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Associations Between Smartphone Screen Time, Sedentary Behavior, and Physical Activity in Young Adults

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ABSTRACT

Screen time has been inconsistently associated with adverse health outcomes such as obesity and depression. The mechanism of this link is not well understood, but it is possible that screen time impacts overall health by altering movement- and non-movement-related behaviors such as sedentary behavior and physical activity. Smartphone screen time is of particular interest because smartphones are universal and portable. The purpose of this study was to determine the associations between total smartphone screen time and sedentary behavior and physical activity. A secondary purpose was to investigate the relationship between frequency of smartphone use and these two behaviors. During a 9-day ambulatory monitoring period, smartphone use was measured using Apple's Screen Time software and activity was measured using a wearable device. Increased total screen time was significantly associated with increased sitting time and decreased step count at the within-person level of analysis. More frequent interactions with the smartphone (pickups) were positively associated with step count at the between-person level and sedentary behavior at the within-person level. This evidence suggests that smartphone screen time has the potential to influence health outcomes by altering physical activity and sedentary behavior.

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Introduction

As digital screens have become increasingly prevalent in our lives, concerns about the effects of screen time on the physical and mental health of young adults have increased. Previous research on digital screen time and wellbeing has shown a relationship between increased screen time and adverse health outcomes, such as obesity and depressive symptoms. These findings are somewhat inconsistent, so sedentary behavior and physical activity are proposed to be mediating factors that account for how screen time gets "under the skin" to impact health. One of the most common screens in daily life is the smartphone; among Americans ages 18-29 years old, smartphone ownership is nearly universal (Pew Research Center, 2019). Smartphones are portable and provide on demand access to digital media, yet little is known about how total smartphone screen time or specific patterns of smartphone usage are associated with physical activity and sedentary behavior. As a result, there is limited evidence to guide practitioners and parents in creating sensible limits to smartphone screen time. This study tests the hypothesis that increased smartphone screen time is associated with decreased physical activity and increased inactivity (i.e., sedentary behavior) using device-based measures of smartphone use and activity behaviors.

Screen Time and Health

Research on screen time and health has yielded mixed but concerning results. Overall screen time has been consistently linked to increased obesity, but this relationship to obesity seems to vary between different digital screen types (Boone et al., 2007; Engberg et al., 2019; Robinson et al., 2017; Stiglic & Viner, 2019). For example, TV watching has a strong and consistent positive association with obesity, whereas computer use has mixed associations (Engberg et al., 2019; Fang et al., 2019; Stiglic & Viner, 2019). Research on smartphone use and obesity risk is still too limited to draw conclusions. The evidence also suggests that there is a small, negative association between screen time and mental health (Dienlin & Johannes, 2020). Specifically, screen time has been associated with depressive symptoms, anxiety, and negative affect (Dienlin & Johannes, 2020; Stiglic & Viner, 2019). However, the evidence linking screen time and anxiety and negative affect is weak (Dienlin & Johannes, 2020; Stiglic & Viner, 2019).

Two limitations of this literature may help to explain these results. First, screen time has largely been defined in terms of TV watching, but different types of screens may have different associations with health outcomes. Smartphone use has received limited attention and should be prioritized based on the ubiquity of smartphones in daily life and the potential for large volumes of screen time to accumulate on these devices. Previous work has shown that young adults report spending approximately 4-6 hours per day using their smartphone (Lepp et al., 2014, 2014, p. 2015). Second, prior work has focused on total screen time, but this exposure alone may not be sufficient to understand how screen time impacts health. Other factors, such as the frequency that a person picks up and activates their phone, may disrupt other behaviors. This study will address the first limitation by specifically examining smartphone screen time. Secondly, this study will examine both total screen time and the frequency of smartphone pickups as predictors of health-related outcomes.

The inconsistent links between screen time and health outcomes may also reflect that different types of digital screen use engage different mediators. Physical activity and sedentary behavior may act as mediating variables that account for how smartphone use gets "under the skin" to influence health. That is, smartphone use may alter physical activity and sedentary behavior in ways that stimulate dysfunctional adaptations in key physiological systems (e.g., cardiovascular, metabolic). Over time, those adaptations may increase the incidence of chronic disease and shorten the lifespan.

Physical activity mitigates risk of premature mortality and prevents many chronic illnesses such as cardiovascular disease and type 2 diabetes (Physical Activity Guidelines Advisory Committee, 2018; Warburton & Bredin, 2017). Sedentary behavior increases risk for type II diabetes, cardiovascular disease, and all-cause mortality (Keadle et al., 2017). Both of these behaviors are impacted by factors at multiple levels of the physical and sociocultural environment (McLeroy et al., 1988; Sallis et al., 2006; Spence & Lee, 2003). For example, reviews of environmental correlates of physical activity and sedentary behavior have found correlates in the social environment (McNeill et al., 2006; Mendonça et al., 2014; Scarapicchia et al., 2017) built environment (Sallis et al., 2020), and natural environment (Turrisi et al., 2021). Similarly, the digital environment of screens may have characteristics that alter sedentary behavior or physical activity in ways that contribute to adverse health outcomes.

Screen Time and Movement-Related Behaviors

One mechanism by which screen time may modulate health outcomes is by reducing physical activity. Attaining at least 150 minutes per week of moderate-to-vigorous physical activity (MVPA) reduces the risk of chronic disease (Physical Activity Guidelines Advisory Committee, 2018). MVPA is defined as activity requiring ≥3 metabolic equivalents of task (METs) (Physical Activity Guidelines Advisory Committee, 2018). Increased duration of screen time has been associated with decreased volume of physical activity in adolescents (Sandercock et al., 2012; Serrano-Sanchez et al., 2011; Xu, 2021) although this finding is inconsistent (O'Brien et al., 2018). The limited number of studies on smartphone screen time and physical activity have not found an association between these behaviors (Barkley & Lepp, 2016; Lepp & Barkley, 2019; Penglee et al., 2019). However, the findings of those studies are limited by their reliance on self-reported measures of smartphone use and physical activity.

Screen usage may also contribute to adverse health outcomes by driving an increase in sedentary time. Sedentary behavior is defined as activity requiring 1.0 to 1.5 METs and is a risk factor for many chronic diseases (Physical Activity Guidelines Advisory Committee, 2018). Screen time is largely assumed to be sedentary and is often used as a measure of sedentary behavior (Rhodes et al., 2012). Traditional screen-viewing behaviors, such as TV watching, are inherently sedentary activities that have links to adverse health outcomes that are in line with those of sedentary behavior: obesity, type 2 diabetes, and metabolic syndrome (Williams et al., 2008). Newer screen-viewing behaviors, such as smartphone use, have not been thoroughly researched and may impact sedentary behavior differently. Studies that have examined cell phone screen time and sedentary time have found them to be correlated but have relied on self-reported measures of smartphone use and sedentary behavior (Barkley et al., 2016; Barkley & Lepp, 2016; Lepp & Barkley, 2019). Research with more rigorous measures of smartphone use and sedentary behavior is needed to validate this relationship. Whereas traditional forms of screen time are known to be equivalent to sedentary time, the association between smartphone use and sedentary behavior remains uncertain.

The hypothesis that digital screen usage increases sedentary time and decreases physical activity rests on two assumptions: (1) that screen time is a sedentary activity, and (2) that screen time displaces time spent being physically active. These assumptions may not translate to smartphone usage, because a person can be mobile while using a smartphone. Therefore, findings that overall screen time was associated with decreased physical activity and increased sedentary activity may not generalize to smartphone screen time.

Another reason to interpret these hypotheses with caution is that most studies of screen time have relied on self-report measures. Self-reports are vulnerable to social-desirability and cognitive biases (Bauhoff, 2014). Comparisons of actual and self-reported screen time have yielded conflicting results. Some studies have shown that self-reports underestimate screen time, while others have shown that self-reports overestimate screen time (Araujo et al., 2017; Naab et al., 2019; Sewall et al., 2020). Overall, there only seems to be moderate agreement between measured and retrospectively reported screen time (Parry et al., Unpublished). This study addressed these biases by using a device-based measure of smartphone screen time, Apple's Screen Time software.

In addition to total screen time, specific characteristics of smartphone screen time, such as pickups, could modulate movement. Apple Screen Time's 'pickups' is a count of the times a user picks up their device (Apple, n.d.). Third-party definitions of this feature note that a pickup designates an instance of engaging with the phone, for example, by unlocking the device, accelerometer detection, receiving a notification, or utilizing Siri (*What Are Pickups in Screen Time on IPhone,* 2020). Each of these pickups has the potential to disrupt other activities that require attention because humans have a limited capacity for attention and information processing (Marois & Ivanoff, 2005; Miller, 1956). Although movement is usually well-learned by young-adulthood and does not require much attention, navigation through the environment still requires some attention (e.g. avoiding obstacles). If attention is diverted to picking up and engaging with a smartphone, total demands on attention may exceed information processing capacity (Wickens, 1976). To reduce the risk of navigational errors or falls, movements may be halted. Thus, we would expect that frequently picking up a smartphone is associated with decreased physical activity.

The Current Study

The purpose of this study was to determine the relationship between smartphone screen time and movement-related behaviors in young adults. During a 9-day ambulatory monitoring period, a wearable activity monitor and Apple's Screen Time software were used to measure activity and smartphone usage, respectively. It was hypothesized that smartphone screen time would be positively associated with sedentary behavior, and that there would be no association between smartphone screen time and physical activity. Smartphone pickups were predicted to be inversely associated with physical activity. We expected to see these associations at the day level and person level.

Methods

Participants

Participants in this study were young adult smartphone users. Participants were eligible if they were (1) 17 – 29 years of age, (2) the sole user of an iPhone that was version 5S or more recent and secured with a passcode or Face ID lock, (3) not limiting their smartphone or app use, (4) resided in the state of Pennsylvania, (5) willing to allow researchers to view their smartphone use and app use data, (6) willing to wear an activity monitor almost continuously for the duration of the study, (7) able to read, speak, and understand English, and (8) were not a ward of the state. Participants were recruited using flier advertisements placed in communal locations around Penn State's University Park campus, an online research recruitment platform, emails to graduate student listservs, and direct-mail postcards.

Demographic characteristics were self-reported at the baseline sessions. Participants reported their height, weight, age, sex, ethnicity, race, education level, employment status, and occupation (if applicable). Response options for ethnicity were Hispanic/Latino or not Hispanic/Latino. Response options for race included American Indian/Alaska Native, Asian, Native Hawaiian/Other Pacific Islander, two or more races, Black/African American, or White. Response options for highest education level attained included grade school or less, some high school, completed high school or GED, trade or technical school certificate, some college or Associate's degree (e.g., AA degree), college (e.g., BA, BS degree), and graduate or professional degree (e.g., MA, MS, MD, DDS, PhD). Response options for employment status included full-time, part-time, student, retired, unemployed and looking for work, or unemployed and not looking for work. Participants who identified themselves as employed full- or part-time were asked to report their occupation in an open-ended response.

Sedentary behavior. Sedentary behavior was measured using both self-reports and a device. The ActivPAL4 micro activity monitor (PAL Technologies, LLC, Glasgow, Scotland) was used as a device-based measure of sedentary behavior. This device includes a 3-dimensional accelerometer and is worn on the thigh. The PALanalysis software has proprietary algorithms for classifying both posture (lying in bed, sitting, standing, moving) and activity (step counts). The monitor was waterproofed with a nitrile sleeve and worn continuously on the front of the thigh (midway between the knee and hip), where it was attached with hypoallergenic surgical tape. Participants maintained paper-and-pencil logs of wear time, wake time, and bedtime. These logs were reviewed to cross-validate automated classifications of time-in-bed from the algorithm. Inactivity due to sleep or non-wear was removed from the data set. A valid day of wear for the monitor was ≥10 hours of wear time during waking hours. The ActivPAL4 monitor has been shown to classify movement data accurately and reliably (Grant et al., 2006).

Smartphone use. Smartphone screen time and app use were monitored using the Screen Time setting in iOS. On day 10, participants captured screen recordings of daily summaries of their total smartphone screen time (duration recorded as minutes) and pickups from the Screen Time settings.

At the end of the study, perceptions of smartphone use were measured. These questions included: “Do you feel that your smartphone screen time is…” (response options: too little, just right, or too much) and “In the future, would you want to decrease your smartphone use?” (response options: No, Yes). If participants responded that they would want to decrease their smartphone use in the future, they were also asked “Would you be interested in using a smartphone app to decrease your smartphone screen time?” (response options: No, Yes).

Procedures

Approval for this study was granted by the Institutional Review Board of the Pennsylvania State University (STUDY00014879).

Screening. Potential participants completed a screening questionnaire by phone (n = 35) or on a website (n = 70). The researcher contacted eligible participants to schedule the initial study meeting and obtain a current mailing address. The researcher then mailed a packet of study materials in advance of the meeting. This study packet contained a consent form, an initialized ActivPAL4 micro activity monitor, a participant training guide, hypoallergenic surgical tape, alcohol-based sanitizing hand wipes, and a prepaid return envelope.

Session 1 (day 0). The initial study meeting was conducted using Zoom videoconferencing software. The researcher described the study and interested participated provided informed consent via an electronic consent document module in the REDCap system. Participants then completed a baseline questionnaire to report their demographic characteristics. The researcher trained participants how to wear the activity monitor, completing end-of-day web questionnaires, and how to log the times which they went to sleep, woke up, and removed the activity monitor. The researcher then walked the participant through the procedures for enabling the Screen Time feature in iOS with the following settings: Downtime – off, App Limits – off, Content & Privacy Restrictions – off, and Share Across Devices – off.

Ambulatory monitoring (days 1-9). For a 9-day monitoring period, participants wore the activity monitor continuously. Each night, they received an email with a link to a short questionnaire to report the time when they went to sleep the previous night, woke up that morning, and removed the activity monitor during the day. They were asked to complete these questionnaires as close as possible to the time that they fall asleep. Participants also logged the times when they went to sleep, woke up, and removed the activity monitor on a paper-and-pencil log and in the daily questionnaire.

Session 2 (day 10). On the last day of the 10-day observation period, the researcher held the final Zoom meeting with the participant. Participants followed a video tutorial that instructed them how to take a screen recording of the day-level usage data displayed in the Screen Time and Battery tools in iOS Settings. Participants uploaded their screen recording to a OneDrive folder shared with them and completed a questionnaire about perceived smartphone use.

Participants returned the activity monitors and sleep logs in a prepaid addressed envelope that was included in the original study packet. Upon receipt of these materials, monetary compensation was calculated and mailed to participants. Participants received up to $25 for completion of study procedures. Compensation was conditional on daily survey completion, Screen Time data collection, and activity monitor wear time ≥ 10 waking hours each day.

Data Analysis

Pre-processing. The PALconnect (v8.11.5.64; PAL Technologies, LLC, Glasgow, Scotland) software was used to download data files. The PALanalysis software was used to classify physical activity, sedentary behavior, and time in bed. Paper-and-pencil logs were compared with the automated classifications of time in bed and adjustments were made as needed. Days with less than 20 hours of valid wear time were excluded from analyses. All participants had at least four valid days by that criterion.

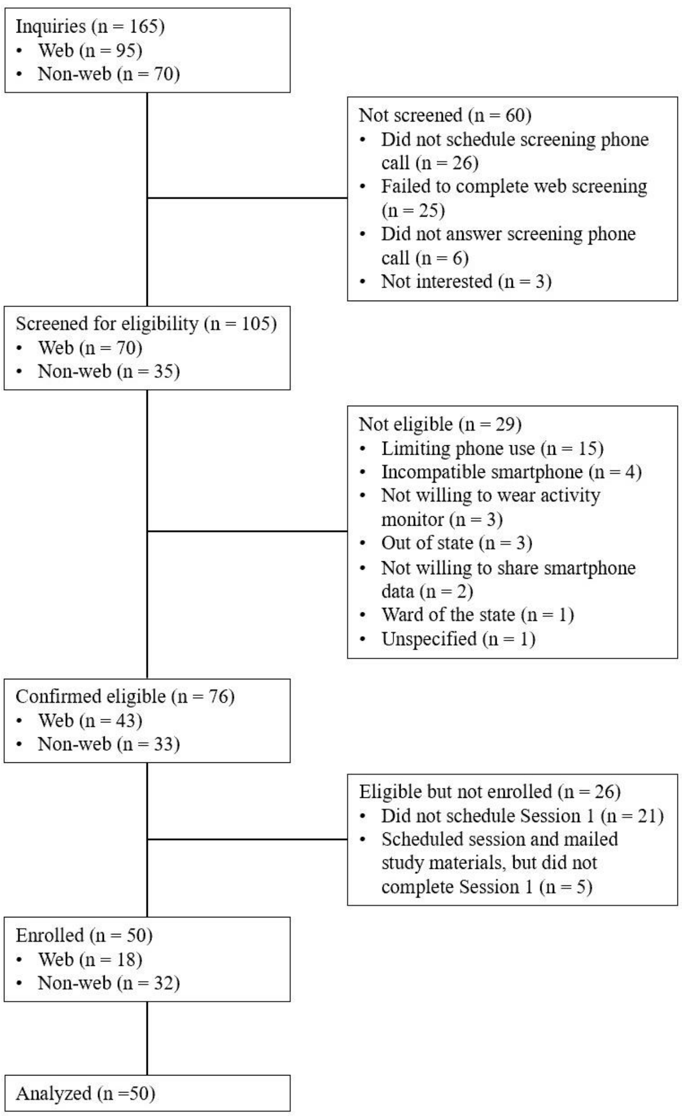
Descriptive statistics were calculated to summarize central tendencies and variability in each study variable. Distributional characteristics were examined to determine if any data transformations would be appropriate. (Snijders & Bosker, 2012).

Daily data were nested within people so multilevel models were estimated to account for dependencies in observations. Screen time and pickups were decomposed into within- and between-person components using standard multilevel modeling procedures (Bolger & Laurenceau, 2013) For both variables, within-person scores were person-mean centered and between-person scores were grand-mean centered (Enders & Tofighi, 2007). Age was person-mean centered. Sex and weekend were dummy-coded, and women and weekdays set as the reference categories. Random effects were included for the intercept and pickups but not for screen time duration because of convergence problems. All data analysis was conducted using the Statistical Package for the Social Sciences (SPSS version 26).

Results

A sample of 50 young adults (22.2 ± 3.4 years old) were eligible, enrolled, and completed the study protocol (Figure 1). The majority of this sample was female (n = 42, 84%), white (n = 37, 74%), and non-Hispanic/Latino (n = 43, 86%) (Table 1). On average, participants were overweight (BMI M±SD = 25.5 ± 5.9), and many body mass classifications were represented in this sample (BMI 16.5-51.7) (Table 1).

Figure 1. Participant flow diagram



As shown in Table 2, participants took 7,365 steps per day on average (SD = 2,874) and sat for about 8 hours each day (M±SD = 518 ± 84 min). Over half of the variance in daily step counts (58%) and sedentary time (72%) was between-person with the remainder due to within-person and random variation. Participants also averaged 6 hours of total smartphone screen time per day (M±SD = 353 ± 120 min) and picked up their phone 136 times per day (SD = 52 pickups). Over half of the variance in daily screen time (63%) and pickups (73%) was between-person with the remainder due to within-person and random variation.

Tables 3 and 4 summarize coefficients from the mixed model analyses of daily step counts and sedentary time, respectively. Participants' usual number of pickups were positively associated with step counts. For each pickup that exceeded the sample average of 136 pickups, person-level average step count increased by 19 additional steps (Table 3). This was the only significant relationship found with either step counts or sedentary time at the between-person level; step counts and sedentary time did not differ significantly between age or sex.

Within-person mixed model analyses found that daily screen time was negatively related to daily step count and positively related to sitting time. On days that participants' screen time exceeded their person-level average, they tended to move less and sit more. Specifically, for each minute of screen time that exceeded the person-level average screen time, participants took 6 fewer steps and spent 15 seconds sitting. Daily pickups were positively associated with sitting time. Each pickup beyond the person-level average pickups was associated with spending about additional 30 seconds sitting.

End-of-study survey responses showed that most participants had a negative perception of their smartphone use. A majority of respondents (80%, n = 40) felt that their smartphone use was 'too much' and 86% (n = 43) replied that they wanted to decrease their smartphone use. Only 32% (n =16) responded that they would be interested in using a smartphone app to decrease their smartphone screen time.

Table 1. Sample descriptive statistics

	Mean	SD	Range	N (%)
Age (years)	22.2	3.4	17 - 29	--
Height (in.)	64.6	3.1	59.0 - 72.0	--
Weight (lbs.)	151.0	37.3	93.0 - 350.0	--
BMI	25.5	5.9	16.5 - 51.7	--
Underweight	--	--	--	2 (4.0%)
Normal weight	--	--	--	24 (48.0%)
Overweight	--	--	--	16 (32.0%)
Obese	--	--	--	7 (14.0%)
Sex				
Female	--	--	--	42 (84%)
Male	--	--	--	8 (16%)
Ethnic Identity				
Non-Hispanic/Latino	--	--	--	43 (86.0%)
Hispanic/Latino	--	--	--	7 (14.0%)
Racial Identity				
White	--	--	--	37 (74%)
Asian	--	--	--	5 (10.0%)
Black/African American	--	--	--	3 (6.0%)
Two or more races	--	--	--	3 (6.0%)
Native Hawaiian/Other Pacific Islander	--	--	--	1 (2.0%)
Highest level of education				
Some high school	--	--	--	3 (6.0%)
Completed high school or received GED	--	--	--	8 (16.0%)
Trade/technical school certificate	--	--	--	1 (2.0%)
Some college/Associate's degree	--	--	--	20 (40.0%)
Completed college	--	--	--	14 (28.0%)
Graduate or professional degree	--	--	--	4 (8.0%)
Work Status				
Student	--	--	--	36 (72%)
Employed full-time	--	--	--	11 (22.0%)
Employed part-time	--	--	--	2 (4.0%)
Unemployed and looking for work	--	--	--	1 (2.0%)

Table 2. Day-level behavioral descriptors

Behavior	Mean	SD	Range	ICC
ActivPAL Recordings				
Step counts	7365.20	2874.24	1375.00 - 17036.57	0.58
Sitting time (min)	517.91	84.46	337.40 - 644.96	0.72
Smartphone Recordings				
Screen time (min)	353.49	120.21	165.22 - 623.11	0.63
Pickups	136.22	52.14	51.78 - 262.33	0.73

Table 3. Multilevel model coefficients for daily step counts

	Estimate	SE	d.f.	Test Statistic	P Value	95% CI
Fixed effects						
Intercept	7441.38	475.34	39.41	15.66	.00	(6480.24, 8402.53)
Age	564.80	1232.90	35.18	0.46	.65	(-1937.66, 3067.26)
Sex	59.87	138.33	35.80	0.43	.67	(-220.73, 340.48)
Weekend day	-693.81	357.30	300.34	-1.94	.05	(-1396.93, 9.31)
Daily screen time	-6.17	1.91	288.17	-3.23	.001	(-9.94, -2.41)
Usual screen time	-5.85	3.75	35.80	-1.56	.13	(-13.46, 1.76)
Daily pickups	10.84	6.44	34.89	1.68	.10	(-2.24, 23.92)
Usual pickups	19.37	8.92	35.62	2.17	.04	(1.28, 37.46)
Random effects						
Residual	8418007.28	721604.28	--	--	.00	(7116115.97, 9958079.22)
Intercept	6449631.74	1775441.41	--	--	.00	(3760260.23, 11062465.63)
Pickups	339.47	304.47	--	--	.27	(58.53, 1969.03)

Age, sex, and usual screen recordings were grand-mean centered. Daily screen recordings were person-mean centered. Weekend coded as 1 (Saturday, Sunday) or 0 (all other days).

Table 4. Multilevel model coefficients for daily sitting time

	Estimate	SE	d.f.	Test Statistic	P Value	95% CI
Fixed effects						
Intercept	518.99	15.08	41.69	34.41	.00	(488.55, 549.43)
Age	4.38	4.34	36.16	1.01	.32	(-4.42, 13.17)
Sex	30.21	38.59	35.29	0.78	.44	(-48.11, 108.52)
Weekend day	-13.79	13.73	301.10	-1.01	.32	(-40.81, 13.23)
Daily screen time	0.25	0.09	33.60	2.89	.01	(0.074, 0.43)
Usual screen time	0.12	0.12	36.13	1.03	.31	(-0.12, 0.36)
Daily pickups	0.47	0.22	290.69	2.18	.03	(0.045, 0.90)
Usual pickups	-0.17	0.28	35.90	-0.61	.55	(-0.74, 0.40)
Random effects						
Residual	12598.70	1080.97	--	--	.00	(10648.59, 14905.93)
Intercept	5802.28	1738.81	--	--	.00	(3224.88, 10439.60)
Pickups	0.06	0.06	--	--	.25	(0.012, 0.36)

Age, sex, and usual screen recordings were grand-mean centered. Daily screen recordings were person-mean centered. Weekend coded as 1 (Saturday, Sunday) or 0 (all other days).

Discussion

It was hypothesized that smartphone screen time would be associated with increased sedentary time and decreased physical activity. These associations were not found at the between-person level; participants who used their smartphones more than average did not spend more time seated or take fewer steps on average. However, our analyses confirmed that these associations were significant at the within-person level; on the days that participants used their smartphones more than they typically did, they also sat more and took fewer steps. For each additional hour of smartphone screen time, participants would spend 15 additional minutes sitting and take 370.2 fewer steps.

These findings are consistent with most of the research on overall and smartphone-specific screen time. Other studies have found that overall screen time is associated with decreased physical activity (Sandercock et al., 2012; Serrano-Sanchez et al., 2011; Xu, 2021) and increased sedentary behavior (Lepp & Barkley, 2019). However, the finding that smartphone screen time is associated with decreased physical activity contrasts with the results of studies which have specifically examined smartphone screen time; these studies found no association between these behaviors (Barkley et al., 2016; Barkley & Lepp, 2016; Lepp & Barkley, 2019).

A possible explanation for these discrepant findings is that the research of Barkley and Lepp has relied on self-reported measures of smartphone use and physical activity behaviors (Barkley et al., 2016; Barkley & Lepp, 2016; Lepp & Barkley, 2019). Self-reported smartphone use only modestly correlated with actual smartphone use and has been shown to be prone to both over- and under-estimates, so the use of self-reported measures in prior work may have obscured relations between screen time and physical activity (Araujo et al., 2017; Naab et al., 2019; Parry et al., Unpublished; Sewall et al., 2020). Additionally, prior work focused on differences between people in smartphone use. Results from the present study suggest the association is likely to be a within-person process, such that smartphone use on a given day will be associated with physical activity and sedentary behavior on that same day. This finding suggests that limits on daily smartphone use may provide a useful level for modifying daily physical activity and sedentary behavior.

It was also hypothesized that increased frequency of engagement with a smartphone (pickups) would interrupt and, thus, decrease physical activity. However, this analysis uncovered the opposite relationship; increased pickups were significantly correlated with increased physical activity at the between-person level. Each pickup was associated with taking an additional 29.37 steps. This finding suggests that pickups are not sufficiently attention-demanding to disrupt daily activity patterns; however, these findings are limited to the daily level and may not generalize to the momentary level. Future research should examine momentary pickups and their immediate and delayed effects on stepping behavior after the pickup. Although it was not hypothesized, pickups were associated with increased sitting time at the within-person level. On days that participants picked up their phone more than usual, they also tended to sit more. This evidence suggests that picking up our phones more often may stimulate both increased physical activity and increased sedentary behavior at the daily level.

Further research into specific usage contexts and characteristics of smartphone screen time is needed to inform guidelines surrounding smartphone use and activity promotion. Beyond total screen time, certain characteristics of smartphone screen time may have greater health-relevance based on their effects on physical activity and sedentary behavior. For example, entertainment apps such as YouTube and Netflix fulfill functions that are similar to traditional TV watching and may promote sedentary behavior. In contrast, apps related to health and fitness such as Map My Run may promote physical activity. Knowledge of the specific characteristics of smartphone screen time that promote inactivity can inform guidance surrounding smartphone use. Currently, there is not enough evidence to support a threshold limit to smartphone screen time, and even less evidence is available on which types of media are more harmful than others (Ashton & Beattie, 2019). Knowing which characteristics of screen time confer increased risk of inactivity could also provide intervention targets to reduce sedentary behavior and increase physical activity. For example, the findings of this study suggest that reducing pickups could serve as a potential intervention target for reducing sedentary behavior. Further research into specific characteristics of smartphone use is needed to determine which characteristics promote sedentary behavior and decrease physical activity and should be limited.

This study has several limitations. This sample was more active than the average American and included several very active individuals who took upwards of 10,000 steps per day. Comparatively, Americans tend to take 5,133 steps a day on average (Bassett et al., 2010). Thus, our finding that increased smartphone use is associated with decreased physical activity may not generalize to less-active populations. Similarly, our sample consisted of young adults, who may have different smartphone use behavior patterns than other age groups. Screen time was only measured for a single device, but other digital devices such as computers, video games, and tablets have the potential to influence health behaviors as well. Notably, data collection for this study occurred during the COVID-19 pandemic, and early research has shown that lockdowns have decreased physical activity and increased sedentary behavior (Stockwell et al., 2021). The pandemic may have also altered the associations between smartphone use and movement behaviors. When people resume their normal patterns of behavior, the associations that this study found may change. Lastly, our analyses focused on daily- and person-level data and these findings may not generalize to momentary behaviors.

This study adds to the literature by utilizing device-based measures of smartphone screen time and physical activity, which are more objective than the self-reported measures that previous research has relied on. The findings provide evidence that smartphone screen time alters daily movement- and non-movement-related behaviors. Specifically, daily smartphone screen time is associated with increased sedentary behavior and decreased physical activity at the within-person level. Furthermore, this study provides evidence that specific characteristics of smartphone screen time, such as frequency of interaction, can have different associations to movement than total smartphone screen time. These behavioral effects may mediate effects of smartphone use on adverse health outcomes. Future research should continue to investigate associations between specific characteristics of smartphone use and movement- and non-movement-related behaviors to determine how these characteristics may impact overall health.

Appendix A

Example Activity Data

Figure 2 displays the activity data of a participant visualized using an events spiral. Each loop of the spiral represents one valid day (wear time ≥ 20 h). The legend indicates whether movement was classified as upright, sedentary, or 'time in bed'. If movement was classified as sedentary time, the bout was further categorized by the duration of sedentary time. This participant had 8.6 hours of time in bed on average.

Figure 2. Example activity data

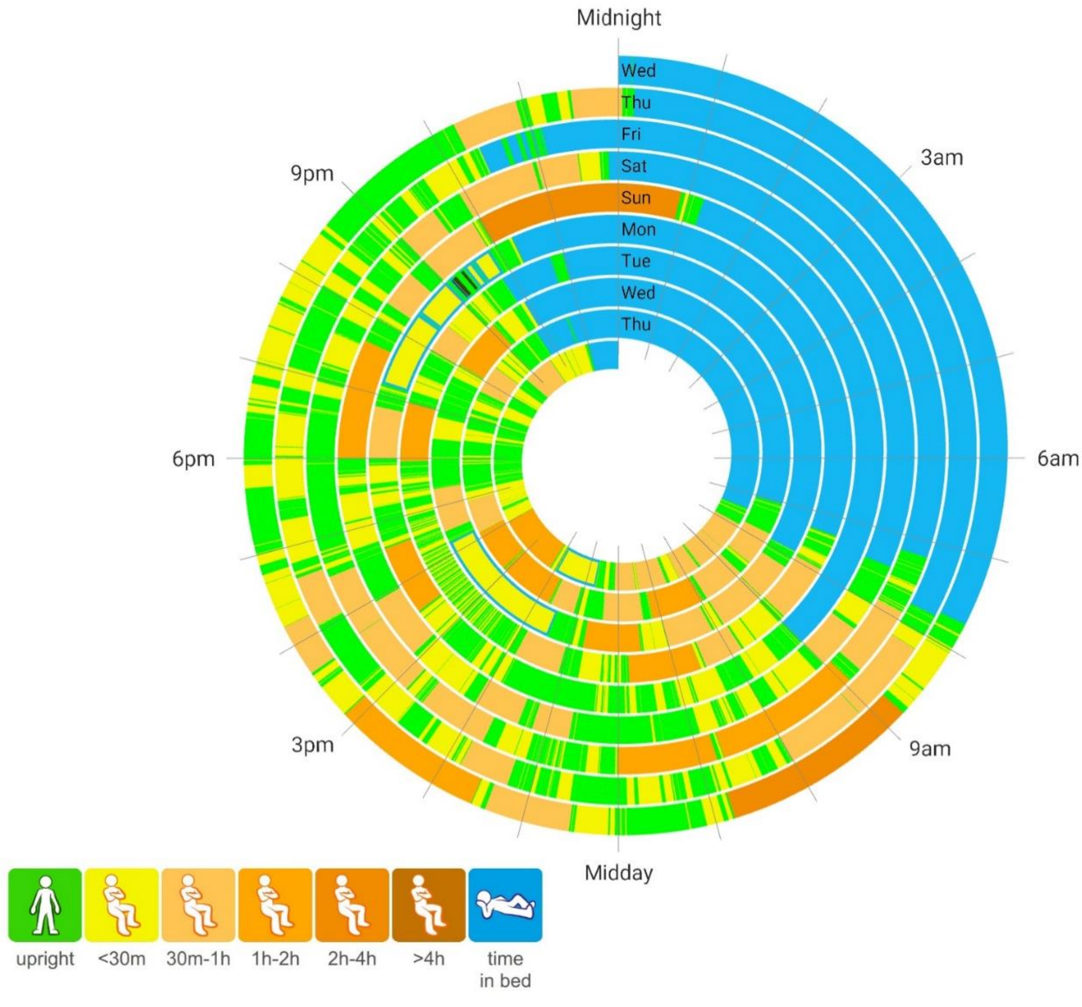


Figure 3. Example activity data with extended time in bed

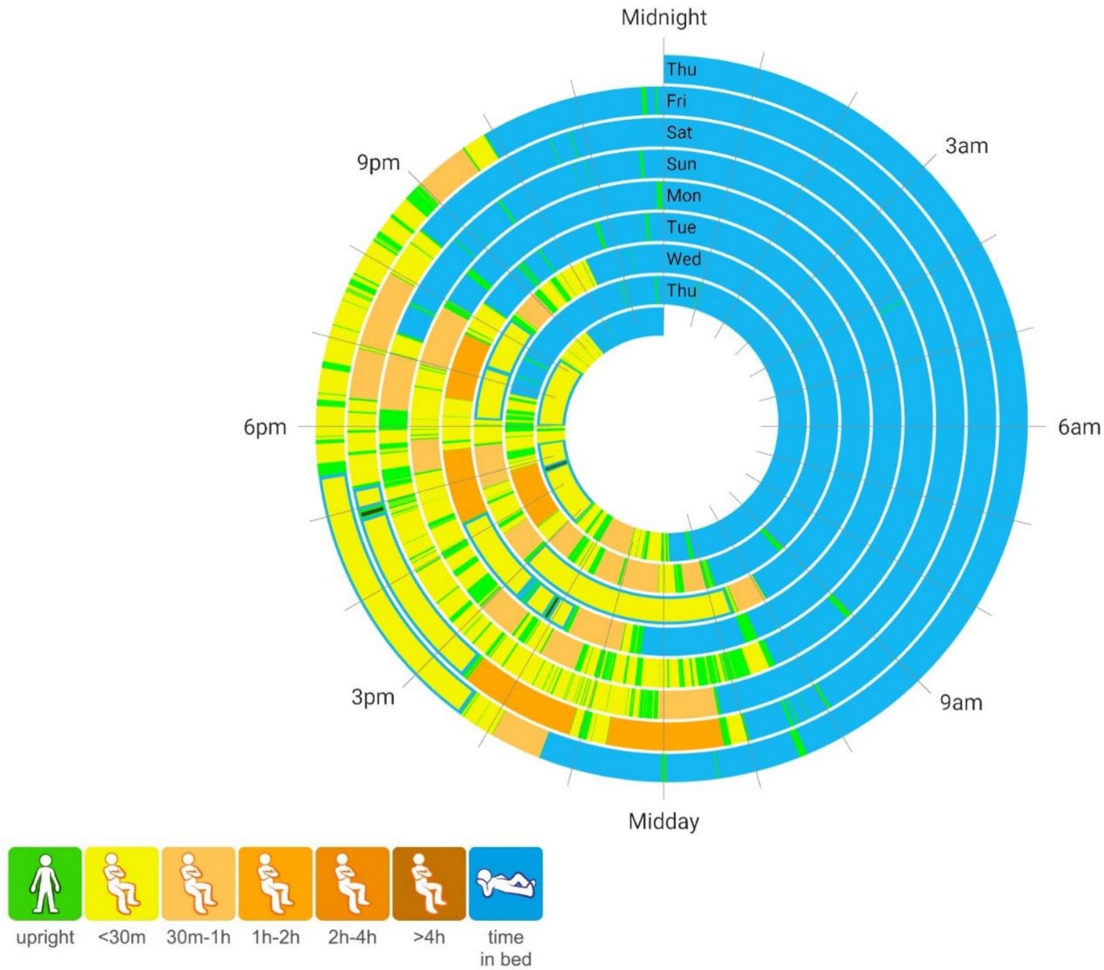


Figure 3 shows a participant that displayed extended overnight time in bed (14.6 h on average). 'Time in bed' was classified by the PALanalysis algorithm and excluded from analysis. The exact sleep/wake times of participants were unknown, so waking horizontal behavior was classified as time in bed if it occurred immediately before or after sleep. Thus, this type of sedentary behavior was excluded from our analysis and is a potential limitation of our study.

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