

Elucidating the associations among objective smartphone use metrics, physical activity, and sedentary behavior in physically active university students: A cross-sectional study.

PEDRO DÍAZ-VÁSQUEZ¹, JOSÉ HENRÍQUEZ-MACHUCA², PABLO GAJARDO-CÁCERES³, ESTEBAN QUEZADA-CORNEJO⁴, CARLOS POBLETE-ARO⁵, JAVIER RUSSELL-GUZMÁN⁶.

^{1,2,3} Pedagogía en Educación Física, Universidad Autónoma de Chile (CHILE).

⁴ Escuela de Enfermería, Universidad Santo Tomás (CHILE).

⁵ Escuela de Ciencias de la Actividad Física, Universidad de las Américas (CHILE).

⁶ Escuela de Kinesiología, Universidad Santo Tomás (CHILE).

⁶ Centro de Investigación en Prevención y Cuidados de la Salud (+SALUD), Universidad Santo Tomás (CHILE).

Published online: September 30, 2026

Accepted for publication: September 15, 2026

DOI:10.7752/jpes.2026.09160

Abstract:

Introduction: Clarifying the behavioral mechanisms linking lifestyle factors to movement patterns is essential for advancing health promotion and preventing chronic disease. Although smartphone use has been linked to sedentary behavior (SB), evidence remains limited when both variables are assessed objectively, particularly among physically active populations. **Objective:** This study investigated the association between device-derived smartphone metrics and accelerometer-based movement behaviors in physically active university students, while also examining their potential utility as markers of sedentary patterns relevant to cardiometabolic health. **Material and methods:** A cross-sectional study was conducted in 44 Physical Education students (75.0% men; 21.8 ± 2.1 years) who met the World Health Organization PA recommendations. Screen time and unlock frequency were recorded over seven days using built-in smartphone applications, while SB, light-intensity PA (LPA), and moderate-to-vigorous PA were assessed with hip-worn triaxial accelerometers. Anthropometric and cardiovascular parameters were also measured. Correlation and exploratory moderation analyses were performed. **Results:** Participants averaged 349 ± 101 min/day of screen time and 122 ± 50 unlocks/day. Screen time was not associated with SB or PA. In contrast, unlock frequency was positively associated with SB ($r = .311$, $p = .040$), LPA ($r = .311$, $p = .040$), and combined SB + LPA ($r = .421$, $p = .004$), but not with anthropometric or cardiovascular indicators. Moderation analysis suggested that the association between unlock frequency and SB was significant only at higher waist-to-height ratio values ($WtHR \geq 0.505$). **Discussion:** The absence of associations with screen time may reflect the portable and multifunctional nature of smartphones, which allows their use in both sedentary and active contexts, so that total usage aggregates heterogeneous behaviors. In contrast, unlock frequency captures how often ongoing activities are interrupted to engage with the device, which may be more closely linked to the accumulation of low-intensity movement patterns. **Conclusions:** Unlock frequency may be a more informative digital indicator of sedentary patterns than screen time in active young adults. These preliminary findings support incorporating digital behavior metrics into future research and health-promotion strategies targeting SB.

Keywords: Accelerometry; Sedentary time; Screen Time; Cardiometabolic Risk; Young adults

Introduction

Regular physical activity (PA) has consistently been considered a key strategy for health promotion and the prevention of chronic non-communicable diseases (Ekelund et al., 2019). However, despite these recommendations, the prevalence of insufficient PA has increased globally in recent decades (Strain et al., 2024). In parallel, sedentary behavior (SB), characterized by low energy expenditure, occupies a substantial portion of daily time, reaching up to 8.2 hours per day (Bauman et al., 2018). Prolonged SB is independently associated with increased risk of all-cause mortality and adverse cardiometabolic outcomes, particularly when not offset by adequate moderate-to-vigorous-intensity physical activity (MVPA) (Ekelund et al., 2019).

SB is defined as any waking behavior characterized by an energy expenditure ≤ 1.5 metabolic equivalents while in a sitting, reclining, or lying posture (Tremblay et al., 2017); therefore, it represents a distinct construct rather than merely the absence of MVPA. Importantly, relatively high volumes of moderate-intensity PA (approximately 60–75 min/day) appear to be required to attenuate the increased mortality risk associated with prolonged sitting (Ekelund et al., 2016). Consequently, individuals who meet current PA recommendations may still accumulate large amounts of sedentary time, a pattern that may partially offset the health benefits of being active. Beyond total volume, the way sedentary time and light-intensity physical activity (LPA) are

accumulated throughout the day also appears to be relevant for cardiometabolic health (Amagasa et al., 2018; Sjöros et al., 2020).

Young adults (18–39 years) tend to spend more time engaged in sedentary activities than middle-aged adults (Silva et al., 2023). Within this group, university students represent a population at increased risk of sedentary lifestyles, accumulating between 9 and 10 hours of SB per day (Castro et al., 2018). This scenario is particularly relevant in Chile, where approximately three out of four adults present overweight or obesity (Ministerio de Salud de Chile, 2017), and where abdominal adiposity tends to increase during university years, contributing to long-term cardiometabolic risk (Castro et al., 2018; Cossio-Bolaños et al., 2016). In this context, the waist-to-height ratio (WtHR) has emerged as a simple and sensitive indicator of early cardiometabolic risk (Ashwell & Gibson, 2016). Physical Education students deserve special attention, as they will be responsible for promoting active lifestyles in school settings and act as role models for future generations. Although these students generally exhibit higher PA levels, they still accumulate considerable daily SB (Souza et al., 2021), and unhealthy lifestyle behaviors may coexist with high PA levels in this population (Corvalán-Luengo et al., 2023; Garrido-Méndez et al., 2024). This paradox highlights the need to better understand the behavioral patterns that coexist with active lifestyles and may attenuate their health benefits.

In this context, smartphone use has emerged as a potential behavioral factor influencing movement patterns. University students report extensive daily use of electronic devices, particularly smartphones (Corvalán-Luengo et al., 2023), and approximately half exhibit problematic or excessive smartphone use (Candussi et al., 2023). Factors contributing to problematic use include social media engagement, video games, internet browsing, screen time, and frequent phone unlocking (Prasad et al., 2018; Ryding & Kuss, 2020; Tomczyk & Selmanagic Lizde, 2023). Such behaviors have been associated with adverse mental health outcomes (Wacks & Weinstein, 2021), disrupted sleep quality (Yang et al., 2020), eating disorders (Wang et al., 2023), and increased risk of overweight and obesity (Andersen et al., 2024; Brodersen et al., 2023).

Previous studies examining the relationship between smartphone use, PA, and SB have reported inconsistent findings. While some evidence suggests that excessive smartphone use is associated with lower PA levels and prolonged sitting time (Grimaldi-Puyana et al., 2020), another study found no clear associations between screen time and PA (Fennell et al., 2019). Conversely, smartphone-based interventions have shown potential to promote PA and reduce SB (Laranjo et al., 2021), highlighting the dual role of these devices as both risk and protective factors.

One possible explanation for these inconsistencies is that most studies have characterized smartphone use exclusively through total screen time. However, smartphone use typically occurs in brief and frequent sessions, often triggered by notifications or habitual checking (Oulasvirta et al., 2012; Ryding & Kuss, 2020). Moreover, because smartphones are portable, screen time can accumulate while standing, walking, or commuting. A recent study that temporally aligned passive smartphone sensing with accelerometry showed that a substantial and highly variable proportion of screen use occurs during non-sedentary behavior (Culverhouse et al., 2026). Similarly, among university students, associations between smartphone use and accelerometer-measured PA and SB appear to differ according to the type of application used (Shi et al., 2025). Together, these findings suggest that total screen time may be an imprecise indicator of movement-related behavior. In contrast, unlock frequency reflects how often individuals interrupt their ongoing activities to engage with the device, a dimension that may be more closely related to how movement is patterned throughout the day, but which has rarely been examined in relation to device-measured SB and PA.

A major limitation of the current literature is the reliance on self-reported measures, which tend to underestimate SB and overestimate PA (Meh et al., 2023; Prince et al., 2020). Furthermore, studies using objective methods to assess smartphone use remain limited (Christensen et al., 2016; Grimaldi-Puyana et al., 2020). To address these gaps, we combined seven days of device-derived smartphone metrics obtained from built-in applications with hip-worn accelerometry in a sample of Physical Education students who met the World Health Organization PA recommendations. This population provides a unique context in which to examine whether digital behaviors relate to low-intensity movement patterns when MVPA is not a limiting factor. Identifying simple, low-cost digital indicators of sedentary patterns could inform health-promotion strategies in university settings and teacher-training programs. Therefore, the aim of this study was to examine the associations of screen time and unlock frequency with accelerometer-derived SB, LPA, and MVPA in physically active university students, and to explore whether abdominal adiposity, assessed by WtHR, moderated these associations. We hypothesized that unlock frequency, rather than total screen time, would be positively associated with SB.

Material & methods

Participants

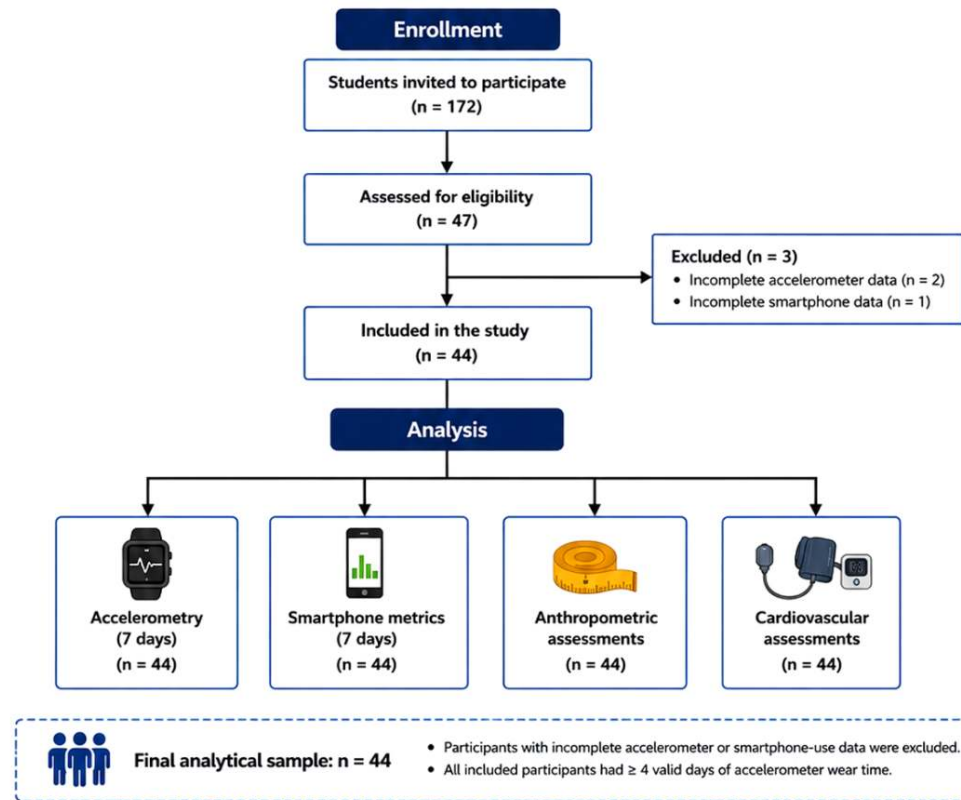
This observational cross-sectional study followed the STROBE guidelines. The study population comprised young adults enrolled in a Physical Education program at a university in Santiago, Chile. Participants were considered physically active if they met the current World Health Organization recommendations for aerobic physical activity in adults, namely engaging in at least 150 min/week of moderate-intensity physical

activity, 75 min/week of vigorous-intensity physical activity, or an equivalent combination of both (Bull et al., 2020). We objectively assessed compliance with these recommendations using accelerometry.

Given the exploratory nature of the study and the limited evidence from studies concurrently assessing smartphone use and accelerometer-derived movement behaviors, we adopted a convenience sampling strategy to enable an initial examination of these associations in a physically active university population. This approach was appropriate for generating preliminary evidence and informing future studies with larger, more representative samples.

A total of 172 students were invited to participate. Of these, 47 agreed to participate, and 3 were excluded due to incomplete device data or failure to meet the predefined minimum accelerometer wear-time criteria, resulting in a final analytical sample of 44 participants (Fig. 1). Eligibility criteria included being actively enrolled in the Physical Education program during the 2022–2023 academic year. Participants with medical conditions affecting physical activity or mobility, including musculoskeletal injuries, mobility impairments, or chronic diseases, were excluded. Recruitment and data collection were conducted between August 2022 and April 2023.

Fig. 1. Flow diagram illustrating participant inclusion in the sample.



The Ethics Committee of Universidad Autónoma de Chile approved the study (CEC 33-22), and it was conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent before participation.

Procedure

Participants attended two morning laboratory visits between 8:00 and 11:00 a.m., scheduled without disrupting their regular academic activities. During the first visit, participants completed questionnaires on sociodemographic characteristics and lifestyle habits. Accelerometers were then provided for seven consecutive days of monitoring. The availability of the built-in smartphone applications required to retrieve smartphone-use metrics was verified, and participants received a logbook to record daily screen time and smartphone unlock frequency.

During the second visit, participants returned the accelerometers and their completed logbooks. Prior to this visit, they were instructed to avoid caffeine and refrain from eating for at least two hours before the assessment. Anthropometric and cardiovascular measurements were subsequently performed under standardized laboratory conditions.

Measures and instruments

Sociodemographic characterization

Following procedures previously described, a 17-item questionnaire was used to collect demographic and lifestyle information, including sex, age, place of residence, socioeconomic status, tobacco use, and alcohol consumption (Corvalán-Luengo et al., 2023).

Device-based assessment of smartphone use

Following previously described procedures (Christensen et al., 2016), participants recorded screen time (min/day) and smartphone unlock frequency (unlocks/day) over seven days using built-in smartphone monitoring applications (Digital Wellbeing for Android and Screen Time for iOS). Participants manually recorded these metrics in a daily logbook. For statistical analyses, the mean daily value over the seven-day monitoring period was calculated separately for each smartphone-use metric and used as an indicator of habitual smartphone use. To improve data completeness and minimize recording errors, the research team provided instructions and support throughout the monitoring period. Participants with incomplete smartphone-use data were excluded from analyses involving the corresponding variable.

Objective assessment of SB and PA

Both SB and PA were objectively assessed using wGT3X-BT triaxial accelerometers (ActiGraph, Pensacola, USA). Participants wore the accelerometers on the right hip for seven consecutive days during usual activities and waking hours, except during bathing, aquatic activities, and nighttime sleep (Migueles et al., 2017). Hip placement was selected to ensure comparability with established accelerometer cut-points and to minimize potential interference associated with smartphone use.

Raw acceleration data were collected at a sampling frequency of 30 Hz with a dynamic range of ± 8 G and subsequently aggregated into 60-s epochs for analysis. Non-wear time was defined as ≥ 60 min of zero counts, allowing interruptions of up to 2 min with values between 0 and 100 counts/min. A valid day required ≥ 600 min of wear time, and participants were required to accumulate at least four valid days, including one weekend day (Migueles et al., 2017). Activity intensity was classified using established cut-points as SB (< 100 counts/min), light-intensity physical activity (LPA: 100–2019 counts/min), and MVPA (≥ 2020 counts/min) (Troiano et al., 2008). Step count was also estimated. Data were processed using ActiLife Pro 6 software (ActiGraph LLC, Pensacola, FL, USA).

Anthropometric parameters and abdominal obesity

Body mass and body fat percentage were measured using an electronic scale, BC-568 InnerScan Segmental Body Composition Monitor (Tanita Corp., Tokyo, Japan), with a maximum capacity of 150 kg and an accuracy of 0.1 kg. Height was measured using a stadiometer (Health o meter® 402KL ROD) with an accuracy of 0.1 cm. Waist circumference (WC) was assessed twice at the midpoint between the iliac crest and the lower rib using a measuring tape (SECA® 201) with an accuracy of 0.1 cm.

Body mass index (BMI) was calculated as body mass (kg) divided by height squared (m^2). Participants with a BMI of 25.0–29.9 kg/m^2 were classified as overweight, and those with a BMI ≥ 30.0 kg/m^2 were classified as obese. Waist-to-height ratio (WtHR) was calculated as waist circumference divided by height, with values ≥ 0.500 indicating increased abdominal adiposity (Ashwell & Gibson, 2016).

Cardiovascular outcomes

Systolic blood pressure (SBP), diastolic blood pressure (DBP), and resting heart rate (RHR) were measured using an Omron® Hem 7120 monitor (Kyoto, Japan). Participants remained seated for 10 min before assessment. Two measurements were obtained at 5-min intervals, and the lowest value was recorded.

Data collection and statistical analyses

Statistical analyses were performed using the Statistical Package for the Social Sciences (SPSS), version 26.0. The normality of continuous variables was assessed using the Shapiro–Wilk test. Descriptive statistics were expressed as mean $\pm$ standard deviation (SD) for normally distributed variables and median (interquartile range [IQR]) for non-normally distributed variables. Categorical variables were reported as frequencies and percentages. Between-sex comparisons were performed using the independent-samples Student's t-test or the Mann–Whitney U test, as appropriate according to the distribution of the data. Associations between continuous variables were examined using Pearson's or Spearman's correlation coefficients, as appropriate. Given the potential influence of sex-related physiological differences on the outcomes, sex was included as a covariate in analyses where such differences could confound the associations of interest. Statistical significance was set at $p < .05$. Moderation analyses were conducted using the PROCESS macro for SPSS, version 2.16 (Model 1), following an approach previously described (Hayes & Rockwood, 2017). Ordinary least squares regression with bias-corrected bootstrap resampling based on 5,000 samples was used. The WtHR was selected as the moderator because it is a simple indicator of abdominal adiposity associated with early cardiometabolic risk (Ashwell & Gibson, 2016), and because both excessive smartphone use and SB have been independently linked to adiposity (Andersen et al., 2024; Brodersen et al., 2023; Sjöros et al., 2020). Statistically significant interaction effects were further examined using simple slopes analysis and the Johnson–Neyman technique to determine the range of moderator values for which the association between the predictor and outcome was statistically significant ($p < .05$).

Results

Among participants, 25.0% (n = 11) were women and 75.0% (n = 33) were men. Most resided in urban areas (97.7%, n = 43), and 65.9% (n = 29) reported a medium-to-low socioeconomic status. Regarding nutritional status, 70.5% (n = 31) were classified as overweight or obese, while 43.2% (n = 19) exhibited abdominal obesity (WtHR $\geq$ 0.500). Tobacco and alcohol consumption prevalence were 9.1% (n = 4) and 61.4% (n = 27), respectively. The average age was 21.82 ± 2.06 years (Tables 1 and 2).

Table 1. Description of categorical variables.

Variable	Frequency (n)	%
Sex		
Men	33	75.0
Women	11	25.0
Sociodemographic location		
Urban	43	97.7
Rural	1	2.3
Socioeconomic level		
Medium-high	15	34.1
Medium-low	29	65.9
Nutritional status (BMI)		
Underweight	1	2.3
Normal	12	27.3
Overweight	21	47.7
Obesity	10	22.7
Abdominal obesity		
Low (WtHR < 0.500)	25	56.8
High (WtHR $\geq$ 0.500)	19	43.2
Tobacco consumption		
No	40	90.9
Yes	4	9.1
Alcohol consumption		
No	17	38.6
Yes	27	61.4

Note: Data are presented as sample frequencies (n) and percentages (%).

Significant sex-based differences were observed for height ($p < .001$), body mass ($p = .014$), body fat percentage ($p < .001$), systolic blood pressure ($p = .005$), and resting heart rate ($p = .015$). No significant differences were found for BMI, waist circumference, WtHR, PA, SB, or smartphone-use variables. Participants accumulated an average of 313.70 ± 66.02 min/day of LPA and 70.37 ± 36.85 min/day of MVPA. Mean daily screen time was 349.46 ± 101.20 min/day, with an average of 121.57 ± 49.95 smartphone unlocks/day (Table 2).

Table 2. Description of numerical variables by sex.

Variables	Total (n = 44) Mean $\pm$ SD	Women (n = 11) Mean $\pm$ SD	Men (n = 33) Mean $\pm$ SD	p-value
General features				
Age (years)	21.82 ± 2.06	22.00 ± 1.41	21.76 ± 2.25	.740
Height (cm)	169.06 ± 8.74	158.53 ± 6.57	$172.56 \pm 6.20^{***}$	< .001
Body mass (kg)	75.65 ± 13.01	67.42 ± 10.33	$78.39 \pm 12.77^*$	.014
Overweight and abdominal obesity outcomes				
BMI (kg/m ²)	26.43 ± 3.78	26.83 ± 3.84	26.30 ± 3.82	.690
Body fat (%)	23.58 ± 9.02	$33.52 \pm 8.11^{***}$	20.26 ± 6.59	< .001
WC (cm)	83.59 ± 8.94	79.11 ± 8.05	85.09 ± 8.83	.054
WtHR	0.495 ± 0.049	0.500 ± 0.052	0.493 ± 0.049	.715
Cardiovascular outcomes				
SBP (mm Hg) ^a	117.25 ± 17.25	102.50 ± 17.00	$118.50 \pm 11.25^{**}$	.005
DBP (mm Hg)	72.33 ± 8.09	69.59 ± 6.69	73.24 ± 8.40	.198
RHR (beats/min)	69.76 ± 10.30	$76.18 \pm 9.19^*$	67.62 ± 9.86	.015
Physical activity and sedentary behavior				
SB (min/day)	302.68 ± 98.39	311.48 ± 111.25	299.75 ± 95.43	.736
LPA (min/day)	313.70 ± 66.02	337.14 ± 67.19	305.89 ± 64.77	.177
SB + LPA (min/day)	616.38 ± 121.54	648.62 ± 122.59	605.64 ± 121.14	.327
MVPA (min/day) ^a	70.37 ± 36.85	68.53 ± 33.11	75.28 ± 41.60	.196
Steps (steps/day) ^a	12540.60 ± 3653.19	12375.80 ± 1222.75	12817.00 ± 4444.98	.789
Smartphone use				
Screen time (min/day)	349.46 ± 101.20	339.31 ± 99.13	352.84 ± 103.16	.706
Unlocks (unlocks/day)	121.57 ± 49.95	124.73 ± 37.92	120.52 ± 53.84	.812

Note: BMI (body mass index), WC (waist circumference), WtHR (waist-to-height ratio), SBP (systolic blood pressure), DBP (diastolic blood pressure), RHR (resting heart rate), SB (sedentary behavior), LPA (light-intensity physical activity), and MVPA (moderate to vigorous-intensity physical activity). ^a Indicates non-parametric variables. For parametric data, the t-Student's test was applied. For non-parametric data, the U-Mann Whitney test was applied. Data are expressed as mean $\pm$ standard deviation for parametric data and median $\pm$ interquartile range for non-parametric data. * $p < .05$; ** $p < .01$; *** $p < .001$.

Correlation analyses (Table 3) showed no significant associations between screen time and study variables. In contrast, smartphone unlock frequency was positively associated with SB ($r = .311$, 95% CI [0.02, 0.56], $p = .040$), LPA ($r = .311$, 95% CI [0.02, 0.56], $p = .040$), and the combined SB + LPA variable ($r = .421$, 95% CI [0.14, 0.64], $p = .004$). No associations were observed between unlock frequency and anthropometric indicators.

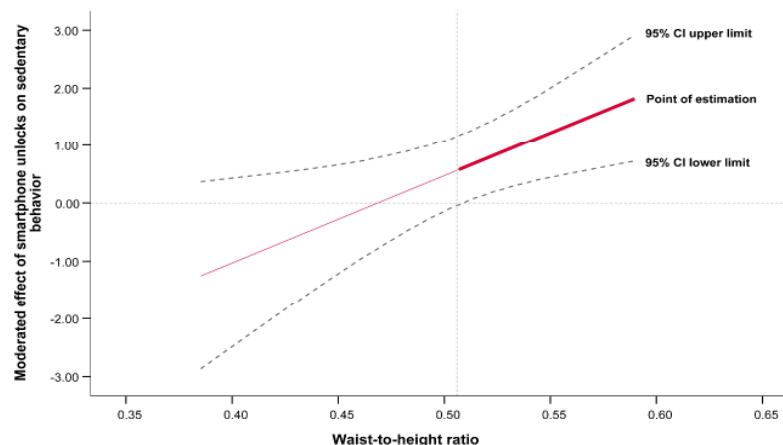
Table 3. Correlations between smartphone use and study outcomes.

Variables	Screen time (min/day)		Unlocks (unlocks/day)	
	r [95% CI]	p-value	r [95% CI]	p-value
Overweight and abdominal obesity outcomes				
BMI (kg/m ²)	.036 [-.263; .330]	.815	.051 [-.249; .343]	.740
Fat mass (%) ^b	-.002 [-.217; .224]	.992	-.038 [-.310; .248]	.810
WC (cm)	.113 [-.191; .396]	.466	.084 [-.219; .371]	.590
WtHR	.130 [-.174; .411]	.401	.106 [-.197; .391]	.493
Cardiovascular outcomes				
SBP (mm Hg) ^{a,b}	-.211 [-.453; .123]	.175	-.066 [-.363; .228]	.676
DBP (mm Hg)	-.159 [-.436; .144]	.301	-.143 [-.422; .161]	.355
RHR (beats/min) ^b	.048 [-.266; .374]	.762	-.036 [-.304; .248]	.821
Physical activity and sedentary behavior				
SB (min/day)	-.198 [-.467; .106]	.199	.311 [.015; .557]*	.040
LPA (min/day)	-.019 [-.314; .280]	.904	.311 [.015; .556]*	.040
SB + LPA (min/day)	-.170 [-.445; .134]	.270	.421 [.141; .638]**	.004
MVPA (min/day) ^a	.010 [-.222; .369]	.947	-.218 [-.467; .150]	.155
Steps (steps/day) ^a	.065 [-.143; .437]	.677	-.095 [-.331; .262]	.541

Note: BMI (body mass index), WC (waist circumference), WtHR (waist-to-height ratio), SBP (systolic blood pressure), DBP (diastolic blood pressure), RHR (resting heart rate), SB (sedentary behavior), LPA (light-intensity physical activity), and MVPA (moderate to vigorous-intensity physical activity). ^a Indicates non-parametric variables. ^b Indicates partial correlations, adjusted by sex. Data are presented as correlation coefficients and p-values. For parametric data, the Pearson test was applied. For non-parametric data, the Spearman test was applied. * $p < .05$; ** $p < .01$.

Moderation analysis revealed a significant interaction between smartphone unlock frequency and WtHR on SB ($b = 15.008$, $t = 2.474$, $p = .017$). Johnson–Neyman analysis indicated that the association appeared to be significant only above WtHR values of 0.505 ($b = 0.562$, $SE = 0.278$, 95% CI [0.000, 1.124]; **Fig. 2**). No significant interaction effects were observed when LPA ($p = .321$) or the combined SB + LPA variable ($p = .156$) were included as dependent variables.

Fig. 2. Abdominal obesity moderates the association between smartphone unlocks and sedentary behavior.



Note: Johnson–Neyman plot exhibiting the conditional effects of smartphone unlocks on sedentary behavior at values of the moderator waist-to-height ratio. Data are point estimates with upper and lower 95% confidence intervals (CI). The plot shows the zone of significance in a bold line.

Discussion

The present study examined the association between device-based smartphone metrics and accelerometer-derived movement behaviors in physically active university students. The main findings suggest that smartphone unlock frequency, rather than total screen time, was associated with SB, LPA, and their combined duration. Additionally, abdominal obesity moderated the relationship between smartphone unlock frequency and SB, suggesting stronger associations in individuals with higher cardiometabolic risk.

Among participants, 75.0% were male, reflecting sex-based disparities previously reported in Physical Education programs (Corvalán-Luengo et al., 2023). Although overweight/obesity prevalence (70.5%) was slightly lower than national Chilean estimates (Ministerio de Salud de Chile, 2017), 43.2% exhibited abdominal obesity ($WtHR \geq 0.500$), a threshold associated with elevated cardiometabolic risk (Ashwell & Gibson, 2016). Despite generally higher PA levels among Physical Education students (Souza et al., 2021), unhealthy lifestyle behaviors such as poor dietary habits may still coexist within this population (Garrido-Méndez et al., 2024). Participants showed high smartphone use, with an average screen time of 349.5 min/day and 122 unlocks/day, exceeding previously reported values (Grimaldi-Puyana et al., 2020). These differences may reflect greater familiarity with digital technologies among younger adults and increased smartphone reliance following the COVID-19 pandemic (Corvalán-Luengo et al., 2023).

Previous evidence has suggested that excessive smartphone use is associated with increased SB and reduced PA (Grimaldi-Puyana et al., 2020). However, even when smartphone use has been objectively recorded, movement behaviors have frequently been assessed through questionnaires, which tend to underestimate SB and overestimate PA (Prince et al., 2020). In the present study, no associations were observed between screen time and SB or PA when both variables were assessed with devices, a finding consistent with previous reports showing no clear associations between smartphone use and PA (Fennell et al., 2019). A plausible explanation is that, because of their portability and multifunctionality, smartphones can be used across both sedentary and active contexts (Laranjo et al., 2021). Supporting this interpretation, a recent study that temporally aligned passive smartphone sensing with accelerometry found that approximately one quarter of smartphone screen time occurred during non-sedentary behavior, with marked variability across individuals and applications (Culverhouse et al., 2026). Likewise, in university students, associations between smartphone use and accelerometer-measured SB appear to depend on the type of application used rather than on total usage (Shi et al., 2025). Taken together, these findings suggest that total screen time aggregates heterogeneous behaviors that may have opposite relationships with movement, which could mask associations at the individual level. Therefore, screen time alone may not adequately capture movement-related behavioral patterns, and complementary metrics reflecting how, when, and in what context the device is used may be more informative. In contrast, smartphone unlock frequency was significantly associated with SB and LPA. Frequent checking behavior may reflect repeated micro-interruptions that fragment habitual movement patterns and facilitate transitions toward lower-intensity or sedentary states. This interpretation aligns with evidence showing that smartphone use may induce cognitive–motor interference, affecting attention, gait performance, and movement coordination during walking (Haga et al., 2015; Lee & Shin, 2024). Furthermore, unlock frequency has been proposed as a behavioral marker of problematic smartphone use (Ryding & Kuss, 2020), supporting its relevance as an indicator of habitual digital engagement.

Excessive smartphone use has also been linked to overweight and obesity (Andersen et al., 2024; Brodersen et al., 2023), while SB has been associated with increased adiposity and cardiometabolic risk (Sjöros et al., 2020). Although no direct associations emerged between smartphone metrics and anthropometric indicators, abdominal obesity moderated the relationship between unlock frequency and SB, with the association appearing significant only above a $WtHR$ value of 0.505. While these findings should be interpreted cautiously because of the modest sample size, they suggest that individuals with greater abdominal adiposity may be more susceptible to the behavioral correlates of frequent smartphone checking. Therefore, these results should be considered preliminary and hypothesis-generating.

Interestingly, no associations were observed between abdominal obesity and PA levels. The relatively high baseline PA levels of this population may have attenuated these relationships. Previous evidence indicates that MVPA may mitigate the adverse effects of SB (Ekelund et al., 2019; Koemel et al., 2025), and reduce abdominal obesity independently of body mass changes (Ekelund et al., 2011). In addition, LPA has been associated with lower cardiometabolic risk (Amagasa et al., 2018). Although LPA correlated with smartphone unlock frequency, abdominal obesity did not moderate this relationship.

Several limitations should be acknowledged. First, the relatively small sample size and convenience sampling from a single Physical Education program may limit the generalizability of the findings and increase the risk of selection bias, particularly because all participants were physically active university students. Second, the cross-sectional design prevents causal inference or determination of the directionality of the observed associations. Although movement behaviors were objectively assessed using accelerometry, smartphone metrics were extracted from device-based applications and manually recorded by participants, which may have introduced measurement errors. Furthermore, these applications did not provide contextual information regarding the timing or distribution of smartphone interactions throughout the day. Multiple correlation analyses

were performed without correction for multiple comparisons, increasing the risk of type I error. Likewise, the moderation analysis should be considered exploratory, as interaction models are particularly sensitive to limited sample sizes and may yield unstable estimates. Future studies should include larger and more diverse samples, longitudinal designs, automated passive logging of smartphone use, and appropriate adjustments for multiple testing.

Conclusion

This study shows that, among physically active university students, smartphone unlock frequency is more closely related to accelerometer-derived SB and LPA than total screen time. Importantly, meeting international physical activity recommendations does not preclude the accumulation of substantial sedentary time, highlighting the need to consider how individuals interact with their smartphones rather than focusing exclusively on cumulative screen exposure.

These findings contribute to the field in several ways. First, they provide preliminary evidence supporting the potential value of interaction-based digital behavior metrics for understanding lifestyle patterns associated with health and suggest that research should move beyond screen time as the default indicator of smartphone use. Second, they demonstrate the feasibility of combining built-in smartphone applications with accelerometry in a simple and low-cost assessment protocol. Third, they extend this line of research to a physically active university population, in which high levels of physical activity may coexist with substantial SB and LPA.

From a practical perspective, unlock frequency is readily available through built-in features on most smartphones and requires no additional monitoring equipment, making it a potentially feasible complementary indicator for university health services, Physical Education programs, and health professionals. Health-promotion strategies could address frequent smartphone checking by encouraging notification management, device-free periods during study or leisure time, and brief standing or walking breaks associated with smartphone use. Such approaches may be particularly relevant in Physical Education teacher training, where students are preparing for professional roles related to the promotion of active lifestyles. Furthermore, the exploratory finding that the association between unlock frequency and SB varied according to WtHR suggests that individual cardiometabolic characteristics may be relevant when examining the relationship between digital behavior and movement patterns.

Future longitudinal and experimental studies are needed to determine whether reducing smartphone checking frequency leads to measurable reductions in sedentary time, to establish reference values for unlock frequency in young adults, and to examine whether similar associations are observed in populations with different physical activity levels. Further research should also clarify the potential relevance of these digital behavior metrics for interventions aimed at reducing SB. Until these relationships are confirmed, the present findings should be interpreted as preliminary evidence and as a first step toward integrating interaction-based smartphone metrics into the assessment and promotion of active lifestyles.

Declaration of generative AI and AI-assisted technologies in the writing process:

During the preparation of this work, the authors used ChatGPT 5.6 Sol (OpenAI), Claude Opus 5.5 (Anthropic), and Grammarly (Grammarly Inc.) to improve the clarity, readability, grammar, and writing style of the text. These tools were not used to generate scientific content, analyze data, or interpret results. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Conflicts of interest: The authors declare no conflicts of interest.

Limitations:

The main limitations of this study include its relatively small convenience sample from a single Physical Education program, the cross-sectional design, and the manual recording of device-based smartphone metrics. In addition, the moderation analysis should be considered exploratory given the sample size. These limitations should be considered when interpreting and generalizing the findings.

Acknowledgments: The authors would like to thank all participants who voluntarily took part in this study.

Funding source: This research received no external funding.

Ethics approval:

This study was approved by the Ethics Committee of the Universidad Autónoma de Chile with the code CEC 33-22 and conducted in accordance with the principles of the Declaration of Helsinki. All participants provided written informed consent and voluntarily agreed to take part in the study.

Data availability:

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

References

- Amagasa, S., Machida, M., Fukushima, N., Kikuchi, H., Takamiya, T., Odagiri, Y., & Inoue, S. (2018). Is objectively measured light-intensity physical activity associated with health outcomes after adjustment for moderate-to-vigorous physical activity in adults? A systematic review. *The International Journal of Behavioral Nutrition and Physical Activity*, 15(1), 65. <https://doi.org/10.1186/S12966-018-0695-Z>
- Andersen, T. O., Sejlund, C., Jensen, A. K., Dissing, A. S., Severinsen, E. R., Drews, H. J., Sørensen, T. I. A., Varga, T. V., & Rod, N. H. (2024). Self-reported and tracked nighttime smartphone use and their association with overweight and cardiometabolic risk markers. *Scientific Reports* 2024 14:1, 14(1), 1–13. <https://doi.org/10.1038/s41598-024-55349-2>
- Ashwell, M., & Gibson, S. (2016). Waist-to-height ratio as an indicator of ‘early health risk’: simpler and more predictive than using a ‘matrix’ based on BMI and waist circumference. *BMJ Open*, 6(3), e010159. <https://doi.org/10.1136/BMJOPEN-2015-010159>
- Bauman, A. E., Petersen, C. B., Blond, K., Rangul, V., & Hardy, L. L. (2018). *The Descriptive Epidemiology of Sedentary Behaviour* (Springer International Publishing, Ed.). Springer, Cham. https://doi.org/10.1007/978-3-319-61552-3_4
- Brodersen, K., Hammami, N., & Katapally, T. R. (2023). Is excessive smartphone use associated with weight status and self-rated health among youth? A smart platform study. *BMC Public Health*, 23(1). <https://doi.org/10.1186/S12889-023-15037-8>
- Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J. P., Chastin, S., Chou, R., Dempsey, P. C., Dipietro, L., Ekelund, U., Firth, J., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., ... Willumsen, J. F. (2020). World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *British Journal of Sports Medicine*, 54(24), 1451–1462. <https://doi.org/10.1136/bjsports-2020-102955>
- Candussi, C. J., Kabir, R., & Sivasubramanian, M. (2023). Problematic smartphone usage, prevalence and patterns among university students: A systematic review. *Journal of Affective Disorders Reports*, 14, 100643. <https://doi.org/10.1016/J.JADR.2023.100643>
- Castro, O., Bennie, J., Vergeer, I., Bosselut, G., & Biddle, S. J. H. (2018). Correlates of sedentary behaviour in university students: A systematic review. *Preventive Medicine*, 116, 194–202. <https://doi.org/10.1016/j.ypmed.2018.09.016>
- Christensen, M. A., Bettencourt, L., Kaye, L., Moturu, S. T., Nguyen, K. T., Olgin, J. E., Pletcher, M. J., & Marcus, G. M. (2016). Direct measurements of smartphone screen-time: Relationships with demographics and sleep. *PLoS ONE*, 11(11). <https://doi.org/10.1371/journal.pone.0165331>
- Corvalán-Luengo, M., Díaz-Vásquez, P., Uribe-Uribe, N., & Russell-Guzmán, J. (2023). Self-reported physical activity, screen time and their association with sleep quality and quality of life in Physical Education Pedagogy students during the COVID-19 pandemic: A cross-sectional study [in Spanish]. *Retos*, 2041, 321–331. <https://doi.org/10.47197/retos.v50.97777>
- Cossio-Bolaños, M., Vilchez-Avaca, C., Contreras-Mellado, V., Andruske, C. L., & Gómez-Campos, R. (2016). Changes in abdominal obesity in Chilean university students stratified by body mass index. *BMC Public Health*, 16(1). <https://doi.org/10.1186/S12889-015-2587-3>
- Culverhouse, J., Finnegan, O. L., Bowen, K., Nelakuditi, S., Ghosal, R., Radesky, J. S., Adair, T., Restino, M., White, J. W., Zhong, Z., Hadj-Amar, B., Holmes, A., Kiely, K., Burkart, S., Adams, E. L., Weaver, R. G., Beets, M., & Armstrong, B. (2026). Not all screen time is sedentary: evidence from aligned smartphone sensing and accelerometry data in adults. *Journal of Activity, Sedentary and Sleep Behaviors* 2026. <https://doi.org/10.1186/S44167-026-00109-Y>
- Ekelund, U., Besson, H., Luan, J., May, A. M., Sharp, S. J., Brage, S., Travier, N., Agudo, A., Slimani, N., Rinaldi, S., Jenab, M., Norat, T., Mouw, T., Rohrmann, S., Kaaks, R., Bergmann, M. M., Boeing, H., Clavel-Chapelon, F., Boutron-Ruault, M. C., ... Peeters, P. H. (2011). Physical activity and gain in abdominal adiposity and body weight: prospective cohort study in 288,498 men and women. *The American Journal of Clinical Nutrition*, 93(4), 826–835. <https://doi.org/10.3945/AJCN.110.006593>
- Ekelund, U., Steene-Johannessen, J., Brown, W. J., Fagerland, M. W., Owen, N., Powell, K. E., Bauman, A., Lee, I. M., Ding, D., Heath, G., Hallal, P. C., Kohl, H. W., Pratt, M., Reis, R., Sallis, J., Aadahl, M., Blot, W. J., Chey, T., Deka, A., ... Yi-Park, S. (2016). Does physical activity attenuate, or even eliminate, the detrimental association of sitting time with mortality? A harmonised meta-analysis of data from more than 1 million men and women. *The Lancet*, 388(10051), 1302–1310. [https://doi.org/10.1016/S0140-6736\(16\)30370-1](https://doi.org/10.1016/S0140-6736(16)30370-1)
- Ekelund, U., Tarp, J., Steene-Johannessen, J., Hansen, B. H., Jefferis, B., Fagerland, M. W., Whincup, P., Diaz, K. M., Hooker, S. P., Chernofsky, A., Larson, M. G., Spartano, N., Vasan, R. S., Dohrn, I. M., Hagströmer, M., Edwardson, C., Yates, T., Shiroma, E., Anderssen, S. A., & Lee, I. M. (2019). Dose-response associations between accelerometry measured physical activity and sedentary time and all cause mortality: Systematic review and harmonised meta-analysis. *The BMJ*, 366, 1–10. <https://doi.org/10.1136/bmj.14570>

- Fennell, C., Barkley, J. E., & Lepp, A. (2019). The relationship between cell phone use, physical activity, and sedentary behavior in adults aged 18–80. *Computers in Human Behavior*, 90, 53–59. <https://doi.org/10.1016/J.CHB.2018.08.044>
- Garrido-Méndez, A., Carlos-Matus, C., Araneda, C. P., Villouta, P. L., Lamana, R. Z., Ramírez, O. A., Rivera, C. F., Monsalve, R. C., & Morales, C. C. (2024). The lifestyle of the Pedagogy in Physical Education students at a university in south-central Chile [in Spanish]. *Retos*, 59, 316–323. <https://doi.org/10.47197/RETOS.V59.106334>
- Grimaldi-Puyana, M., Fernández-Batanero, J. M., Fennell, C., & Sañudo, B. (2020). Associations of Objectively-Assessed Smartphone Use with Physical Activity, Sedentary Behavior, Mood, and Sleep Quality in Young Adults: A Cross-Sectional Study. *International Journal of Environmental Research and Public Health*, 17(10). <https://doi.org/10.3390/IJERPH17103499>
- Haga, S., Sano, A., Sekine, Y., Sato, H., Yamaguchi, S., & Masuda, K. (2015). Effects of using a Smart Phone on Pedestrians' Attention and Walking. *Procedia Manufacturing*, 3, 2574–2580. <https://doi.org/10.1016/J.PROMFG.2015.07.564>
- Hayes, A. F., & Rockwood, N. J. (2017). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy*, 98, 39–57. <https://doi.org/10.1016/J.BRAT.2016.11.001>
- Koemel, N. A., Ahmadi, M. N., Biswas, R. K., Koster, A., Atkin, A. J., Sabag, A., & Stamatakis, E. (2025). Can incidental physical activity offset the deleterious associations of sedentary behaviour with major adverse cardiovascular events? *European Journal of Preventive Cardiology*, 32(1), 77–85. <https://doi.org/10.1093/EURJPC/ZWAE316>
- Laranjo, L., Ding, D., Heleno, B., Kocaballi, B., Quiroz, J. C., Tong, H. L., Chahwan, B., Neves, A. L., Gabarron, E., Dao, K. P., Rodrigues, D., Neves, G. C., Antunes, M. L., Coiera, E., & Bates, D. W. (2021). Do smartphone applications and activity trackers increase physical activity in adults? Systematic review, meta-analysis and metaregression. *British Journal of Sports Medicine*, 55(8), 422–432. <https://doi.org/10.1136/BJSPORTS-2020-102892>
- Lee, Y., & Shin, S. (2024). Risk of using smartphones while walking for digital natives in realistic environments: Effects of cognitive–motor interference. *Heliyon*, 10(7), 2405–8440. <https://doi.org/10.1016/J.HELİYON.2024.E28901>
- Meh, K., Sember, V., Sorić, M., Vähä-Ypyä, H., Rocha, P., & Jurak, G. (2023). The dilemma of physical activity questionnaires: Fitter people are less prone to over reporting. *PLOS ONE*, 18(8). <https://doi.org/10.1371/JOURNAL.PONE.0285357>
- Miguelés, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., Labayen, I., Ruiz, J. R., & Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine (Auckland, N.Z.)*, 47(9), 1821. <https://doi.org/10.1007/S40279-017-0716-0>
- Ministerio de Salud de Chile. (2017). National Health Survey 2016–2017. In *Departamento de Epidemiología, División de Planificación Sanitaria, Subsecretaría de Salud Pública*. http://www.minsal.cl/wp-content/uploads/2017/11/ENS-2016-17_PRIMEROS-RESULTADOS.pdf%0Ahttp://web.minsal.cl/wp-content/uploads/2017/11/ENS-2016-17_PRIMEROS-RESULTADOS.pdf
- Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2011). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 2011 16:1, 16(1), 105–114. <https://doi.org/10.1007/S00779-011-0412-2>
- Prasad, S., Harshe, D., Kaur, N., Jangannavar, S., Srivastava, A., Achanta, U., Khan, S., & Harshe, G. (2018). A study of magnitude and psychological correlates of smartphone use in medical students: A pilot study with a novel telemetric approach. *Indian Journal of Psychological Medicine*, 40(5), 468–475. https://doi.org/10.4103/IJPSYM.IJPSYM_133_18
- Prince, S. A., Cardilli, L., Reed, J. L., Saunders, T. J., Kite, C., Douillette, K., Fournier, K., & Buckley, J. P. (2020). A comparison of self-reported and device measured sedentary behaviour in adults: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity* 2020 17:1, 17(1), 1–17. <https://doi.org/10.1186/S12966-020-00938-3>
- Ryding, F. C., & Kuss, D. J. (2020). Passive objective measures in the assessment of problematic smartphone use: A systematic review. *Addictive Behaviors Reports*, 11, 100257. <https://doi.org/10.1016/J.ABREP.2020.100257>
- Shi, M., Zhao, Z., & Fan, X. (2025). Associations of accelerometer-measured physical activity, sedentary behaviour and different types of smartphone apps usage among university students: a 7-day tracking study. *BMC Public Health*, 25(1). <https://doi.org/10.1186/s12889-025-25588-7>
- Silva, G. O., Cunha, P. M., Oliveira, M. D., Christofaro, D. G. D., Tebar, W. R., Gerage, A. M., Kanegusuku, H., Correia, M. A., & Ritti-Dias, R. M. (2023). Patterns of sedentary behavior in adults: A cross-sectional study. *Frontiers in Cardiovascular Medicine*, 10, 1116499. <https://doi.org/10.3389/FCVM.2023.1116499>

- Sjöros, T., Vähä-Ypyä, H., Laine, S., Garthwaite, T., Lahesmaa, M., Laurila, S. M., Latva-Rasku, A., Savolainen, A., Miikkulainen, A., Löyttyniemi, E., Sievänen, H., Kalliokoski, K. K., Knuuti, J., Vasankari, T., & Heinonen, I. H. A. (2020). Both sedentary time and physical activity are associated with cardiometabolic health in overweight adults in a 1 month accelerometer measurement. *Scientific Reports* 2020 10:1, 10(1), 1–11. <https://doi.org/10.1038/s41598-020-77637-3>
- Souza, K. C. de, Mendes, T. B., Gomes, T. H. S., Silva, A. A. da, Nali, L. H. da S., Bachi, A. L. L., Rossi, F. E., Gil, S., França, C. N., & Neves, L. M. (2021). Medical Students Show Lower Physical Activity Levels and Higher Anxiety Than Physical Education Students: A Cross-Sectional Study During the COVID-19 Pandemic. *Frontiers in Psychiatry*, 12, 804967. <https://doi.org/10.3389/FPSYT.2021.804967>
- Strain, T., Flaxman, S., Guthold, R., Semenov, E., Cowan, M., Riley, L. M., Bull, F. C., Stevens, G. A., Raheem, R. A., Agoudavi, K., Anderssen, S. A., Alkhatib, W., Aly, E. A. H., Anjana, R. M., Bauman, A., Bovet, P., Moniz, T. B., Bulotait, G., Caixeta, R., ... Zoma, L. R. (2024). National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: a pooled analysis of 507 population-based surveys with 5·7 million participants. *The Lancet Global Health*, 12(8), e1232–e1243. [https://doi.org/10.1016/S2214-109X\(24\)00150-5](https://doi.org/10.1016/S2214-109X(24)00150-5)
- Tomczyk, Ł., & Selmanagic Lizde, E. (2023). Is real screen time a determinant of problematic smartphone and social network use among young people? *Telematics and Informatics*, 82, 101994. <https://doi.org/10.1016/J.TELE.2023.101994>
- Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., Chastin, S. F. M., Altenburg, T. M., Chinapaw, M. J. M., Aminian, S., Arundell, L., Hinkley, T., Hnatiuk, J., Atkin, A. J., Belanger, K., Chaput, J. P., Gunnell, K., Larouche, R., Manyanga, T., ... Wondergem, R. (2017). Sedentary Behavior Research Network (SBRN) - Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity*. <https://doi.org/10.1186/s12966-017-0525-8>
- Troiano, R. P., Berrigan, D., Dodd, K. W., Mâsse, L. C., Tilert, T., & McDowell, M. (2008). Physical activity in the United States measured by accelerometer. *Medicine and Science in Sports and Exercise*, 40(1), 181–188. <https://doi.org/10.1249/MSS.0B013E31815A51B3>
- Wacks, Y., & Weinstein, A. M. (2021). Excessive Smartphone Use Is Associated With Health Problems in Adolescents and Young Adults. *Frontiers in Psychiatry*, 12, 669042. <https://doi.org/10.3389/FPSYT.2021.669042/FULL>
- Wang, J., Hao, Q. H., Peng, W., Tu, Y., Zhang, L., & Zhu, T. M. (2023). Relationship between smartphone addiction and eating disorders and lifestyle among Chinese college students. *Frontiers in Public Health*, 11. <https://doi.org/10.3389/FPUBH.2023.1111477/FULL>
- Yang, J., Fu, X., Liao, X., & Li, Y. (2020). Association of problematic smartphone use with poor sleep quality, depression, and anxiety: A systematic review and meta-analysis. *Psychiatry Research*, 284, 112686. <https://doi.org/10.1016/J.PSYCHRES.2019.112686>