Links Between Objectively-Measured Smartphone Use and Adolescent Wake Events across Two Weeks

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Abstract

Purpose: Psychosocial and bioregulatory pressures threaten sleep during adolescence. Although recent work suggests that the ubiquity of smartphone use throughout adolescence may also relate to poorer sleep outcomes, most existing research relies upon self-report and retrospective measures. This study drew upon objective measures of smartphone use and sleep at the hourly level to understand how smartphone use was associated with the duration of wake events during sleeping hours.

Methods: Across a 14-day daily study, 59 racially and ethnically diverse adolescents ages 15 to 18 had their sleep assessed via Fitbit Inspire 2 devices and uploaded screenshots of their screen time, pickups, and notifications as logged by their iPhone's iOS. Multi-level modeling was performed to assess hourly-level associations between adolescent smartphone use and wake-events during their sleep sessions (N= 4,287 hourly cases).

Results: In hours during adolescents' sleep session with more screen time or pickups, adolescents had longer wake event duration. More notifications in a given hour were not associated with wake event duration in the same hour.

Conclusions: Using objectively-measured smartphone and sleep data collected at the hourly level, we found that during sleeping hours, when adolescents are actively engaging with their smartphones their sleep is disrupted, such that their wake events are longer in that hour.

Keywords: smartphone, sleep, wake events, adolescence, daily diary

Links Between Objectively-Measured Hourly Smartphone Use and Adolescent Wake Events across Two Weeks

Approximately one-third of adolescents in the US get inadequate sleep (Tsao et al., 2021). With 60% of adolescents reporting that they use their smartphones an hour before bed and 29% reporting that they sleep with their smartphone in bed (e.g., Hysing et al., 2015; Rideout & Robb, 2019), smartphones may, in part, exacerbate sleep disruptions. Indeed, increased digital media use relates to poor sleep outcomes, such as reduced quality sleep and less sleep quantity as well as increased daytime sleepiness (Brand & Kirov, 2011). Though smartphone use immediately prior to bedtime may disrupt sleep, only self-report and cross-sectional studies have examined links between smartphone use and awakenings during the night (Fobian et al., 2016; Murdock et al., 2017). In this daily diary study, we utilize objective (i.e., wearable sleep devices) measures of sleep, and hourly measures of smartphone use (i.e., minutes of screentime, smartphone pickups, and notifications) collected daily across 14-days to examine if smartphone use in the same hour is associated with longer duration of wake events in an ethnically-racially diverse sample of adolescents.

Sleep is critical for adolescent neural development, mental wellbeing, and physical health, especially during a period where key developmental tasks may be jeopardized due to sleep disruptions (Brand & Kirov, 2011; Tarokh et al., 2016). Though widespread, relatively few studies have examined sleep disruption among children and adolescents (Medic et al., 2017). The confluence of psychosocial (e.g., bedtime autonomy, school, peer relations) and bioregulatory (i.e., sleep homeostasis, circadian phase delay) pressures prime adolescence as a stage for sleep disruptions, including nighttime wakings (Crowley et al., 2018). Sleep disruptions have been linked to both short-term consequences like harmful risk-taking behavior, mood disturbances such as depression, reduced executive functioning, poorer academic performance, and substance use, and long-term consequences like cardiovascular effects, metabolic disorders, cancer, and suicidality (Medic et al., 2017; Owens & Weiss, 2017). Furthermore, daily variability in sleep duration has been consistently linked to increased internalizing and externalizing symptoms among adolescents (Bei et al., 2016; Fuligni et al., 2018) as well as to altered integrity of white matter brain development (Telzer et al., 2015).

As smartphones connect adolescents with their social lives and augment their environment (e.g., produces lights and sounds), one potential stressor on adolescent sleep is smartphone use (Carter et al., 2016). Given that 90% of studies examining the link between smartphones and sleep find more screen time is associated with poorer sleep outcomes, researchers have proposed potential mechanisms to explicate the deleterious effect of smartphones on sleep (Cain & Gradisar, 2010; LeBourgeois et al., 2017). First, time spent on smartphone use may displace time that would otherwise be used for sleeping. Second, digital media may expose adolescents to physiologically arousing content which increases their alertness and prolongs sleep latency. Third, light emitted from smartphone screens may impact circadian timing, sleep physiology (i.e., melatonin), and alertness (Arora et al., 2014; Cain & Gradisar, 2010; LeBourgeois et al., 2017).

Researchers have begun incorporating wearable sleep devices to examine the links between self-reported smartphone use and adolescent sleep. Indeed, advances in passive sensor technologies, smartphone sensitivity, and other devices help researchers in better approximating everyday contexts, experiences, and behavior in real time (Russell & Gajos, 2020). For example, wearable sleep trackers were used to find that self-reported smartphone use in bed (e.g., text messages, notifications, video and phone calls) and awakenings by a smartphone were linked with decreased objectively measured sleep efficiency (Cabré-Riera et al., 2019). Further, adolescents with more self-reported problematic phone use and more tablet use had lower subjective sleep quality, and lower sleep efficiency, and increased minutes of wake time after sleep onset as recorded by wearable devices (Cabré-Riera et al., 2019). Similarly, adolescents who send more messages throughout the day on average have shorter sleep duration as recorded by wearable devices (Burnell et al., 2022).

While overall smartphone use during the day or before bedtime has been linked to overall poorer sleep quality, smartphone use following a nighttime waking may be particularly disruptive by prolonging the wake event when an adolescent otherwise would be sleeping. Emerging work suggests that adolescent smartphone use elicits small, short-term gratifications (e.g., Marciano et al., 2022). Following a wake event, if an adolescent accesses their phone, the immediate stimulation may further disrupt their sleep and prolong sleep latency. Increased sleep fragmentation, and more frequent and longer wake events are associated with less overall time sleeping (Kuula et al., 2015). There remains a scarcity of well-documented questionnaires to assess smartphone and media use at bedtime (e.g., Hsying et al., 2015). Furthermore, there is little work characterizing how bedtime smartphone use contributes to variations in adolescents' wake events and broader sleep fragmentation. Such work should serve as critical for informing interventions and developing new technology features that protect adolescent sleep.

Given than most prior research has examined smartphone use measured retrospectively or averaged across a large time span, researchers have underscored the need to refine methodological techniques to better reflect specific time frames of smartphone use (Orben, 2020). Objective measures may be especially useful for capturing nighttime behavior as adolescents may struggle to accuracy recall smartphone use because they felt groggy during that time. To that aim, the Screen Time feature provides iPhone users with hourly summaries of their smartphone screen time, number of pickups (i.e., times users unlocked their smartphone), and number of notifications received (Apple, 2018). Still, researchers have primarily used these *weekly* reports logging objective smartphone behavior (Bradley et al., 2023; Fumagalli et al., 2021), with fewer capitalizing on the *daily* reports (Hartanto et al., 2023). Daily-level designs are an important step but may still obfuscate important within-person associations due to being too coarse to effectively reflect the ephemeral nature of smartphone use. To date, no study has utilized *hour-to-hour* smartphone use to examine the potential effects on adolescents' sleep in the hours they occur.

The current study examined how smartphone use (i.e., screen time minutes, pickups, notifications) related to adolescents' wake events (i.e., periods of awake time during their nightly sleep sessions), collected over 14 days using ecological momentary assessment. This study extends prior research in three valuable ways. First, rather than relying on traditional self-report approaches, this study employed actigraphy via wearable sleep devices and objectively measured smartphone use within a racially-ethnically diverse sample of adolescents. Wearable sleep-trackers have been found to measure sleep duration just as well as actigraphy (e.g., Lee et al., 2019), and wearable sleep-trackers are comparable to polysomnography for assessing sleep sensitivity (Haghayegh et al., 2019). Second, this study focuses on within-person associations when assessing smartphone use and sleep outcomes by using an intensive longitudinal design by having adolescents provide objective sleep and screentime behavior across a 14-day period. In focusing on within-person, rather than person-level associations, this study avoids mistakenly generalizing group-level observations onto individuals and hold individual-level factors (e.g., biological sex, prior sleep history) constant (Fisher et al., 2018). Finally, to our knowledge, no other studies have extracted hour-by-hour measures of objectively measured smartphone use. Granulating objective measures through hourly-level assessments may be a more appropriate temporal scale with which to examine associations between smartphone use and sleep by strengthening confidence in the synchronicity of these behaviors. Accordingly, the primary aim of the study was to leverage objectively measured hour-by-hour smartphone use (i.e., minutes of screen time, pickups, notifications) to test the hypothesis that smartphone use during adolescents' sleep sessions (i.e., sleep occurring after nighttime sleep onset measured via wearable devices) is associated with longer duration of wake events in the same hour. Examining hourly level associations should help in illuminating the mechanisms potentially underlying the links between adolescent smartphone use and sleep outcomes in the moments they are occurring. Identifying aspects of smartphone use in adolescents' daily lives that may impact their sleep has potential impactful consequences with downstream effects on adolescents' health and wellbeing through its utility for finding areas of intervention and informing tech features that can improve sleep outcomes.

Method

Participants and Procedure

The sample consisted of 59 adolescents (33 girls, 25 boys, 1 outside of gender binary) between the ages of 15 and 18 (M_{age} = 16.45 years, *SD* = 0.63 years) and who identified as 31% Hispanic/Latinx, 31% White, 29% Black/African American, and 9% Multiracial/Other. The study procedures were approved by the university Institutional Review Board. Participants came from a predominately low-income community in rural southeast region of the United States, with the sample's median parent-reported household income between $45,000 - $59,999. Participants were recruited as part of the fifth wave (Wave 5) of a larger longitudinal school-based study between December 2016 to February 2022. Among study participants, adolescents were compensated $50 contingent upon the percentage of ecological momentary assessments completed. During Wave 5, a total of 103 adolescents participated. A subsample (n = 83) opted to wear sleep devices (Fitbit Inspire 2) for a 14-day period; of these 83, 59 uploaded daily screenshots of their iOS-recorded screen time, pickups, and notifications between April 2021 and November 2021. Twenty-four adolescents opted to wear sleep devices but were not included in analysis because they either did not have an iPhone or did not successfully upload any useable iOS screenshots. The analytic sample of 59 did not differ from non-participants from the larger sample of the original 103 adolescents on age, race/ethnicity, gender, or parent-reported income (ps > .249).

Measures

Covariates

All participants reported their date of birth (converted to age at time of study completion), gender, and race/ethnicity at Wave 1. Participants' caregivers reported their household income at Wave 5. Each night during the EMA period, participants reported if that day was a school day, and if so, if they attended school; a single variable representing school attendance was converted based on these responses.

Smartphone Use

Participants uploaded screenshots of their iOS screen use each day throughout the 14-EMA period. Participants took screenshots of their iPhone's iOS screen time output from the prior day, which presented graphical displays of their smartphone use per hour for the prior 24 hour day, which included screen time (minutes), number of pickups, and number of notifications. From these graphical displays, research assistants used a raster graphic editor, Adobe Photoshop, to decode the exact value of smartphone use per hour. We tested the accuracy of the hourly-level smartphone values by calculating their daily sum (i.e., summing each of the hours that were extracted (24 total) and correlated it with the total daily smartphone use calculated from the iOS (i.e., iOS calculates a total screentime for 24 hour period) – these measured values were highly correlated with their respective daily values calculated from iOS (screen time: $r(512) = 1.00$, $p < .001$; pickups: $r(512) = 1.00$, $p < .001$; notifications: $r(503) = 1.00$, $p < .001$).

Wake Events

Participants' Fitbit Inspire 2 devices provided data on participant sleep stages in thirty-second epochs, including sleep and wake classification. Research on the sleep staging Fitbit models (i.e., Fitbit models that differentiate between wake, light, REM, deep sleep) indicate these devices classifying sleep vs wake with high sensitivity (.88 - .95), but variable sleep staging specificity (.51 - .90) (Lee et al., 2019). Though self-report measures may be ideal for assessing subjective sleep, wearable derived sleep metrics are only moderately correlated with self-report (e.g., $r = .58$; Matthews et al., 2014), and clinical sleep studies find that wearable metrics have comparable sensitivity to polysomnography (e.g., $r = .90$; Lee et al., 2019). Wake events were aggregated within an hour and then divided by two, to create a variable (in minutes) of total time spent awake in a given hour (*wake duration*). For example, if a participant was logged as awake at 1:58:00, 1:58:30, 1:59:00, and 1:59:30, these wake events were summed into a variable that reflected total wake events (4 30-second wake events), and then divided by two to reflect this value in minutes (2 minutes). Cases were limited to sleep time hours, with sleep time hours starting at the hour in which sleep onset was recorded through the hour in which sleep logging ended. As benchmark hours (e.g., the hours where participants began their bedtime and waketime) may confound associations between wake events and smartphone use, analyses were limited to non-benchmark hours (see Figure 1). For example, if a participant fell asleep at 12:30am (meaning that their bedtime benchmark was the 12:00am hour) and woke up at 8:30am (meaning that their waketime benchmark hour was the 8:00am hour), then analyses for this participant's sleep session were limited to the hours starting at 1:00am and through 7:59am.

As we were primarily interested in assessing linkages between smartphone use and wake duration when participants had wake events during their overall daily sleep session, analyses were limited to days in which sleep data were available. Thus, data were complete for the wake duration variable. Missingness was allowed on the smartphone use variables, with some stipulations. First, participants were only included if they had at least one day of smartphone data. Accordingly, the number of analytic sleep sessions with both screen use and wearable sleep device data for each participant ranged from 1 to 13 (M = 7.12 days). Second, as smartphone use was collected in traditional 24-hour increments (with participants providing screenshots for data on a midnight through 11:59pm scale), there were a handful of days in which smartphone data were only available for a small number of hours in a participant's nightly sleep session. For example, if a participant went to bed at 10:15pm on Monday and woke up at 6:15am on Tuesday, and smartphone data were only available for Monday, then values would only be available for the 11:00pm hour in this particular sleep session and missing for all other hours. This poses problems when aggregating data at the daily-level, as the participant's day-level smartphone use value would potentially be inaccurate (e.g., if the participant struggled to stay asleep early in their sleep session and engaged in higher-than-usual smartphone use). These cases (4%) were recoded as missing to avoid potentially inaccurate inflation for day-level variables. Syntax and output can be found on Open Science Framework: https://osf.io/veyuc/?view_only=796cea0a554849d5850a4d7559c8d9cb

Data Analytic Plan

A three-level random intercept multilevel model (with robust standard error estimation) was used to test if screen time, pickups, and notifications were associated with duration of sleep time wake events. All three smartphone variables were included in the same model to examine unique associations that each variable had with wake events. Out of 4,287 hourly cases included in the analysis, the data were complete on the wake event duration variable but missing at 33% for screen time, 34% for pickups, and 35% for notifications. Full Information Maximum Likelihood was used to adjust for missingness.

Descriptive statistics were run in SPSS Version 28 (IBM, 2016) and the main analysis was run in M*Plus* Version 8.8 (Muthén & Muthén, 2015). Data were organized in three levels, in which hours were nested within days, which were nested within participants. The level 1 hourly variable was person-centered, in which the person-level smartphone use variable of interest (each smartphone variable aggregated within each participant) was subtracted from the raw hourly-level smartphone use variable. Additionally, models included each daily-level smartphone use variable (each smartphone use variable aggregated within a day, person-centered) and person-level smartphone use variable (each smartphone use variable aggregated within participant, grand-mean centered). This approach helps to isolate within-subject effects from within-days and between-subject effects (Curran & Bauer, 2011). The primary analysis was structured as follows:

Level 1: $\text{Wake Duration}_{ijk} = \beta_{0jk} + \beta_{1jk}(\text{hST}_{ijk}) + \beta_{2jk}(\text{hPU}_{ijk}) + \beta_{3jk}(\text{hNOT}_{ijk}) + r_{ijk}$

Level 2: $\beta_{0jk} = \beta_{00k} + \beta_{01k}(\text{dST}_{jk}) + \beta_{02k}(\text{dPU}_{jk}) + \beta_{03k}(\text{dNOT}_{jk}) + u_{0jk}$

$\beta_{1jk} = \beta_{10k}$

$\beta_{2jk} = \beta_{20k}$

$\beta_{3jk} = \beta_{30k}$

Level 3: $\beta_{00k} = \gamma_{000} + \gamma_{001}(\text{mST}_{k}) + \gamma_{002}(\text{mPU}_{k}) + \gamma_{003}(\text{mNOT}_{k}) + u_{00k}$

$\beta_{01k} = \gamma_{010}$

$\beta_{02k} = \gamma_{020}$

$\beta_{03k} = \gamma_{030}$

$\beta_{10k} = \gamma_{100}$

$\beta_{11k} = \gamma_{110}$

$\beta_{21k} = \gamma_{210}$

$\beta_{31k} = \gamma_{310}$

At Level 1, wake duration for hour *i*, day *j*, and person *k* was modeled as a function of the intercept term (β_{0jk}), hourly screen time (hST_{ijk}), hourly pickups (hPU_{ijk}), hourly notifications ($hNOT_{ijk}$), and the residual (ε_{ijk}). Level 2 included daily screen time (dST_{jk}), daily pickups (dPU_{jk}), and daily notifications ($dNOT_{jk}$) as predictors of the intercept. Likewise, Level 3 included person-average screen time (mST_j), pickups (mPU_j), and notifications ($mNOT_j$) as predictors of the intercept.

Results

On average, participants woke up during 2.77 sleep session hours throughout a typical night (range = 0 – 8 hourly periods). An average of 30.03 wake duration events were recorded across a participant's EMA period (14 days). Descriptive statistics are in Table 1. The average number of screen time minutes, pickups, and notifications per sleep session hour are in Figures 2a – 2c. In nearly 70% of total sleeping hours across participants, 0 minutes of screen time were recorded, indicating that participants generally did not use their phones in a given hour after falling asleep. In a notable minority of cases (11%), 60 minutes of screen time was observed[1]. Pickups demonstrated the same frequency pattern, in which 0 pickups were recorded in 69% of total sleeping hours. Notifications were more diverse, in which 41% of total sleep session hours

[1] These cases may not represent active screen use (e.g., an adolescent falling asleep while watching Netflix or listening to Spotify). Additionally, the data cleaning process revealed that several of these cases demonstrated irregularities in which screen time was logged throughout the night but not appropriately categorized by type of app. Further probing of these irregularities indicated that the iOS Screen Time app may erroneously log screen time when the device is not auto-locked. Because of these issues, a sensitivity analysis was conducted in which cases of 60 minutes of screen time were recoded as missing. Results did not change.

had 0 notifications, 22% had one notification, 13% had two notifications, and 15% had three or more notifications. Figure 3 demonstrates average duration of wake events per sleep session hour. Although the duration of wake events was 9.8 minutes at 10:00pm (for participants who were already asleep by this time), the duration of wake events plateaued in the remaining hours, staying level at approximately 3 – 4 minutes per hour.

Primary results are in Table 2. During sleep sessions, adolescents who had more screen time minutes relative to their own average recorded longer wake event duration (hourly-level associations), above and beyond pickups and notifications. Likewise, adolescents who had more pickups relative to their own average recorded longer wake event duration, above and beyond screen time and notifications. This association was not significant for notifications.

Discussion

Adolescent sleep is critical for physical, neural, and mental health (Brand & Kirov, 2011; Tarokh et al., 2016), and is implicated in both short- and long-term negative consequences for adolescent development (Medic et al., 2017). The present study examined the hourly associations between a diverse sample of adolescents' objectively measured smartphone use and their wake event durations within a 14-day ecological momentary design. These analyses indicate that hours during an adolescent's sleep session with more minutes of screen time or more pickups were associated with longer wake event durations in the same hour. In other words, if an adolescent engaged in greater screen time and pickups in a given hour, they also were awake for a greater period of time in that hour. Notifications, however, were not associated with wake event duration in the same hour. In all, these findings suggest that smartphone use is linked to increased wake events durations during adolescent sleep sessions.

Hourly Associations

During sleeping hours, more screen time or pickups than a participant's own average was linked to longer wake durations. Specifically, both increased screen time and more pickups uniquely, above and beyond other smartphone use variables, were linked with longer wake duration within the same hour. These findings provide even more nuance than past daily studies by examining how smartphone use occurs on the hour-by-hour level – likely a more appropriate temporal scale for understanding smartphone behavior since the effects of digital experiences have been found to be finite and ephemeral (Bayer et al., 2016; Bentley et al., 2015). As such, while other within-person analyses examining smartphones and sleep outcomes among adolescents have garnered mixed findings (e.g., Burnell et al., 2022; Cabré-Riera et al., 2019; Lee et al., 2021; Mac Cárthaigh et al., 2022) the novel analyses on the hourly-level within this paper reveal more consistent evidence of within-person effects.

Our findings suggest that when adolescents wake up during their nightly sleep, they may turn to their smartphones. One plausible explanation is that nighttime smartphone use may prolong what may have been a typical wake event (Grimaldi-Purana et al., 2020). The pattern of significant effects for screen time and pickups, while null effects with notifications is that screen time, pickups, and notifications characterize different levels of smartphone engagement (Valkenburg et al., 2022). Specifically, screen time and pickups, both of which were associated with increased wake event duration, characterize more active smartphone behaviors. Notifications, however, characterize passive and low levels of smartphone engagement. As increased screen time and pickups requires the adolescent to engage with their phone, receiving more notifications is not within control of adolescents – as such, this metric only provides insight into the communication attempts from other external parties. Though it is plausible that notifications could wake up an adolescent, our data find no links between notifications and wake events. Perhaps this is because notifications were inaudible or adolescents use nighttime ‘do not disturb’ features on their phone which silent incoming notifications. Indeed, the audibility of notifications may moderate the link between notifications and wake event durations (i.e., louder notifications may disrupt sleep).

Another plausible explanation is that during normative wake events, adolescents may turn to their smartphones as a sleep aid. A 2022 review identifies nearly 400 smartphone apps in the Google Play and Apple App stores designed for enhancing sleep quality with 27.1% of those apps designed for use while sleep (Doty et al., 2023). Because many sleep enhancement apps rely on calming auditory and non-verbal stimuli (e.g., instrumentation, guided meditation; Becker, 2023), it is possible that adolescents’ screen time and pickups may reflect attempts to fall asleep quicker. Though empirical evidence linking sleep enhancement apps with improved sleep outcomes is scarce (e.g., O’Daffer et al., 2022), some report that smartphones are valuable tools by distracting or calming high-arousal emotions (Lukoff et al., 2018). This is in line with an experimental study which found no difference between a 30-min passive social media use before bed and a 30-min progressive muscle relaxation intervention before bed on subjective sleep quality (Combertaldi et al., 2021).

Limitations and future directions

Several limitations should be acknowledged. First, our sample size of 59 adolescents, though racially and ethnically diverse, is small and may limit the generalizability of the findings. Second, the novel nature of the hourly-level smartphone data necessitated participants to have their own iPhones. Though sensitivity analyses indicated that the analytic sample did not differ on key demographics compared to non-participants from the larger original sample, future work encompassing all types of smartphones would be more representative of the general adolescent population with smartphones. Third, the naturalistic design of this study necessitated we use non-intrusive sleep tracking devices. Though these Fitbits offer accurate sensitivity for detecting sleep epochs, they have poorer specificity when classifying exact sleep stages (i.e., wake, light, REM, deep) (Hagheyegh et al., 2019). Finally, it should be noted that minutes of screen time as measured by the iOS output may not reflect adolescents' active engagement with their phone. For example, if participants briefly checked their phone during their sleep session, depending on how much inactivity is needed before their phone's auto-lock is initiated, it's plausible that a few additional minutes of screen time could have been logged. To mitigate this concern, future work utilizing this iOS feature should ensure that participants set their system settings to initiate after only auto-lock to 30 seconds of inactivity.

Conclusion and Implications

In summary, the present study capitalized on novel approaches to investigate how smartphone use relates to adolescent sleep outcomes. Findings give insight into the potential mechanisms underlying smartphone use and wake events as they occur throughout the night. Implications from the current study are relevant to researchers, practitioners, and parents. Interventions aimed at improving sleep outcomes should consider removing smartphones from adolescents' bedrooms during the night, developing technology that restricts the functionality of smartphones during nighttime hours, or furthering empirical inquiry into the efficacy of sleep enhancement nighttime apps. In adolescence, sleep disruptions impact short-term outcomes like psychosocial health, academic achievement, and risk-taking behavior, and increased risks of long-term health risks like cardiovascular disease, diabetes, and colorectal cancer to name a few (Medic et al., 2017). Researchers concerned with adolescent development and sleep should consider the important role of nighttime smartphone use and its impact on sleep health. This study, in conjunction with other recent work, suggest that the effects of smartphones are ephemeral (e.g., Bayer et al., 2016; Bentley et al., 2015) and potentially harmful for sleep outcomes.

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Figure 1

Illustration of hours used for analysis. Figure represents one example night for one adolescent, in which their Fitbit logged their sleep onset as 11:20 and their waketime as 7:45am.

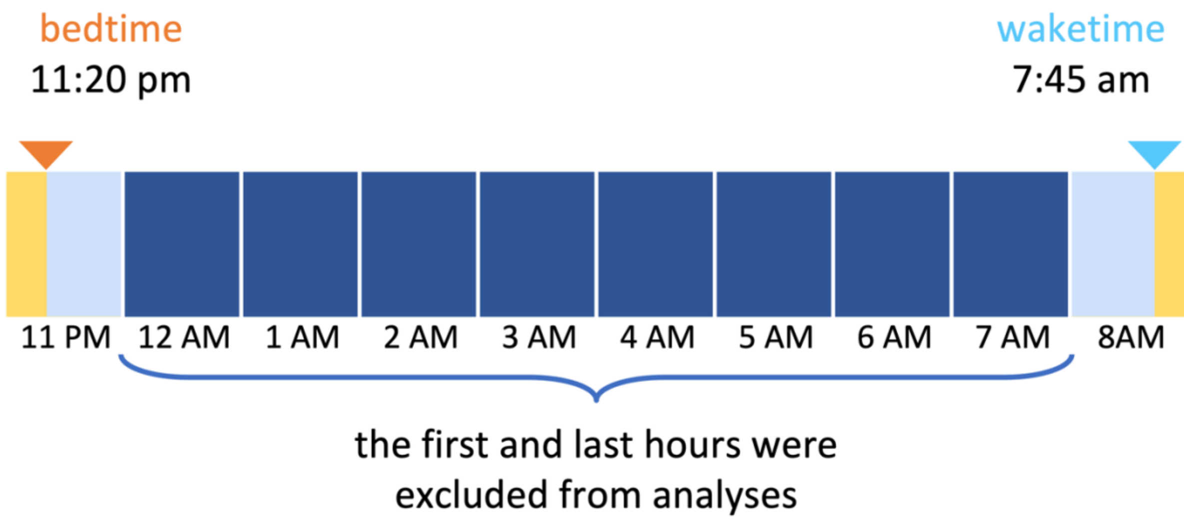


Table 1

Means, Standard Deviations, and Within-Person Correlations for Key Study Variables

	1	2	3	4
Hourly Within-person				
1. Wake Duration	1			
2. Screen Time	.06**	1		
3. Pickups	.23***	-.06**	1	
4. Notifications	.16***	.09***	.56***	1
Between-person				
1. Wake Duration	1			
2. Screen Time	-.05	1		
3. Pickups	.24*	-.10	1	
4. Notifications	.10	.17	.56***	1
Mean	3.79	8.50	0.78	1.95
SD	6.30	19.68	1.78	3.69

Note. Cases are limited to case-by-case non-benchmark hours (e.g., if a participant went to bed in the 10:00pm hour, this single case was excluded in analyses). Mean and standard deviation values are not person-centered.

***$p < .001$; ** $p < .01$; * $p < .10$

Figure 2a

Average number of screen time minutes by nighttime hour

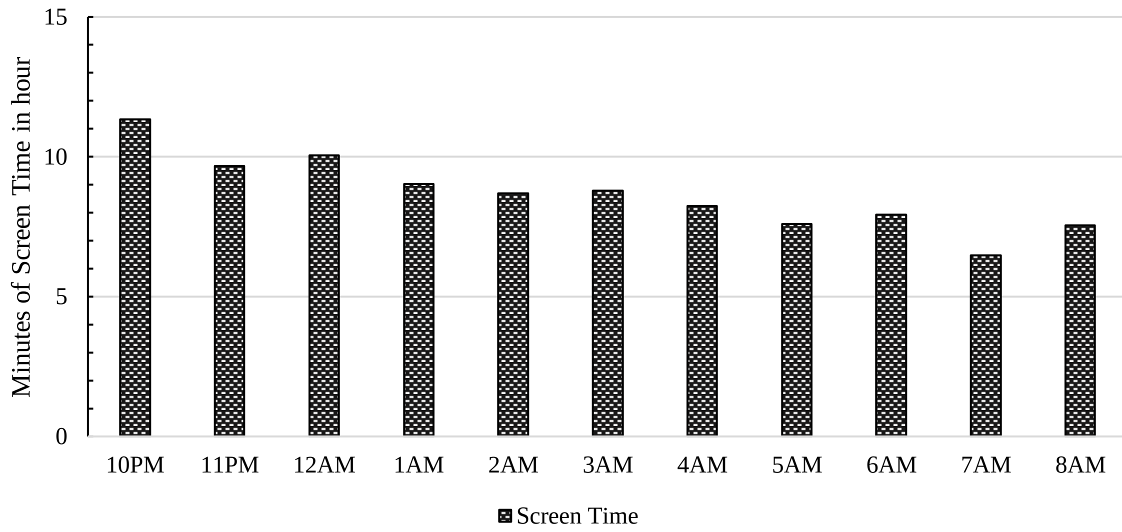


Figure 2b

Average number of pickups by nighttime hour

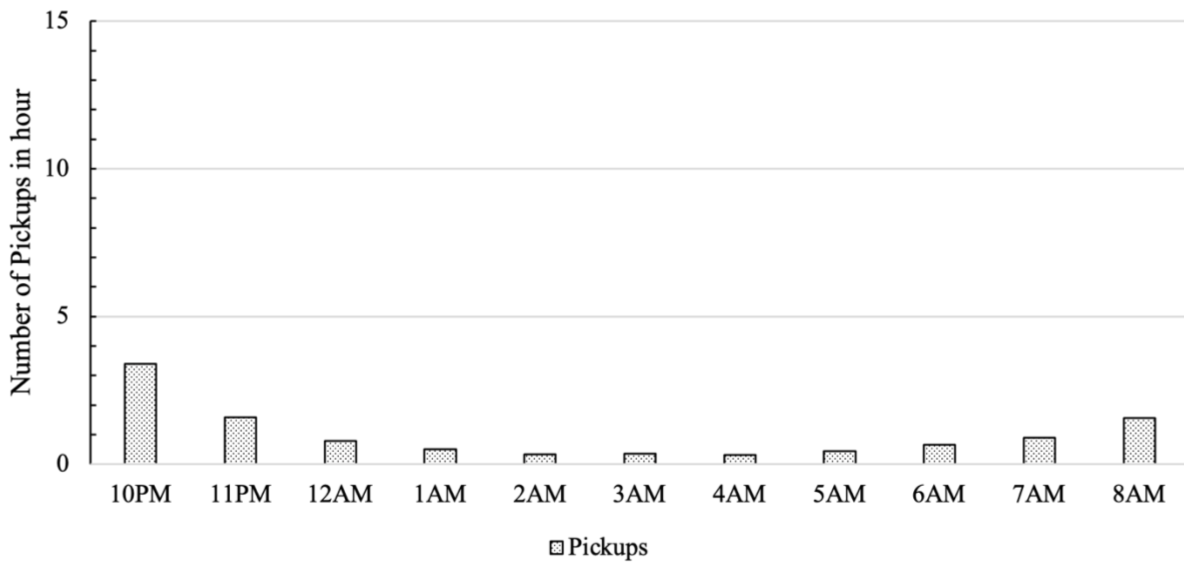


Figure 2c

Average number of notifications by nighttime hour

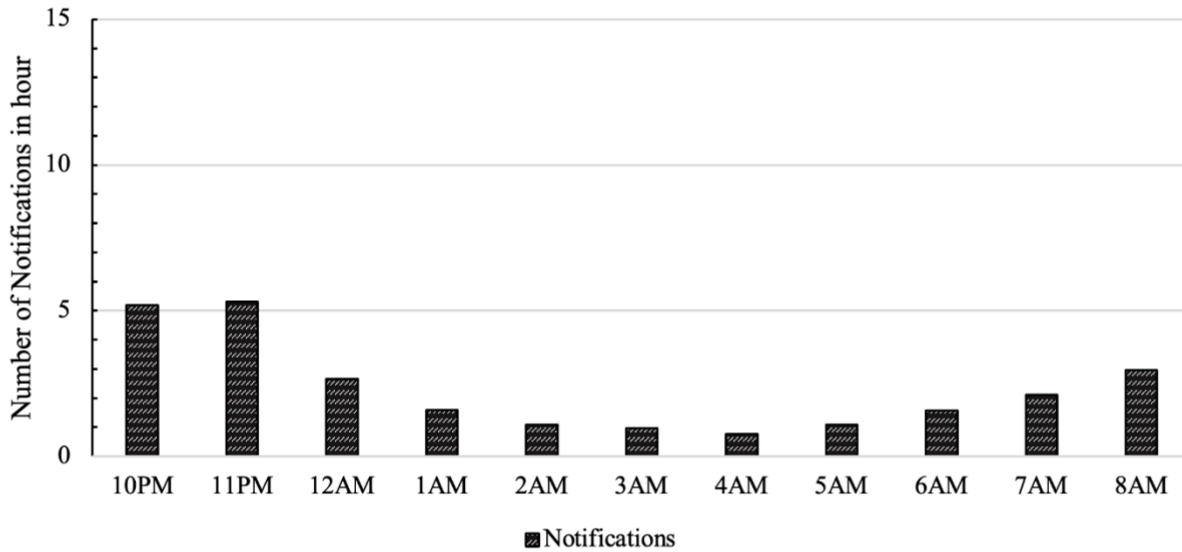
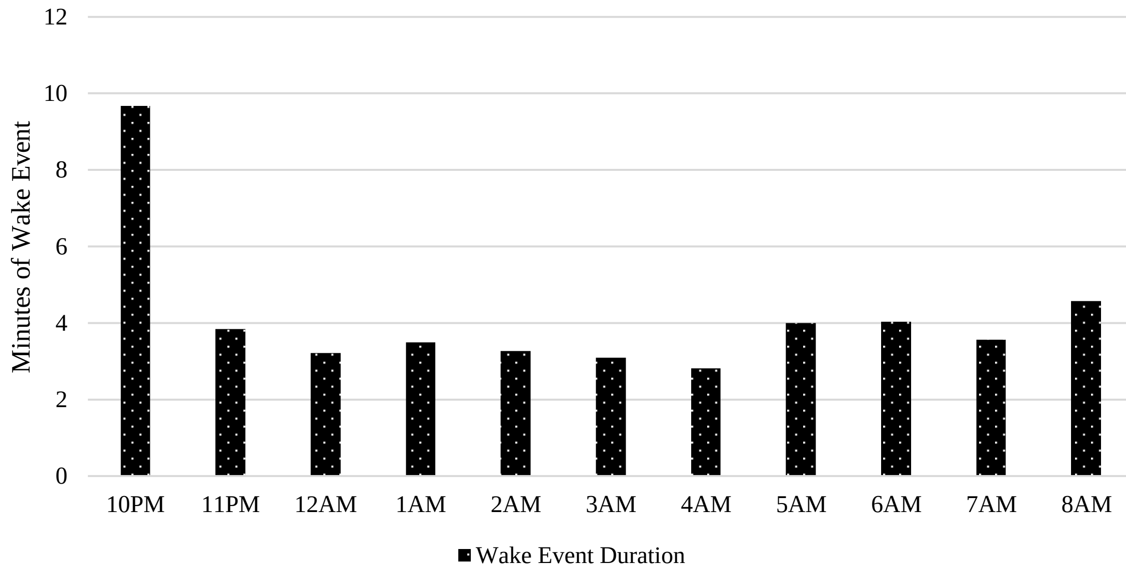


Figure 3

Average Duration of Wake Events by Nighttime Hour



Note. Hours are limited to nighttime hours and case-by-case non-benchmark hours.

Table 2

Results from Multilevel Regression in Which Smartphone Use Predicts Wake Duration

	b [95% CI]	*SE*	*p*
Hour			
Screen Time	0.06 [0.03, 0.10]	.02	<.001
Pickups	0.90 [0.43, 1.37]	.24	<.001
Notifications	0.08 [-0.08, 0.25]	.08	.314
Day			
Screen Time	-0.04 [-0.08, -0.01]	.02	.012
Pickups	-0.46 [-0.84, -0.08]	.19	.017
Notifications	-0.11 [-0.23, 0.02]	.06	.102
Person			
Screen Time	0.01 [-0.02, 0.03]	.01	.742
Pickups	0.59 [0.09, 1.09]	.26	.021
Notifications	-0.13 [-0.42, 0.16]	.15	.382
Intercept	3.78 [3.47, 4.09]	.16	<.001

Note. Presented results are without covariates. Results did not change with covariates included (age, gender (dummy coded 0 = female, 1 = male, non-binary missing), income, minority status (dummy coded 0 = non-Hispanic white, 1 = race/ethnicity other than non-Hispanic white), proportion of (completed) study days in which school was attended, and school attendance (dummy coded 0 = did not attend school, 1 = attended school; person-centered)).