Nighttime Smartphone Use: Evaluating the effect of reducing blue light emissions from smartphones on sleep onset latency and duration

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Abstract

Insufficient sleep – in terms of both quantity and quality – is a public health concern, and a risk factor for a range of adverse physical and mental health conditions. A growing body of research points to a significant association between smartphone use and sleep impairment, with a primary hypothesized pathway being the disruptive effects of blue light upon sleep processes. New software and functional improvements to smartphones in recent years provide the opportunity to better quantify, and potentially limit, the detrimental impact that smartphones may have on sleep. The principal purpose of the current study was to examine the degree to which activating Night Shift® mode on an iPhone® before sleep onset, thereby decreasing the amount of blue light emitted from the device, improves sleep onset latency and sleep quantity. This study also examined the relationship between objectively recorded smartphone use on both previously stated sleep measures. Ninety-one undergraduates were randomized to either have their Night Shift® mode settings automatically activated from 9pm to 5am or turned off for the duration of the study. Self-reported sleep onset latency, and objectively recorded sleep quantity and smartphone use data was collected over a 7-day study period. For sleep reported to conform to regular sleep patterns, there were no significant main effects of Night Shift® condition or pre-sleep smartphone use, nor an interaction effect of these two variables, on either sleep onset latency or total sleep quantity. Exploratory analyses of the entire dataset, combining sleep data reported to both conform and not conform to regular sleep patterns, revealed a significant interaction between Night Shift® condition and quantity of smartphone use on sleep onset latency. These findings suggest future research of Night Shift® mode may be warranted.

Keywords: Blue light, Nigh Shift, smartphone use, sleep

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Objective Smartphone Use and Sleep

More than one-third of Americans sleep less than the 7 hours per night recommended by the Centers for Disease Control and Prevention's (CDC; Liu et al., 2016). It is estimated this collective sleep deficit reduces the country's gross domestic product by 2.3% (Hafner, Stepanek, Taylor, Troxel, & van Stolk, 2017), and places sleep-deprived individuals at increased risk for a range of physical and mental health disorders, including cardiovascular disease, metabolic disturbance, clinical depression, and anxiety (Baglioni et al., 2016; Cappuccio & Miller, 2017; Javaheri & Redline, 2017; Roberts & Duong, 2014). Further, sleep durations below the CDC's recommended guidelines are even more prevalent in younger Americans (Wheaton, 2016), who are also more likely than older adults to experience cognitive deficits arising from sleep deprivation (Zitting et al., 2018). Adding to the concern is the reported 16% increase from 2009 to 2015 in young Americans who do not meet their recommended sleep quantity (Twenge, Krizan, & Hisler, 2017).

One prominent hypothesis for the growing sleep debt among these younger individuals involves the increasing use of electronic devices prior to sleep onset (Christensen et al., 2016). In fact, it has been reported that 67% of young adults use their phones within the hour before they fall asleep (Gradisar et al., 2013), and that engagement with smartphones during this time frame is significantly more detrimental to ensuing sleep quantity than the use of televisions or personal computers (Lanaj, Johnson, & Barnes, 2014). Not only does nighttime utilization of smartphones carry the potential to suppress melatonin release, but applications including social networking or gaming on these devices may displace time that could otherwise be spent sleeping; such applications may also delay the onset of sleep through physiological and psychological arousal (Cain & Gradisar, 2010; Twenge et al., 2017). Despite accumulating evidence for the negative effects of nighttime smartphone use on sleep, this extant body of research is characterized by some important limitations, most notably a reliance upon self-reported smartphone utilization and a lack of objective sleep data.

Smartphones and sleep

Since the commercial release of the first smartphone by Apple® in 2007, the public's adoption of these devices has expanded exponentially. A recent survey found that 77% of all American adults own a smartphone, with ownership rates rising to 94% among young adults (18-24 years old; Pew Research Center, 2018, February 5). Differentiated from their "non-smart" cellphone predecessors, smartphones have the capability not just to perform basic functions such as voice calls and texting, but also to implement more complicated applications – which provide the ability to play games, connect to social media, navigate driving routes, shop online, monitor biometric data, and a vast array of other capabilities. Although the functionality of smartphones has yet to be fully realized, these devices can significantly increase productivity, and their capabilities may also be harnessed to improve some physical and mental health domains (Cho, 2015; Mantani et al., 2017).

Despite their undisputed benefits, smartphones have also been associated with several potential adverse effects, including the impairment of sleep (Hale & Guan, 2015). While most of the evidence reporting on the negative relationship between smartphone use and sleep quantity and quality is cross-sectional in nature (Christensen et al., 2016; L. Exelmans & Van den Bulck, 2016; Fossum, Nordnes, Storemark, Bjorvatn, & Pallesen, 2014; Lanaj et al., 2014; Lemola, Perkinson-gloor, Brand, Dewald-kaufmann, & Grob, 2015), such a link is also supported by a recent 2-year prospective study by Schweizer, Berchtold, Barrense-Dias, Akre, and Suris (2017). Schweizer et al. (2017) observed 591 high school students who either owned a smartphone at the start of the study, received a smartphone during the course of the study, or never owned a smartphone for the duration of the study. Smartphone ownership at the start of the study was significantly related to lower sleep quantity. Further, while all students reported a decrease in sleep quantity over the study period, those who received a smartphone during the observation period reported the greatest average decline.

Although research on the psychological and physiological effects of smartphones is still relatively limited, there are three potential pathways through which these devices may impair sleep: (a) the effect of blue wavelengths of light (blue light) emitted from the devices in suppressing melatonin, leading in turn to delayed sleep onset; (b) physiological and psychological arousal arising from the use of smartphone apps; and (c) the direct displacement of sleep time with time spent on these devices (LeBourgeois et al., 2017).

Blue light

There is substantial evidence that exposure to the blue light emitted from electronic devices (e.g. televisions, computer monitors, and energy efficient light bulbs) can increase nighttime alertness and disrupt sleep initiation through suppression of the body's natural release of melatonin (Cajochen et al., 2011; Figueiro, Wood, Plitnick, & Rea, 2013; van der Lely et al., 2015). The physiological pathway through which this process occurs was only recently clarified with the discovery of a new class of photopigments highly sensitive to blue light, melanopsin (for a full review of the biological pathway see Lazzerini Ospri, Prusky, & Hattar, 2017). These photopigments reside inside retinal ganglion cells, which project into the suprachiasmatic nucleus that controls the release of melatonin from the pineal gland. Based on this new knowledge researchers are beginning to determine the extent to which melanopsin impacts other alerting neuropathways, including the emerging link between melanopsin and dopamine release in animal models (Lazzerini Ospri et al., 2017).

In attempts to attenuate the adverse sleep effects of blue light, several studies have examined the use of amber-tinted spectacles in the hours before sleep onset (Perez Algorta et al., 2018; Shechter, Kim, St-Onge, & Westwood, 2018). The amber tinting filters out blue light, and it appears to significantly improve self-reported levels of sleepiness and sleep initiation (Burkhart & Phelps, 2009; Esaki et al., 2016; Shechter et al., 2018). However, self-reported adherence – wearing these tinted spectacles during the pre-bedtime window – has been unimpressive during the typical 2-week study duration, which suggests potential challenges with long-term adherence (Esaki et al., 2017; Perez Algorta et al., 2018).

In recent years, the study of the negative sleep effects from exposure to blue light has been extended to the light emitted from the much smaller screens of smartphones (Heo et al., 2017; Wood, Rea, Plitnick, & Figueiro, 2013). In a crossover study by Mortazavi et al. (2018), college students used their smartphone to view a one-hour video at 11:00 pm on three separate nights, with one of three different light filters placed successively on their screens. The participants were randomly assigned to the order in which they viewed the video through either an amber-filter, blue-filter, or no-filter control condition. In comparison with the control condition, the amber-filter (which attenuated the quantity of blue light) significantly decreased sleep onset latency – the time gap between initially attempting to sleep and subsequently falling asleep. In contrast, the blue-filter, which amplified the effect of the blue wave lengths, significantly increased sleep onset latency.

The results coincide with that of a previous crossover study by Heo et al. (2017), in which young adult males played video games between 7:30 pm and 10:00 pm on either unadulterated smartphones or those modified to reduce the quantity of blue light emitted. The smartphones that attenuated blue light significantly increased reported levels of sleepiness. These congruent findings for televisions, computer monitors and smartphones are likely the result of the underlying technology used across all of these devices which emit a significant proportion of blue light: compact fluorescent light bulbs (CFLs) and light emitting diodes (LEDs; Jou et al., 2017). Unfortunately, alternative screen technologies that reduce blue light emission are prohibitively expensive, impractical, or experimental (Jou et al., 2017).

In response to the substantial body of research highlighting the negative effect of blue light on the psychological and biological markers of sleep, Apple® introduced the Night Shift® interface with the release of iOS 9.3® in 2016. The interface allows iPhone® and iPad® owners to schedule an automatic reduction in the quantity of blue light emitted by the device's screen, resulting in a red-shifted color temperature. The Night Shift® function was recently examined in a crossover study by Nagare, Plitnick, and Figueiro (2017), wherein participants engaged with an iPad® both with and without Night Shift® activated. Across the two-hour intervention, activation of Night Shift® resulted in significantly reduced nighttime melatonin suppression in comparison with the unmodified iPad. Although this preliminary finding in support of Night Shift® is encouraging, the effects of this modification on sleep quantity and quality have yet to be examined.

Arousal

Beyond the disruptive effects of blue light emitted from smartphones on sleep and sleep-related processes, researchers have also theorized that smartphone content could disrupt sleep by eliciting psychological and physiological arousal (Twenge et al., 2017). The idea that electronic device use near bedtime can disrupt sleep through increased arousal is not new, inasmuch as researchers have long been interested in the effects of arousal from media consumption and video games on sleep (Ivarsson, Anderson, Akerstedt, & Lindblad, 2013; Zillmann, 1991). While smartphones certainly offer access to media and video games, the devices also make it possible to send and receive text messages throughout the night. The potentially arousing nature of the latter interaction has been well documented, with texting found to increase heart rate, respiration and muscle tension, to yield unique electro-encephalogram readings, and ultimately to negatively affect sleep (Dowdell & Clayton, 2018; Kietrys, Gerg, Dropkin, & Gold, 2015; Lin & Peper, 2009; Tatum, DiCiaccio, Kipta, Yelvington, & Stein, 2016).

In addition to these aforementioned arousing and sleep-disruptive behaviors (media consumption, gaming, and texting), smartphones provide access to a plethora of other stimulating activities from the comfort of bed: online-shopping, online-gambling, vacation planning, managing finances, and more (Hartston, 2012; Matthews, Farnsworth, & Griffiths, 2009; Menon & Kahn, 2002; Reed et al., 2017). Although some smartphone-based activities increase arousal as a mere unintended side-effect (e.g., accessing financial records), other applications are explicitly designed to boost arousal in order to drive increased use of the applications themselves (Weinstein, 2010). For example, research suggests that one-way for the online-retail sector to increase consumer purchasing behavior is to design websites that increase consumer stimulation (Menon & Kahn, 2002). And there is at least indirect evidence that online retailers have taken the finding to heart, inasmuch interaction with retail websites has been shown to elevate both emotional and physiological arousal (Guo, Cao, Ding, Liu, & Zhang, 2015). Because most people appear to conduct the majority of their online shopping while they are in bed at night, the practice would appear to conflict with sound sleep hygiene (Hillman, Neustaedter, Bowes, and Antle (2012).

While many smartphone programs likely interfere with sleep onset through increasing bedtime arousal, this hypothesized effect is difficult to quantify due to the diverse range of programs to which smartphones provide access. Not only do different genres of programs elicit different patterns of arousal, some programs are in fact designed to assist users in falling asleep (Koffel et al., 2018; Shin, Kim, & Grigsby-Toussaint, 2017). Although very few of these sleep-assist programs are developed on the basis of evidence-based practices (Yu, Kuhn, Miller, & Taylor, 2019), a recent review by Shin et al. (2017) reported that those smartphone programs which *are* evidence-based generally do improve sleep outcomes. Due to the extreme variability of the goals of different smartphone programs, an important first step towards elucidating the relationship between smartphone use and sleep disturbances (particularly those mediated through arousal) is to objectively document how individuals are use their smartphones prior to bedtime, and to examine the empirical effects of engagement with specific applications on ensuing sleep onset and sleep duration.

Sleep displacement

A third potential mediator of the relationship between nighttime smartphone use and sleep impairment is the displacement of sleep time by engagement with the device (LeBourgeois et al., 2017). While sleep displacement is not confined to the use of smartphones - as chores, television, reading, and other behaviors may all compete for sleep time – these easily portable devices are reported to account for the largest average share of time use during the temporal windows both immediately before and after entering bed (Lemola et al., 2015). This finding is particularly characteristic of young adults, and L. Exelmans and Van den Bulck (2017) reported that phone use accounts for nearly one-third of the time young adults spend between entering bed and attempting to fall asleep.

Although research into the displacement of sleep by smartphone use at bedtime is limited, studies have consistently reported a pattern of overuse of these devices in other contexts, leading to impairment in other domains. In a study of 10,191 adolescents, Yen et al. (2009) found that 27% of their participants reported using their phone for longer than they intended, with 7% having discontinued or reduced “important social, academic, or recreational activities” as a direct consequence of their phone use. Likewise, in a sample of predominantly young adults, Parasuraman, Sam, Yee, Chuon, and Ren (2017) reported that 70% of their participants endorsed using their smartphones for longer than intended, with 37% having missed work because of smartphone use. While neither of these studies specifically assessed for the possibility of smartphone use displacing sleep, they suggest that a significant number of individuals are likely to be so engrossed with their phones that they may be induced to delay sleep for additional screen time.

Notably, the extant research examining the sleep-displacement potential of smartphones has been stymied by methodological limitations. In particular, it has primarily relied on self-reported smartphone use, which not only limits the granularity of examination regarding the effects of specific smartphone applications being used, but also the ability to examine effects associated with the timing of smartphone use vis-à-vis one’s targeted bedtime.

Limitations of previous research

The preponderance of relevant evidence suggests that smartphones negatively affect sleep processes through the mechanisms of blue light emission, increased arousal (both psychological and physiological), and sleep displacement. However, there are several limitations that characterize the body of published research that underlies these conclusions. The first is the field’s nearly universal reliance upon self-reported smartphone use metrics. As examined by

Andrews, Ellis, Shaw, and Piwek (2015), self-reported estimates are poorly correlated with objective recordings of both the frequency and duration of smartphone use. This issue has been a constraint to previous research, which has typically been limited to the collection of participant self-reported smartphone use patterns by the absence of software capable of objectively recording the exact timing and duration of smartphone use, as well as a more fine-grained recording of the specific smartphone applications engaged at each timepoint (Smetaniuk, 2014). But with recently improved software functionality, objective data have now become more accessible to researchers. Particularly notable is the addition of screen-time tracking as a standard feature of Apple's® mobile operating system, beginning with iOS11® in 2017. With the retention of the screen-time tracking feature into even more recent versions of iOS®, smartphone owners and researchers are now able to track the precise duration of time each smartphone application is projected onto the device's screen. This functionality offers an unobtrusive way for researchers to collect objective smartphone use, and provides the requisite granularity for future research to explore the degree to which specific categories of programs may differentially affect users.

A second limitation of existing research is the lack of objective sleep data. It has been well-established that objective sleep indices and self-reported sleep measures are only moderately inter-correlated, and that they are respectively associated with different psychological and physiological measures (Jackowska, Ronaldson, Brown, & Steptoe, 2016). Whereas self-reported sleep is significantly correlated with psychological measures, including overall wellbeing and state affect (Jackowska, Dockray, Hendrickx, & Steptoe, 2011), objective measures of sleep appear to be more strongly associated with physiological processes, such as blood pressure, and an elevation of inflammatory factors like tumor necrosis factor alpha

(Jackowska et al., 2016; Patel et al., 2009). Because objective and self-reported sleep appear to reflect rather different psychological and physiological processes, there is a significant gap in the literature arising from the field's nearly exclusive reliance upon self-reported sleep data.

Current study

Smartphones have become ubiquitous in the lives of most young adults. While smartphones are regarded as highly desirable by most users, the observed link between nighttime smartphone use and diminished sleep may warrant societal concern (Twenge et al., 2017). Although previous research examining this relationship has typically relied upon self-reported smartphone use, the recent addition of screen-time tracking with the release of iOS11® now affords the opportunity to unobtrusively and objectively examine the relationship between nighttime smartphone use and sleep – and to do so using both objective and self-reported sleep measures. Such an examination is a primary goal of the present investigation. To the author's knowledge, this study is the first to examine the degree to which activation of Night Shift® on a smartphone – decreasing the amount of blue light emitted from the device – can improve sleep onset latency and sleep quantity in a naturalistic setting. Finally, in an early step towards addressing the potentially arousing nature of certain smartphone applications in the hours immediately preceding bedtime, this study explored whether or not certain categories of smartphone apps are more closely associated with aberrant sleep.

On the basis of the aforementioned review, the following hypotheses are of primary interest in the present investigation:

Hypotheses 1: Total objective smartphone use during the two hours prior to attempted sleep onset will be associated with increased sleep onset latency and reduced sleep quantity.

Hypotheses 2: Sleep onset latency and sleep quantity will be improved among participants while they are utilizing the Night Shift® feature.

Hypotheses 3: There will be a significant interaction between Night Shift® mode and total objective pre-bedtime smartphone use in the prediction of sleep onset latency and sleep quantity, respectively. Specifically, if there is a significant main effect of Night Shift® mode on improving sleep onset latency and quantity compared to the no Night Shift® mode control condition, this effect will be larger at greater levels of pre-bedtime smartphone use.

Additionally, this study entailed a set of exploratory analyses. This study examined for a potential effect Night Shift has on smartphone use in the two-hours prior to sleep onset as well as the degree to which the pre-bedtime use of different smartphone applications (i.e., the quantity of time different smartphone application categories are activated in the two hours before sleep onset) are differentially associated with sleep onset latency and total sleep quantity.

This study also explored the relationship between nighttime screen brightness settings on sleep onset latency and total sleep quantity.

Method

Participants

This study enrolled undergraduate students from introductory psychology courses at a large midwestern university between September 2019 and November 2019. Inclusion criteria required being between the ages of 18 and 25 years old at the start of the study, as well as the ownership and use of an iPhone® loaded with iOS11® or iOS12®. Due to the limitations of Android®, BlackBerry OS®, and Windows OS® individuals who owned smartphones utilizing these operating systems were not eligible to participate. Participants were also ineligible to participate if during the initial screening they reported the regular use of substances that can assist with falling asleep (e.g. melatonin, cannabinoid oils, anxiolytic or anti-depressant medications), depression symptomatology suggestive of clinical depression on the 9-item Patient Health Questionnaire (score equal to or greater than 14; Kroenke & Spitzer, 2002), or anxiety symptomatology suggestive of clinical anxiety on the 7-item Generalized Anxiety Disorder Assessment (score equal to or greater than 15; Spitzer, Kroenke, Williams, & Löwe, 2006).

Measures

The study incorporated an array of self-report measures of sleep onset latency and psychological distress, in addition to objective measures of both sleep quantity and smartphone use, as follows:

The 9-item Patient Health Questionnaire (PHQ-9; Kroenke & Spitzer, 2002) – A 9 - item questionnaire, scored on a 0 to 3 Likert-type scale, used to quantify depression symptomatology. Questions posed required participants to report the frequency they experienced depression symptom statements over the previous two weeks as, "not at all," "several days," "more than half the days," or "nearly every day." A score of 14 or greater is reported to optimize specificity and approximates prevalence rates of depressive disorders in line with epidemiological studies (Kroenke & Spitzer, 2002; Mitchell, Yadegarfar, Gill, & Stubbs, 2016).

The 7-item Generalized Anxiety Disorder Assessment (GAD-7; Spitzer et al., 2006) – A 7-item measure scored on a 4-point scale assessing anxiety symptomatology. Questions assess the frequency of feelings such as "feeling nervous, anxious or on edge." A score of 15 or greater is reported maximize specificity and results in a prevalence rate of Generalized Anxiety Disorder comparable to national averages (Spitzer et al., 2006).

Consensus Sleep Diary (CSD; Carney et al., 2012) – This sleep diary is a 17-item questionnaire designed to standardize self-reported sleep data. Questions include time the participant attempted to go to sleep, estimated time when they fell asleep, as well as time woken up. Sleep onset latency was extracted from the CSD for analyses. The CSD is completed each day and is strongly predictive of daily fatigue (Russell, Wearden, Fairclough, Emsley, & Kyle, 2016). It has also been successfully used to document changes in sleep over the course of a Cognitive Behavioral Treatment for Insomnia intervention (Maich, Lachowski, & Carney, 2018).

Objective sleep quantity was collected via a FitBit® Charge 3® actigraphy tracker (California, USA). While polysomnography is considered the most accurate measure for monitoring sleep, research has reported no significant differences between polysomnography and FitBit® actigraphy for total sleep time and sleep efficiency (Mantua, Gravel, & Spencer, 2016). Each FitBit® Charge 3® had its settings adjusted to limit screen illumination as well as had opaque tape placed over its face to prevent users from adjusting these settings.

Smartphone use was collected via the screen-time monitoring application that is pre-installed on iOS11® and iOS12® (Figure 1.). For each hour throughout the day, the screen-time monitoring application records the number of minutes the iPhone's® screen displayed content. This monitoring application provides further granularity by recording the number of minutes individual software applications (Apps) contributed to phone usage. These Apps were categorized based upon their assigned category in Apple's® App Store®. Category examples include: Social Networking, Games, Health and Fitness, and Productivity.

Screen brightness was collected using a LX1010B Digital Illuminance Meter (Dr. Meter, USA). Manufacture specifications report the LX1010B Digital Illuminance Meter's sensor has a peak sensitivity at 500nm and an illuminance accuracy of +/- 5%.

Reaction time – To obscure the nature of the study participants completed a reaction time experiment. Utilizing the Qualtrics® survey system, participants were instructed to tap on all areas of a picture containing a randomly selected color (Appendix C). The data from this task was not analyzed.

Procedure

Participants completed three parts over eight consecutive days: (a) an initial in-person consent, screening, Night Shift® condition randomization, and data collection session (Day 0); (b) a six-day at home period reporting period (Days 1 through 6); and (c) a final in-person data collection and debriefing session (Day 7).

On Day 0, following participant consent, researchers verified that the participant was in possession of an iPhone® with iOS11® or iOS12®. Participants were then screened utilizing the screener questionnaire (Appendix A), PHQ-9 (Kroenke & Spitzer, 2002), and GAD-7 (Spitzer et al., 2006).

Participants had their nighttime screen brightness settings measured. Utilizing a research laboratory with a single, dimmable fluorescent light, participants adjusted the room brightness to replicate the illumination intensity in their bedroom during the hour before sleep onset. Under this brightness condition, which was frequently set to have no illumination, participants adjusted the brightness setting on their smartphone screens to the level they use in the hour before sleep onset. Two samples of screen brightness, using the native "settings" screen as the screen image, were taken under these conditions by the LX1010B Digital Illuminance Meter (Dr. Meter, USA).

Participants randomized to the condition of activating Night Shift® set the mode to activate at 9:00 pm and to end at 5:00 am, with the color temperature set to the high end of the range of possibilities. This range was chosen to maximize the attenuation of the blue light emitted from the smartphones. Participants randomized to the Night Shift® off condition were required to deactivate this setting on their phone. Participants were then provided a waterproof actigraphy monitor (FitBit® Charge 3®; California, USA) and instructed to wear the device for the duration of the study. In an attempt to obscure the study hypotheses (and thereby to minimize the influence of any demand characteristics), participants were informed that a purpose of the study was to examine the influence of Night Shift® mode on reaction times measured through a daily online survey. To provide the participants an opportunity to have questions answered and to reinforce the importance of completing the daily Qualtrics® surveys, in the presence of a researcher, participants were walked through the survey they would receive on a daily basis until their follow-up visit.

Over the six-day at home reporting period, participants were texted a link to a Qualtrics® survey at 9:00 AM. These Qualtrics® surveys required participants to report if their sleep the previous night was significantly different from their usual sleep patterns for that day of the week or if they consumed any substances the previous night known to affect sleep (Appendix B). Participants also completed the CSD (Carney et al., 2012), a reaction time test (Appendix C), and uploaded screen captures of their Night Shift® settings for condition verification (Figure 2), as well as their screen-time use for the two hours before falling asleep (
Figure 1).

On Day 7 participants returned to the laboratory where they completed several additional questionnaires, had additional screen time information collected from their phones, and were debriefed about the purpose of the study.

Statistical Analyses

Analyses were conducted using R software (R Core Team, 2020). Data from participants who withdrew during the study were removed from analyses. Data points were also excluded from the analyses if a specific night was reported to be inconsistent from regular sleep habits for that day of the week, or if participants reported utilizing substances known to affect sleep processes. Unless noted otherwise, all models were performed using multilevel regression with random intercept and fixed slope parameters. Diagnostic plots of residuals were visually examined to confirm normal distribution of data. Parameters were estimated using maximum likelihood, and parametric bootstrapping was used to calculate 95% confidence intervals. Estimated parameters were considered statistically significant if confidence intervals excluded zero.

To examine Hypothesis 1, total objective smartphone use two hours prior to sleep onset is positively related to sleep onset latency and sleep quantity, two separate models were examined. The predictor variable, "smartphone use" was the sum of the screen-time reported by the iPhone® in the two hours prior to the time participants reported falling asleep on the CSD (Carney et al., 2012).

Hypothesis 2, self-reported sleep onset latency, and separately, sleep quantity will be improved in the Night Shift® On condition of the study, was tested by two separate multilevel models with the predictor variable of Night Shift® condition.

Hypothesis 3, the potential interaction between smartphone use and Night Shift® condition on sleep onset latency and sleep quantity was tested using two models including the predictors of smartphone use in the two hours prior to sleep, Night Shift® condition, and the interaction between these predictors.

This study included several exploratory analyses. Examining the potential of Night Shift® mode to decrease smartphone use in the two hours prior to sleep onset was tested using with the predictor of Night Shift® condition on smartphone use. Two separate models were analyzed to explore the degree to which different smartphone applications in the two hours leading up to falling asleep were differentially correlated with sleep onset latency and total sleep quantity. Predictors included the minutes of use from each of the categories of applications used by participants in the 2 hours prior to sleep onset (smartphone app categories were extracted from the Apple® App Store® in May 2020).

Additional exploratory analyses examined the relationship between nighttime screen brightness settings, as well as a potential interaction between Night Shift® condition and screen brightness settings, on sleep onset latency and total sleep quantity.

A final set of exploratory analyses examined the a priori hypotheses utilizing the complete data set which included sleep diaries reported to significantly differ from regular sleep habits or involved the use of substances known to affect sleep processes. Specifically, an examination of the potential interaction between smartphone use in the 2 hours before sleep onset and Night Shift® condition on sleep onset latency and sleep quantity while controlling for the significant difference between regular sleep patterns and/or use of substances known to affect sleep processes.

Results

Of the 104 participants screened for eligibility, 13 were excluded based on their response to the screening questionnaire (Appendix A), the PHQ-9, or GAD-7 (see Figure 3 for a comprehensive participant flow diagram). Among the resulting 91 eligible participants, 67 (74%) identified both their gender and biological sex as female, and the remainder identified as male (n = 24). Five participants withdrew during the study period, with four declining to cite a reason and one reporting withdrawal from their introductory psychology course. Accordingly, the complete study sample included 86 participants.

Sample characteristics are provided in Table *1*. There was a significant difference in the randomization of male and female participants between the Night Shift® conditions, X^2 (1, N = 86) = 6.8, p = .009. Post hoc analysis revealed a greater ratio of female to male participants in the Night Shift® On condition. Because preliminary multilevel regressions revealed no significant main effect of sex on the study's primary dependent variables of either sleep onset latency or total sleep quantity (p > .05), sex was not included as a covariate in subsequent analyses.

Student's *t*-tests revealed no statistically significant differences between experimental conditions regarding mean participant age, initial PHQ-9 nor GAD-7 scores, nor pre-bedtime screen brightness settings. Additional chi-square tests also revealed no significant differences between groups with respect to pre-study use of Night Shift® mode.

Participants completed an average of 95.3% (*SD* = 3.8%) of the study-assigned daily sleep diaries (N = 516). All participants reported on at least one night of sleep for both the weekday (Sunday thru Tuesday) and weekend (Thursday thru Saturday). However, approximately 35% (n = 181[1]) of the daily sleep diary entries were flagged by participants as aberrant for one of two possible reasons: either (a) having significant variance from their regular sleep patterns, or (b) the pre-sleep use of substances known to affect sleep processes. (The specific daily sleep diary queries are included in Appendix B). There were no significant differences in the rate of flagged sleep diary entries across the different days of the week, X^2 (5, N = 492) = 2.76, p = .737. An additional 4.7% (n = 24) of the sleep diary entries failed to include a response to the aforementioned queries, so these were also excluded from study

[1] Sleep reported to be significantly different or following the use of substances known to affect sleep processes was an average of 45 minutes shorter in total sleep quantity, 3 minutes greater in sleep onset latency, and corresponded to an average of 6 minutes greater total phone usage in the 2 hours prior to sleep onset compared to the analyzed dataset.

analyses, resulting in a primary data set of 311 sleep diaries for 86 participants (Table *2*). Due to the substantial loss of statistical power through removal of these data points, additional exploratory analyses were also performed utilizing the entire data set (N = 516), i.e., including the many sleep diary entries flagged as being potentially non-representative.

Preliminary multilevel regression analyses revealed significant differences between weekday (Sunday thru Tuesday) and weekend (Thursday thru Saturday) sleep onset latency (means of 16 minutes and 20 minutes respectively, $p < .01$) and total sleep quantity (means of 421 minutes and 408 minutes respectively, $p = .02$). Accordingly, primary study analyses were run separately for the two different time frames (weekday versus weekend).

Overall, across both weekdays and weekends, there were no significant main effects of total duration of smartphone usage (in the 2 hours before sleep onset) or of Night Shift® condition on either sleep onset latency or total sleep quantity (Table 3 and Table 4 respectively). Further, the interaction of total smartphone usage and Nigh Shift® condition did not significantly predict either sleep onset latency or total sleep quantity. An exploratory multilevel regression also failed to detected a significant effect of Night Shift® condition on the total time devoted to smartphone usage in the two hours prior to sleep onset (Table 5).

Exploratory multilevel regressions examining the relationship between the use of smartphone applications from distinct categories and sleep processes were conducted utilizing a Bonferroni correction for multiple comparisons (Table *6* and Table *7*), which resulted in an adjustment of significant alpha level to a conservative value of 0.003. The use of entertainment applications (e.g. Netflix®) in the two hours before sleep onset was significantly positively associated with greater sleep onset latency during the weekday, $\beta = 0.45$, 95% CI [0.21, 0.72], p = <.001, and usage of music applications (e.g. Spotify®) during the same 2-hour time frame were positively related to greater sleep onset latency during the weekend, β = 0.78, 95% CI [0.37, 1.22], p = <.001. These exploratory results suggest that utilizing smartphones to watch shows and listen to music, during weeknights and weekend nights, respectively, may be related to increased difficulty falling asleep. There were no significant observed relationships between any smartphone application category and total sleep quantity (Table *8*).

As reported in Table *9*, exploratory multilevel regressions also revealed a significant negative relationship between nighttime screen brightness settings and total weekend sleep quantity, β = -0.40, 95% CI [-0.71, 0.03], p = .044, with brighter smartphone settings corresponding to decreased total sleep quantity. However, the relationship between screen brightness settings and total sleep quantity was not statistically significant during the weekday, β = -0.26, 95% CI [-0.56 0.10], p > .05.

Exploratory analyses maximizing statistical power (Table *10* and Table *11*) - utilizing the entire dataset (including the many sleep diary entries flagged for being potentially unrepresentative) and combining weekday and weekend entries - revealed a significant interaction between pre-sleep smartphone use (in the 2 hours before sleep onset) and Night Shift® condition in the prediction of sleep onset latency, β = -0.39, 95% CI [-0.76, -0.004], p < .050. Specifically, increased smartphone use in the two hours before sleep onset was associated with increased sleep onset latency for participants in the Night Shift® off condition, whereas there was generally no relationship between smartphone use and sleep onset latency in the Night Shift® on condition (Figure *4*). There were no main effects nor interaction effect between smartphone use and Night Shift® condition in the prediction of total sleep quantity (Table *11*).

Discussion

The growing magnitude of sleep deprivation reported by young Americans is worrisome, and it is hypothesized to be partly attributable to the increased use of electronic devices immediately prior to attempted sleep onset (Hale & Guan, 2015). Some researchers have identified smartphones as particularly problematic in this regard (Christensen et al., 2016). Smartphone use may carry the potential to impair sleep by increasing the user's blue light exposure, spiking their physiological and psychological arousal and directly displacing sleep time (LeBourgeois et al., 2017). Accordingly, the primary goals of this study were to elucidate the relationship between smartphone use and salient sleep processes, as well as to examine the potential effect of reducing blue light exposure through activation of the Night Shift® mode on participants' phones.

Study participants used their smartphones for an average of 44 minutes in the two hours immediately before attempted sleep. Despite this substantial level of nighttime smartphone use, and in contrast with the study hypotheses, the primary study analyses do not support a relationship between objectively recorded smartphone use and either sleep onset latency or total sleep quantity. This finding suggests there may not exist any simple linear relationship between nighttime smartphone use and subsequent sleep processes. Importantly, smartphones allow individuals to access a multitude of possible programs and applications, and a more granular review of the apps utilized by the study participants before sleep onset revealed regular engagement with a range of different app categories – some such as texting, that have been linked to increased arousal (Lin & Peper, 2009), and others (e.g., meditation apps) that might actually facilitate sleep onset (Koffel et al., 2018). It is therefore possible that a more fine-grained approach to measuring smartphone use at the app level will be necessary in order to reliably assess the device's impact on each specific user's sleep.

A large body of research has reported that blue light exposure disrupts melatonin release, with downstream effects on sleep processes (Cajochen et al., 2011; Lazzerini Ospri et al., 2017). Nevertheless, the primary analyses yielded no evidence of a significant effect of activating Night Shift® mode, and thereby reducing blue light, on either sleep onset latency nor sleep quantity. Previous research has often examined the effect of blue light on sleep under controlled laboratory settings (Mortazavi et al., 2018) or by utilizing blue-light filtering glasses that attenuate all blue light sources in the hours before sleep onset (Shechter et al., 2018). Such rigorous experimental designs likely induced stronger effects than this study's more modest blue-light manipulation, which was limited to attenuating only the blue light output from smartphones. Compared to previous laboratory studies which manipulated experimental sources of blue light, the attenuation of the weaker blue light luminance from smartphone screens may have resulted in an effect size of insufficient magnitude to be discernable by this study's design.

Also contrary to study hypotheses, primary analyses did not reveal a significant interaction between use of Night Shift® mode and pre-sleep smartphone use on either sleep onset latency or sleep quantity. However, with about 40% of sleep diary entries excluded from the main analysis due to self-reported usual sleep patterns or the consumption of a substance known to affect sleep processes, this study was potentially underpowered to detect significant interaction effects. To address this limitation, exploratory analyses of Night Shift® effects were also conducted utilizing the entire sleep diary dataset (combining the entries reported to conform to regular sleep habits together with those reported to be significantly different or following the consumption of substances known to affect sleep processes). In congruence with *a priori* study hypotheses, these more powerful analyses of sleep onset latency revealed both a significant main effect of smartphone use and a significant interaction between smartphone use and Night Shift® condition. Participants in the Night Shift® Off condition – i.e., those exposed to greater intensity of blue light – evidenced greater sleep onset latency in tandem with increased pre-sleep smartphone use, while those in the Night Shift® On condition experienced no such effect (see Figure *4*). These findings are consistent with the emerging body of research implicating pre-sleep blue light exposure as a source of sleep disruption (Cajochen et al., 2011). Further, they suggest that reducing the blue light emitted from smartphones in the hours leading up to sleep may potentially attenuate the devices' negative effects, at least with respect to onset latency. If this exploratory finding is validated through robust replication, it would support the widespread adoption of Night Shift® mode, or its equivalent, across electronic devices in the hours leading up to bed as a simple step to improve sleep efficiency.

One potential concern over mass implementation of Night Shift® mode is the adverse effect it could have on user experience. Specifically, the reduction of blue light can cause images to lose their color accuracy, which could conceivably deter overall smartphone engagement. However, this study's preliminary exploration of the relationship between the use of Night Shift® mode and overall duration of smartphone use before sleep onset revealed no significant association. While Night Shift® mode did not have a significant effect on the overall duration of smartphone use, it remains unknown if the subjective user experience during the time spent with their smartphones declined under Night Shift® activation, or if Night Shift® mode perhaps altered the types of applications with which users engaged.

Because previous studies have reported differential patterns of arousal and affect with the use of different apps, this study also explored the relationship between sleep processes and the pre-sleep use of smartphone application categories. For context, the 1.8 million apps available for download in the Apple® App Store® (Clement, 2020, May 4) are each classified according to 24 distinct categories designated by Apple®. These range from entertainment apps (e.g. Netflix®) to productivity apps (e.g. Google Spreadsheets®), to lifestyle (dating) apps such as Tinder® and Grindr®. Of the 24 designated app categories, 17 were utilized by study participants (in aggregate) in the 2 hours before bed (Table 6). Exploratory analyses revealed that pre-sleep use of entertainment and music apps was significantly associated with an increase in sleep onset latency. It is important, of course, to highlight the unknown directionality of these observed associations. Individuals regularly listen to music or watch shows to assist with falling asleep (Tartan et al., 2018), so anticipated onset insomnia could conceivably prompt the greater use of music and entertainment apps. Conversely, the use of such stimulating apps could also carry the potential to interfere with sleep onset. It remains to future research to clarify, in greater detail, the ways that specific smartphone apps may impair or facilitate subsequent sleep processes.

It is also notable that none of the other categories of smartphone apps were significantly related to sleep onset latency or total sleep quantity. For example, in contrast with previous reports that playing video games on consoles increases sleep onset latency (Weaver, Gradisar, Dohnt, Lovato, & Douglas, 2010), there was no significant relationship observed between nighttime gaming on smartphones and sleep. Excluding music and entertainment app categories, the effect on sleep of the other apps might have been small enough to avoid detection in the exploratory analyses. It is also possible that the smartphone medium results in novel relationships between sleep and these previously studied screen-based behaviors. Software developed for video game consoles, for example, may be significantly different from that developed for smartphones in multiple domains, from user interface thru monetization, resulting in potentially different effects on sleep (Rutz, Aravindakshan, & Rubel, 2019).

Because Cajochen, Zeitzer, Czeisler, and Dijk (2000) previously reported a dose-response relationship between light intensity and sleep processes, this study also explored the relationship between participants' sleep and the pre-sleep brightness levels on their smartphones. Although smartphone screen brightness was not manipulated within this study paradigm, each participant's default screen brightness was measured in the laboratory under simulated nighttime conditions. As expected, brighter nighttime smartphone settings were significantly associated with reduced objectively measured sleep quantity. This exploratory finding is the first known report of the potential impact of nighttime smartphone illuminance on objectively measured sleep quantity, and it supports the recommendation of reducing smartphone illumination as a way to improve sleep.

Limitations

Despite the study's strong daily diary completion rate (95.3%), its findings are limited in several important ways. The relatively high proportion (35.0%) of sleep diary entries flagged as inconsistent with participants' normal sleep habits – for example, due to an unusually late bedtime – led to substantially reduced statistical power to test the study's main *a priori* hypotheses. It has been well established that early adulthood encompasses numerous social and biological developments that significantly contribute to inconsistent sleep patterns (Owens, Christian, & Polivka, 2017). These distinctive characteristics of a college-aged sample not only limit the study's generalizability to other populations, but also highlight the need to accurately contextualize results to account for the characteristic qualities of this specific population.

Another notable study limitation is the lack of objectively recorded sleep onset latency. The advancement in technologies afforded this study the ability to capture objectively recorded total sleep quantity (utilizing Fitbits®) and smartphone use (using the screen time tracking app native to iOS®). While these data collection methods provide an important step forward in reducing the error related to self-report data (Andrews et al., 2015), there is not yet an easily accessible method to record sleep onset latency objectively. It is certainly possible to combine self-reported bedtime with objective measures of sleep onset – thereby yielding a hybridized sleep onset latency measure – but such an approach is still far from ideal, and it is one without any published validation to date. It is also worth noting that self-report and objectively recorded sleep data, respectively, have distinctly different relationships to physiological and affective outcomes. As reviewed by Jackowska et al. (2016), self-report sleep data are differentially predictive of affective responses, such as feeling "refreshed," while objective sleep data are more predictive of physiological states, such as circulating cortisol levels. It remains unknown if similar differences in predictive outcomes might exist between self-reported and objectively recorded sleep onset latency measures.

The findings of this study are also limited by the fact that the smartphone represents only one of numerous electronic devices available to college students in a naturalistic setting (Hysing et al., 2015). This caveat is particularly applicable when it comes to examining the effects of blue light attenuation on sleep processes, as well as the impact of pre-sleep media consumption. Moreover, Liese, Exelmans, Gradisar, and Van den Bulck (2018) found that people frequently utilize multiple different devices in the hours before sleep. A college student may, for example, write a class paper on their laptop while simultaneously streaming a show on a tablet and intermittently texting with friends on their phone. Disentangling the unique effects of each screen (and each application) in such real-world multi-device contexts clearly poses formidable research challenges.

Future directions

In light of the burgeoning body of research linking poor sleep to negative health outcomes (Javaheri & Redline, 2017), and the high prevalence of sleep deprivation among young adults (Owens et al., 2017) and other US demographic subgroups (Liu et al., 2016), finding ways to improve sleep processes is an important priority for clinical researchers. And given the ubiquity of nighttime smartphone use, clarifying the devices' potential adverse impact on sleep – and steps to ameliorate it – represents an obvious investigational focus. Results of this study provide preliminary evidence that some application categories, namely music and entertainment, are significantly related to negative sleep outcomes. But due to the exploratory nature of these findings, they are in need of replication and extension – for example, an examination of the differential potential of various genres of music and shows to differentially affect sleep.

Subsequent research could also examine strategies to decrease blue light sources more broadly in the hours before bed. In just the seven months since data collection for the present study began, additional electronic device manufacturers and software developers have expanded the devices on which Night Shift®, or its equivalent, can be scheduled to automatically activate. These devices now include not only smartphones and tablets, but also TVs, laptops and desktops as well. Increasing the range of devices that reduce blue light emissions in the hours before bed, and even experimenting with the use of blue-light-free light bulbs, could increase the potential to achieve sleep improvements equivalent to those associated with the use of amber-tinted glasses (Perez Algorta et al., 2018; Shechter et al., 2018).

Additionally, with the increasing implementation of negative contrast polarity settings – commonly referred to as “dark mode” – into operating systems and applications, it will be important to investigate the effects of this functionality on sleep. Activation of this setting turns dark regions of an image light, and vice versa. This process results in an overall reduction in screen illuminance and thereby potentially improved sleep processes. Early research in this field has often focused on image and word detection, and while negative contrast polarity settings decrease overall light emitted from devices, there is emerging evidence that they also result in increased effort expenditure to read text (Buchner & Baumgartner, 2007; Dobres, Chahine, & Reimer, 2017). It thus remains unknown if the resulting increase in effort and arousal from negative contrast polarity settings negate the potential benefits decreased illumination would have on sleep.

Conclusion

Although primary study analyses revealed no significant main effects or interaction between Night Shift® mode and pre-sleep smartphone use on either sleep onset latency or total sleep quantity, exploratory results suggest that the use of Night Shift® mode might still confer some benefits towards improving sleep onset latency. These exploratory findings support future research into the potential improvements of sleep through nighttime attenuation of blue light from electronic devices. Importantly, if decreasing nighttime blue-light emissions from electronic devices is found to improve sleep processes, this intervention has the potential to improve the sleep of many, especially considering the ease with which this functionality can be implemented across a range of devices,

In congruence with findings by Cajochen et al. (2000), the results of this study also support a possible dose-response relationship between nighttime screen brightness and impaired sleep processes. Specifically, greater nighttime screen brightness settings were related to longer periods of sleep onset latency. It is important to note that smartphones are not the only light source in the hours preceding sleep, and the field would benefit from more sophisticated research designs that can accurately measure, and unobtrusively manipulate, total nighttime light exposure.

This study has also provided a preliminary examination of the relationship between smartphone app categories and the relationship they have with sleep. Aligned with previous research, this study suggests that nighttime smartphone consumption of both music and media may be related to impaired sleep. However, despite previous research suggesting additional app categories, such as gaming, would likely be related to sleep, no other significant relationships were observed. But with the continuous improvements in data gathering tools, which could allow researchers to contextualize smartphone use within the larger nighttime electronic device ecosystem, future research has the potential to further elucidate the relationships between specific device usage and sleep processes, ultimately leading to more targeted recommendations to improve sleep.

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Table 1

Participant characteristics

	Overall (N = 86)	**Condition On** (n = 44)	**Condition Off** (n = 42)
Gender *n* (%)			
Female	64 (74)	38 (86)	26 (62)
Male	22 (26)	6 (14)	16 (38)
Age in years *M* (*SD*)	18.4 (0.9)	18.2 (0.6)	18.4 (1.2)
Race *n* (%)			
Caucasian	63 (73.2)	35 (80.0)	28 (66.7)
African American	6 (7.0)	4 (9.1)	2 (4.8)
Asian	11 (12.8)	2 (4.5)	9 (21.4)
Multiple Races	5 (5.8)	2 (4.5)	3 (7.1)
Decline to answer	1 (1.1)	1 (2.3)	0 (0)
Aware of Night Shift *n* (%)	60 (70)	30 (68)	30 (71)
Using Night Shift *n* (%)	35 (41)	19 (43)	16 (38)
Initial PHQ-9 *M* (*SD*)	3.6 (2.9)	3.6 (2.9)	3.6 (3.1)
Initial GAD-7 *M* (*SD*)	3.7 (3.5)	3.5 (3.2)	4.0 (3.8)

Note. Condition On – Experimental Night Shift Condition On; Condition Off – Experimental Night Shift Condition Off; PHQ-9 – Patient Health Questionnaire 9 item; GAD-7 – Generalized Anxiety Disorder Assessment 7 item.

Table 2

Study Data

	Overall (*N* = 86)	Condition On (*n* = 44)	Condition Off (*n* = 42)
Weekdays *M* (*SD*)			
Total sleep in mins	421 (80)	422 (63)	421 (96)
Sleep onset latency in mins	16.3 (18.3)	15.6 (13.2)	17.0 (22.6)
Phone usage 0-1h in mins	21.0 (16.9)	21.4 (18.0)	21.0 (15.7)
Phone usage 1-2h in mins	25.3 (18.1)	23.6 (17.5)	27.2 (18.6)
Weekend *M* (*SD*)			
Total sleep in mins	408 (76)	416 (78)	400 (74)
Sleep onset latency in mins	20.0 (23.0)	20.9 (25.7)	19.1 (20.1)
Phone usage 0-1h in mins	20.5 (16.1)	21.0 (16.1)	20.0 (16.2)
Phone usage 1-2h in mins	22.3 (16.1)	21.8 (16.7)	22.8 (15.7)
Screen Brightness in Lux *M* (*SD*)	42.7 (74.0)	42.4 (67.1)	44.6 (70.7)
PHQ-9 *M* (*SD*)			
Initial Session	3.6 (2.9)	3.6 (2.9)	3.6 (3.1)
Follow-up Session	3.4 (3.6)	3.1 (2.7)	3.7 (4.4)
GAD-7 *M* (*SD*)			
Initial Session	3.7 (3.5)	3.5 (3.2)	4.0 (3.8)
Follow-up Session	5.2 (4.4)	4.4 (3.1)	5.9 (5.4)

Note. Condition On – Experimental Night Shift Condition On; Condition Off – Experimental Night Shift Condition Off; Weekdays – Sunday thru Tuesday nights; Weekends – Thursday thru Saturday nights; Total sleep – as recorded by Fitbit Charge 3; Sleep onset latency – self-reported data derived from the Consensus Sleep Diary; Phone usage 0-1h and 0-2h respectively– Screen-time tracking app recorded phone use 0 to 60 minutes and 60 to 120 minutes before self-reported sleep onset respectively; PHQ-9 – Patient Health Questionnaire 9 item; GAD-7 – Generalized Anxiety Disorder Assessment 7 item.

Table 3

Regression Results for Sleep Onset Latency

Variable	Weekday			Weekend		
	***β* (SE)**	**95% CI**	***p***	***β* (SE)**	**95% CI**	***p***
Intercept	10.77 (4.65)	[1.69, 19.82]	.022*	17.94 (5.36)	[8.03, 29.44]	.001*
2h Phone Use	0.13 (0.08)	[-0.01, 0.28]	.943	0.01 (.09)	[-0.16, 0.18]	.942
Nightshift	3.14 (6.09)	[-9.04, 15.55]	.607	6.10 (7.78)	[-8.39, 20.67]	.434
Level 2 Interactions						
2h Phone Use*Nightshift	-0.09 (.10)	[-0.29, 0.10]	.386	-0.07 (0.13)	[-0.35, 0.17]	.583

Note. Coefficient values represent the effect on unstandardized sleep onset latency reported on the Consensus Sleep Diary. CI = Confidence interval; 2h Phone Use = Minutes of phone use in the 2 hours before sleep onset; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 4

Regression Results for Sleep Quantity

Variable	**Weekday**			**Weekend**		
	***β* (SE)**	**95% CI**	***p***	***β* (SE)**	**95% CI**	***p***
Intercept	486.3 (25.8)	[429.4, 536.8]	<.001*	460.6 (23.2)	[405.5, 505.9]	<.001*
2h Phone Use	-0.03 (0.42)	[-0.97, 0.71]	.934	-0.05 (0.41)	[-1.01. 0.91]	.904
Nightshift	30.43 (34.09)	[-42.6, 110.3]	.374	5.66 (33.43)	[-63.1, 106.9]	.866
Level 2 Interactions						
2h Phone Use*Nightshift	-0.53 (0.55)	[-1.69, 0.72]	.340	0.18 (0.62)	[-1.26, 1.33]	.775

Note. Coefficient values represent the effect on unstandardized sleep quantity as measured by the Fitbit® Charge 3®. CI = Confidence interval; 2h Phone Use = Minutes of phone use in the 2 hours before sleep onset; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 5

Regression Results for Smartphone Use

Variable	**Weekday**			**Weekend**		
	β (SE)	**95% CI**	***p***	**β (SE)**	**95% CI**	***p***
Intercept	51.53 (3.60)	[44.06, 59.33]	<.001*	46.03 (3.82)	[38.22, 53.73]	<.001*
Nightshift	-1.67 (5.00)	[-11.99, 8.60]	.739	-1.09 (5.36)	[-12.77, 8.41]	.839

Note. Coefficient values represent the effect on unstandardized smartphone use in the 2 hours before sleep onset. CI = Confidence interval; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 6

Regression Results for Sleep Onset Latency

Variable	**Weekday**			**Weekend**		
	β (SE)	**95% CI**	***p***	**β (SE)**	**95% CI**	***p***
Intercept	14.48 (2.22)	[10.41, 18.68]	<.001*	19.5 (2.71)	[13.87, 25.00]	<.001*
Music	0.06 (0.17)	[-0.26, 0.39]	.705	0.78 (0.22)	[0.37, 1.22]	<.001*
Photos and Videos	0.02 (0.13)	[-0.22, 0.29]	.853	0.01 (0.14)	[-0.29, 0.29]	.968
Social Networking	0.06 (0.22)	[-0.41, 0.49]	.799	-0.43 (0.26)	[-0.97, 0.08]	.096
Entertainment	0.45 (0.13)	[0.21, 0.72]	<.001*	0.70 (0.29)	[0.15, 1.38]	.020
Education	12.41 (7.06)	[-0.86, 26.50]	.081	3.75 (5.37)	[-6.85, 14.56]	.486
Finance	-6.12 (7.88)	[-20.44, 9.48]	.439	-2.22 (3.27)	[-8.22, 4.83]	.499
Health	-0.20 (0.54)	[-1.14, 0.89]	.706	-0.52 (0.96)	[-2.41, 1.34]	.591
Utilities	0.04 (0.25)	[-0.43, 0.54]	.867	0.17 (0.32)	[-0.51, 0.82]	.604
News	-0.09 (0.46)	[-1.04, 0.86]	.838	-0.06 (0.96)	[-1.87, 1.92]	.945
Shopping	-0.23 (2.95)	[-5.54, 5.43]	.939	-1.99 (3.47)	[-8.40, 4.94]	.568
Travel	-1.43 (0.85)	[-3.02, 0.15]	.094	-7.29 (2.95)	[-13.07, -1.04]	.016
Lifestyle	-0.44 (0.51)	[-1.46, 0.55]	.389	-0.16 (1.11)	[-2.12, 2.43]	.884
Sports	0.01 (17.09)	[-35.59, 34.11]	.999	-0.75 (9.50)	[-19.24, 19.45]	.937
Weather	-7.53 (6.51)	[-22.33, 5.49]	.249	0.14 (2.13)	[-3.91, 4.56]	.946
Games	0.17 (0.28)	[-0.32, 0.77]	.545	-0.55 (0.60)	[-1.70, 0.55]	.362
Reference	0.43 (0.65)	[-0.89, 1.68]	.506	-0.23 (0.32)	[-0.82, 0.47]	.475
Productivity	-0.21 (2.98)	[-6.12, 5.32]	.942	-0.58 (1.54)	[-3.58, 2.32]	.707

Note. Coefficient values represent the effect on unstandardized sleep onset latency reported on the Consensus Sleep Diary; CI = Confidence interval.
*Statistically significant at $p < .003$.

Table 7

Regression Results for Sleep Quantity

Variable	Weekday			Weekend		
	β (SE)	**95% CI**	***p***	**β (SE)**	**95% CI**	***p***
Intercept	428.45 (9.83)	[409.48, 449.78]	<.001*	407.17 (9.19)	[390.46, 424.67]	<.001*
Music	0.95 (0.82)	[-0.76, 2.59]	.252	0.21 (1.02)	[-1.88, 2.37]	.836
Photos and Videos	-0.36 (0.58)	[-1.54, 0.84]	.534	-0.96 (0.57)	[-2.10, 0.13]	.096
Social Networking	-0.68 (1.04)	[-2.91, 1.25]	.515	0.85 (1.12)	[-1.63, 3.03]	.449
Entertainment	-0.48 (0.58)	[-1.64, 0.68]	.406	1.48 (1.32)	[-1.23, 4.22]	.264
Education	18.72 (33.44)	[-51.60, 85.35]	.576	-26.85 (24.14)	[-82.57, 20.05]	.268
Finance	34.93 (37.91)	[-38.50, 108.24]	.358	-3.89 (13.78)	[-29.37, 21.39]	.778
Health	-1.61 (2.51)	[-6.74, 3.86]	.523	-2.44 (3.35)	[-9.86, 4.41]	.467
Utilities	-1.50 (1.16)	[-3.79, 0.81]	.200	1.62 (1.17)	[-0.77, 3.89]	.168
News	-1.81 (2.27)	[-6.65, 2.79]	.427	-1.59 (3.78)	[-9.44, 5.94]	.675
Shopping	-6.52 (14.04)	[-34.57, 19.63]	.643	-3.38 (20.50)	[-45.68, 41.41]	.869
Travel	-8.17 (4.07)	[-15.79, -0.44]	.047	13.64 (13.82)	[-11.39, 41.65]	.326
Lifestyle	1.93 (2.38)	[-3.08, 6.29]	.420	13.46 (6.65)	[0.22, 27.60]	.045
Sports	-0.53 (81.36)	[-175.40, 167.61]	.995	2.54 (42.75)	[-91.16, 87.34]	.953
Weather	42.08 (30.32)	[-18.11, 103.59]	.167	2.27 (9.54)	[-16.09, 20.77]	.813
Games	1.56 (1.36)	[-1.00, 4.44]	.253	-3.17 (2.68)	[-8.96, 2.65]	.239
Reference	3.70 (2.87)	[-2.33, 9.35]	.201	1.10 (1.33)	[-1.86, 3.60]	.412
Productivity	-12.52 (14.13)	[-37.57, 14.02]	.377	10.81 (5.36)	[0.97, 21.33]	.046

Note. Coefficient values represent the effect on unstandardized sleep quantity as measured by the Fitbit® Charge 3®. CI = Confidence interval.
*Statistically significant at $p < .003$.

Table 8

Regression Results for Sleep Onset Latency

Variable	**Weekday**			**Weekend**		
	***β* (SE)**	**95% CI**	***p***	***β* (SE)**	**95% CI**	***p***
Intercept	18.60 (2.94)	[12.6, 25.3]	<.001*	19.79 (4.05)	[11.73, 25.95]	<.001*
Lux	-0.03 (0.04)	[-0.13, 0.04]	.399	-0.06 (0.07)	[-0.18, 0.06]	.367
Nightshift	-3.20 (4.11)	[-11.49, 4.42]	.439	-0.38 (5.71)	[-10.15, 10.22]	.948
Level 2 Interaction						
Lux*Nightshift	0.05 (0.05)	[-0.05, 0.17]	.378	0.10 (0.09)	[-0.05, 0.26]	.241

Note. Coefficient values represent the effect on unstandardized sleep onset latency reported on the Consensus Sleep Diary. CI = Confidence interval; Lux = Screen brightness setting at bedtime measured at the phone screen; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 9

Regression Results for Sleep Quantity

Variable	Weekday			Weekend		
	***β* (SE)**	**95% CI**	***p***	***β* (SE)**	**95% CI**	***p***
Intercept	431.66 (12.3)	[407.9, 455.9]	<.001*	412.86 (11.88)	[393.3, 434.2]	<.001*
Lux	-0.26 (0.15)	[-0.56, 0.10]	.093	-0.40 (0.20)	[-0.71, -0.03]	.044*
Nightshift	-8.19 (17.44)	[-46.50, 18.48]	.640	10.06 (17.05)	[-21.60, 45.52]	.557
Level 2 Interactions						
Lux*Nightshift	0.24 (0.22)	[-0.27, 0.68]	.283	0.25 (0.27)	[-0.29, 0.81]	.365

Note. Coefficient values represent the effect on unstandardized sleep quantity as measured by the Fitbit® Charge 3®. CI = Confidence interval; Lux = Screen brightness setting at bedtime measured at the phone screen; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 10

Regression Results for Sleep Onset Latency

Variable	***β* (SE)**	**95% CI**	***p***
Intercept	19.43 (4.09)	[10.82, 26.94]	<.001*
Regular Sleep	-2.35 (2.02)	[-5.95, 1.45]	.246
2h Phone Use	0.36 (0.15)	[0.05, 0.67]	.019*
Nightshift	5.46 (3.41)	[-1.35, 12.49]	.113
Level 2 Interaction			
2h Phone Use *Nightshift	-0.39 (0.20)	[-0.76, -0.004]	<.050*

Note. Coefficient values represent the effect on unstandardized sleep onset latency reported on the Consensus Sleep Diary. CI = Confidence interval; Regular Sleep = if sleep was reported as significantly different or included the use of substances known to affect sleep processes; Lux = Screen brightness setting at bedtime measured at the phone screen; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

Table 11

Regression Results for Sleep Quantity

Variable	***β* (SE)**	**95% CI**	***p***
Intercept	331.4 (16.0)	[299.7, 364.4]	<.001*
Regular Sleep	39.2 (8.25)	[21.81, 54.30]	<.001*
2h Phone Use	-0.08 (0.58)	[-1.25, 1.21]	.887
Nightshift	4.02 (12.12)	[-17.72, 28.03]	.741
Level 2 Interaction			
2h Phone Use *Nightshift	0.34 (0.76)	[-1.06, 1.71]	.654

Note. Coefficient values represent the effect on unstandardized sleep quantity as measured by the Fitbit® Charge 3®. CI = Confidence interval; Regular Sleep = if sleep was reported as significantly different or included the use of substances known to affect sleep processes; Lux = Screen brightness setting at bedtime measured at the phone screen; Nightshift = Nightshift Condition.
*Statistically significant at $p < .05$.

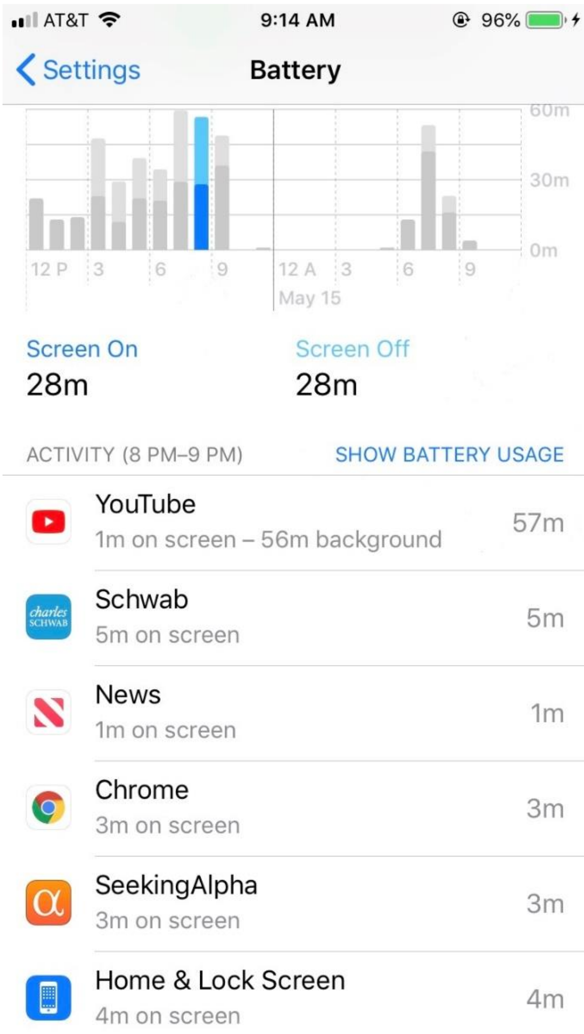

Figure 1. Example screen-time use image

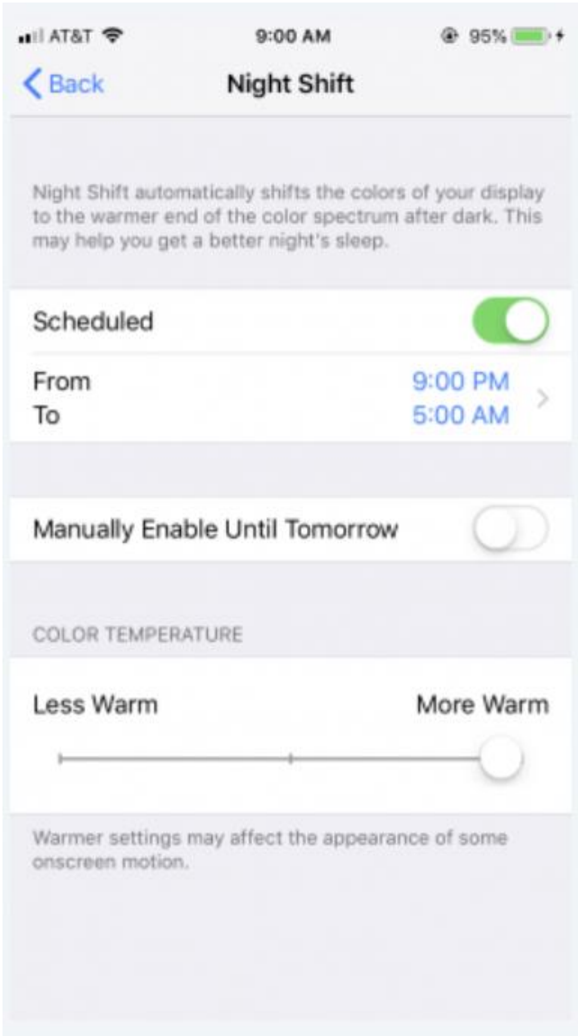

Figure 2. Example verification image of Nigh Shift settings

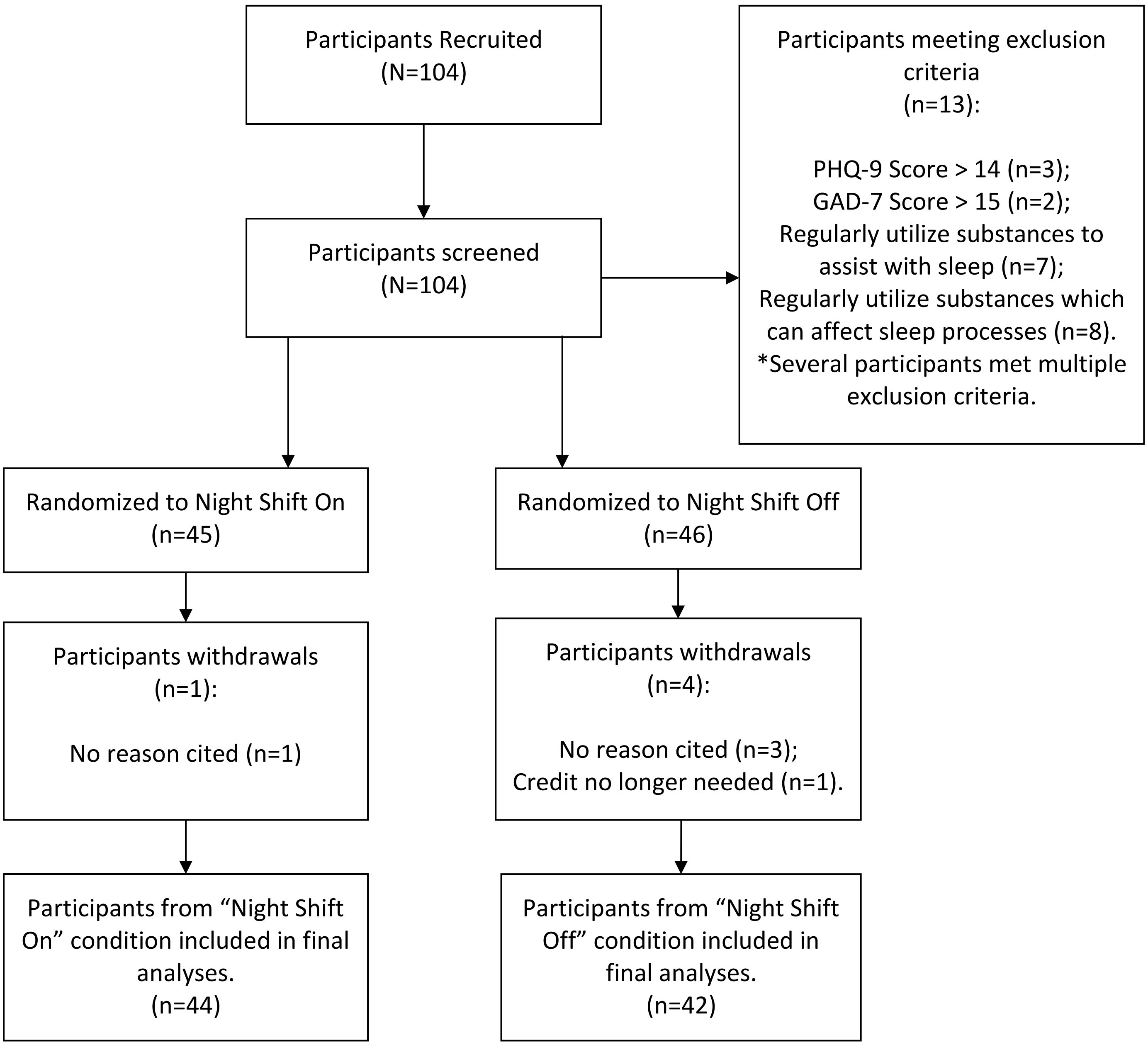

Figure 3. Participant flow diagram

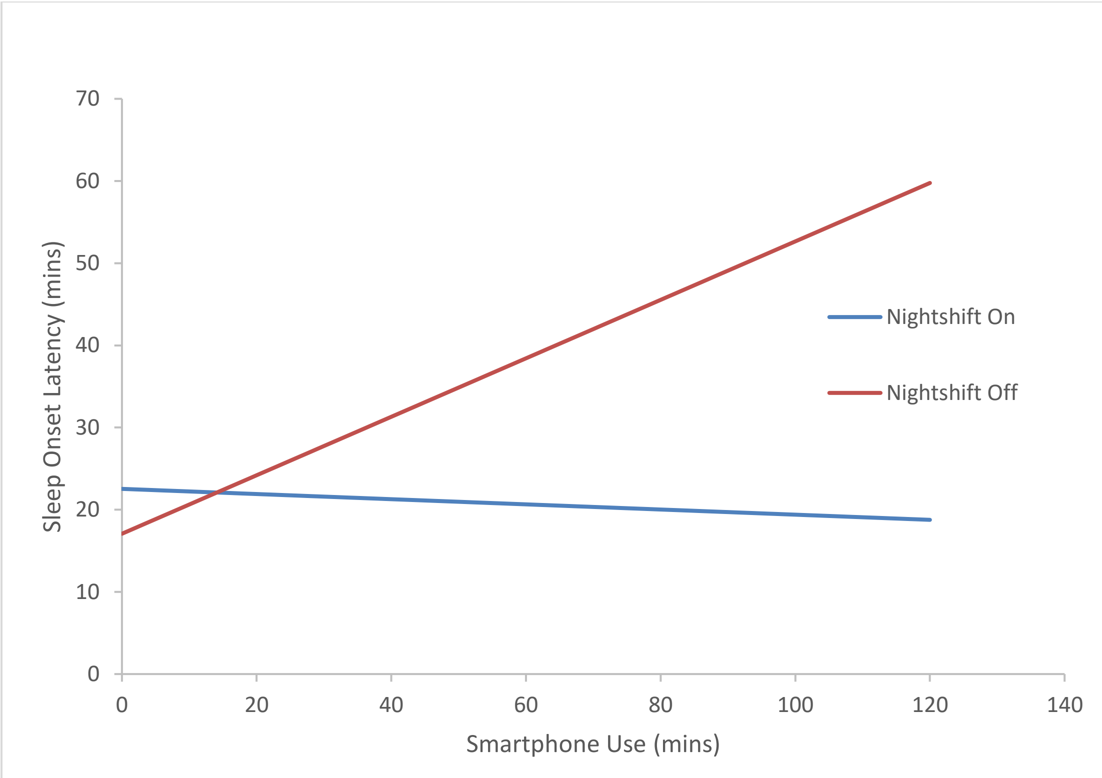

Figure 4. Exploratory plot of sleep onset latency and smartphone use 2 hours before sleep

Appendix A

Day 0 Screener Questionnaire

It is very important to this research that you answer the questions in this survey honestly and accurately. Your name will not be associated with the data you provide.

Age (years)

Do you **regularly** use any substances to help you fall asleep? Examples include: melatonin, antihistamines, alcohol, or CBD oils.

- ○ Yes
- ○ No

Do you currently use any medications which are reported to affect sleep? Examples include: antidepressants, anxiolytics, typical or atypical antipsychotics.

- ○ Yes
- ○ No

Appendix B

Daily screener questions: Example for Tuesday morning questionnaire

Was your sleep last night **significantly** different from your usual sleep on a **Monday** night? For example, did you go to bed later than usual for a Monday night to complete an assignment, or go to bed earlier than usual for a Monday night because of an upcoming usual event?

- ○ Yes
- ○ No

Did you use any substances to help you fall asleep? Examples include: melatonin, antihistamines, alcohol, or CBD oils.

- ○ Yes
- ○ No

Appendix C

Reaction time test instructions and image

Timer Instructions

Q31

The final question will be a picture of different colored leaves. You will have 5 seconds to click on as many **RED** leaves as possible.

Import Questions From... Create a New Question

Add Block

Leaves

Q29

This question lets you record and manage how long a participant spends on this page. This question will not be displayed to the participant.

Q30

Click on all the **RED** leaves.