequently expanded with a model-agnostic version in (37, 38).

By using algorithms and ML techniques, the aim of this research was to determine the impact of the following factors on the development of PIU: sociodemographic factors, the intensity of using the Internet, different contents accessed on the Internet by adolescents, adolescents' online activities, life habits and different affective temperament types.

2 Methods

2.1 Sample

High school students, aged 16 and 17, were included in the research. The research was conducted as an observational cross-sectional study. In selecting schools, in which the research was conducted, the representation of the school was respected according to the official regionalization of the Republic of Serbia, which includes five regions (39). At the time when the research was created in the Republic of Serbia, 462 high schools existed, based on the data from the Ministry of Education and Science of the Republic of Serbia (40). The sample was stratified first by regions, then by cities within regions and finally by schools within cities. In schools, based on the number of classes, a random sample determined which departments would participate. The final stratified proportional sample included 48 high schools (about 10% of all schools). The study was conducted within a time frame of 45 days.

In accordance with the Law on the patients' rights, each participant was informed about the research. In the results of the survey, questionnaires filled in by the participants who gave their written consent for the participation in the research were included, in accordance with Article 25, paragraph 6 of the stated law. The questionnaires were filled out during school classes.

2.2 Instruments

The following questionnaires were used in the research:

2.2.1 A four-part questionnaire

A four-part questionnaire was created for this research, within which data was obtained about:

- The socio-demographic characteristics of the participants (gender, age, satisfaction with socio-economic status, academic achievement).
- The intensity of the Internet use: Internet Use (in years); Internet Use (hours per week); Internet Use (hours per day); Internet Use (on holiday) – The given question was: Do you use the Internet more while on holiday? Attitude about the time on the Internet –the given question was: If it were possible, would he/she spend more time on the Internet?
- In the third part, subjects answered questions about the searched content (Politics, Business, Sports, Computers and technology, Arts and culture, Education, Pop culture, Pornography, Music, Travel/Tourism, Health and medicine, Science, Religion) and types of activities (Communication by e-mail, Social networks, Communication on the forum, Communication on the blog, Targeted Internet search, Surfing, Expert Advice, Search for favorite websites, Reading the news, Online games, Reading and downloading books and texts, Downloading music and movies, Internet for school, Online courses) on the Internet. A five-level Likert scale (from 1 "never "to 5 "frequently") was given for every online content category and online activity category. Also we asked participants about the Facebook use (Everyday FB use, Average time spent on FB, FB use for gaming, FB use for– chatting, FB use for– visiting groups, FB use for- reading posts, FB use for- publishing statuses, FB use for- sharing music, photos etc.).
- In the fourth part, subjects answered questions about habits (playing sport, eating fast food, drinking alcohol, drinking energetic drinks, coffee consumption and smoking).

2.2.2 Internet use disorder scale – IUDS

The instrument was standardized and validated into the Serbian language (41). The scale consists of 18 items which participants rate according to a five-level Likert's scale (from 1 "minimally" to 5 "completely"), including the questions connected with the compulsive Internet use, the symptoms of abstinence and increased tolerance, as well as the questions linked with the problems at work and school (Cronbach's alpha coefficient $\alpha = 0.815$). According to subjects' scores on the scale (cut-off 39/40), they were divided into two groups (with or without PIU).

2.2.3 Temperament evaluation of Memphis, Pisa, Paris, and San Diego-autoquestionnaire (TEMPS-A) for adolescents – A- TEMPS-A

TEMPS-A is a self-evaluation questionnaire which determines the belonging to one of the following affective temperaments:

depressive, cyclothymic, hyperthymic, irritable and anxious. According to the definition of affective temperament, hyperthymic temperament is released from depressive characteristics, and vice versa, depressive temperament does not contain any of hyperthymic components. Cyclothymic and irritable temperaments are the successive and simultaneous mixture of hyperthymic and depressive characteristics, while anxious are closely connected with depressive temperament (42–44). The current version of the questionnaire has been developed over the last 10 years. The questionnaire is standardized in psychometric studies firstly in six languages and in six cultures: American English (Memphis and San Diego), Italian, French, German (versions from Minster and Hall), as well as, Turkish and Japanese. The factorial structure is consistent in all the mentioned cultures, and the scale has a high internal consistency. The scale is validated also in Serbian (45). A- TEMPS-A is a completely new version of the scale adjusted to the adolescents' age [Cronbach's alpha coefficient $\alpha = 0.77$, and the average test–retest coefficient (rho = 0.84)] (46).

2.2.4 Statistical analysis

Primarily obtained data were analyzed using descriptive statistical methods. Measures of central tendency (arithmetic mean), measures of variability (standard deviation) and indicators of structure expressed as percentages were used as descriptive statistical methods. For these analyses, the data were processed using the IBM SPSS Statistics 22 software package – SPSS Inc., Chicago, IL, United States.

2.2.4.1 ML algorithms and ML techniques

For the purpose of this paper, authors used different machine learning models and techniques implemented as a part of the of the Python scikit-learn ML framework (version 1.2.2) (38). The ML pipeline used in this paper was implemented as a Python (version 3.8) (47) script using Jupyter notebook tool (48). The implemented pipeline consists of the following steps:

- Data set preprocessing.
- Attribute selection using filter methods.
- Training binary classification models (for data points labeled with PIU present or not) using cross validation (24) to assess and compare results of different models.
- Optimization of classification models hyperparameters.
- Attribute selection using embedded methods.
- Attribute selection using wrapper methods.

These ML pipeline steps will be explained in detail later when discussing machine learning results. The results are presented in both tabular and graphical form.

3 Results

3.1 Socio – demographic characteristics of participants

The final sample included 2,113 adolescents, out of 2,239 initially surveyed and out of which 56% were female and 44% male, with a mean age of 16.73. Detailed data concerning socio-demographic characteristics of the sample is shown in Table 1.

TABLE 1 Characteristics of participants according to academic achievement and economic status.

Characteristics	*n*	%
Academic achievement		
Best	806	38.1
Very good	782	37.2
Good	475	22.6
Passable	40	2.0
Insufficient	–	
Economic status		
Low	105	5.0
Lower middle	223	10.7
Middle	830	39.7
Upper middle	574	27.5
High	357	17.1

3.2 The intensity of internet use

The biggest percent of adolescents in Serbia weekly spends over 20 h on the Internet.

According to the obtained data, the maximum time spent in continuity in 62.8% of participants was 5 h. In total, about a fourth of participants spent 5–10 h on the Internet in continuity, and 4.5% of participants spent over 20 h in continuity. It needs to be noted that this was not the case with every day continual Internet use (Table 2).

3.3 Interests and behavior of participants on the internet and FB

The participants in this study more often search the Internet for contents related to music, followed by online content categories regarding education, sports and health and medicine (Table 3).

Our participants' most frequent online activity is Social networks, targeted search for information and, after that, downloading music and movies (Table 4).

When it comes to activities on FB, a detailed results was given in Table 5. Every day, FB is used by 83.3% of participants. On average, participants spend 4.09 ± 4.92 h on FB. The most frequent participants' activity on FB is chatting.

3.4 Characteristics of participants according to affective temperaments and internet use disorder scale – IUDS

The correlation among temperaments was fluctuating from weak to medium (Table 6). The strongest positive correlation was among depressive, cyclothymic, and anxious temperaments. Hyperthymic temperament was in negative correlation with all other temperaments. The prevalence of PIU in our sample was 28%.

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TABLE 2 The Intensity of Internet use.

Characteristics	Mean ± SD
Number of years of internet usage	5.54 ± 2.27
Weekly use in hours	n (%)
Up to 2 h	216 (10.4)
2–5 h	363 (17.2)
5–10 h	396 (19.0)
10–15 h	354 (17.0)
15–20 h	304 (14.6)
Over 20 h	446 (21.4)
Maximum time spent on the Internet in continuity daily	*n* (%)
Up to 5 h	1281 (62.8)
5–10 h	454 (22.2)
10–15 h	127 (6.2)
15–20 h	79 (3.9)
Over 20 h	99 (4.5)
Time spent on the Internet in the period of studying in relation to holidays	*n* (%)
More	638 (30.5)
Less	428 (20.5)
The same	1022 (49.0)
Attitude about time on the Internet	*n* (%)
If they could, they would spend more time	315 (15.1)
If they could, they would spend less time	1771 (84.9)

TABLE 3 Self reported frequency of searching for content on Internet (on the scale between 1–5).

Online content categories	Whole sample
	Mean ± SD
Politics	1.65 ± 0.94
Business	1.68 ± 0.99
Sports	3.23 ± 1.38
Computers and technology	2.46 ± 1.28
Arts and culture	2.73 ± 1.25
Education	3.27 ± 1.17
Popular culture	2.85 ± 1.33
Pornography	2.28 ± 1.60
Music	4.82 ± 0.57
Travel/Tourism	2.94 ± 1.22
Health and medicine	3.04 ± 1.21
Science	2.92 ± 1.24
Religious content	2.0 ± 1.14

3.5 Characteristics of participants according to selected lifestyle habits

Our participants, on average, play sports 4 days in a week (3.94 ± 1.99), with the average duration of training a bit longer than 1 h (64.91 ± 41.36). A bit less than a half of participants consume energy drinks every day (43.6%) and that, on average, 136 mL. The great majority of participants (81.1%) eat fast food every day. A bit less than a third of participants are smokers-in total, 494 of them (23.6%). Coffee is also consumed by about a third of participants, more precisely, 661 (31.8%) participants. Alcoholic drinks are consumed by 482 participants, which makes up for 23.0% of the sample.

TABLE 4 Self-evaluation of Internet activities (on the scale between 1 and 5).

Online activity categories	Whole sample
	Mean ± SD
Communication by e-mail	2.73 ± 1.37
Social networks	4.45 ± 0.96
Communication on a forum	1.73 ± 1.02
Communication on a blog	2.56 ± 1.30
Targeted search for information	4.31 ± 0.88
Network search – surf	3.12 ± 1.32
Expert advice	1.57 ± 0.93
Search for favorite websites	3.95 ± 1.17
Reading the news	3.35 ± 1.27
Online games	2.44 ± 1.49
Reading and downloading books and texts	2.81 ± 1.36
Downloading music and movies	4.25 ± 1.06
Internet for school	3.72 ± 1.17
Online courses	1.68 ± 1.03

TABLE 5 Interests and behavior of participants in relation to FB.

Characteristics	Whole sample
Uses FB everyday B	*n* (%)
Yes	1735 (83.3)
No	273 (13.1)
Does not have FB	76 (3.6)
Average time spent on FB, mean ± SD	4.09 ± 4.92
Activities on FB	*n* (%)
Reads posts on FB	1040 (49.2)
Writes FB statuses	331 (15.7)
Shares content on FB	720 (34.1)
Plays games on FB	272 (12.9)
Chats on FB	1459 (69.0)
Visits groups on FB	476 (22.5)

3.6 Machine learning results

Before creating different machine learning models, the original data set was prepared using different techniques for data cleansing and pre-processing. After that, data points that had a missing value for the class-label attribute were deleted from the data set. Missing values for other attributes were handled using most frequent value or mean value depending on the nature of the attribute using KNNImputer

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TABLE 6 Correlation among affective temperaments.

	Cyclothymic	Hyperthymic	Irritable	Anxious
Depressive	0.399**	−0.379**	0.307**	0.427**
Cyclothymic		−0.147**	0.381**	0.395**
Hyperthymic	−0.147**		−0.025	−0.198**
Irritable	0.381**	−0.025		0.259**
Anxious	0.326**	−0.202**	0.219**	

**$p < 0.01$.

implementation from the scikit-learn framework (38). During the pre-processing step, data outliers were detected using the isolation forest approach (49) implementation from the scikit-learn framework. Detected outliers were removed from the data set. At the end of this step, the values of all attributes are normalized and standardized using RobustScaler, MinMaxScaler, and StandardScaler implementations from scikit-learn framework (38).

The next step was attribute selection using filter methods. As already mentioned, these methods are independent from ML models and can be applied separately. CFS calculates the Pearson correlation between each attribute and the class-label attribute, selecting only those attributes that have a moderate-to-high positive or negative correlation (close to −1 or 1) and drops those features with a low correlation (a value close to zero) (Figure 1). As seen in Graph 1, time spent online – Internet use (hours per week) is of the highest importance. It is followed by cyclothymic temperament, Internet use (hours per day), then attitude about time on the Internet and, immediately after, irritable temperament and online gaming.

In the third step, various ML classification models like decision tree, Naïve Bayes, *K*-Nearest Neighbors, Random forests and Gradient boosting on our data set were trained. Binary classification models were created (class-label attribute was PIU value). The dataset was divided into training and test sets in a 90:10 ratio (stratified split with a shuffle). Hyperparameter optimization was performed for all models using the grid search with cross-validation method (24), and the validation of the obtained models was performed using *k*-fold cross-validation with the value of *k* set to 10 and stratified shuffle splits.

Trained models were compared using standard classification metrics: accuracy, precision, recall, and F1-measure. Different classification metrics were used to analyze the quality of the trained models (24). Accuracy is the most common classification metric and it measures how often the classifier models correctly predicts results. The accuracy can be defined as the ratio of the number of correct predictions and the total number of predictions. Accuracy metric can be misleading in situations where the dataset is not well balanced regarding class-label attributes. In such scenarios additional metrics are usually employed. Precision explains how many of the correctly predicted cases actually turned out to be positive and this metric is useful in the cases where false positive predictions are a higher concern than false negative predictions. Recall (or sensitivity) metric explains how many of the actual positive cases we were able to predict correctly with our model. Recall is a useful metric in cases where false negative predictions are of higher concern than false positive predictions. F1-measure is the harmonic mean of precision and recall and gives a combined idea about precision and recall metrics. Because the used dataset is not well balanced, we have more data points with PIU value of zero, we cannot rely only on accuracy. For that reason,

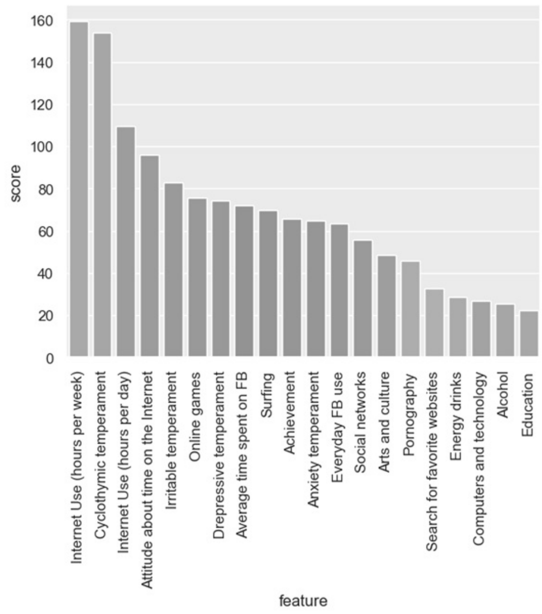

FIGURE 1
Feature selection using Pearson's coefficient.

additional metrics were computed and from Figure 2 we can see that Random forest was the model with the best overall results.

After creating models, the first embedded feature selection approach using Random forest can be applied (Figure 3). Measures which are used to evaluate classifier algorithms show that the accuracy of a classifier is acceptable and that the percentage of correctly classified positive tuples is 74, while the percentage of positive tuples that are correctly classified in relation to the total number of positive tuples is 77 and 68% (Table 7). Because of this, it can be concluded that the classifier accuracy is high and that its quality is acceptable.

If the graph showing the most important features selection for random forest are viewed, it can be seen that the variable of highest importance is Average time spent on FB, then Cyclothymic temperament, Internet use (hours per week) but also Anxiety and Irritable temperament. They are closely followed by Online games.

Next, Lasso and ElasticNet embedded feature selection methods were applied (Figures 4, 5).

On Figure 4, the feature selection for the most important feature using Lasso techniques can be seen. Variables which are most important for the development of PIU can be seen. It is especially important to note that a group of variables having a protective effect

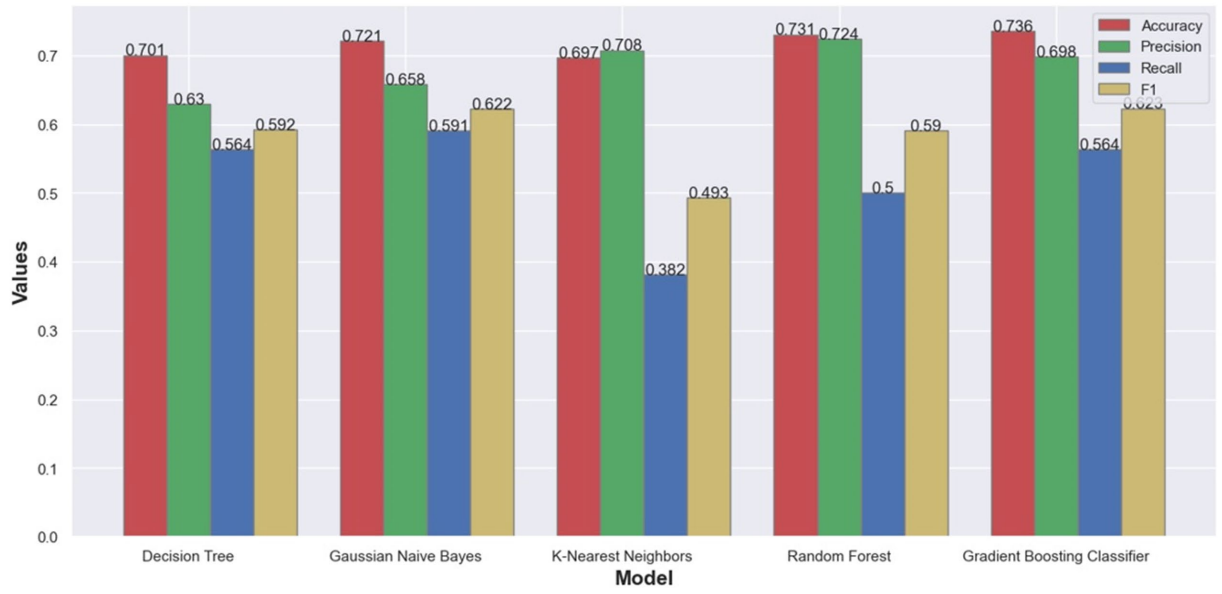

FIGURE 2
Bar Chart with classification metrics on our dataset from different machine learning algorithms.

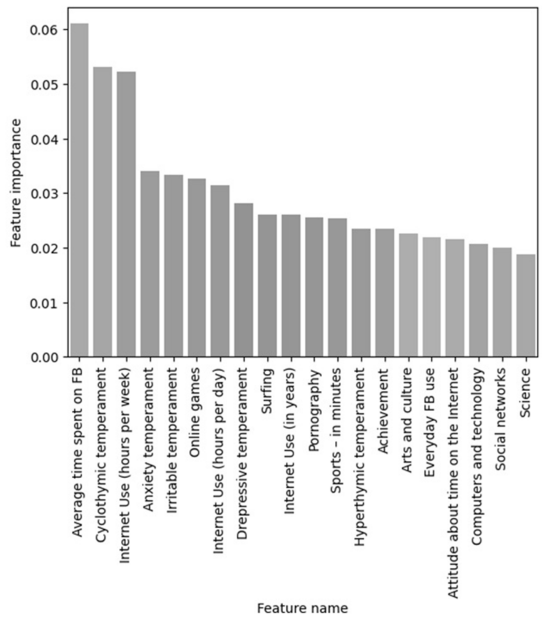

FIGURE 3
Feature selection – random forest.

(regarding the prevention of the development of PIU) was found with these techniques.

In the first group, the variables are: Cyclothymic temperament, Internet use (hours per week), Attitude about the time on the Internet, Average time spent on FB, Internet use (hours per day) but also aimless Internet browsing, i.e., Surfing as well as Pornography.

Variables with protective effect are: Sports, Smoker, Hyperthymic temperament, Arts and culture, and Academic Achievement. On

TABLE 7 Evaluation of classifiers – random forest.

Accuracy for the model with all features:0.74				
Classification report for the model with all features:				
	Precision	Recall	f1-score	Support
0.0	0.77	0.85	0.81	242
1.0	0.68	0.56	0.61	140
Accuracy			0.74	382
Macro avg.	0.73	0.70	0.71	382
Weighted avg.	0.74	0.74	0.74	382

Figure 5, the feature selection for the most important feature can be seen by using ElasticNetCv. It can be observed that both techniques have led to the selection of identical variables of importance.

In the final step of the created ML pipeline, genetic algorithm wrapper feature selection was applied. Thirty-four important variables that explain 0.76% of variance were detected using the genetic algorithms. The variables of importance are: Arts and culture, Average time spent on FB, Business, Coffee, Communication by e-mail, Communication on the blog, Communication on the forum, Cyclothymic temperament, Downloading music and movies, Depressive temperament, Energy drinks, Everyday FB use, Expert Advice, FB use – reading posts, Fast food, Gender, Health and medicine, Hyperthymic temperament, Internet use (hours per day) Internet use (hours per week), Internet use (on holiday), Irritable temperament, Online games, Politics, Pop culture, Pornography, Reading and downloading books and texts, Religion, Science, Search for favorite websites, Sports – days in a week, Surfing, Travel/tourism (Table 8).

Finally, an artificial neural network model for binary classification (class-label attribute was PIU value) was created

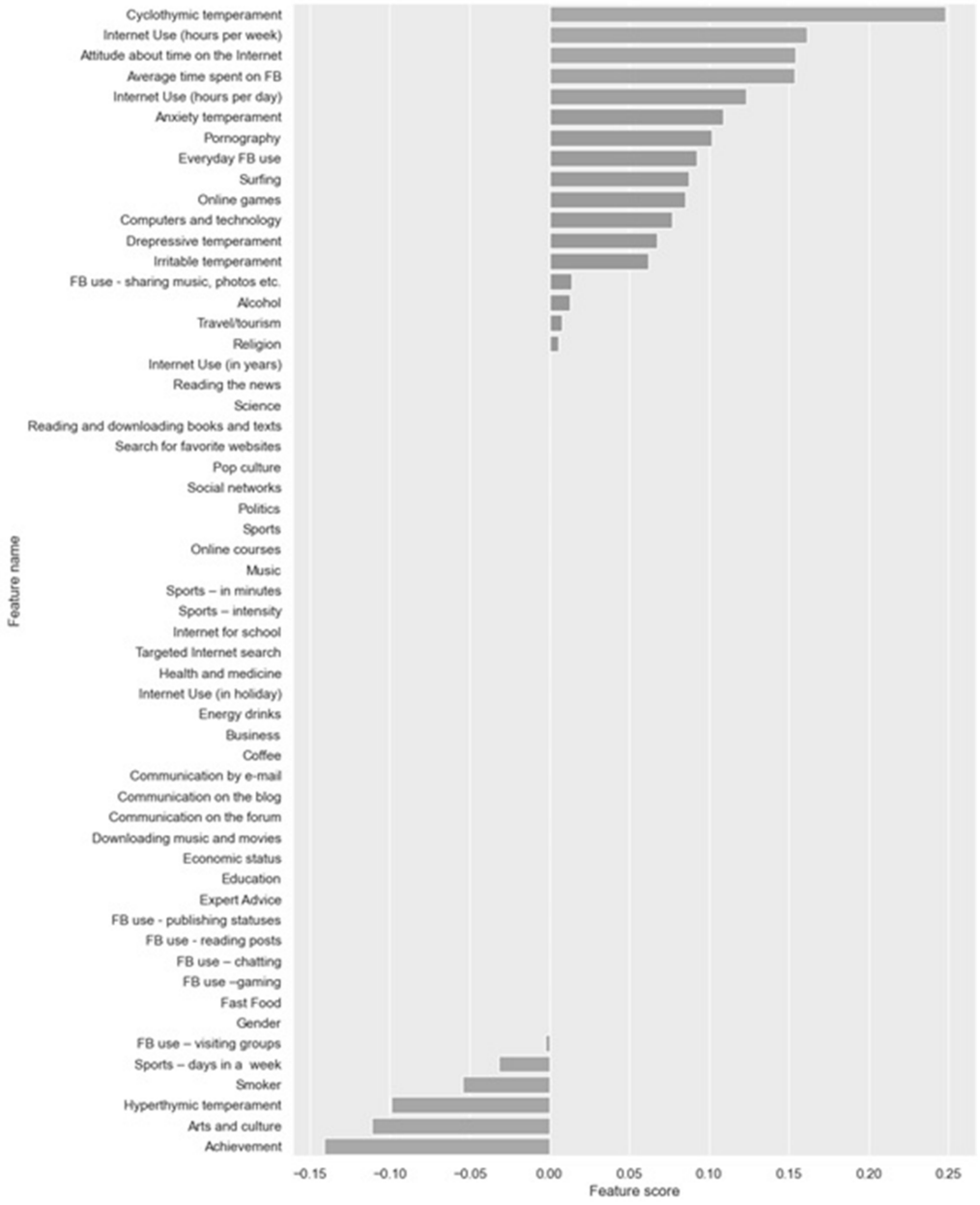

FIGURE 4
Feature selection using LassoCV.

using our data set. This model performs best among all classification models trained using our data set (Figure 6). Classification metrics for the artificial neural network model were: accuracy 0.80, precision 0.82/0.78, recall 0.77/0.83, and F1 0.80/0.80.

A permutation feature importance method was applied on a trained ANN classification model in order to obtain feature importance measures. ELI5 implementation of permutation feature importance method was used (Table 9). As can be seen, variables of importance are Internet use (hours per week), FB use – reading posts, Sports, Pornography, Internet use (hours per day), Alcohol, Irritable temperament, Achievement, Coffee.

4 Discussion

By applying a ML model, we tried to contribute to a better understanding of the multifactorial nature of PIU. ML has been applied for enabling data analysis to be done in the best possible way and, thereby, in order to overcome eventual deficiencies that standard statistical methods may lead to. Namely, ML determines various models and when a model that yields the best results is obtained, an analysis of features (variables) for that model follows. Their importance is examined and, in this way, it can be concluded what the real-world impact of these variables is, or in this case, the effect on the development of PIU of the analyzed variables.

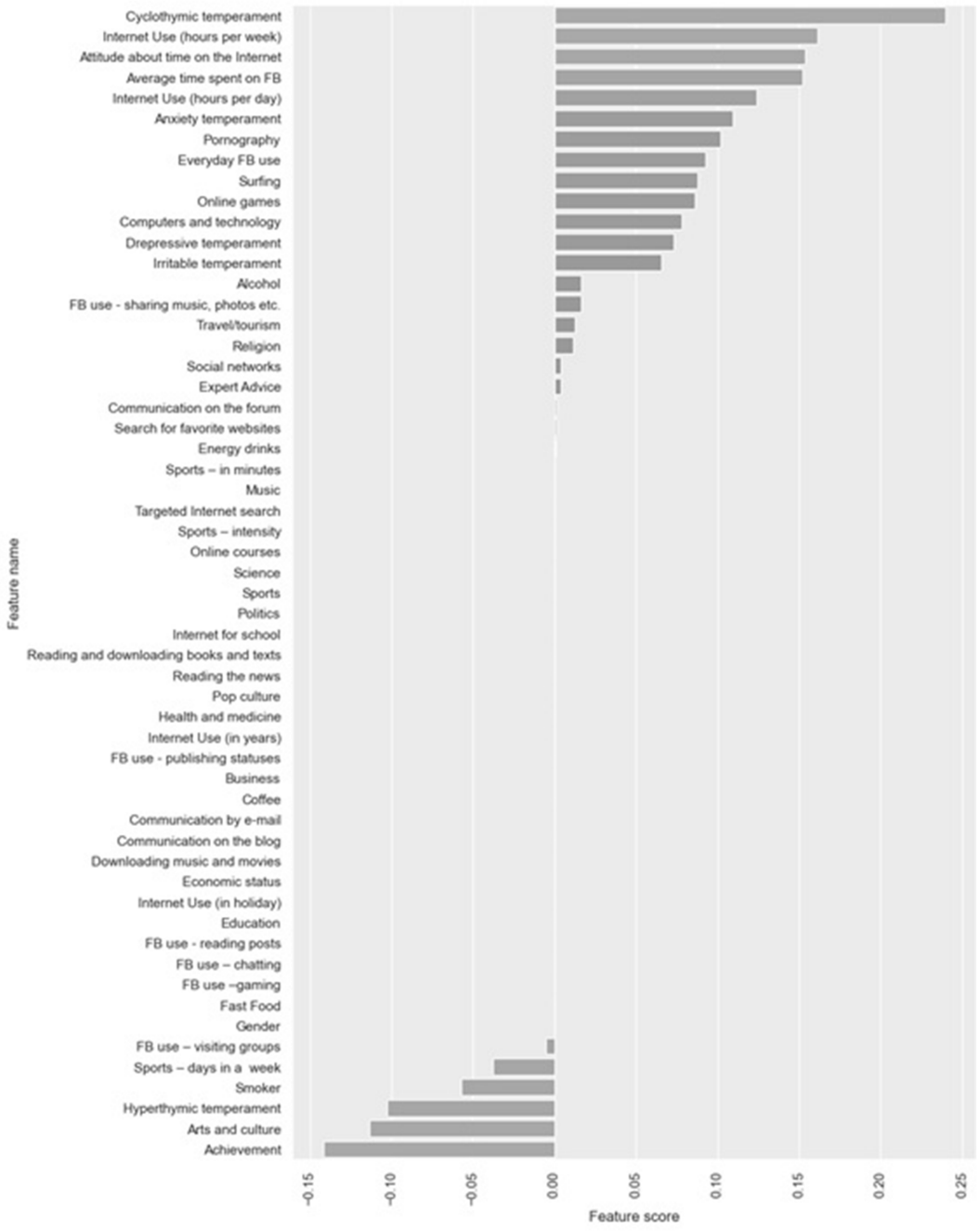

FIGURE 5
Feature selection using ElasticNetCV.

By applying the IUDS scale, it was determined which participants have PIU and which do not- while the score on the scale that classifies the participants into one of the mentioned categories became the class attribute. The classification's role is to select a model that describes the class attribute as function of the values of the other attributes. While, classifier evaluation actually estimates the model, i.e., to what extent what is determined by the model corresponds to actual classification of examples. Each of the obtained models, through the analysis of the obtained most important variables (features) for that model, will enable us to understand the factors that affect the development of risky adolescent Internet behavior which ultimately leads to PIU.

Assessing the prevalence of PIU is challenging due to the initial absence of consensus diagnostic criteria. In studies employing a cut-off at an Internet Addiction Test (IAT) score of ≥50, the prevalence ranged between 8 and 27.2% (50–58). This huge variability in prevalence rates may be due to the overall poor quality of epidemiological studies in this field (59) related to the constant evolution of the technology itself, the screening instruments used, the target population and the lack of consensus about the establishment

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TABLE 8 Genetic algorithm feature selection.

Feature importance	
Achievement	False
Alcohol	False
Anxiety temperament	False
Arts and culture	True
Attitude about time on the Internet	False
Average time spent on FB	True
Business	True
Coffee	True
Communication by e-mail	True
Communication on a blog	True
Communication on a forum	True
Computers and technology	False
Cyclothymic temperament	True
Downloading music and movies	True
Depressive temperament	True
Economic status	False
Education	False
Energy drinks	True
Everyday FB use	True
Expert Advice	True
FB use – publishing statuses	False
FB use – reading posts	True
FB use – sharing music, photos etc.	False
FB use – chatting	False
FB use – visiting groups	False
FB use –gaming	False
Fast Food	True
Gender	True
Health and medicine	True
Hyperthymic temperament	True
Internet use (hours per day)	True
Internet use (hours per week)	True
Internet use (on holiday)	True
Internet use (in years)	False
Internet for school	False
Irritable temperament	True
Music	False
Online courses	False
Online games	True
Politics	True
Pop culture	True
Pornography	True
Reading and downloading books and texts	True
Reading the news	False
Religion	True
Science	True
Search for favorite websites	True
Smoker	False
Social networks	False
Sports	False
Sports – days in a week	True
Sports – in minutes	False
Sports – intensity	False
Surfing	True
Targeted Internet search	True
Travel/tourism	True

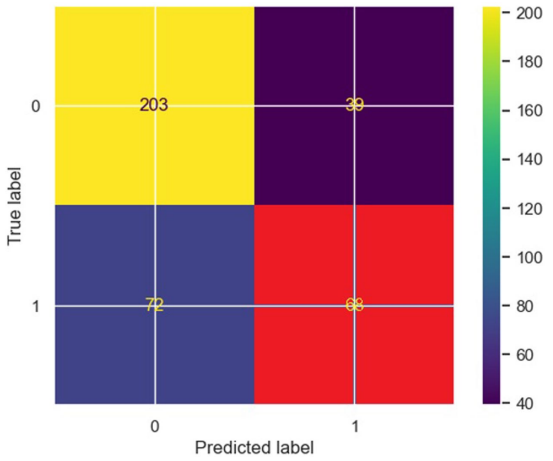

FIGURE 6
Neural network confusion matrix.

of cut-off points or the criteria used to define a "disorder" (60–62). The prevalence of PIU in our sample was 28%. Nogueira-López et al. (63) introduced a new approach to determining the prevalence of PIU. It is important to stress that different prevalence were obtained, depending on the framework which had been used. According to DSM-5 framework, they found a prevalence of 33% for problematic Internet use and 3.1% for problematic gaming. However, when a more conservative approach was implemented, there was a decrease in prevalence rates – 2.98% for problematic Internet use and 1.8% for problematic gaming.

We believe that this analysis contributes to a better and clearer understanding of the frequency of PIU and opens up new possibilities for further research. However, we must note that in our study, we used the only scale that measured PIU and was validated in the Serbian language.

Through the analysis of variables highlighted by various models, it becomes evident that time-related factors, including daily and weekly internet usage, are important for understanding development of Problematic Internet Use (PIU). From the moment when researches

TABLE 9 Feature importance neural network.

Internet use (hours per week)	0.0541 ± 0.0089
FB use – reading posts	0.0426 ± 0.0060
Sports	0.0406 ± 0.0115
Pornography	0.0371 ± 0.0099
Internet use (hours per day)	0.0362 ± 0.0074
Alcohol	0.0320 ± 0.0055
Irritable temperament	0.0304 ± 0.0060
Achievement	0.0292 ± 0.0076
Coffee	0.0283 ± 0.0084
FB use – visiting groups	0.0267 ± 0.0086
Smoker	0.0267 ± 0.0087
Online games	0.0266 ± 0.0067
Arts and culture	0.0261 ± 0.0074
Communication on the blog	0.0261 ± 0.0061
Cyclothymic temperament	0.0257 ± 0.0078
Sports – days in a week	0.0257 ± 0.0061
FB use – chatting	0.0252 ± 0.0056
Fast food	0.0239 ± 0.0094
Computers and technology	0.0233 ± 0.0086
Attitude about time on the Internet	0.0223 ± 0.0055

about the Internet started, time determinant has been examined in the context of their influence on the PIU development. They are not a certain indicator of addictive behavior, but they have proved to be very reliable, except in the cases when the Internet is used for professional purposes or for school obligations. Although today we know that contents are also essentially important, the time spent on the Internet impacts a lot on development the PIU, especially in the adolescents' group.

When employing a feature selection approach, such as Random Forest, in addition to the previously mentioned time-related variables, important factors for PIU development include cyclothymic, anxious, and irritable temperaments, as well as online gaming. Notably, it's interesting to analyze the importance of time spent on Facebook as a variable of utmost importance at this point. The first which draws the attention in our results is a fact that the time spent on the Internet and time spent on FB do not overlap. Maybe the reason for that is because our participants see FB totally separated from the Internet, and they do not experience it as a part of the Internet. It surely shows that adolescents compared to adults differently perceive the Internet and contents on it.

Let us now analyze the potential influence of different types of affective temperaments on the development of PIU. For now, based on our information, there is only one research with the model similar to ours, and in it anxious affective temperament was in the greatest correlation with the PIU (64). The common neurobiological base for the development of behavioral addictions and substance addiction is today explained very well. Following this parallel, we may find answers to the question of the influence of temperament on the development of PIU.

Namely, in a large number of study, cyclothymic temperament is always in the strongest relationship with substance addiction (65). The assumption is that in the foundation of cyclotomy is a biological mechanism which leads to the emotional instability and which makes people with predominant cyclothymic temperament in the greatest risk for addiction development. In short, the cyclothymic temperament might impact the development of drug dependence by facilitating the initial engagement with the substance at different stages, driven by an unregulated pursuit of pleasure. Later, this temperament may contribute to the progression of the addiction by enhancing the euphoric effects and gratification experienced in response to the substance (66, 67). Our results also have indicated the influence of anxious and irritable temperament on the development of PIU According to some studies, irritable temperament is the next in the correlation with addictions but based on some others it is anxious (68). Although there are above - mentioned parallels between these two types of addiction, our assumption is that anxious temperament almost certainly singled out as a special predictive factor for PIU because of the one Internet specificity. The Internet use gives adolescents a certain feeling of freedom in expression and communication. Therefore, we can assume that anxious people especially suits to be on the Internet, because it excludes exactly that what is a problem to them, a social contact face to face. Again, this is just on the level of assumption founded on the well-known clinical characteristics of the anxiety disorder, with the fence that anxious temperament can only represent the foundation for its development.

As we have already said, online gaming is today recognized as a special type of behavioral addiction, so the importance of its component in the development of PIU disorder is not surprising. Gaming disorder is fundamentally defined by a presence of a persistent and dysregulated pattern of engagement that is linked to adverse consequences in social, occupational, familial, and educational aspects, as well as functional impairment (69, 70).

The most important features using Lasso techniques were divided into two groups: variables s important for the development of Internet Use Disorder (IUD) and variables with a protective effect regarding the prevention of PIU.

In the first group of variables, among those we have described, other important variables include: Attitude about the time on the Internet and Pornography. Variable Attitude about the time on the Internet is actually the answer to this question: "If you could, would you spend more time on the internet?" Those who answered positively have a higher risk of developing PIU. This result is expected because one of the characteristics of addiction is the increase of tolerance (71).

As for the Pornography variable in our research, the question was only aimed at pornographic contents, which is the most popular type of activities from this group of contents (72–74). Apart from the fact that pornographic contents are easily available, they enable adolescents to be totally anonymous on one hand and to be engaged in sexual experiences on the other hand, without those risks which these experiences exists in everyday life (75). However, although pornographic and other contents of sexual connotation are most frequently researched from the aspect of the possible impact on the development of the PIU, they are not always harmful (e.g., social personal) (76, 77). On the other hand, for the important percentage of adolescents in researches, they clearly show a seriously bad impact on their life (78–80).

However, a much more interesting group of variables is those with a protective effect. Lasso and ElasticNet features selection methods are recognized same variables: Sport, Cigarettes, Hyperthymic temperament,

Arts and culture and Academic Achievement. It is interesting that, except in two studies (81, 82), according to our information, it is not monitored what on the Internet might recommend to adolescents to work or follow, which would be protective for them. Such a concept would even be a foundation for a preventively protective model, which would be further developed. Adolescents who engage in sports more frequently during the week are somehow protected from the development of PIU. Playing sport, they decrease the time spent on the Internet and have healthier habits. A series of studies speak about the protective role of sport compared with the development of mental disorders, and addiction, as well. Also, it is known that playing sport is frequently included in some of the therapeutic programs in rehabilitation centers.

Hyperthymic factor clearly stands as a protective factor. In many earlier types of research which results are united in a meta-analysis of the TEMPS –A scale use (83), hyperthymic temperament clearly differs on one hand and others affective temperaments on the other hand (65). Characteristics of the mere temperament which is active, hilarious, full of life, but also responsible, with the strongly developed sense for leadership do not go with any psychopathology form. What is completely new in our paper is that A-TEMPS-A scale showed as good for identification of this temperament in the adolescent population. Regarding academic achievement, based on earlier research (82, 84–86), we know that family economic disadvantage and poorer academic performance are predictors of PIU. What makes this result particularly noteworthy is that through complex machine learning methods, good academic achievement has been singled out as a variable with strong protective effect (regarding the prevention of the development of PIU).

An artificial neural network model for binary classification has identified "FB use – reading posts" as one of the most important variables. In addition to this, two more variables not previously mentioned in the analysis have been recognized in this model: Alcohol and Coffee. The assumption is that the connection between alcohol and coffee consumption and PIU might be attributed to the fact that bad habits often co-occur. However, it's important to mention that our question was only related to whether our respondents consume coffee and alcohol. We did not ask in detail when and how much they consume it. We cannot know if our participants, for example, consumed them while they were using the Internet. Nevertheless, this is certainly a result worthy of attention. Finally, let us analyze the variable related to Facebook usage. Let us briefly touch on Facebook as the only social network we analyzed in our research. We did not have a structured questionnaire, but the questions were quite detailed. It's not surprising that in several models, some aspects of using this social network emerged as strong predictors of PIU. Nowadays, Facebook (FB) is an inseparable component of the adolescent 'social lives. Among other functions, it contributes to improved information exchange of diverse content and serves as a platform for communication. Nevertheless, recent studies indicate that the prominent social network may pose as an emerging mental health concern (87). Neurobiological processes such as sensory associative learning and emotions, that underlie adaptive responses to environmental stimuli have evolved over time in an environment distinct from the current one. The rise of the social media introduces a constant interaction with new types of stimuli and rewards associated with social media. This exposure may trigger maladaptive social-media–related decision-making and behaviors. Therefore, it is unsurprising that the growing global prevalence of social media use has been accompanied by rising concerns regarding its impact on psychobiological processes and problematic use of social media (88–90).

Our study has certain limitations. Firstly, it was conducted before the COVID-19 pandemic. It is known that Internet usage in all age groups has changed (91). Meng et al. (92) specify a higher prevalence of different forms of addiction associated with PIU (smartphone addiction, social media addiction, cybersex addiction) in their meta-analysis. Furthermore, the results of the research conducted in Serbia indicate that there is a potential correlation between the changes in Internet usage during the COVID-19 pandemics and the symptoms of depression, anxiety, and stress (93).

Also, although the assumption is that the majority of our respondents are healthy, it is certain that this was not the case for all of them. For further research, a similar study should include a psychiatric interview as part of the methodology. Additionally, there are new scales that more precisely measure what we tracked in this study. Their application in some future research, along with the mentioned psychiatric interview, would certainly contribute to a higher quality and clearer understanding of complex PIU.

In conclusion, we can say that variables related to the temporal determinants of Internet usage, then cyclothymic temperament, the desire for increased Internet usage, irritable temperament, on line gaming, pornography, and some variables related to Facebook usage consistently appear as important variables for the development of PIU. This conclusion is in some way in line with the predictions made by Fineberg et al. (16) in their recent overview of PIU in Europe. They emphasize that, considering the strength of current scientific evidence and striking a balance between avoiding the over-pathologization of everyday behaviors and recognizing conditions of clinical importance that warrant public health attention, behaviors identified as most likely to qualify for diagnosis within this category include problematic online pornography viewing, shopping/buying and potentially social media use (16). It is also worth noting that academic achievement and engagement in sports consistently emerge in three models as variables with a protective factor. At the end, let us mention that as medical doctors working with adolescents (both in clinical practice and in the development and implementation of preventive programs), when forming this research, we had the idea of obtaining several factors that can be reasonably associated with PIU. When we look at our results, we can assume that we have to some extent succeeded in doing so.

Data availability statement

The datasets presented in this article are not readily available because our participants were 16 and 17 years old. Requests to access the datasets should be directed to jelena.jovic@med.pr.ac.rs.

Ethics statement

The study obtained the approval of the Ethical Committee of the Faculty of Medicine, University of Pristina in Kosovska Mitrovica, Serbia. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

JJ: Conceptualization, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. AĆ: Methodology, Writing – review & editing. AS: Conceptualization, Formal analysis, Writing – review & editing. MN: Formal analysis, Writing – review & editing. MS: Funding acquisition, Writing – review & editing. ZB: Formal analysis, Writing – review & editing. DI: Methodology, Writing – review & editing.

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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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The interplay of psychological resilience and adolescent mobile phone addiction in Henan province, China: insights from latent class analysis

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Background: The aim of this study was to classify distinct subgroups of adolescents based on the severity levels of their mobile phone addiction and to investigate how these groups differed in terms of their psychosocial characteristics. We surveyed a total of 2,230 adolescents using three different questionnaires to assess the severity of their mobile phone addiction, stress, anxiety, depression, psychological resilience, and personality. Latent class analysis was employed to identify the subgroups, and we utilized Receiver Operating Characteristic (ROC) curves and multinomial logistic regression for statistical analysis. All data analyses were conducted using SPSS 26.0 and Mplus 8.5.

Methods: We classified the subjects into subgroups based on their mobile phone addiction severity, and the results revealed a clear pattern with a three-class model based on the likelihood level of mobile phone addiction ($p < 0.05$). We examined common trends in psychosocial traits such as age, grade at school, parental education level, anxiety levels, and resilience. ROC analysis of sensitivity versus 1-specificity for various mobile phone addiction index (MPAI) scores yielded an area under the curve (AUC) of 0.893 (95% CI, 0.879 to 0.905, $p < 0.001$). We also determined diagnostic value indices for potential cutoff points ranging from 8 to 40. The optimal cutoff value for MPAI was found to be >14, which corresponded to the maximum Youden index (Youden index = 0.751).

Results: The latent classification process in this research confirmed the existence of three distinct mobile phone user groups. We also examined the psychosocial characteristics that varied in relation to the severity levels of addiction.

Conclusion: This study provides valuable insights into the categorization of adolescents based on the severity of mobile phone addiction and sheds light on the psychosocial characteristics associated with different addiction levels. These findings are expected to enhance our understanding of mobile phone addiction traits and stimulate further research in this area.

KEYWORDS

adolescent, resilience, mobile phone addiction, DASS-21, ROC curve, cut-off point, latent class analysis

1 Introduction

In the past decade, the number of adolescents that use the internet has grown enormously. Latest figures show that approximately 5.3 billion of the Earth's 8 billion people used the internet in 2022, or roughly 66% of the world's population. At the same time, three quarters of the population aged 10 years and over owned a mobile phone. The statistics further show that young people are the driving force of connectivity, with 75% of 15–24 year olds now regularly online (1). According to the 51st Statistical Report on Internet Development in China published in December 2022, the proportion of individuals using the internet via mobile phones reached 99.8%. Among them, users aged 10–19 now account for 14.3% of the total number of users (2). In mainland China, around 80% of teenagers possess mobile phones, with nearly 40% of them using mobile phones without restrictions (3). While advances in the availability of the internet have brought many benefits to its users, its widespread adoption has also led to various types of harm, particularly to adolescents who are in a rapid stage of physical and psychological development and are susceptible to external influences. Therefore, excessive mobile phone usage may lead to unhealthy physical and psychological outcomes in teenagers.

Many studies have identified the predictors of mobile phone addiction: excessive use of mobile phones can contribute to negative physiological and psychological consequences, such as headaches and sleep disorders (4), neuroticism (5), trouble concentrating (6), and stress, anxiety, and depression (7). Although some studies have established the relationship between mental health and mobile phone addiction (8–10), all have ignored the within-class correlation between mobile phone addiction and other phenotypes. Therefore, the present study used latent class analysis to narrow the research gap in the field of psychological resilience and mobile phone addiction.

2 Literature review

2.1 Mobile phone addiction

Mobile phone addiction can be classified as a behavioral addiction, exhibiting four typical features: compulsion, functional impairment, tolerance, and withdrawal (11). The addictive nature of mobile phones aligns with behavioral addiction, a disorder characterized by behavioral symptoms linked to pleasure and craving (12). Mobile phone addiction has been referred to as one of the most important social problems of the modern era (13). Problematic mobile phone use has been related to cognitive impairments (14) and depression (15). Addiction to mobile phones can be described as a secretive disease that as it results in damaging psychological health and impacting the quality of life, it is only natural to try to understand the behaviors associated with it (16).

Abbreviations: DASS, depression, anxiety, and stress; MPAI, mobile phone addiction index; RSCA, the Resilience Scale for Chinese Adolescents; ROC, receiver operating characteristic; LCA, Latent Class Analysis; AUC, area under the curve.

2.2 Psychological distress

Psychological distress includes symptoms of stress, anxiety, and depression. Significant psychological distress indicates impaired mental health and may reflect common mental disorders such as depression and anxiety disorders (17).

Severe psychological distress is connected with problematic health behaviors such as extreme alcohol consumption, smoking, and a propensity to commit (or an attempt to commit) suicide (18). Psychological distress among students is influenced by sociodemographic and contextual factors, academic-related factors such as performance and achievement at school or college, as well as personality and individual differences (18). Many studies have reported a high prevalence of psychological distress among adolescents. Prevalence rates of 40% have been recorded in China (19), 54% in Saudi Arabia (20), and 20.6% in Tanzania (21). Academic stress and adverse life events may account for much of this high prevalence of psychological distress among adolescents (22). However, a growing number of adolescents now spend a good deal of their time on their mobile phones, leading to an increasing incidence of mobile phone addiction. Mobile phone addiction has been regarded as an important cause of a variety of psychological and behavioral problems (23). Adolescents immersed in the content of their mobile phones may experience added psychological distress due to poor sleep quality and a tendency to procrastinate resulting from excessive or uncontrolled phone usage. The extent of disruption caused by mobile phone usage on anxiety and sleep quality exacerbates the deterioration of mental health, increasing levels of psychological tension and physiological agitation. This can have negative repercussions, leading to stress and poor health outcomes.

2.3 Psychological defensive features

"Defense mechanisms" are a psychological process, typically accompanied by a behavioral response, used to cope with challenging situations, to manage conflicts, and to safeguard the basic functioning from disturbances caused by distressing, painful, and unacceptable thoughts, feelings, and experiences (24). Psychological protection plays a crucial role in the process of forming the individual and the individual's needs. These mechanisms shield individuals from negative emotional experiences, facilitate the maintenance of psychological equilibrium, resolve interpersonal conflicts, and occur at the unconscious and subconscious levels of the psyche. Adolescent crisis is one of the most intricate issues within individual development. Adolescents are in a continuous state of adapting to physical and physiological changes, undergoing what is often termed a "hormonal storm." In its most general form, it can be said that adolescents appear to be consistently under stress, and attempts at restoring personal equilibrium should be considered a central feature of adolescence.

The psychological resilience of adolescents, as one of the psychological defenses, has been confirmed by numerous researchers (25–27).

Cong et al. (28) verified that heightened psychological resilience may reduce the rate of suicide ideation in adolescents. Resilience has been related to decreased psychological distress and to increased positive experiences (29). Resilience can enhance self-assessment and

recognized social support and thus favor the high level of emotional regulation skills in adolescents (30). Moreover, psychological resilience serves as a protective factor against smartphone addiction. Zhao et al. (7) revealed that psychological resilience has a significant negative impact on mobile phone addiction, that is, the stronger the psychological resilience, the less likely the mobile phone addiction. Resilience appears to negatively predict mobile phone addiction among minority preparatory students (31).

3 The present study

Based on our literature review, the present study focused on the relationship between mobile phone addiction and the unique characteristics of addicted mobile phone users. This study performed Latent Class Analysis (LCA) within the adolescent sample to identify subgroups representing mobile phone addiction and high-risk usage based on the severity of an individual's mobile phone usage. Then, cross-sectional comparisons were conducted on the psychological characteristics of each group, leading to an estimate of the ratios of these groups in the population.

4 Materials and methods

4.1 Participants

In this study, 2,300 adolescents from middle schools and high schools in Henan province of China were asked to complete the questionnaires from June 1 to August 30, 2022. In total, 2,230 valid questionnaires were procured, with an effective rate of 96.96%. Among the respondents, the mean age was 14.92 years (SD = 1.867, range 12–19 years), including 962 boys (43.1%) and 1,268 girls (56.9%). Voluntary participation was highlighted in an announcement. The questions of the survey covered the background and confidentiality information of this study, and participants' privacy was protected. The participants completed the questionnaires at their own school and no incentives were provided. Incomplete questionnaires were excluded from this study.

4.2 Measurement of structures

4.2.1 DASS-21

The DASS-21 was used to evaluate *the* key symptoms of depression, anxiety, and stress (32) and collected information referred to the week prior to completing the questionnaire. The DASS-21 has been proven to have competent psychometric properties and is equivalent to other accurate questionnaires. This scale is classified into a 4-Likert reply from 0 to 3, where 0 = Nothing and 3 = Most of the time. This self-report instrument was designed to assess DASS, and includes three subscales: (1) the stress subscale, which measures tension, agitation, difficulty relaxing, and negative effect; (2) the anxiety subscale, which assesses autonomic arousal, skeletal musculature effects, situational anxiety, and subjective experience of anxiety arousal; and (3) the depression subscale, which measures hopelessness, dysphoria, lack of interest, self-deprecation, and inertia. The reliability coefficients of depression, anxiety and stress were 0.82, 0.82 and 0.79, respectively. The Cronbach's alpha of the total scale was 0.89.

4.2.2 MPAI

The MPAI has been used to identify the symptoms of mobile phone addiction among adolescents in Hong Kong (33). The scale includes 17 items and 4 subscales answered on a five-point Likert scale (5 = Always; 4 = Often; 3 = Occasionally; 2 = Rarely; and 1 = Not at all). The 4 subscales included "Inability to control craving"; "Anxiety and feeling lost"; "Productivity loss"; "Withdrawal and escape." The Chinese version of the MPAI has had good reliability and validity when used with students (34, 35). The higher the score indicates a higher degree of mobile phone addiction. The Cronbach's alpha of scale was 0.886. In addition, items 3, 4, 5, 6, 8, 9, 14, and 15 were designed to be mobile phone addiction screening questions. If participants answered five or more questions with a three or above score, they were regarded as mobile phone addicts. The others were categorized as non-phone addicts.

4.2.3 RSCA

The RSCA was developed by Chinese scholars Hu and Gan (36) according to the process model of the resilience concept and applied to Chinese adolescents. There are 27 items divided into five factors: goal focus, emotion control, positive cognition, family support and interpersonal assistance. This scale is a five-point Likert-type scale from 1 = Completely disagree to 5 = Completely agree. This scale is especially appropriate in the evaluation of Chinese adolescents' resilience, and is widely used in China under various situations. The reliability of the total scale was 0.85.

4.3 Data analysis

All data analyses were performed using SPSS 26.0 and Mplus 8.5 (37). First, descriptive data were received using SPSS 26.0, and correlation variables were calculated using Pearson's correlations. Second, the present study used Latent Class Analysis (LCA) to identify latent mobile phone addiction class among Chinese adolescents, and the LCA performed by Mplus 8.5 to discover subgroups that displayed similar patterns of individual characteristics (i.e., class homogeneity) and diverse patterns across subgroups (i.e., class separation). LCA is a form of finite mixture modeling which involves clustering, density estimation, and random-effects modeling. The data analysis used fit indices to evaluate the best fitting model, including maximum log likelihood (LL), Akaike information criterion (AIC), the Bayesian information criteria (BIC), the sample-size adjusted Bayesian information criteria (SABIC), entropy (an indication of classification uncertainty), the Lo Mendell and Rubin likelihood ratio test (LMR), and the bootstrap likelihood ratio test (BLRT). Higher entropy values suggest a model that better divides the data into profiles, with values of >0.80 encouraging the minimal uncertainty of the profile classification of adolescents, and a significant BLRT, which compares the fit of the k-profile model with the k-1 profile model. The means of each class were stabilized using the logit values procured from the initial mix model, thus the latent class categorization was not influenced by subsequently added covariates. Finally, the ultimate class model was subsequently returned on the covariates.

5 Results

5.1 Descriptive statistics

We included 2,230 participants, including 962 boys and 1,268 girls in the final analysis. The proportion of girls was slightly higher than that of boys (56.9% vs. 43.1%, respectively). The mean age was 14.92 years (SD = 1.867, range 12–19 years). There were 1,223 (54.84%) participants from middle school, 1,007 (45.16%) from high school, 161 (7.2%) from one-child families, and 2,069 (92.8%) from multi-child families. The other results are shown in Table 1.

5.2 Correlation analysis of major study variables

The variables correlated with the constructs in Table 2 were less than 0.85. The discriminant validity value (<0.85) was met in the construct correlation (38). We found that some demographic characteristics were related to the participants' mobile phone addiction. The results of the analysis showed that academic performance, the primary caregiver, parenting style, family style, and financial status were positively correlated with the adolescents' mobile phone addiction. Conversely, the education level of the parents, the educational level of the primary caregiver, and family history of psychosis were negatively correlated with the adolescents' mobile phone addiction.

The major study variables correlated with the constructs in the present study. Stress, anxiety, depression, and psychological resilience were correlated with the adolescents' mobile phone addiction (Table 3). Furthermore, the correlations suggest that there is an association between the psychological variables and mobile phone addiction.

5.3 Detecting latent class

This study involves five different model fit statistics that were used to assess which LCA model fits the data best. We detected that AIC values decreased gradually from the 2- to 5-class models, BIC values decreased gradually from the 2- to 4-class models, while BIC did not decrease from the 4- to 5-class model, which the 3-class model had SABIC as well as significant LMR and BLRT. The 3-class model also had the highest entropy score, reflecting the best classification accuracy among other models, suggesting that participants were ranged into three mutually exclusive classes. To sum up, the 3-class model was determined the optimal latent class, therefore we selected the 3-class model as the best fitting model (Table 4). Figure 1 shows the different classes and their means for each mobile phone use subscale. The first profile is called the "normal mobile phone use class" ($n = 482$, 21.50%), and included the least number of adolescents in all subscales of mobile phone use. The opposite class, namely the class in which mobile phone adoption was highest for all subscales of mobile phone use, is called the "mobile phone addiction class" (46.65%). The third class included the most adolescents ($n = 1{,}058$) and is called the "high-risk mobile phone use class." Adolescents in this class are characterized by a moderate population in all mobile phone use subscales.

5.4 ROC analysis

Using the binary outcomes ("non-case" and "case") procured from LCA as the reference standard, the receiver operating characteristic (ROC) plot of the sensitivity versus 1-specificity of various MPAI scores revealed the area under the curve (AUC) of 0.893 (95% CI, 0.879 to 0.905, $p < 0.001$) (Figure 2). The diagnostic value indices for potential generated cut-off points from 8 to 40. The optimal cut-off value of MPAI was >14, which corresponded to the maximum Youden index (Youden index = 0.751). In this case, the sensitivity was 96.5%, specificity was 78.64%, PPV and NPV were 86.7 and 93.9%, respectively (Table 5). The positive group (defined as MPAI score > 14) included 59.13% of the participants.

5.5 Predicting mobile phone addiction LCA membership

A multinomial logistic regression is conducted with goal focus, interpersonal support emotional control, positive cognition, and family support as possible psychological resilience predictors of LCA membership as well as age, grade, academic performance, and family financial status as possible background characteristic predictors of LCA membership. As shown in Table 6, the multinomial logistic regression was employed by us to analyze Cluster normal mobile phone use, high-risk mobile phone use and mobile phone addiction as outcomes. Academic performance and grade negatively predicted memberships in cluster high-risk mobile phone use vs. normal mobile phone use and mobile phone addiction vs. normal mobile phone use. Goal focus, interpersonal support emotional control, positive cognition, and family support positively predicted memberships in cluster high-risk mobile phone use vs. normal mobile phone use, mobile phone addiction vs. normal mobile phone use, and mobile phone addiction vs. high-risk mobile phone use. Family financial status negatively predicted membership in cluster high-risk mobile phone use vs. normal mobile phone use, in contrast to cluster mobile phone addiction vs. high-risk mobile phone use.

6 Discussion

Despite the growth in the incidence of mobile phone addiction among adolescents, many researchers tend to focus on potential risk factors contributing to mobile phone addiction, but few empirical studies have examined typologies of mobile phone addiction in a sample of Chinese adolescents. The current study empirically showed that a three-class model most effectively classified Chinese adolescents giving different degrees of problematic mobile phone usage. The three classes affected by the LCA were as follows: normal mobile phone use, high-risk mobile phone use, and mobile phone addiction. 21.25% of the mobile phone users fell into the category of normal, 32.1% of the mobile phone users were categorized as high-risk, and the rest (46.65%) were placed into the addiction group. When compared with the normal group, participants in the other two groups manifested more severe mobile phone-related problems. They also revealed a poorer psychosocial profile in the matter of stress, anxiety, depression, goal focus, interpersonal support, emotional control, and positive cognition.

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TABLE 1 Demographic profiles and descriptive statistics of the participants.

Dependent variable	Frequency	Percentage
Gender		
Boy	962	43.1
Girl	1,268	56.9
One-child		
yes	161	7.2
no	2069	92.8
Birth order		
1st	1,025	46.0
2nd	1,029	46.1
3rd	176	7.9
Nationality		
Han	2,222	99.6
Hui	7	0.4
Miao	1	0.0
Grade		
Middle school 7th	163	7.3
Middle school 8th	625	28.0
Middle school 9th	435	19.5
High school 1st	34	1.5
High school 2nd	464	20.8
High school 3rd	509	22.8
Education level of father		
Elementary school and below	156	7.0
Middle school	1,275	57.2
High school	572	25.7
Bachelor's degree	214	9.6
Master's degree and above	13	0.6
Education level of mother		
Elementary school and below	276	12.4
Middle school	1,217	54.6
High school	518	23.2
Bachelor's degree	206	9.2
Master's degree and above	13	0.6
Average monthly household income *per capita* (RMB)		
≧8,000	156	7.0
6,000 ~ 7,999	226	10.1
4,000 ~ 5,999	455	20.4
2000 ~ 3,999	788	35.3
1,000 ~ 1999	386	17.3
<600 ~ 999	118	5.3
200 ~ 599	67	3.0
<200	34	1.5
Total	2,230	100.0

The present study proposes that different classes of mobile phone users may be recognized through LCA, supplying a comprehensive view of the patterns of adolescents' mobile phone use. This result was consistent with the findings of previous studies (39, 40). Given the fact that a mobile phone can provide more media resources than just a few years ago, mobile phone addiction may have more underlying groups. For this reason, personal characteristics may be a possible interpretation. Participants categorized in the LCA of mobile phone addiction were adolescents. The physical and psychological growth of adolescents is easily affected by many factors. The current study showed that academic performance, the education level of the mother, the educational level of the primary caregiver, the type of family education, family history of psychosis, stress, anxiety, depression, and psychological resilience were all related to mobile phone addiction of the adolescent participants. This result is consistent with findings of previous studies (10, 41, 42).

When compared with the high-risk mobile phone use group and the normal mobile phone use group, the result demonstrated that age, grade, psychological resilience and academic performance were negatively correlated with problematic mobile phone use. In other words, introducing mobile phones to children at a young age can lead to problematic mobile phone usage; the better the academic performance, the less likely an individual will develop problematic mobile phone usage. In this study, although grade was related to high-risk mobile phone use, middle school (9th grade) was not associated with high-risk mobile phone use. Due to the transition to higher education, 9th grade students have to deal with academic pressure, leading them to invest more time and energy into their studies.

Fischer-Grote et al. (43) suggested that gender, age, family, and personality might be risk factors for problematic smartphone use. Comparison between the mobile phone addiction group and the normal mobile phone use group revealed that psychological resilience and school grade were significantly negatively related to mobile phone addiction. There was a negative correlation between moderate academic performance and smartphone addiction. This study was consistent with previous research findings (7, 10, 44). Abd Rashid et al. (45) considered that an individual's attention on academic study may be diverted if they have a severe addiction to their mobile phone. Bai et al. (46) regarded the effect of mobile phone addiction on academic rank was significant, pointing to a strong association between these two variables. When mobile phone addiction vs. high-risk mobile phone use, psychological resilience, gender, school grade (except for the 9th grade and the freshman year of high school), and family financial status had an effect on mobile phone addiction.

Liu et al. (47) considered that gender moderated the association between peer victimization and mobile phone addiction, with this association being stronger in girls than in boys. Korean girls were likely to more use their mobile phones and were at higher risk of mobile phone addiction (48). Borislav and Dijana (49) thought that age had a negative correlation with mobile phone addiction, while family risk factors were positively associated with disorder of early psychological development and mobile phone addiction. The subjective economic level, academic stress, and parental support were associated with a tendency to become addicted to the smartphone (50). In another study, Lee et al. (51) revealed that mobile phone addiction was related to higher levels of depression among low-income boys.

TABLE 2 Correlation analysis of Sample characteristics and MPAI.

	1	2	3	4	5	6	7	8	9
MPAI	1								
Academic performance	−0.162**	1							
Education level of father	−0.026	−0.084**	1						
Education level of mother	−0.054**	−0.113**	0.612**	1					
Primary caregiver	0.021	0.036	0.018	0.008	1				
Educational level of the primary caregiver	−0.086**	−0.087**	0.519**	0.723**	0.005	1			
Parenting style	−0.190**	0.075**	−0.075**	−0.042*	0.086**	−0.047*	1		
Family financial status	0.028	−0.014	−0.127**	−0.131**	−0.026	−0.118**	0.003	1	
Family history of psychosis	−0.069**	0.019	−0.024	−0.008	−0.070**	−0.056**	−0.027	0.019	1

**$p < 0.01$ (two side), *$P < 0.05$ (two side), sig.

TABLE 3 Correlation analysis of study variables.

	1	2	3	4	5	6	7	8	9
MPAI	1								
Stress	0.415**	1							
Anxiety	0.361**	0.871**	1						
Depression	0.374**	0.849**	0.858**	1					
Goal focus	−0.236**	−0.174**	−0.156**	−0.241**	1				
Interpersonal support	−0.275**	−0.455**	−0.421**	−0.464**	0.317**	1			
Emotional control	−0.475**	−0.609**	−0.571**	−0.567**	0.298**	0.575**	1		
Positive cognitive	−0.081**	−0.139**	−0.154**	−0.196**	0.650**	0.215**	0.187**	1	
Family support	−0.285**	−0.366**	−0.347**	−0.395**	0.448**	0.466**	0.420**	0.377**	1

**$P < 0.01$ (two side), sig.

TABLE 4 Fit indices for latent class analysis.

Model	*K*	Log likelihood	AIC	BIC	SABIC	Entropy	LMR *p*-value	BLRT *p*-value
2	65	−11837.617	23805.235	24132.413	23925.954	0.843	0.000	0.000
3	98	−11537.976	23271.952	23765.236	23453.959	0.895	0.000	0.000
4	131	−11407.301	23076.602	23735.992	23319.897	0.804	0.7822	0.000
5	164	−11310.716	22949.431	23774.926	23254.014	0.790	0.7635	0.000

Based on the selected cut-off value, the prevalence of MPA among our sampled adolescents of Henan province in China was 59.13%. Alavi et al. (52) used the Mobile phone abuse questionnaire (MPA) to measure mobile phone usage of students, which showed that the cut-off point was 46 participants (31.2%) who were identified as having mobile phone addiction. The Smartphone Addition Inventory in Spanish (SPAI-Spain) was employed to investigate mobile addiction in a number of university communities in Spain. The result revealed that 23.67% of the participants were classified as dependent on the smartphone. As for gender, the percentage of women who suffered smartphone addiction accounted for 53.88% of the total (53). The literature review also revealed that the prevalence of smartphone addiction was 32% in Iran (54), 30.9% of middle school students in South Korea were categorized as a high-risk group (55), and 33.1% of secondary school students (56). Elsewhere, the rate of smartphone addiction among children and adolescents was 40.4% in 31 provinces of China (57), 46.1% of adolescents in Nigeria had moderate to high problematic phone usage (58), 71.9% of Saudi Arabian dental students had a mobile phone addiction (59), as did 85.4% of medical students in India (60). These variances could be partially assigned to the differences in participants and measurement tools. In this study, excessive use of mobile phone was due to the utilization of the virtual environment that was prevalent during the COVID-19 pandemic. At this time, many schools adopted online formats for teaching and various other educational activities, leading adolescents to primarily use smartphones or computers for remote learning. As a result, they spent more time on screens. Moreover, in China, socializing, shopping, recreation, and payment is now often done using social media such as TikTok, Wechat, QQ, interactive computer games, and so on, and this has become a principal factor of mobile phone addiction.

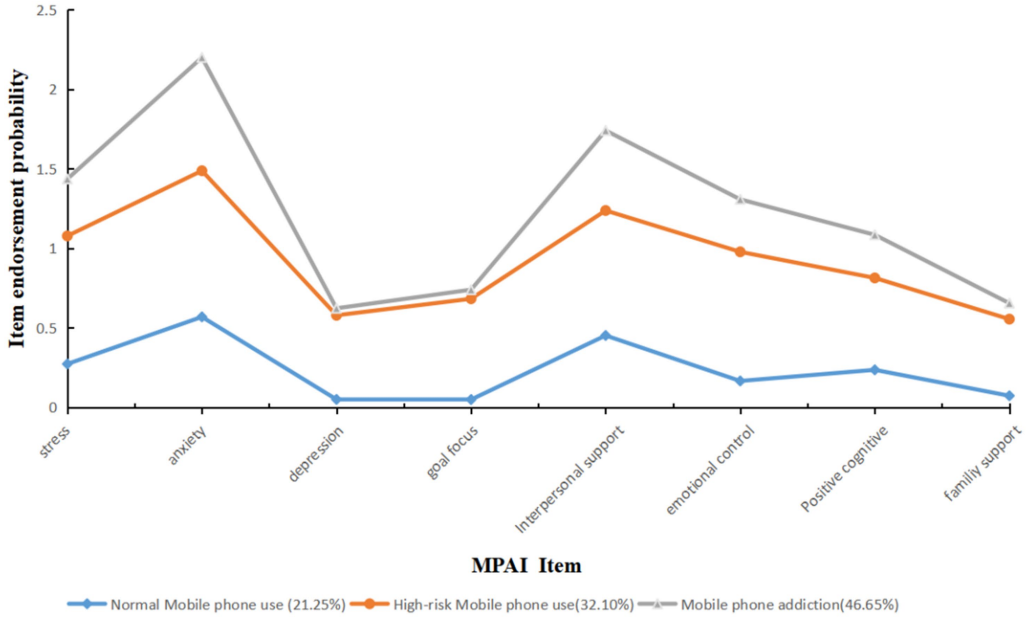

FIGURE 1
Profiles for 3-class LCA model of MPAI.

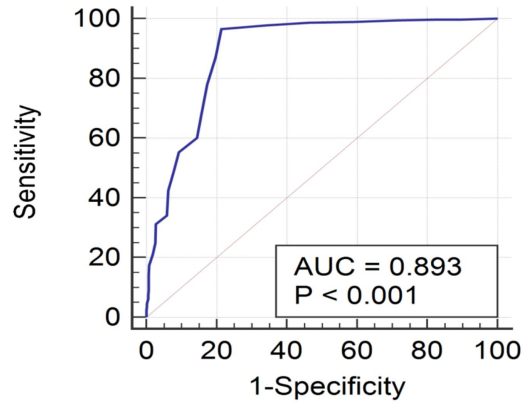

FIGURE 2
ROC curve of the MPAI using the high-risk class derived from latent class model as gold standard.

Based on these results, we suggest these cutoff point scores should be used as a threshold for normal mobile phone users as distinct from addicted mobile phone users. In research or diagnosis of mobile phone addiction, these results should be illustrated with care to sustain the validity of the questionnaire. Some consideration should be given when reporting cutoff value in interpretation, utilization of the cutoff value will rely on the purpose of the questionnaire and the popularity of mobile phone usage in the population under study. Moreover, no cutoff value is 100% accurate, so diagnostic errors will exist (61).

In sum, the current study used a sophisticated latent class analysis, and it highlights the differential associations between heterogeneous classes of multidimensional mental health and psychological resilience indicators for addictive mobile phone use in adolescents. Our discovery of the individual differences in factors that cause mobile phone addiction emphasizes the need to focus more on mobile phone users' discrete psychological resilience and family status in future research. Further, the consideration of multidimensional pointers in our research spreads understanding of the united operation of various individual difference components in connection with varying degrees of risk for mobile phone addiction. Moreover, our results carry important real-world implications, in that suitable prevention or intervention methods for mobile phone addiction should target the particular psychological dimensions that are associated with mobile phone addiction, especially those that indicate a personal uneven psychological profile. For example, those whose latent classes are characterized by poor psychological resilience and high psychological distress will require stronger social support to improve their ability to regulate themselves psychologically. This appears to be a valid intervention device to reduce psychological dilemma with regards to addictive mobile phone use.

6.1 Limitations

This report must address several limitations of the study. The research used cross-sectional data. Given the nature of cross-sectional data, this study was unable to infer temporal sequence relationships, limiting its capacity for causal inferences and instead focused on correlation. The data were self-reported and may have been influenced by social desirability bias, despite efforts in this study to reduce bias through measures such as anonymity and absence of teachers. As this study drew on a relatively small number of schools in two cities in Henan province, the generalizations should be approached with

TABLE 5 ROC analysis of the MPAI using the high-risk class derived from latent class model as gold standard.

Cut-off value	Sensitivity (100%)	Specificity (100%)	PPV (100%)	NPV (100%)	Youden index
≥8	100.000	0.000	59.100		
8	99.700	10.900	61.800	96.200	0.106
9	99.700	18.020	63.800	97.700	0.177
10	99.480	28.690	66.900	97.400	0.282
11	98.960	40.990	70.800	96.400	0.400
12	98.660	53.510	75.400	96.500	0.522
13	97.760	65.700	80.500	95.300	0.635
14	**96.500**	**78.640**	**86.700**	**93.900**	**0.751**
15	87.020	80.260	86.400	81.000	0.673
16	78.000	82.630	86.700	72.200	0.606
17	68.830	84.140	86.300	65.100	0.530
18	60.100	85.540	85.700	59.700	0.456
19	55.330	90.720	89.600	58.400	0.461
20	48.620	92.230	90.100	55.400	0.409
21	42.430	93.740	90.700	53.000	0.362
22	34.150	94.170	89.500	49.700	0.283
23	31.250	97.300	94.400	49.500	0.286
24	24.910	97.410	93.300	47.300	0.223
25	21.030	98.170	94.300	46.200	0.192
26	17.520	99.140	96.700	45.400	0.167
27	14.390	99.240	96.500	44.500	0.136
28	11.190	99.350	96.200	43.600	0.105
29	9.250	99.350	95.400	43.100	0.086
30	7.460	99.460	95.200	42.600	0.069
31	6.190	99.460	94.300	42.300	0.056
32	4.550	99.780	96.800	42.000	0.043
33	3.580	99.780	96.000	41.700	0.034
34	2.610	99.890	97.200	41.500	0.025
35	2.090	99.890	96.600	41.400	0.020
36	1.420	100.000	100.000	41.200	0.014
40	0.000	100.000		40.900	0.000

Bold value means best cut-off value.

caution. Therefore, in the future, more complicated longitudinal studies will be needed to establish the directionality of the relationship between these latent classes and mobile phone addiction. Future research should include more representative and diverse samples, as well as investigate the relationship between psychological characteristics and mobile phone addiction in other populations.

7 Conclusion

The current study discovered different patterns of problematic mobile phone use among adolescents living in Henan province. Three latent classes were recognized among the whole population. This is particularly important, as misuse of mobile phones is prevalent among adolescents, and ever-developing mobile phone technology may be perceived as a risk for increasing prevalence rates. Individual academic performance, parental education level, low psychological resilience, and a family history of mental illness appear to contribute to smartphone addiction amongst adolescents. In our study, we found that in the high-risk mobile phone addiction vs. normal mobile phone use, age, psychological resilience, school grade, and academic performance play a role in problematic phone usage. In the mobile phone addiction vs. normal smartphone use, psychological resilience, school grade, and academic performance influence mobile phone addiction. In the high-risk smartphone addiction vs. mobile phone addiction, psychological resilience, gender, and school grade contribute to smartphone addiction. The family's economic status seems to have minimal impact on an adolescent's mobile phone addiction. These results give a reliable basis to evaluate a lot of problems emanating from excessive mobile phone use. The increase

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TABLE 6 Multinomial logistic regression predicting LCA membership.

		B	*SE*	*P*	OR	95%CI	
						Low	Up
High-risk mobile phone use vs. Normal Mobile phone use							
Age		−0.112	0.048	0.020	0.894	0.814	0.983
RSCA	Emotional control	−0.105	0.052	0.042	1.11	1.004	1.228
	Positive cognitive	−0.185	0.056	0.001	1.203	1.078	1.343
	RSCA Total	−0.089	0.047	0.060	0.915	0.834	1.004
Grade	Primary schools (6th)	−6.093	1.086	0.000	0.002	0.000	0.019
	Middle school (7th)	−6.422	0.805	0.000	0.002	0.000	0.008
	Middle school (8th)	−6.09	0.783	0.000	0.002	0.000	0.011
	Middle school (9th)	12.219	4000.037	0.998	202540.474	0.000	.c
	High school (1st)	−6.006	0.866	0.000	0.002	0.000	0.013
	High school (2st)	−6.582	0.769	0.000	0.001	0.000	0.006
	High school (3st)	0b					
Academic performance	Top 10	−1.017	0.364	0.005	0.362	0.177	0.739
	Above-average	−0.807	0.334	0.016	0.446	0.232	0.859
	Average	−1.116	0.334	0.001	0.327	0.170	0.63
	Below average	−0.578	0.328	0.079	0.561	0.295	1.068
	Bottom 10	0b					
Family financial status (LAINCOME, RMB)	≥8,000	−0.791	0.661	0.232	0.453	0.124	1.657
	6,000–7,999	−1.225	0.649	0.059	0.294	0.082	1.049
	4,000–5,999	−0.800	0.632	0.206	0.449	0.130	1.551
	2000–3,999	−0.799	0.621	0.198	0.450	0.133	1.52
	1,000–1999	−1.379	0.636	0.030	0.252	0.072	0.877
	600–999	−0.365	0.697	0.601	0.694	0.177	2.723
	200–599	0.363	0.766	0.636	1.437	0.320	6.446
	<200	0b					
Mobile phone addiction vs. normal mobile phone use							
RSCA	Goal focus	−0.181	0.058	0.002	1.198	1.069	1.344
	Interpersonal support	−0.191	0.065	0.003	1.21	1.065	1.375
	Emotional control	−0.173	0.066	0.009	1.189	1.045	1.353
	Positive cognitive	−0.299	0.072	0.000	1.349	1.171	1.554
	Family support	−0.233	0.077	0.003	1.263	1.085	1.469
	RSCA Total	−0.206	0.061	0.001	0.814	0.722	0.918
Grade	Middle school (7th)	−7.654	0.886	0.000	0.000	0.835	0.003
	Middle school (8th)	−9.228	0.893	0.000	0.983	1.717	0.001
	Middle school (9th)	−5.227	5530.468	0.999	0.005	0.000	.c
	High school (1st)	−5.344	0.864	0.000	0.005	0.001	0.026
	High school (2st)	−3.178	0.752	0.000	0.042	0.010	0.182
	High school (3st)	0b					
Academic performance	Top 10	−0.61	0.422	0.148	0.543	0.238	1.242
	Above-average	−0.665	0.393	0.091	0.514	0.238	1.111
	Average	−1.237	0.385	0.001	0.290	0.137	0.617
	Below average	−0.722	0.391	0.065	0.486	0.226	1.046
	Bottom 10	0b					

(Continued)

TABLE 6 (Continued)

		B	SE	P	OR	95%CI	
						Low	Up
Mobile phone addiction vs. high-risk mobile phone use							
RSCA	Goal focus	−0.110	0.053	0.038	1.116	1.006	1.238
	Interpersonal support	−0.120	0.059	0.043	1.127	1.004	1.266
	Family support	−0.162	0.070	0.021	1.176	1.025	1.350
	RSCA total	−0.117	0.056	0.036	0.890	0.797	0.992
Gender	Male	0.440	0.170	0.010	1.553	1.112	2.169
	Female	0b					
Grade	Middle school (7th)	−1.232	0.451	0.006	0.292	0.121	0.705
	Middle school (8th)	−3.138	0.464	0.000	0.043	0.017	0.108
	Middle school (9th)	−16.446	2316.422	0.994	7.20E-08	0.000	.c
	High school (1st)	0.662	0.513	0.197	1.939	0.710	5.296
	High school (2st)	3.405	0.228	0.000	30.100	19.258	47.044
	High school (3st)	0b					
Family financial status (LAINCOME, RMB)	≥8,000	1.101	0.715	0.124	3.007	0.741	12.21
	6,000–7,999	1.403	0.678	0.039	4.066	1.076	15.369
	4,000–5,999	1.335	0.644	0.038	3.798	1.075	13.425
	2000–3,999	1.217	0.632	0.054	3.376	0.978	11.651
	1,000–1999	1.321	0.639	0.039	3.747	1.072	13.100
	600–999	1.127	0.687	0.101	3.087	0.803	11.862
	200–599	0.693	0.743	0.351	2.000	0.466	8.588
	<200	0b					

in the proportion of mobile phone addiction among adolescents provides a rationale for implementing preventive measures and conducting further research.

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 Ethics Committee of Nanyang Medical College (number: NYYZ20240001). The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

JW: Conceptualization, Writing – original draft. LJ: Investigation, Writing – review & editing. YL: Data curation, Investigation, Writing – review & editing. QL: Investigation, Writing – review & editing. YZ: Data curation, Investigation, Writing – review & editing. JZ: Data curation, Writing – review & editing. YJ: Data curation, Writing – review & editing. ZF: Conceptualization, Investigation, Supervision, Writing – review & editing.

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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.

Publisher's note

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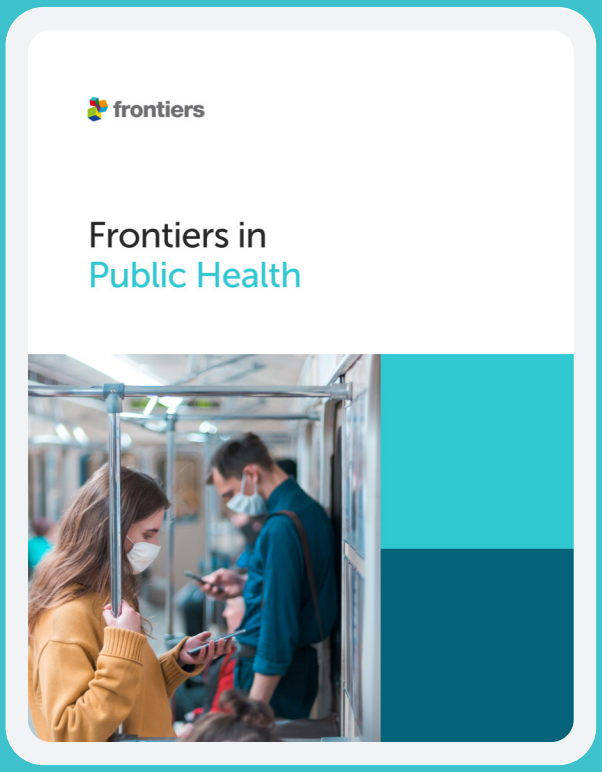

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