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ORIGINAL RESEARCH

The Impact of Smartphone Addiction on Chinese University Students' Physical Activity: Exploring the Role of Motivation and Self-Efficacy

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Background: Previous studies showed that smartphone addiction (SA) can lead to reduced physical activity (PA), but only a few studies have explored the impact of SA from psychological perspective closely related to PA. This study aimed to examine the extrinsic and partial psychological factors leading to decrease in PA using structural equation modelling analysis.
Methods: We conducted an online survey on 628 males and 1159 female students from 10 universities in Henan Province, China, through a questionnaire survey application "Questionnaire Star". This study used three models to test the mediating effects of three types of motives (intrinsic motives, body-related motives, and social motives) and self-efficacy, respectively, in the relationship between smartphone addiction and physical activities.
Results: Our result confirmed that smartphone addiction leads to lower physical activities. Secondly, self-efficacy mediates smartphone addiction and physical activities, but the mediating effect of all three types of motivation is not significant. Thirdly, smartphone addiction did not affect intrinsic motivation and body-related motivation, but positively affects social motivation. Finally, as the motivation type changes from internal to external, the mediating effect of self-efficacy becomes stronger.
Conclusion: This study showed that smartphone addiction lead to increase social motivation and decreased self-efficacy, and is a potential barrier to personal participation in physical activities. Our findings provide a new perspective for future design physical activities interventions in China and worldwide especially among university students where smartphone addiction is a problem.
Keywords: smartphone use, smartphone addiction, physical activity, motivation, self-efficacy, physical health

Introduction

The last decade has seen rapid mobile technology development across the globe. In 2020, Statista[1] reported that the number of smartphone users worldwide has surpassed three billion and is forecast to grow further by several hundred million in the next few years. China, India, and the United States are the countries with the highest number of smartphone users, with each country easily exceeding the 100-million-user mark. Among them, university students are considered to be one of the most important target markets and the largest consumer group for smartphone services.[2,3]

The mobility of smartphones and the convenience of surfing the internet meet the needs of university students for social interaction, entertainment, and access to information, and have become an important part of university students' daily university life. However, using smartphone excessively might possess certain negative outcomes such as decreased sense of volitional control as well as persistent smartphone activity.[4] The concept and connotation of SA were developed from extensive research on internet addiction. Although the use of the term "addiction" to describe excessive smartphone use is still controversial,[5] it is undeniable that the usage characteristics of high-frequency smartphone users are remarkably similar to those of other addictive behaviors. Lin et al[6] explained that SA is mainly manifested in four aspects: (1) obsessive phone use, (2) tolerance or longer and more intense use, (3) withdrawal or feelings of agitation or suffering without the phone, and (4) functional impairment or interference with other life activities and face-to-face

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social relationships. A wide array of studies had confirmed that SA causes either directly or indirectly issues to university students' physical health,[7,8] mental health,[9–11] and interpersonal relationships.[12,13] The university students represent educated emerging adults whose SA status has raised public concerns about its negative health consequences. In a study in China, it was reported that the rate of SA was estimated at 38.6% among university students.[14] This rate was 46.9% in Malaysia,[15] 48% in Saudi Arabia,[16] and 39–44% in India.[17]

Many scientists expressed their concern that when the amount of time spent on digital technology increases, it indirectly results in less time spent on physical activity (PA), which may be a factor contributing to adolescent obesity and physical health problems.[18] It is now well established from many studies that the prolonged use of smartphones is strongly related to sedentary lifestyles and physical inactivity.[19–22] A major study of 4964 Chinese university students reported that 78.4% failed to achieve 150 minutes of moderate-intensity aerobic exercise per week or at least 75 minutes of high-intensity physical exercise or a combination of medium-high intensity exercise per week, as recommended by the World Health Organization.[23] WHO (2010) also reported that 49.7% of university students spent at least two hours on screen time per day.[24] Physical inactivity can lead to various health problems for smartphone users, such as shoulder pain,[25] neck pain and disability,[26] wrist and hand pain,[27] and posture and respiratory problems.[28] Unfortunately, it has become a cultural norm for university students living in the digital age to integrate digital technology into their daily lives.[29] Therefore, a detailed understanding of the relationship between SA and PA is of great significance in promoting university students' participation in PA and improving their health.

In the past few decades, the study on motivation and self-efficacy (SE) in relation to PA have received substantial attention and are considered important predictors of persistency toward PA.[30–33] Although previous studies have revealed a significant correlation between SA and PA, there is insufficient empirical evidence targeting student population to explain the specific relationship between SA, motivation, and SE. Moreover, this study presents a significant contribution to enriching the literature on SA, and the findings will help in formulating well-informed PA intervention blueprints and reduce SA's impact on the healthy lifestyles of Asian populations, especially Chinese university students.

Literature Review

Smartphone Usage and Smartphone Addiction

The alarming increase in smartphone usage, as well as the widespread availability of a wide range of user-friendly smartphone applications, has heightened the issue of SA. Compared to the older generation, the younger generation uses smartphones more often.[34] SA is considered to be a technological addiction similar to the symptoms of substance addiction,[35] but some scientists have argued that it is more akin to pathological use.[36,37] "Smartphone-addicted" students spent significantly more time on their phones compared to non-addicted ones.[38] Many young people admitted that they never turned off their smartphones, that they put them aside to sleep, and were obsessed with checking their phones during the daytime.[39] The tendency of young people to suffer from SA is directly proportional to their smartphone usage (eg, the length of usage time and checking times) and has been confirmed in numerous studies.[40–43] As a result, it was hypothesized that SA would grow in tandem with increased smartphone usage.

H1: An increase in smartphone usage has a positive effect on smartphone addiction.

Smartphone Addiction and Physical Activity Self-Efficacy

SE for exercise or PA—a concept from Bandura social cognitive theory[44,45] —refers to one's beliefs about the capability of successfully engaging in regular exercise routines (three or more times a week).[46] Taylor[47] concluded that individuals with higher levels of exercise SE were likelier to participate in an exercise or sports program and to recognize that they were benefiting from its effects than individuals with lower SE levels. SE is the key determinant of consistent, health-promoting levels of PA, according to the social cognitive model of PA. Furthermore, there is a reciprocal relationship between exercise conviction and exercise activity.[44,48,49] In a few available studies investigating the relationship between SA and SE for PA, SA was found to significantly affect SE in relation to learning behavior.[50,51] Therefore, we aimed to further explore the impact of SA on SE for PA.

H2: Smartphone addiction has a negative effect on self-efficacy for physical activity.

Smartphone Addiction and Physical Activity Motivation

A key issue in PA research is developing an understanding of the motivation to engage in PA or exercise. Currently, several studies have concentrated on the use of smartphone technology to track or interfere in PA motivation[52–55] while ignoring the detrimental effect of SA on the motivation to be physically active. A study by Doree[56] based on 200 US university students, reported that high smartphone usage (> 180 min per day) resulted in greater amotivation for exercise, while users with low usage (≤ 180 min per day) showed higher intrinsic motivation (IM). Since the newly developed scale employed in this study to measure PA motivation includes nine different types of motivation, based on Rogers and Morris[57] and self-determination theory (SDT)[58] on the classification of motivation types, the motives of mastery and enjoyment are classified as intrinsic motivation (IMs), appearance, stress management, and health benefits are classified as body-related motives (BRMs), and others' expectations, affiliation, competition, and policy intervention are classified as social motives (SMs). The latter two categories are both regarded as extrinsic motivation.[59–61] Based on exhaustive literature reviews, this research proposes the following hypotheses:

H3. Smartphone addiction has a negative effect on intrinsic motivation.

H4. Smartphone addiction has a positive effect on body-related motivation.

H5. Smartphone addiction has a positive effect on social motivation.

Motivation, Self-Efficacy, and Physical Activity

Motivation and SE are two key factors that are often used to explain engagement in PA. Deci and Ryan[62] posited in SDT that amotivation, extrinsic motivation, and IM were considered to be on a continuum reflecting the degree of self-determination behavior. As individuals progress along this continuum from amotivation to IM, their motivation becomes less controlled and more self-determined. These different motivational states are associated with important health outcomes. IM, characterized by enjoyment and interest, has been shown to be closely related to continuous exercise.[63–66] On the contrary, extrinsic motivation is believed to be only mildly correlated with exercise commitment or negatively correlated with exercise commitment.[67] Specifically, all types of motives for participating in activities for reasons other than the activity itself can be categorized as extrinsic motivations. According to Ryan et al,[61] body-related extrinsic motivations, such as getting fitter, improving appearance, weight loss, or toning up, are negatively correlated with participation time and exercise duration per week, while enjoyment and competence are positively correlated with these measures. Similarly, it has been proven that SE is another psychological factor closely related to changes in exercise behavior. In general populations, as well as in some medical and demographic sub-groups, such as older adults, patients with multiple sclerosis, and patients in cardiac rehabilitation, SE has shown substantial associations with the intention to adopt exercise and actual activity levels.[68–73] In parallel with these studies, the following hypotheses are suggested:

H6. Intrinsic motivation positively predicts physical activity.

H7. Body-related motivation negatively predicts physical activity.

H8. Social motivation negatively predicts physical activity.

H9. Self-efficacy positively predicts physical activity.

Motivation and Self-Efficacy

Although SE and motivation are different concepts and have different structures within the domain of sports and exercise, SE is based on one's confidence or belief in maintaining regular physical exercise, while motivation is based on a person's force to stimulate and direct PA and exercise behavior,[74] but they are deeply entwined. In SE theory, self-beliefs become a primary, explicit explanation for motivation.[44,45,75] A study in the Netherlands based on adults over 50 years of age found that although both SE and attitude were variables that impacted motivation, only SE significantly predicted changes in PA. A related cross-sectional study based on patients with a history of heart failure showed that exercise SE fully mediated the relationship between exercise motivation and PA. This indicates that higher motivation is likelier to bring about higher SE and increase PA.[76] In another longitudinal study, at 6 months post-discharge from hospital for coronary heart disease, SE to exercise played a partial mediating role between autonomous exercise motivation and exercise behavior. This finding highlights the major role of autonomous motivation in exercise maintenance.[77] The current literature results show that most studies recruited pathological populations, and only a few studies focused on healthy populations. Therefore, it is necessary for us to explore the relationship between these variables in a young, healthy population (ie, university students). Therefore, we propose the following hypotheses:

H10. Self-efficacy positively predicts intrinsic motivation.

H11. Self-efficacy positively predicts body-related motivation.

H12. Self-efficacy positively predicts social motivation.

Smartphone Addiction and Physical Activity

The popularity and dependency of network and cyber technology leads to drastic increase in sedentary lifestyles caused by long-term Internet and computer use. This phenomenon has received widespread attention, as it may reduce time spent on leisure and recreational activities.[78–80] Smartphones' portability and attractive applications have made users spend more time on smartphones than computers.[81] As a result, a growing body of researchers has turned their attention to the direct impact of smartphone overuse on PA. Lepp et al[82] found that high-frequency users were likelier to report forgoing physical activities to use their smartphones for various sedentary activities. A study of Chinese international students studying in South Korea reported that SA can have a detrimental impact on physical health by decreasing engagement in physical activities, such as walking, resulting in a rise in fat mass and a decrease in muscle mass, both of which are linked to negative health outcomes.[83] In another cross-sectional study, Gumusgul[84] demonstrated that participants who engaged in physical and recreational sports had a lower risk of SA, which may point to smartphones being constraints for PA. In general, although there are a few studies showing that there is no significant correlation between smartphones and PA,[85,86] the conclusion that SA negatively affects participation in PA is well supported by numerous studies.[87,88] In parallel with these studies, we suggest the following hypothesis:

H13. Smartphone addiction has a negative effect on physical activity.

In summary, based on an extensive literature review, we propose a hypothetical model for this study (Figure 1). The purpose is to establish a model to examine the relationship among smartphone usage, SA, and PA, and to test the mediating role of SE and motivation based on structural equation modeling (SEM).

Methods

Participants and the Recruitment Process

We recruited 2289 undergraduate students from 10 universities in Henan Province, China, through convenience sampling methods between August 2020 and September 2021. A total of 1787 (M_{age} = 18.85, SD_{age} = 0.93, 35.1% male) valid questionnaires were obtained after data cleaning, with a response rate of 78%. The participants were non-sports major students from various faculties. Participants identified themselves as smartphone users, and their average cell-phone use was 4.71 (mean) ± 2.40 (SD) years.

This study complies with the principles of the Declaration of Helsinki and was approved by the Ethics Committee of the University of Malaya (Reference Number: UM. TNC2/UMREC-977). The distribution and collection of online questionnaires were carried out via a Chinese smartphone application called "Questionnaire Star." After uploading the

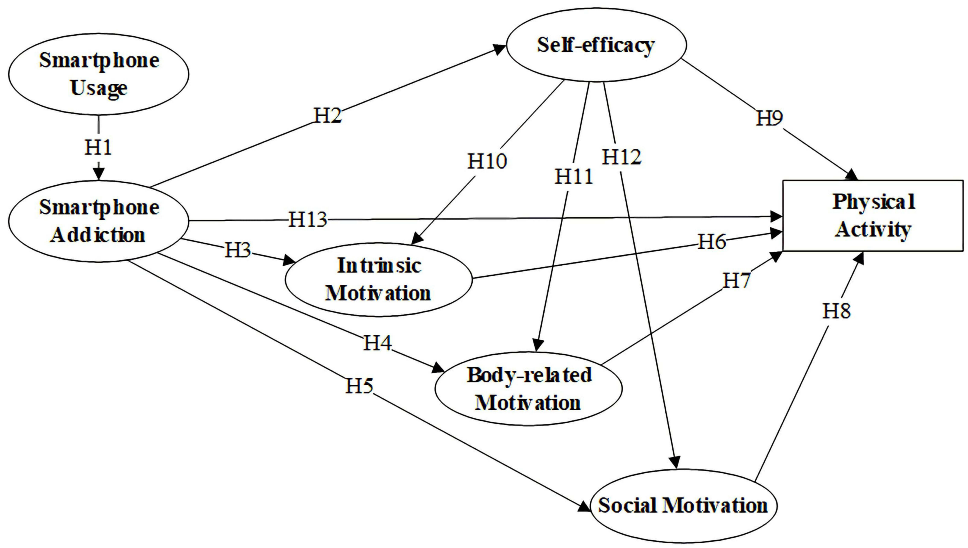

Figure 1 Hypothetical model diagram.

survey items to the application, the link and QR code for filling in the online survey were automatically generated. Permissions to access the requested groups were obtained from the administrations of 10 universities prior to data collection. Potential participants received the link and informed consent e-form in their class WeChat group established in advance by the respective university's lecturers, and students were invited to participate (on a voluntary basis). The personal information of the participants (ie, name, e-mail address, phone number) was excluded from this online survey to ensure anonymity, and to maintain confidentiality, the data will not be accessed by members outside the research team. The online survey-filling process took approximately 10 minutes.

Measures

The online survey mainly included the participants' socio-demographic characteristics, smartphone usage, SA risk, motivation, and SE for participating in physical activities, as well as their PA measurements.

Smartphone usage was measured with two items related to the average number of smartphone usage hours per day and the number of times they unlocked their screens. According to Zhitomirsky-Geffet and Blau[89] and Oulasvirta et al,[90] checking habits and daily usage times are important predictors of SA in the younger generation. The first question participants needed to answer was: On average, how long have you used your smartphone for every day in the last three months? The options given were less than 1 hour, 1–2 hours, 2.1–3 hours, 3.1–4 hours, 4.1–5 hours, 5.1–6 hours, 6.1–7 hours, 7.1–8 hours, and more than 8 hours. The second question was: How many times have you unlocked your phone every day in the last three months? The options given were less than 10, 10–20, 21–30, 31–40, 41–50, 51–100, 100–150, 151–200, and more than 200. A higher mean score corresponds to a higher frequency of smartphone usage behavior.

The Smartphone Addiction Scale (SAS) was originally developed by Kwon et al[91] to measure undergraduate SA risk. Subsequently, to evaluate SA in a simple and easy way, Kwon et al[34] selected 10 items from 33 items in the original SAS and created a shorter form to describe five factors: overuse and tolerance, withdrawal, cyberspace-oriented relationship, positive anticipation, and daily-life disturbance. The Chinese version of the SAS-SV was translated and validated by Luk et al[92] and showed good internal consistency (Cronbach's $\alpha = 0.844$). The SAS-SV-C retained the same scale as the original version, with scores ranging from 1 (strongly disagree) to 6 (strongly agree) for each item. In this study, the Cronbach α of all items measured their internal consistency, which was over 0.80, indicating good reliability. It had good construct validity, and the estimates of the measurement model were good, with the value of chi square divided by the degree of freedom (χ^2/df), the comparative fit index (CFI), the Tucker–Lewis Index (TLI), and the root mean square error of approximation (RMSEA) being determined as follows: χ^2 (137) = 1093.972, CFI = 0.927, TLI = 0.908, and RMSEA = 0.063.

The Chinese University Students' Physical Activity Motivation Scale (CUSPAMS) was developed by Lin et al[93] specifically to measure the different types of motives for PA participation targeting university and college students. The CUSPAMS consists of 32 items with nine factors measuring different types of motives: enjoyment, mastery, stress management, health benefit, appearance, affiliation, competition, policy intervention, and others' expectations. All the response options were in the form of a 7-point Likert scale ranging from 1 (not at all true for me) to 7 (very true for me), with higher scores indicating higher PA motivation. The results of the confirmatory factor analysis (CFA) were χ^2 (288) = 2334.469, CFI = 0.938, TLI = 0.924, and RMSEA = 0.063, indicating good construct validity. Based on the classification approach of motivation types from Rogers and Morris[57] and SDT,[58,62] the nine factors measured by the CUSPAMS can be categorized as aspects of IMs (mastery and enjoyment), BRMs (stress management, health benefits, and appearance), and SMs (affiliation, competition, policy intervention, and expectations from others). The second-order CFA for CUSPAMS produced a good model fit: χ^2 (312) = 3504.868, CFI = 0.903, TLI = 0.891, and RMSEA = 0.076. In the subsequent SEM analysis, we included these three types of motivation to explore their roles in the model. The Cronbach's α of the intrinsic motivation subscale, body-related motivation subscale, and social motivation subscale were 0.88, 0.91, and 0.85, respectively.

The Exercise Self-Efficacy Scale (ESES) was developed by Bandura[45] and has shown good structural stability during cross-cultural testing in the Korean,[94] Malay,[95] and Iranian[96] populations. The scale has a total of 18 items, which are used to measure the confidence level of the respondents in terms of sticking to an exercise routine (three or more times a week) with potential barriers (eg, during bad weather). Bandura[45] adopted a response format in his article ranging from 0 to 100 in 10-unit intervals (0 = cannot do at all, 50 = moderately can do, and 100 = highly certain can do). However, the Chinese version of the ESES was not available. Therefore, it was necessary to validate the reliability and validity of the Chinese version of the ESES. In this research, we retained the same scale structure and replaced the original format with a simpler response from 0 to 10. Following the suggestion of Brislin,[97] two bilingual psychology researchers translated the original English ESES into Chinese and examined the suitability of each item in the Chinese context. Then, two professional bilingual translators who had not read the original version of the ESES performed a back translation of the Chinese version. The discrepancies between the back-translated version and the original English version were further discussed until the experts came to a consensus. Then, a panel of six specialists in sport sciences, sport psychology, physical education, and linguistics examined and finalized the Chinese version. The three-factor model of the ESES consists of internal feelings, competition, and situation. The Cronbach's α of all items, which measured their internal consistency, was 0.89, and the α for the three subscales was 0.81, 0.81, and 0.81, indicating superior reliability. The results of the CFA were χ^2 (41) = 373.596, CFI = 0.970, TLI = 0.959, and RMSEA = 0.067, indicating good construct validity.

The level of PA was estimated from the International Physical Activity Questionnaire (Short Form) (IPAQ-SF). The validity of the IPAQ-SF as a measure of PA behavior in the Chinese population has been previously established.[98,99] This self-administered questionnaire assessed participants' frequency and duration of vigorous PA (eg, heavy lifting, fast bicycling), moderate PA (eg, bicycling at a regular pace), walking, and sedentary behavior during the previous seven days to include only physical activities done for at least 10 minutes at one time. Following the guidelines of the Short-form IPAQ,[100] we separately calculated the total number of minutes (minutes/per day × days) that each university student spent on three PA intensities and sedentary non-PA per week. Subsequently, the volume for each type of PA, with the exception of sedentary non-PA, was calculated by weighting each type of activity by its energy requirements, defined in metabolic equivalent tasks (METs). The total energy expenditure for each type was calculated by multiplying the MET score by the time (in minutes) required to perform the activity. Specifically, we calculated the walking MET (minutes/week = 3.3 × walking minutes × walking days), moderate MET (minutes/week = 4 × moderate-intensity activity minutes × moderate days), and vigorous MET (minutes/week = 8 × vigorous-intensity activity minutes × vigorous-intensity days). The different activity intensities were added together to yield a total of MET minutes, which represented the amount of energy expended by participants per week when carrying out PA.

Statistical Analyses

We used SPSS 22.0 to set up a database and perform a demographic analysis.

Associations among smartphone usage, SA, PA motivation, PA SE, and PA were analyzed with SEM in SPSS AMOS version 22.0. The dataset was screened for missing data, sample size, univariate and multivariate normality, outliers, multicollinearity, and residual values before being analyzed. Since the MET minutes/week values of PA were positively skewed, the PA skewness was improved with a Log10 transformation. According to the rule-of-thumb SEM sample size, as determined by Kline,[101] each estimated parameter requires at least 10 observations. Therefore, this condition was met in the research. Skewness and kurtosis statistics were used to assess the normality of the univariate distribution. If skewness is below an absolute value of 2, then kurtosis below an absolute value of 7 denotes a normal distribution.[102,103] Since AMOS is based on the covariance technique for analysis, which makes it highly sensitive to data distribution, testing the multivariate normality of the data is a crucial step. We used Mardia's coefficient of multivariate kurtosis and its critical ratio provided by AMOS to measure data normality. In addition, according to Diamantopoulos and Siguaw,[104] we examined the variance inflation factor (VIF) of the variables in the measurement model to avoid multicollinearity. After testing, all VIF scores were below the 3.3 threshold (ranging between 1.03 to 1.65), which indicated that the model had no multicollinearity among its structures.

Three types of PA motivation (IMs, BRMs, and SMs) were put into the SEM as endogenous variables to establish three models, respectively, with the purpose of exploring the relationship between different motivation types and other latent variables. The data obtained as a result of the three structural models were analyzed using various goodness-of-fit indices that are commonly used in SEM to assess the model's suitability. The following approximate fit indices were calculated: χ^2/df, the CFI, the TLI, and RMSEA. As for the baseline fit indices, χ^2/df < 3 indicates an acceptable fit[101] and < 5 indicates a reasonable fit,[105] with the CFI and TLI being at least > 0.90 and ideally > 0.95, and the RMSEA being at least < 0.05 and ideally <0.08.[106] According to Fornell and Larcker,[107] we evaluated the convergent validity of the measurement model by calculating the average variance extraction (AVE) and composite reliability (CR).

This study adopted the bootstrap approach proposed by Preacher and Hayes,[108] which does not require any assumptions about the sampling distribution and can also improve the confidence interval (CI) of hypothesis testing through bias correction and acceleration.[109] It is considered the most reasonable way to obtain confidence limits for specific indirect effects under most conditions.[110] According to the suggestion of Preacher and Hayes,[108] we set the number of repeated samplings to 5000 to obtain the lower and upper limits of the 95% CI of the percentile and we bias-corrected. If the 95% CIs do not contain zero between the upper and lower values, it indicates that a significant indirect effect has been determined by the mediator between the dependent variable and the independent variable.

Results

Table 1 shows the distribution of the participants according to the variables. It can be observed that 64.9% of the participants were female and 35.1% of them were male. The percentage of university students aged 18 to 19 was 79.2%, of those born in rural was 50.1%. 69.6% of students were in the first year of study. 48.9% of university students stated that on average they spend three to six hours on their phones on a daily basis. 76.9% of university students admit that they check their phones less than 50 times daily. The model proposed in this study hypothesized that a significant correlation existed between smartphone usage hours, unlock smartphone times, SA, IM, BRM, SM, SE and PA. Table 2 presents the correlation matrix, means, standard deviations, for all the variables studied. The results show that SA and PA, three types of motivation, as well as SE, significantly correlated with smartphone usage hours daily. SA had a correlation with IM, and a negative correlation with SM. Duration of daily smartphone usage and SA were negatively associated with PA, however, the correlation between smartphone checks daily and PA was not significant.

First, we checked the structural validity, convergent validity, and discriminative validity of each measurement model. A commonly used method to investigate construct validity is CFA.[111] The fit indices showed that the three models that included all factor indicators and structural pathways fit the data acceptably: Model 1 (χ^2 (129) = 769.11, CFI = 0.94, TLI = 0.93, RMSEA = 0.05); Model 2 (χ^2 (318) = 1482.293, CFI = 0.938, TLI = 0.932, RMSEA = 0.05); and Model 3 (χ^2 (344) = 1493.366, CFI = 0.929, TLI = 0.922, RMSEA = 0.04). In Table 3, we can see that the CR of each construct ranged from 0.45 to 0.91, and the AVE ranged from 0.30 to 0.63, which exceeds or is close to the thresholds of 0.70[112] and 0.50.[103] As we can see, the AVE values of some scales are less than 0.50, but their CR values are higher than 0.60, so the convergent validity of the scales is considered adequate.[107,113]

Table 1 Demographic Characteristics of the Participants

Variable	Type	Frequency	Percentage (%)
Gender	Male	628	35.1
	Female	1159	64.9
Age	18	747	41.8
	19	669	37.4
	20	289	16.2
	21	59	3.3
	22	14	1
	22+	4	0.4
Year of study	1st	1244	69.6
	2nd	482	27
	3rd	44	2.5
	4th or more	17	1
Birthplace	Urban	892	49.9
	Rural	895	50.1
Years of cell-phone usage	Less than 1 year	159	8.9
	0–3 years	429	24
	3.1–5 years	577	32.2
	5.1–7 years	413	23.1
	7.1–9 years	165	9.3
	Over 9 years	44	2.5
Average daily duration of smartphone usage (hour)	0–3	191	10.7
	3.1–6	873	48.9
	6.1–9	446	25
	More than 9	277	15.5
Average number of smartphone checks per day	Less than 50	1375	76.9
	51–100	215	12
	101–150	69	3.9
	More than 150	128	7.2

Table 2 Correlation Matrix, Means, and Standard Deviations

Constructs	Mean	SD	1	2	3	4	5	6	7	8
SUH	6.35	3.25	1							
UST	49.33	51.27	0.219**	1						
SA	3.33	0.79	0.280**	0.164**	1					
IM	4.30	1.45	−0.105**	−0.013	−0.058*	1				
BRM	4.81	1.28	−0.064**	0.013	−0.023	0.803**	1			
SM	3.65	1.14	−0.050*	0.033	0.065**	0.683**	0.645**	1		
SE	5.57	1.92	−0.140**	−0.02	−0.102**	0.632**	0.562**	0.450**	1	
PA	4548.46	2995.22	−0.060*	−0.002	−0.153**	0.295**	0.208**	0.145**	0.281**	1

Note: *p < 0.05, **p < 0.01.
Abbreviations: SUH, smartphone usage hours; UST, unlock smartphone times; SA, smartphone addiction; IM, intrinsic motivation; BRM, body-related motivation; SM, social motivation; SE, physical activity self-efficacy; PA, weekly physical activity (MET- minutes); SD, standard deviation.

In the next step, we tested the path coefficients between the latent variables in the structural model to verify the hypotheses proposed above. The structural path estimates are given in Model 1 (Figure 2), Model 2 (Figure 3), and Model 3 (Figure 4). All path coefficients (β) are standard partial regression coefficients.

We hypothesized that increasing the number of hours spent using and checking a smartphone would positively affect university students' SA (H1). The hypothesis was supported in Model 1 ($\beta = 0.52$, $p < 0.001$). We assumed that a higher

Table 3 SEM Results for the Three Models

Construct/Item	Model 1					Model 2					Model 3				
	SL	R^2	p	CR	AVE	SL	R^2	p	CR	AVE	SL	R^2	p	CR	AVE
Smartphone usage (SU)				0.45	0.30				0.45	0.30				0.45	0.30
SUH	0.63	0.40	***			0.63	0.41	***			0.63	0.41	***		
UST	0.44	0.19	***			0.44	0.19	***			0.44	0.19	***		
Smartphone addiction (SA)				0.84	0.34				0.84	0.34				0.84	0.34
SA 1	0.50	0.25	***			0.50	0.25	***			0.50	0.25	***		
SA 2	0.56	0.31	***			0.56	0.31	***			0.56	0.31	***		
SA 3	0.57	0.33	***			0.57	0.32	***			0.58	0.33	***		
SA 4	0.63	0.40	***			0.63	0.40	***			0.63	0.40	***		
SA 5	0.67	0.45	***			0.67	0.45	***			0.67	0.44	***		
SA 6	0.49	0.24	***			0.49	0.24	***			0.49	0.24	***		
SA 7	0.70	0.49	***			0.70	0.49	***			0.70	0.49	***		
SA 8	0.51	0.26	***			0.51	0.26	***			0.52	0.27	***		
SA 9	0.65	0.43	***			0.65	0.42	***			0.65	0.43	***		
SA 10	0.54	0.29	***			0.54	0.29	***			0.54	0.29	***		
Intrinsic motivation (IM)				0.88	0.79										
MEM	0.90	0.81	***												
MMT	0.88	0.77	***												
Body-related motivation (BRM)									0.84	0.64					
MHB						0.92	0.85	***							
MSM						0.84	0.71	***							
MAR						0.60	0.37	***							
Social motivation (SM)														0.76	0.45
MAA											0.70	0.50	***		
MOE											0.57	0.33	***		
MPI											0.55	0.30	***		
MCT											0.83	0.68	***		
Physical activity self-efficacy (SE)														0.90	0.75
Internal	0.88	0.78	***	0.90	0.75	0.88	0.78	***	0.90	0.75	0.88	0.77	***		
Competition	0.90	0.82	***			0.91	0.82	***			0.90	0.81	***		
Situational	0.81	0.66	***			0.81	0.65	***			0.82	0.67	***		

Note: ***$p < 0.001$.

Abbreviations: SL, standardized loading; β, path coefficient; CR, composite reliability; AVE, average variance extracted; SUH, smartphone usage hours; UST, unlock smartphone times; MEM, enjoyment motivation; MMT, mastery motivation; MHB, health benefit; MSM, stress management; MAR, appearance motivation; MAA, affiliation motivation; MOE, others' expectations; MPI, policy intervention; MCT, competition motivation; Internal, internal feeling; Competition, competing demands; Situational, situational/interpersonal.

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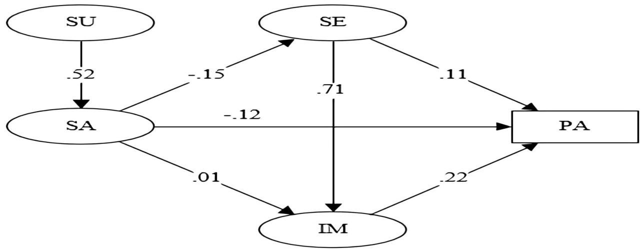

Figure 2 Smartphone addiction, intrinsic motivation, and self-efficacy affects on physical activity.

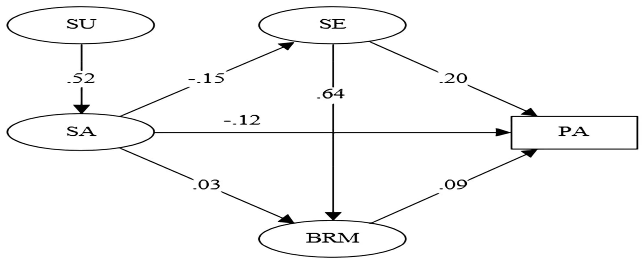

Figure 3 Smartphone addiction, body-related motivation, and self-efficacy affects on physical activity.

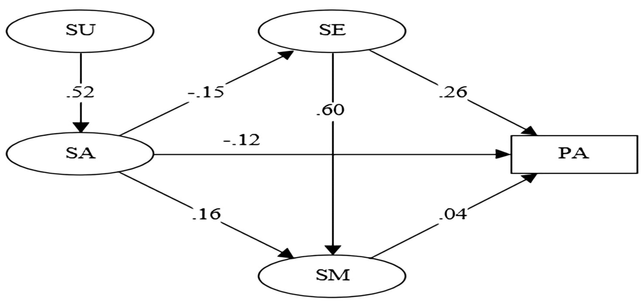

Figure 4 Smartphone addiction, social motivation, and self-efficacy affects on physical activity.

level of SA would negatively predicted students' SE (H2) and their PA behavior (H13). These two hypotheses were also supported in Models 1, 2, and 3. The direct effects of SA on IM and BRM predicted by hypothesized Model 1 ($\beta = 0.01$, $p > 0.05$) and Model 2 ($\beta = 0.03$, $p > 0.05$) were not significant; in Model 3, SM can be positively predicted ($\beta = 0.16$, $p < 0.05$). Hypotheses H3 and H4 were rejected, and H5 was not supported. IM ($\beta = 0.22$, $p < 0.001$) and BRM ($\beta = 0.09$, $p < 0.05$) have a direct positive effect on PA. However, SM cannot predict PA ($\beta = 0.04$, $p > 0.05$). There were statistically significant direct effects between SE and IM ($\beta = 0.71$, $p < 0.001$), BRM ($\beta = 0.64$, $p < 0.001$), and SM ($\beta = 0.60$, $p < 0.001$). In addition, we found that SE had a significant impact on PA. In summary, the 13 hypotheses proposed in this study are supported, except for H3, H4, H7, and H8 (Table 4).

This study asserts that SE is a crucial mediating variable between SA and PA. As shown in Table 5, in the three models, SA not only has a direct impact on PA but also affects PA through the mediating role of SE. The mediating effects of the three different types of motivation were not found in the three models. With the transformation of the types of PA motivation from intrinsic to extrinsic, the negative effects of SA on PA through SE gradually increased. Therefore, this study asserted that, compared with motivation, SE is a more stable and crucial mediating variable in the relationship between SA and PA. Moreover, SE and IM in Model 1 and BRM in Model 2 played a chain-mediating role in the relationship between SA and PA among university students.

Table 4 Summary of SEM Hypothesis Testing

Hypotheses	Model 1			Model 2			Model 3			
	β	C.R.	p	β	C.R.	p	β	C.R.	p	Results
H1: SU→SA	0.52	9.00	***	0.52	9.00	***	0.52	8.99	***	Supported
H2: SA→SE	−0.15	−5.41	***	−0.15	−5.41	***	−0.15	−5.39	***	Supported
H3: SA→IM	0.01	0.67	0.50							Rejected
H4: SA→BRM				0.03	1.50	0.13				Rejected
H5: SA→SM							0.16	5.91	***	Supported
H6: IM→PA	0.22	5.85	***							Supported
H7: BRM→PA				0.09	2.63	*				Rejected
H8: SM→PA							0.04	1.31	0.09	Rejected
H9: SE→PA	0.11	3.085	***	0.20	7.05	***	0.26	8.05	***	Supported
H10: SE→IM	0.71	28.58	***							Supported
H11: SE→BRM				0.64	20.53	***				Supported
H12: SE→SM							0.60	21.90	***	Supported
H13: SA→ PA	−0.12	−4.83	***	−0.12	−4.77	***	−0.12	−4.78	***	Supported

Note: ***p < 0.001, *p < 0.05.
Abbreviations: SU, smartphone usage; SA, smartphone addiction; IM, intrinsic motivation; BRM, body-related motivation; SM, social motivation; PS, physical activity self-efficacy; PA, physical activity; β, path coefficient; C.R., critical ratios.

Discussion

Our research aim was to put self-efficacy (SE) and different types of motivation into three structural equation models to detect the changes and patterns in the effects of smartphone addiction (SA) on the physical activities of Chinese university students. The research results showed that SA can affect motivation and the level of physical activity (PA) to varying degrees and has a more complicated relationship with different types of motivation. Except for H4 (SA has a positive effect on BRM) and H7 (BRM negatively predicts PA), all hypotheses are supported by the empirical evidence via SEM, and the results will contribute to providing a reference point for the international literature on PA interventions in the future. These following observations are noteworthy.

First, the results of this study reconfirmed that SA directly leads to a decrease in PA. In a previous study,[82] it was found that high-frequency university student phone users reported fewer leisure repertoires than low-frequency users. In addition, these high-frequency users described that consuming much time with cell phones facilitated sedentary behaviors, leading to PA disorders.[82] The long-term and high-frequency use of smartphones is just one of the characteristics of addiction. When the phone is not in sight or cannot be reached, the "addicts" often show an uncontrollable desire to use it.[114,115] They cannot control the use of smartphones and become dependent on these devices. This leads to an imbalance in the time allocated to different activities in their lives. These addicts were reported to have a higher fat mass and lower muscle mass[83] and reduced cardiorespiratory fitness.[82] A large number of studies have incorporated smartphones into interventions aimed at increasing PA and have provided modest evidence supporting the effectiveness of smartphone applications to increase PA.[116–119] Unfortunately, these strategies are implemented with the help of smartphone applications, and the participant's smartphone usage characteristics are not included in the factors that may affect the results of the experiments. Therefore, the unique contribution of smartphones to changing behavior has been difficult to discern. However, the exact information we can be certain of is that reduce SA has a preventive effect on declining PA.

Second, the path analysis results of this study showed that SA negatively predicts the intrinsic motivation (IM) of university students to engage in PA, and positively predicts extrinsic motivation. The higher the SA level, the lower the IM is to be physically active. In other words, the more an individual's motivation type is skewed toward extrinsic motivation, the likelier they will be affected by SA. As for exercisers who are skewed toward BRM, such as improving their appearance and physical health, their goals are more focused on the extrinsic outcome of the activity itself.[61] Many initial exercisers regard their appearance and fitness as the main reasons for participating in PA, especially for women.[59,120] The key for exercisers with this type of motivation to adhere to exercising is whether they can derive enjoyment from the activity. If participants in

Table 5 Mediation of the Effect of Smartphone Addiction on Physical Activity Through Self-Efficacy, Intrinsic Motivation, Body-Related Motivation, and Social Motivation

	Point	Product of Coefficients		Bias-Corrected CI	
	Estimation	**Standard Error**	**Z**	**Lower**	**Upper**
		Direct effect (Model 1)			
SA→PA	−0.265	0.056	−4.732***	−0.496	−0.218
		Indirect effect			
SA→SE→PA (Path 1)	−0.044	0.016	−2.75**	−0.016	−0.003
SA→IM→PA (Path2)	0.007	0.011	0.636	−0.003	0.007
SA→SE→IM→PA (Path 3)	−0.051	0.014	−3.642***	−0.019	−0.006
		Total indirect effect			
path1+path2+path3	−0.088	0.023	−3.826***	−0.027	−0.009
		Total effect			
SA→PA	−0.353	0.059	−5.983***	−0.112	−0.062
		Difference			
path1-path3	−0.006	0.021	−0.285	−0.005	0.014
		Ratio			
Path1/Total	0.125	0.048	2.604**	0.033	0.193
Path3/Total	0.143	0.042	3.404***	0.074	0.222
		Direct effect (Model 2)			
SA→PA	−0.265	0.057	−4.649***	−0.370	−0.148
		Indirect effect			
SA→SE→PA (Path 1)	−0.077	0.019	−4.052***	−0.119	−0.044
SA→BRM→PA (Path2)	0.007	0.006	1.166	−0.001	0.021
SA→SE→BRM→PA (Path 3)	−0.018	0.008	−2.250*	−0.036	−0.005
		Total indirect effect			
path1+path2+path3	−0.088	0.021	−4.190***	−0.132	−0.049
		Total effect			
SA→PA	−0.353	0.059	−5.983***	−0.466	−0.236
		Difference			
path1−path3	−0.058	0.021	−2.761**	−0.107	−0.025
		Ratio			
Path1/Total	0.217	0.061	3.557***	0.126	0.368
Path3/Total	0.051	0.023	2.217*	0.016	0.109
		Direct effect (Model 3)			
SA→PA	−0.273	0.058	−4.706***	−0.380	−0.156
		Indirect effect			
SA→SE→PA (Path 1)	−0.086	0.021	−4.095***	−0.132	−0.050
SA→SM→PA (Path2)	0.015	0.012	1.250	−0.006	0.044
SA→SE→SM→PA (Path 3)	−0.009	0.007	−1.285	−0.025	0.003
		Total indirect effect			
path1+path2+path3	−0.079	0.024	−3.451***	−0.129	−0.033
		Total effect			
SA→PA	−0.353	0.059	−6.324***	−0.466	−0.235
		Ratio			
Path1/Total	0.244	0.066	3.723***	0.144	0.405

Notes: The number of bootstrap samples was 5000. *p < 0.05. **p < 0.01. ***p < 0.001. CIs (confidence intervals) not containing zero were considered significant at the 0.05 level.

Abbreviations: SA, smartphone addiction; IM, intrinsic motivation; BRM, body-related motivation; SM, social motivation; SE, physical activity self-efficacy; PA, physical activity.

a PA program can continue to gain a sense of pleasure or enjoyment, then it is possible to maintain or form long-term exercise behaviors; if not, they will gradually withdraw from the PA program.[121,122] BRM is classified as extrinsic motivation; hence, it is closely related to short-term exercise behaviors. Due to the cross-sectional approach, this study did not focus on long-term changes in the exercise behavior of university students with this type of motivation. Therefore, the rejection of the two hypotheses, H4 (SA has a positive effect on BRM) and H7 (BRM negatively predicts PA), which were about BRM, is consistent with the conclusions of previous studies.[61]

Ryan and Deci[123] proposed that the motivation to engage in PA is on a continuum from "non-self-determined to self-determined." With continuous satisfaction arising from the three basic needs of individual autonomy, competence, and relatedness being met, amotivation can gradually be internalized into IM through external regulation, introjected regulation, identified regulation, and integrated regulation. From the results of this study, we can infer that the impact of SA on motivation depends on the type of motivation along the SDT continuum. Motivation types with a higher degree of autonomy, such as enjoyment and mastery, are less affected by SA. For motivation that is low in the degree of autonomy, such as avoiding the punishment of physical education policy, the influence of SA is greater.

Third, by examining the mediating effects of SE and different types of motivation, we found that SA can predict lower levels of IM and SE, and this ultimately leads to a decrease in PA levels. In the three models, the partial mediating effect of SE was always significant. Even if it is placed in Model 1 when compared with IM, there is no difference in the indirect effects of the two. Hence, in future PA interventions or programs, improving SE will be more realistic and effective than changing the motivation type.

Additional knowledge and understanding regarding university students' PA behavior and its determinants can provide a fundamental basis for changing their PA habits and improving the overall health of this population group.[124] It would appear that determining such information is significant from the standpoint of applied and preventative psychology. If SE and IM are identified as mediating variables between SA and PA levels, then the next logical step is to design intervention programs to improve SE or realize the conversion of motivation types from extrinsic to intrinsic. This will reduce the side effects of SA and improve the PA levels of college students.

Limitations

This study is subject to several limitations. First, the cross-sectional design of this study determined the current relationship between SA, motivation type, SE, and PA. However, the SEM analyses used in this study could not determine the causal relationship between these variables. Therefore, experimental and longitudinal approaches could be used in future studies to discover causal correlations between these factors. Second, the two variables proposed in this article, motivation and SE, are only two important factors closely related to PA. There are many other known psychological variables related to PA, such as attitudes, subjective exercise experience, and other variables that were excluded from the current study. Therefore, more research is needed to incorporate more variables to evaluate the role and effect of these variables on smartphones and PA. Finally, this study targeted Chinese university students; hence, the applicability and generalizability of the current results to other population groups is unknown.

Conclusion

This study explored the relationship between SA and PA in college students as well as the mediating role of different types of motivation and SE. Three structural equation models based on different types of PA motivation showed that longer smartphone use times and unlock frequencies led to a higher risk of SA. Second, college students with higher SA scores had correspondingly lower levels of PA. In addition, we found that SA could affect PA through the mediating role of intrinsic motives and SE. By comparing the mediating effects of both variables, SE performance was more stable and extensive. In future, more research attention can be channeled towards the rational usage of smartphones among university students and the practical significance of improving their PA by improving their SE and the internalization of motivational types.

Abbreviations

SA, Smartphone Addiction; PA, Physical Activity; SE, Self-efficacy; IM, intrinsic motivation; BRM, body-related motivation; SM, social motivation; SDT, Self-determination Theory; CFA, Confirmatory Factor Analysis; RMSEA, Root Mean Square Error of Approximation; CFI, Comparative Fit Index; TLI, Tucker Lewis Index.

Data Sharing Statement

The datasets during and/or analyzed during the current study available from the corresponding author on reasonable request.

Ethics Approval and Consent to Participate

This study was approved by the Ethics Committee of the University of Malaya (Reference Number: UM. TNC2/ UMREC-977).

Consent for Publication

We attest to the fact that the authors listed on the title page have read the manuscript, attest to the validity and legitimacy of the data and its interpretation, and agree to its submission to "Psychology Research and Behavior Management" journal.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; All authors took part in drafting, revising or critically reviewing the article; All authors gave final approval of the version to be published; All authors have agreed on the journal to which the article has been submitted; All authors have agreed to be accountable for all aspects of the work.

Disclosure

The authors declare that they have no competing interests.

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