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The impacts of physical activity on domain-specific short video usage behaviors among university students

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Abstract
Short video usage poses risks to the health and academic performance of university students. Physical activity (PA) has been recommended as a potential solution to mitigate excessive short video usage and its associated consequences. However, current research has paid limited attention to the impact of PA on different short video usage behaviors. Therefore, we conducted a cross-sectional survey from April 24 to 30, 2024, to collect data and examine the relationship between PA and short video usage, with depression as a mediator, in domain-specific usage contexts (including short video usage during daytime and nighttime, during study time and leisure time, overall usage, and short video addiction). A total of 1172 students who met the inclusion criteria were included in the analysis. Our structural equation modeling analysis revealed that PA was directly associated only with reduced nighttime short video usage (β = -0.12; $p < 0.05$). Additionally, PA was indirectly associated with reduced short video usage during nighttime (β = -0.03; $p < 0.05$), study time (β = -0.03; $p < 0.05$), and leisure time (β = -0.04; $p < 0.05$), as well as lower levels of short video addiction (β = -0.06; $p < 0.05$), mediated by depression. However, no significant total effects were observed between PA and daytime short video usage (β = -0.02; $p = 0.52$) or overall usage (β = -0.04; $p = 0.27$). In conclusion, our findings suggest that while PA may improve short video addiction and certain specific short video usage behaviors, its actual effects may be limited due to the small effect sizes observed.

Keywords TikTok, Mental health, Physical treatment, Social media addiction

Introduction

Short videos refer to video content with relatively brief durations, typically ranging from a few seconds to a few minutes. These videos are commonly shared and viewed on mobile applications (apps). These apps often provide creators with convenient video editing tools and deliver customized content to viewers based on their preferences, attracting hundreds of millions of users worldwide [1]. In recent years, numerous short video apps have emerged, among them TikTok stands out as one of the most successful examples. Globally, TikTok is available in over 160 countries, with a user base exceeding 1.677 billion as of 2023 [2], becoming the most popular social

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media app. Its widespread influence has led some governments to utilize it as a platform for policy announcements, integrating it into the fabric of daily life [3].

With the rising popularity of short video apps, concerns about their usage behaviors have also emerged. Recent studies have revealed that excessive use of short videos may lead to various negative health outcomes, including poor mental health [4], anorexia [5], sleep disturbances [6], memory loss [4], and other related health issues [7]. In addition to health-related concerns, some researchers have found that excessive use of short videos can also negatively affect students' academic performance [8]. Currently, the primary users of short videos are young people, particularly those aged 18 to 24 [2]. This is because this demographic is typically more exposed to and proficient in adopting new technologies [9, 10], making them more susceptible to the influence of excessive short video use. Therefore, this study will focus on university students to specifically examine this group.

Given the negative impacts of short video overuse mentioned above, identifying effective strategies to address this issue has become a focus of research. Among these, physical activity (PA) has been considered a valuable solution. As a cost-effective and non-pharmacological approach, PA not only plays a positive role in health promotion [11–13], but has also been recommended as an effective strategy for mitigating addictive behaviors, including internet addiction [14], smartphone addiction [15], and even substance addiction [16]. Recently, some researchers have suggested that PA may act as a protective factor against excessive short video usage behavior [6, 17, 18]. This is because current evidence indicates that participation in PA can alleviate mental health problems, such as depression [19]. Depression, in turn, is a key driving factor for short video overuse. A recent study by H Luo, X Zhang, S Su, M Zhang, M Yin, S Feng, R Peng and H Li [17] found that depression may drive short video users to increase their usage, particularly at bedtime. This may be related to the entertainment nature of short videos, as users experiencing higher levels of depression might engage in frequent use as a coping mechanism to mitigate their adverse mental health conditions. Consequently, the positive effects of PA on depression may also contribute to reducing excessive short video usage.

To date, several studies have explored the effects of PA on short video usage, with the mediating role of depression being established [6, 17, 18]. However, social media usage is a complex behavior. For example, individuals may prefer different short video platforms [20], and even users on the same platform may exhibit varying usage patterns, such as favoring bedtime usage or engaging with the platform in other contexts [20]. Despite this, domain-specific usage behaviors among short video users have received limited attention in research. Few studies have examined the relationship between PA and different short video usage behaviors. To bridge this gap, the present study aims to investigate the relationship between PA and short video usage, with depression as a mediator, in domain-specific usage contexts (including short video usage during daytime and nighttime, during study time and leisure time, overall usage, and short video addiction). Furthermore, given the potential for confounding in these relationships [21, 22], we included age and gender as covariates. Ultimately, we developed the conceptual models presented in Fig. 1, as shown below.

Materials and methods

Study design and participants

We conducted a cross-sectional survey from April 24th to 30th, 2024, at five universities in China. The authors

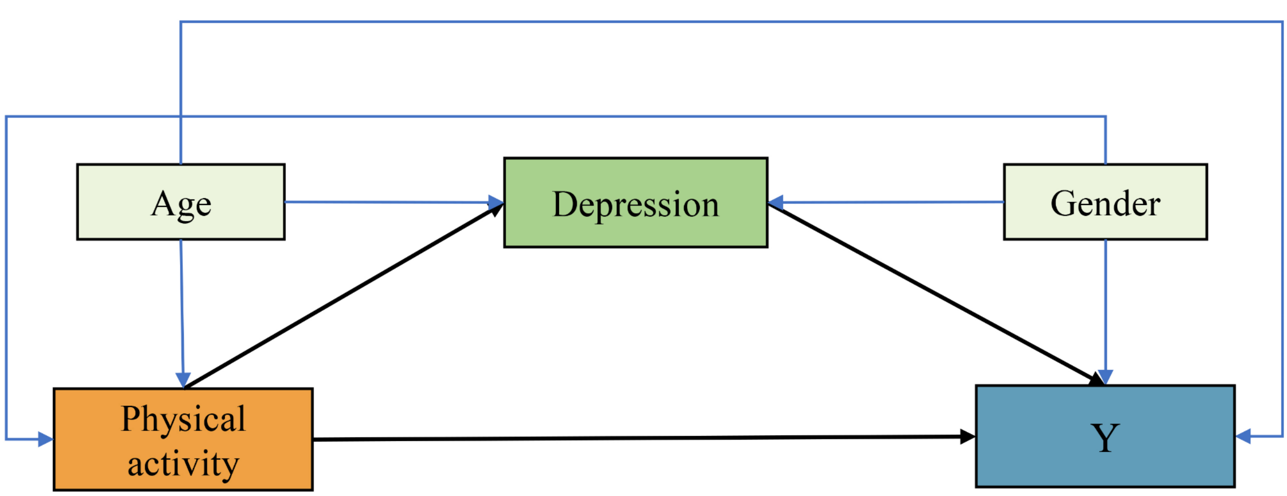

Fig. 1 Conceptual framework (Black lines indicate pathways between core variables, and blue lines indicate confounding pathways between core and control variables; Y represents short video usage during daytime, short video usage during nighttime, short video usage during study time, short video usage during leisure time, overall short video usage, and short video addiction)

initially developed a preliminary questionnaire based on a literature review. This questionnaire was then refined according to feedback from a pilot study. The final version was uploaded to "Sojump" (www.sojump.com), a professional online platform for designing, distributing, collecting, and analyzing questionnaires [23]. To distribute the survey, we enlisted 85 college students who shared a quick response (QR) code linked to our survey in their online class chat groups. We described the study as investigating the mental health and lifestyle habits of college students, without disclosing the specific research questions during participant recruitment. Participation was voluntary, and no rewards were given for completing the questionnaire. Informed consent forms were signed by participants before initiating the survey. This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Review Committee of Southwest University (SWUETH20230912003).

Inclusion criteria: (i) university students aged ≥ 18 years; (ii) had used short videos in the last month. Exclusion criteria: (i) lack of informed consent; (ii) unfinished questionnaires; (iii) individuals who failed verification tests (to confirm that the questionnaire was completed carefully by individuals rather than by a machine, program, or random filling).

Instruments and measurements

Depression

The Patient Health Questionnaire (PHQ-9) was utilized to assess the levels of depression [24]. This scale comprises nine questions, and the PHQ-9 aligns with the criteria for a major depressive episode as outlined in the DSM-IV. Respondents rate the frequency of their depressive symptoms over the past two weeks, with scores ranging from 0 (not at all) to 3 (nearly every day). We utilized a Chinese version of the PHQ-9, which demonstrated strong internal consistency in our study (Cronbach's $\alpha = 0.843$).

Short video addiction

In this study, we employed the Short-Form Video App Addiction Scale to assess addiction to short videos [1]. This scale comprises six self-report items designed to assess individuals' addictive behaviors linked to their usage of short videos. Participants were asked to consider their recent experiences and feelings regarding short video usage, rating on a 7-point Likert scale (1 = strongly disagree and 7 = strongly agree). We utilized a Chinese version of the scale, which demonstrated strong internal consistency in our study (Cronbach's $\alpha = 0.857$).

Short video usage during daytime, nighttime, study time, leisure time, and overall usage

We referred to previous publications and assessed various short video usage behaviors through frequency and duration metrics [6, 25]. For instance, the overall short video usage was evaluated using the following questions:

Frequency: "In the last month, how often did you use short video each week?" Responses were collected across 8 categories: 1 = never, 2 = an average of 1 day per week, 3 = an average of 2 days per week, 4 = an average of 3 days per week, 5 = an average of 4 days per week, 6 = an average of 5 days per week, 7 = an average of 6 days per week, and 8 = an average of 7 days per week.

Duration: "On days when you used short video, how long did you typically use them each day?" Responses were gathered across 8 categories: 1 = less than 30 min, 2 = 31 to 60 min, 3 = 61 to 90 min, 4 = 91 to 120 min, 5 = 121 to 150 min, 6 = 151 to 180 min, 7 = 181 to 240 min, and 8 = more than 240 min.

The product of the frequency and duration scores was calculated as the outcome. Other short video usage behaviors were also assessed using similar methods, with the only difference being the specific questions asked. The detailed information is presented in Supplement 1.

Physical activity

We drew on the design used in the UK Biobank for measuring physical activity (e.g., In a typical week, on how many days did you engage in 10 min or more of moderate physical activities) and insights from related publications [6, 26], assessing physical activity in this study through frequency and duration. The specific question is as follows:

Frequency: "In the last month, how often did you engage in moderate or higher intensity physical activity each week?" Responses were gathered across 8 categories: 1 = never, 2 = an average of 1 day per week, 3 = an average of 2 days per week, 4 = an average of 3 days per week, 5 = an average of 4 days per week, 6 = an average of 5 days per week, 7 = an average of 6 days per week, and 8 = an average of 7 days per week.

Duration: "On days when you participated in moderate or higher intensity physical activity, how long did you typically spend each day?" Responses were collected across 8 categories: 1 = less than 30 min, 2 = 31 to 60 min, 3 = 61 to 90 min, 4 = 91 to 120 min, 5 = 121 to 150 min, 6 = 151 to 180 min, 7 = 181 to 240 min, and 8 = more than 240 min.

The product of the frequency and duration scores was calculated as the outcome. The complete questions are provided in Supplement 1.

Statistical analysis

Demographic information and variables were presented as means with standard deviations (SD) or numbers with percentages. Due to the non-normal distribution of the data, Spearman's rank-order correlation was employed to explore general correlations between variables. Structural equation modeling (SEM) was utilized to investigate the hypothesized directional paths within the conceptual frameworks. Following the guidance of RP Bagozzi and Y Yi [27], our sample size of 1172 exceeded the recommended size of twice the number of model parameters. Variance Inflation Factor (VIF) values less than 5.0 were used to indicate the absence of multicollinearity [28]. Based on this threshold, none of the independent variables exhibited multicollinearity (VIF < 3.0). Due to the non-normality of the data, we employed an asymptotically distribution-free (ADF)/weighted least squares (WLS) estimator for SEM [29, 30], as this estimator is suited for non-normal data when the sample size is large (sample size: 1000 to 5000 and at least 10 times the number of estimated parameters) [31]. The bootstrap method with 10,000 replications was utilized to compute corresponding standard errors and confidence intervals for all paths [32–34]. Based on the ADF/WLS estimator, we evaluated the goodness of fit using the following indices [30, 35]: standardized root mean square residual (SRMR) < 0.08; Tucker–Lewis index (TLI) > 0.95; goodness-of-fit index (CFI) > 0.95, and root mean square error of approximation (RMSEA) < 0.05. We opted not to employ the $\chi 2$ test due to its susceptibility to sample size effects and violations of the multivariate normality assumption [36–38]. An indirect effect (i.e., a product of coefficients for the constituent links) that significantly exceeded zero was evidence of mediation [39, 40].

All statistical analyses were performed using SPSS 26.0 and AMOS 23.0 software (SPSS Inc., Chicago, IL, USA), with p-values < 0.05 considered statistically significant [41, 42].

Table 1 The respondent characteristics

Variable	Category	*N*	Percentage
Gender	male	730	62.3%
	female	442	37.7%
Age (year)			
	18–20	960	81.9%
	21–23	197	16.8%
	> 23	15	1.3%
Academic year			
	freshman year	539	46.0%
	sophomore year	508	43.3%
	junior year	115	9.8%
	senior year	7	0.6%
	others	3	0.3%
Physical activity in the last month			
	no	22	1.9%
	yes	1150	98.1%
Short video usage in the last month			
	no	0	0.0%
	yes	1172	100.0%
Short video usage during nighttime			
	no	6	0.5%
	yes	1166	99.5%
Short video usage during daytime			
	no	3	0.3%
	yes	1169	99.7%
Short video usage during study time			
	no	75	6.4%
	yes	1097	93.6%
Short video usage during leisure time			
	no	47	4.0%
	yes	1125	96.0%
		Mean	SD
Physical activity (score)		10.68	8.63
Overall short video usage (score)		28.32	15.62
Short video usage during night-time (score)		19.26	13.05
Short video usage during daytime (score)		23.53	14.80
Short video usage during study time (score)		16.89	15.17
Short video usage during leisure time (score)		22.25	14.64
Short video addiction (score)		21.12	7.03
PHQ-9 (score)		5.96	4.07

Results

Characteristics of respondents

The final analysis included a total of 1172 university students, with 62.1% males and 37.9% females. Their ages ranged from 18 to 25 years, with the majority being freshmen (46.0%) and sophomores (43.3%). All participants had used short videos in the last month as it was a criterion for inclusion in the study. The detailed information is presented in Table 1.

Correlations between variables

According to Spearman's rank-order correlation analyses, PA exhibited negative associations with short video usage during nighttime, leisure time, overall usage, and short video addiction albeit with relatively low correlation coefficients. Depression was associated with lower PA and higher levels of all five short video usage behaviors and short video addiction. More detailed information can be found in Fig. 2.

	Genmder	Age	AY	PA	OSVU	SVUN	SVUD	SVUS	SVUL	SVA	PHQ-9
Genmder	-	-0.348※	-0.131※	-0.365※	-0.042	-0.008	0.02	-0.036	0.083※	-0.001	0.133※
Age	-0.348※	-	0.620※	0.176※	-0.044	-0.029	-0.064※	0.036	-0.080※	-0.033	-0.048
AY	-0.131※	0.620※	-	0.036	-0.057	-0.018	-0.153※	0.021	-0.084※	-0.093※	-0.013
PA	-0.365※	0.176※	0.036	-	-0.064※	-0.153※	-0.034	-0.011	-0.130※	-0.131※	-0.254※
OSVU	-0.042	-0.044	-0.057	-0.064※	-	0.647※	0.653※	0.416※	0.588※	0.238※	0.173※
SVUN	-0.008	-0.029	-0.018	-0.153※	0.647※	-	0.572※	0.416※	0.612※	0.236※	0.166※
SVUD	0.02	-0.064※	-0.153※	-0.034	0.653※	0.572※	-	0.501※	0.628※	0.169※	0.130※
SVUS	-0.036	0.036	0.021	-0.011	0.416※	0.416※	0.501※	-	0.491※	0.149※	0.123※
SVUL	0.083※	-0.080※	-0.084※	-0.130※	0.588※	0.612※	0.628※	0.491※	-	0.260※	0.200※
SVA	-0.001	-0.033	-0.093※	-0.131※	0.238※	0.236※	0.169※	0.149※	0.260※	-	0.361※
PHQ-9	0.133※	-0.048	-0.013	-0.254※	0.173※	0.166※	0.130※	0.123※	0.200※	0.361※	-

-1 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1

Fig. 2 Correlation Heatmap (※, $p < 0.05$; OSVU, overall short video usage; SVUN, short video usage during nighttime; SVUD, short video usage during daytime; SVUS, short video usage during study time, SVUL; short video usage during leisure time; SVA, short video addiction, PHQ-9, depression)

Results of the SEM analysis

Model modification

In the two models, the total effects were not significant (short video usage during daytime and overall usage) (Table 2), and thus, we did not provide further analysis results for these models. The remaining four models demonstrated good model fit (SRMR < 0.08, TLI > 0.95, CFI > 0.95, and RMSEA < 0.05).

Total effect, direct effect and indirect effect

Short video usage during nighttime.

Physical activity was directly associated with reduced short video usage during nighttime (β = -0.12; $p < 0.05$) (Fig. 3: **model 1**). Additionally, it was indirectly correlated with lower levels of short video usage during nighttime through depression (β = -0.03; $p < 0.05$) (Table 2). In this model, the mediated proportion accounted for 22% of the total effect.

Short video usage during study time.

According to Table 2, PA was indirectly associated with reduced short video usage during study time via depression (β = -0.03; $p < 0.05$). However, no significant direct relationship between them was observed (β = -0.04; $p = 0.19$) (Fig. 3: **model 2**).

Short video usage during leisure time.

Physical activity was indirectly associated with decreased short video usage during leisure time through depression (β = -0.04; $p < 0.05$) (Table 2). However, no significant direct relationship between them was observed (β = -0.05; $p = 0.14$) (Fig. 3: **model 3**).

Short video addiction.

Table 2 revealed that PA was indirectly associated with reduced short video addiction through depression (β = -0.06; $p < 0.05$). However, no significant direct relationship was observed between them (β = -0.05; $p = 0.12$) (Fig. 3: **models 4**).

Table 2 The total and indirect effect of the SEM analysis

Pathway	β	95% CI Low	95% CI High	*p*
Total effect				
PA →SVU during nighttime	-0.148	-0.200	-0.094	< 0.05
PA →SVU during daytime	-0.018	-0.072	0.038	0.522
PA →SVU during study time	-0.070	-0.127	-0.011	< 0.05
PA →SVU during leisure time	-0.087	-0.142	-0.030	< 0.05
PA → short video addiction	-0.110	-0.165	-0.055	< 0.05
PA → overall SVU	-0.037	-0.099	0.029	0.265
Indirect effect				
PA → depression → SVU during nighttime	-0.032	-0.050	-0.017	< 0.05
PA → depression → SVU during study time	-0.028	-0.045	-0.016	< 0.05
PA → depression → SVU during leisure time	-0.042	-0.063	-0.026	< 0.05
PA → depression → short video addiction	-0.063	-0.089	-0.040	< 0.05

Note: PA, physical activity; SVU, short video usage

Discussion

Our findings suggested that short video addiction among university students was associated with multiple short video usage behaviors, including usage during nighttime, daytime, study time, leisure time, and overall usage. This indicates that excessive short video usage in these contexts may be specific expressions of short video addiction. Additionally, we observed a positive association between depression and short video addiction, as well as with the five types of short video usage behaviors (e.g., short video usage during nighttime, daytime, study time, leisure time, and overall usage). A recent study by H Luo, X Zhang, S Su, M Zhang, M Yin, S Feng, R Peng and H Li [17] investigated the factors driving people to use TikTok at bedtime and highlighted the role of depression. Our findings further indicate that depression could be a driving factor for multiple short video usage behaviors beyond just bedtime usage.

Physical activity has emerged as an effective strategy for mitigating addiction behaviors [14–16]. Recent research has suggested its potential in addressing short video addiction. For instance, a study by H Jianfeng, Z Xian and A Zexiu [18] observed that adolescents engaging in PA exhibited lower levels of short video addiction. Consistent with these findings, our study also revealed a negative association between PA and short video addiction among university students. However, our results emphasized the mediating role of depression. In our model, we did not find a significant direct effect of PA on short video addiction; instead, PA exerted an indirect influence on short video addiction by improving depression.

In terms of specific short video usage behaviors, our findings revealed that PA was associated with reduced short video usage during nighttime, study time, and leisure time. Specifically, engagement in PA may directly reduce nighttime short video usage and indirectly improve it through its effect on depression. Nighttime short video usage is typically considered a risk factor for sleep disturbances [43, 44]. A previous study by X Zhang, S Feng, R Peng and H Li [6] found that exercise could mitigate problematic nighttime short video usage by improving mental health. However, a contradictory result was reported in another study, where exercise led to an increase in short video usage at bedtime [17]. The authors attributed this finding to their focus on heavy short video users, who spend at least one hour daily on short videos. These heavy users often exhibit higher dependence and greater difficulty controlling their usage impulses compared to general users, making it challenging for them to benefit from PA [45]. Based on our current findings, we propose that PA may serve as a protective factor against nighttime short video usage among non-heavy users.

Some researchers suggested that students using short videos have poorer academic performance [8, 46]. One reason is that students tend to spend more time on digital devices, resulting in less time dedicated to studying [8]. In the current study, our findings indicate that university students who engage in PA are less likely to use short videos during study time. However, it is important to note that the influence of PA on short video usage during study time is mediated through its improvement of depression in our model, rather than having a direct effect. Moreover, the magnitude of this indirect effect is relatively small. Therefore, while PA is associated with reduced short video usage during study time, its actual impact may be limited.

Short videos serve as entertainment tools, but current studies have placed less focus on short video usage behavior occurring in leisure time. Previous studies have found that adolescents' leisure-time screen use was associated with depression, as adolescents with higher levels of depressive symptoms may be more inclined to engage in less active and more isolating activities such as screen use [47]. Our findings also revealed that depression was associated with increased short video usage during leisure time among university students. However, engaging in PA might act as a protective factor because it could mitigate their depression, thereby potentially contributing to a reduction in short video usage during leisure time.

It is important to note that although our study identified associations between PA and several specific short video usage behaviors, these associations were not observed for all types of usage behaviors. Specifically, our study did not find a significant total effect between

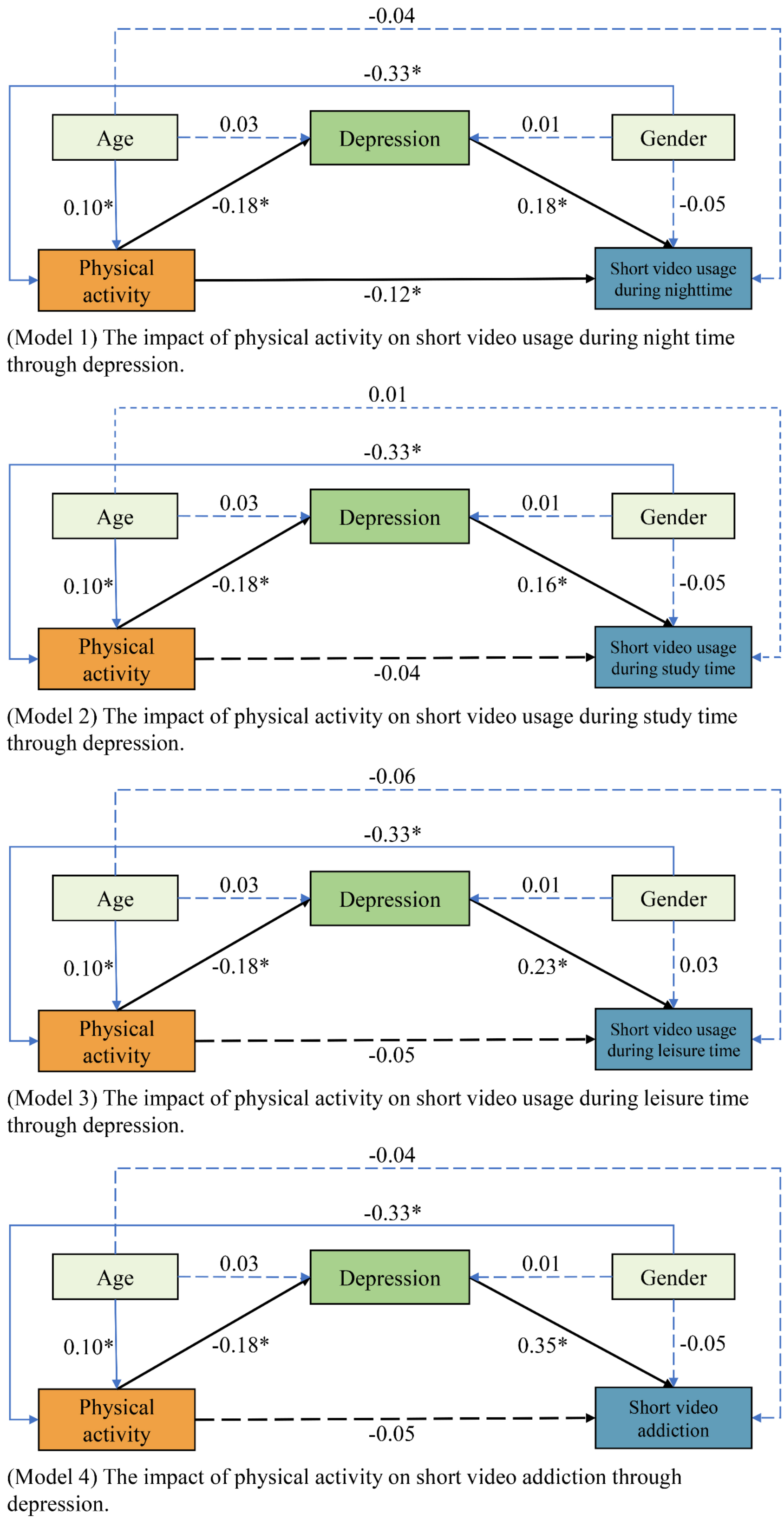

Fig. 3 The results of path analysis (*, $p < 0.05$)

PA and daytime short video usage or overall short video usage. Currently, limited research has focused on domain-specific short video usage behaviors. Our study merely observes a phenomenon in which PA is associated only with certain specific short video usage behaviors, and the underlying reasons for this phenomenon require further investigation. Additionally, it is worth noting that even when significant associations between PA and certain specific short video usage behaviors were found, the direct and indirect effect sizes observed in the four mediation models in this study were weak. This suggests that while PA may act as a protective factor, its actual impact may be quite limited. Therefore, our findings should be interpreted with caution.

Limitations

Some limitations should be acknowledged when interpreting our findings. Firstly, our study focused solely on university students, hence our findings cannot be generalized to other populations, such as working adults or the elderly. Secondly, this study relied on self-reported measures, particularly for PA and short video usage, due to limited experimental conditions. This reliance may have introduced recall bias and social desirability bias. Future research could mitigate these limitations by employing objective data collection methods, such as using accelerometers to measure PA. Additionally, due to suboptimal completion rates of the International Physical Activity Questionnaire in the pilot study, we opted to use frequency and duration to measure physical activity instead of a validated tool, which may have introduced some measurement bias. Thirdly, our questionnaire was distributed through online chat groups, which may have introduced selection bias, as less active individuals might have missed or overlooked our recruitment messages. Future research could consider employing diverse data collection channels (e.g., combining online and offline methods) or using stratified sampling to minimize this bias. Fourthly, our study exhibited an unbalanced gender distribution, with 62.3% of participants being male university students. This could potentially introduce gender bias into our findings. Finally, our study employed a cross-sectional design, which restricts our ability to establish causal relationships between variables. This limitation is inherent in the analysis of cross-sectional data. To further investigate causality in each pathway, longitudinal trials or controlled experiments are warranted.

Conclusions

This study aimed to investigate the relationship between PA and short video usage, with depression as a mediator, in domain-specific usage contexts. Our findings indicate that university students' participation in PA is associated with reduced short video usage during nighttime, study time, and leisure time, as well as a lower level of short video addiction. Depression plays an important mediating role in the relationship between PA and short video usage behaviors. However, while PA may improve several specific short video usage behaviors, its actual effects are likely limited due to the small effect sizes observed. Additionally, it is important to note that we did not find any significant associations between PA and daytime short video usage or overall short video usage.

Abbreviations

PA	Physical activity
apps	Mobile applications
QR	Quick response
PHQ-9	Patient Health Questionnaire
SD	Standard deviations
SEM	Structural equation modeling
VIF	Variance Inflation Factor
ADF	Asymptotically distribution-free
WLS	Weighted least squares
SRMR	Standardized root mean square residual
TLI	Tucker–Lewis index
CFI	Goodness-of-fit index
RMSEA	Root mean square error of approximation
OSVU	Overall short video usage
SVUN	Short video usage during nighttime
SVUD	Short video usage during daytime
SVUS	Short video usage during study time
SVUL	Short video usage during leisure time
SVD	Short video addiction
SVU	Short video usage

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-025-21879-1.

Supplementary Material 1

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Not Applicable.

Author contributions

ZYY and XZ wrote the original draft. ZYY, HSL, MYY, MYZ, ZQL, LH, XZ, and MCG revised the original draft. ZYY, HSL, MYY, and MYZ collected the data. XZ prepared the figures.

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Data availability

The data collected in this study will not be publicly available. However, the corresponding author can be contacted for de-identified data on reasonable request.

Declarations

Ethics approval and consent to participate

Participants from five universities in China received an online survey after providing their consent. This study was approved and supervised by the Ethics Review Committee of Southwest University (SWUETH20230912003). Before starting the survey, subjects were briefed on the overarching research theme, but specific research questions were not disclosed. Informed consent forms were signed by participants prior to beginning the survey. All procedures were conducted in accordance with relevant guidelines and regulations.

Consent for publication
Not Applicable.

Competing interests
The authors declare no competing interests.

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