UNLOCKING THE RELATIONSHIP BETWEEN SMARTPHONE SCREEN TIME AND THE 24-HOUR ACTIVITY CYCLE IN UNIVERSITY STUDENTS

by

BENJAMIN DONALD BOUDREAUX

(Under the Direction of Michael D. Schmidt)

ABSTRACT

Sleep, sedentary behavior (SED), light physical activity (LPA) and moderate to vigorous physical activity (MVPA) are four behaviors that make up the 24-Hour Activity Cycle (24-HAC) model. Traditional methods to measure the 24-HAC behaviors are based upon different self-report instruments or the application of a single wrist worn accelerometer. However, these current approaches are primarily limited by self-report recall errors or overestimations of total physical activity from a single device. Integrating multiple, valid objective measurements may be needed to a) assess the 24-HAC behaviors with acceptable precision and b) to examine the associations of different 24-HAC profiles with important demographic and health outcomes.

The first portion of this dissertation simultaneously used three different research grade monitors (ActiGraph GT3X+=LPA/MVPA, activPAL3=SED, and ActiGraph GT9X=Sleep) to describe the 24-HAC components by demographic, academic, and lifestyle characteristics in university students. Findings from the study concluded that university students spend 34% of their day sleeping, 41% SED, 21% LPA, and 4% MVPA. Mean sleep, SED, and LPA tended to be similar across groups with different demographic and lifestyle characteristics with no significant differences. Mean MVPA significantly differed by sex and race/ethnicity but did not significantly differ by body mass index or academic or lifestyle characteristics.

The second portion of this dissertation explored the associations between smartphone screen time and the 24-HAC in university students. Findings from this study revealed that smartphone screen time had a significant negative association with LPA. After adjusting for confounders and other components of the 24-HAC, smartphone screen time had a significant positive association with SED. Although not significant, smartphone screen time had a positive association with sleep duration and a negative association with MVPA.

Because the measurement of 24-HAC has emerged as a new paradigm, measurement of these components needs additional research. Future studies should examine if using a single objective measurement device can provide similar estimates of the 24-HAC compared to those derived from multiple devices. Future studies should also consider exploring the advantages and disadvantages of simultaneous combined measurement of the 24-HAC in different samples.

INDEX WORDS: Sleep, Sedentary Behavior, Light Physical Activity, Moderate to Vigorous Physical Activity, Cell Phone Usage, Accelerometers

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DEDICATION

To my greatest mentors Michael D. Schmidt and Robert R. Kraemer, who remain persistent to educate, challenge, and provide the best advice that a student can ask for. To my parents Robyn and Brad, who continue to provide endless support, love, and care throughout my lifetime. Finally, to my best friend Paige Menier, who I always cherish for the great memories we have together.

"Here's to the crazy ones, the misfits, the rebels, the troublemakers, the round pegs in the square holes… the ones who see things differently — they're not fond of rules… You can quote them, disagree with them, glorify or vilify them, but the only thing you can't do is ignore them because they change things…they push the human race forward, and while some may see them as the crazy ones, we see genius, because the ones who are crazy enough to think that they can change the world, are the ones who do."
— Apple Inc

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INTRODUCTION

1.1 Significance

The 24-hour activity cycle (24-HAC) is comprised of four behaviors: sleep, sedentary behavior (SED), light intensity physical activity (LPA), and moderate to vigorous physical activity (MVPA) (Rosenberger et al., 2016; Rosenberger et al., 2019). Evidence suggests all four components of the 24-HAC are individually and jointly associated with health outcomes (Chastin et al., 2021). For example, sleeping 3-6 hours per day or 8-11 hours per day compared to 7 hours per day has a 5-18% increased risk of cardiovascular disease, coronary heart disease, and stroke (Yin et al., 2017). Additionally, prolonged SED behavior has a moderate to strong relationship with negative health outcomes (e.g., increased risk of developing health morbidities and/or increased mortality). In contrast, high LPA and MVPA have a moderate to strong relationship with positive health outcomes (Chaput et al., 2013; Jakicic et al., 2019; Katzmarzyk et al., 2019; Pescatello et al., 2019;).

Traditional methods to measure the 24-HAC include self-report or the use of a single objective measure (e.g., wrist-worn accelerometer), but two important limitations should be considered (Chastin et al., 2021). First, utilizing self-report estimates for all components of the 24-HAC are subject to recall bias and may lead to substantial measurement error (Haskell et al., 2012; Cudney et al., 2022). Second, using a single objective measure worn on the wrist can result in substantially higher counts (used to identify activity intensity) and steps compared to a waist-worn accelerometer (Pulakka 2018). To effectively address these limitations, simultaneous combined measurement from valid objective measures may be needed to classify the 24-HAC (Rosenberger et al., 2016; Rosenberger et al., 2019).

One population that appears to have high day-to-day variation across all four components of the 24-HAC is university students (Chim, 2020). Current evidence suggests that between 30-50% of university students do not meet the recommended federal physical activity guidelines (American College Health Association, 2020). University students also spend between 7 to 10.7 hours in SED per day (Castro et al., 2020). Further, it is estimated that only 56% of university students report sleeping an average of seven to nine hours per night (American College Health Association, 2020; Lund et al., 2010). It remains unclear how many university students have adverse behavior profiles across multiple 24-HAC domains, however, such individuals are likely to be at particularly high risk of developing chronic conditions such as obesity, diabetes, and hypertension, or psychological problems such as low feelings of energy and fatigue (Chaput et al., 2013; Yin et al., 2017; Jakicic et al., 2019; Katzmarzyk et al., 2019; Pescatello et al., 2019; Frederick et al., 2022).

Traditional screen time behaviors include watching television, playing video games, and computer usage. These behaviors have been characterized as SED unless modified (i.e., stand up desk). Smartphone screen time is a relatively new behavior that was uncommon before the introduction of the iPhone in 2007. The average adult uses their smartphone between five to eight hours per day compared to two hours per day in 2008 (Butt & Phillips, 2008; M. Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019).

Smartphone screen time is a dynamic behavior that may occur in any component of the 24-HAC except sleep. Although smartphone screen time does not occur during sleep, evidence suggests that interacting with a smartphone during bedtime can result in delayed sleep onset and poor sleep quality (Carter et al., 2016). Recent evidence suggests smartphone screen time is positively associated with SED and negatively associated with physical activity, but does not have a substantial association with total sleep duration in university students (Alshobaili & AlYousefi, 2019; Arshad et al., 2021; Barkley & Lepp, 2016; Barkley et al., 2016; Durracio et al., 2021; Moisés Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019; Lepp et al., 2013; Lin et al., 2020; Penglee et al., 2019; Rafique et al., 2020; Randjelovic et al., 2019; Sanudo et al., 2020; Sohn et al., 2021; Towne et al., 2017).

1.2 Primary Aims

Study 1. Descriptive Characteristics of the 24-Hour Activity Cycle in University Students

AIM 1 Describe time spent in the different components of the 24-HAC by demographic (e.g., sex, race, ethnicity, BMI classification), academic (e.g., year in school), and lifestyle (e.g., living location, # of roommates, Greek life status, caffeine usage, alcohol usage, and daily medication usage) characteristics in university students.

AIM 2 Assess if certain demographic, academic, or lifestyle characteristics are associated with having a high risk 24-Hour Activity profile (low/high sleep time, high sedentary behavior, and low moderate to vigorous intensity physical activity) in university students.

Study 2. Relationship between Smartphone Screen Time and the 24-Hour Activity Cycle in University Students

AIM 1 Describe smartphone screen time by demographic (e.g., sex, race, ethnicity, BMI classification), academic (e.g., year in school), and lifestyle (e.g., living location, # of roommates, Greek life status, caffeine usage, alcohol usage, and daily medication usage) characteristics in university students.

AIM 2 Assess the relationships between smartphone screen time and each component of the 24-HAC unadjusted and adjusted for plausible confounders as well as other components of the 24-HAC.

1.3 Public Health Significance

Presently there is inconsistent evidence regarding associations between smartphone screen time and 24-HAC behaviors in university students. These inconsistencies may be due to the potential error and/or bias inherent in the use of self-report measures to measure these behaviors. A few studies have used a single wrist-worn objective measures to capture one or more component of the 24-HAC; however, this approach can result in inaccurately elevated counts per minute (used to identify different physical activity intensities) and number of steps per day, or may be incapable of accurately classifying different postures that occur throughout the day (Pulakka 2018). The present study sought to address these limitations by creating a standardized approach using multiple objective measures to describe and quantify the relationship between smartphone screen time and the 24-HAC in university students. Measuring the 24-HAC with multiple objective measures allowed the current study to more accurately describe how these important health behaviors vary by demographic, academic and lifestyle factors in university students.

1.4 Limitations

A primary limitation of this study was the use of a cross-sectional design, precluding drawing causal inferences from the observed associations. Second, the 24-HAC behaviors were measured over a short period (i.e., 7-10 days) and may not reflect the habitual behaviors of participants as changes likely occur during the course of a semester. However, data collection occurred throughout both the spring and fall semesters so that, on average, the measured behaviors should reflect the 24-HAC behaviors of university students over an academic year. Third, the study's sample was comprised of primarily females and students identifying as White-Non Hispanic; therefore, these results may not be fully representative of the university student population. Fourth, measurement reactivity may have occurred with some participants due to the awareness of being monitored. By being monitored, it is plausible some participants may alter their daily sitting time or physical activity behaviors, thus influencing time spent in the components of the 24-HAC. Fifth, no criterion measure was used for identifying times in and out of bed, likely leading to errors in our estimates of these times. Finally, the present study did not examine other screen time behaviors that may have occurred while a participant was using their smartphone.

1.5 Delimitations

The current study was delimited to university students between the ages of 18-24 years. Student athletes, students with children, and those reporting a diagnosis of bipolar disorder were ineligible. Also, participants that reported having one or more underlying health condition (e.g., Body Mass Index >35, cancer, chronic kidney disease, chronic obstructive pulmonary disease, immunocompromised from organ donation, sickle cell disease, type 2 diabetes mellitus, and cardiovascular disease) were excluded from this study due to having an increased risk of COVID-19 complications as per the Centers for Disease Control (CDC, 2022).

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CHAPTER 2

ASSOCIATIONS AMONG SMARTPHONE SCREEN TIME, PHYSICAL ACTIVITY, SEDENTARY BEHAVIOR, AND SLEEP IN UNIVERSITY STUDENTS: A SYSTEMATIC REVIEW[1]

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To be submitted to *Undecided*

2.1 Abstract

Purpose: This systematic review analyzed studies that examined relationships between smartphone screen time and the behaviors (i.e., physical activity, sedentary behavior, and sleep-related variables) of the 24-Hour Activity Cycle (24-HAC) in university students. **Methods**: Various databases were searched using terms related to smartphone screen time, cell phone use, physical activity, sedentary behavior, sleep, college students, and university students. Investigations that were peer-reviewed, written in English, and published within the past decade were included. **Results**: Twelve investigations met the eligibility criteria. The relationship between smartphone screen time and physical activity was weak (r range from -0.23 to 0.02; β=-0.25 to 0.03). Smartphone screen time and sedentary behavior had a significant positive relationship (r=0.31; β=0.12 to 0.30). The relationship between smartphone screen time and sleep quality was significant and positive (r=0.36 to 0.65, β=0.36), but total sleep duration, sleep efficiency, wake after sleep onset, and daytime sleepiness were not significantly related to smartphone screen time. **Conclusions**: The relationship between smartphone screen time and physcial activity was negative. The relationships among smartphone screen time, sedentary behavior and sleep quality were positive. No study only used objective measures to examine the relationship between smartphone screen time and all behaviors of the 24-HAC. Future investigations should simultaneously and objectively measure smartphone screen time and all behaviors of the 24-HAC to determine if direct and indirect associations exist.

2.2 Introduction

Sleep, sedentary behavior, light physical activity, and moderate to vigorous physical activity make up the 24-Hour Activity Cycle (24-HAC) (Rosenberger et al., 2016; Rosenberger et al., 2019). For this review, light physical activity and moderate to vigorous physical activity will be combined into one construct called physical activity due to the challenges of effectively measuring and reporting light physical activity. Physical activity, sedentary behavior, and sleep are independently and jointly associated with various positive and negative health outcomes depending on the amount of time spent in each component (Chastin et al., 2021). For example, greater time spent in physical activity can reduce the risk of negative health outcomes such as obesity, diabetes, cardiovascular disease, and all-cause mortality (Jakicic et al., 2019; Katzmarzyk et al., 2019; Kraus et al., 2019; Pescatello et al., 2019). In contrast, greater time spent in sedentary behavior, or sleeping less than 6 hours per night or longer than 9 hours per night, can increase the risk of negative health outcomes such as obesity, diabetes, hypertension, cardiovascular disease, and all-cause mortality (Jakicic et al., 2019; Katzmarzyk et al., 2019; Kraus et al., 2019; Pescatello et al., 2019; Yin et al., 2017). All three behaviors are not stagnant over time and can be influenced by many different factors. One particular factor that may strongly influence 24-HAC is smartphone screen time.

Unlike traditional screen-based activites, such as watching television and playing video games, which occur during discrete times and settings, smartphone screen time has become ubiquitous in all facets and settings of modern life. The behavior can occur at any moment in time, whether an individual is physically active or engaging in sedentary behavior. Although smartphone screen time use does not occur during periods of sleep, emerging evidence suggests that interacting with an electronic device before bedtime can suppress melatonin production and influence sleep (Green et al., 2017). For example, screen time behavior has been associated with inadequate sleep quantity, poor sleep quality, and daytime sleepiness (Carter et al., 2016). Currently, it is estimated that 95% of U.S. adults own a smartphone and spend an average of five to eight hours per day using their device (Butt & Phillips, 2008; Grimaldi-Puyana et al., 2020). Furthermore, the smartphone is classified as the most prevalent technology device used by university students (Towne et al., 2017). University students report insufficient physical activity, prolonged bouts of sedentary behavior, and many sleep less than 6 hours per night. Engaging in these adverse behaviors can increase the risk of developing negative health outcomes that include obesity, diabetes, hypertension, and psychological disruptions such as feelings of low energy and fatigue (Frederick et al., 2022; Jakicic et al., 2019; Katzmarzyk et al., 2019; Pescatello et al., 2019).

A prior systematic review examined the relationship between smartphone screen time and physical activity (Zagalaz-Sanchez et al., 2019). However, the review included only self-reported measures. Besides self-report measures, smartphone screen time and the 24-HAC can be measured objectively using accelerometers or third-party applications, overcoming some of the limitations that exist with self-report. The relationships between smartphone screen time and the 24-HAC behaviors are poorly understood and no prior review including self-report and objective measures in university students has been published.Therefore, the purpose of this review was to summarize the available evidence regarding the relationships between smartphone screen time and the 24-HAC in university students.

2.3 Methods

Search Strategy

Records were identified from three data bases: PubMed, Google Scholar, and Web of Science, from January to February 2022. The following search terms were used to identify records providing information on the relationships between smartphone screen time and all behaviors of the 24-HAC: 1) smartphone screen time and physical activity, 2) cell phone usage and physical activity, 3) smartphone screen time and sedentary behavior, 4) cell phone usage and sedentary behavior, 5) smartphone screen time and sleep, and 6) cell phone usage and sleep. Moreover, a time restriction was applied to the search to include only investigations conducted in the past 10 years due to substantial changes in smartphone technology and behaviors during the past decade compared to previous time periods. All six searches also included “university” or “college” students to isolate the population of interest. Reference lists from identified studies were also examined.

Eligibility Criteria

In order to be eligible, identified studies had to meet the following criteria: 1) provide full-text availability in the English language, 2) be published within the past decade, 3) include students enrolled at a college or university, 4) include either an objective or subjective measure of smartphone screen time, 5) include either an objective or subjective measure of one or more behaviors of the 24-HAC, and 6) published in a peer reviewed journal.

Primary outcomes of interest that were extracted from the eligible investigations were: sample size; geographic location of the investigation; percentage of each sex; research design; instrument used to measure physical activity, sedentary behavior, sleep, and smartphone screen time behavior; descriptive values such as means and standard deviations of the measured 24-HAC behaviors; and estimates of the associations between smartphone screen time and the 24-HAC variables. The Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies by the National Heart, Lung, and Blood Institute was used to assess the quality of each study (NHLBI, 2022).

2.4 Results

Study Selection

Figure 2.1 depicts the results of the search and study selection process in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). The initial database search identified 130 investigations, 100 investigations were screened for eligibility, and 70 investigations were excluded. Of the 30 investigations initially remaining, an additional 18 were excluded due to not reporting total screen time or a behavior of the 24-HAC, not evaluating a sample of university students, or not quantifying one of the relationships of interest. Thus, a total of 12 studies were included in this review.

Study Characteristics

As detailed in Table 2.1, 11 of the 12 investigations had a cross-sectional design (Barkley & Lepp, 2016; Barkley et al., 2016; Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019; Lepp et al., 2013; Lin et al., 2020; Rafique et al., 2020; Randjelovic et al., 2019; Towne et al., 2017; Penglee et al., 2019; Arshad et al., 2021). The final investigation was a crossover randomized controlled trial (Duraccio et al., 2021). A total of seven investigations were conducted in the USA (Barkley & Lepp, 2016; Barkley et al., 2016; Duraccio et al., 2021; Lepp & Barkley, 2019; Lepp et al., 2013; Penglee et al., 2019; Towne et al., 2017). The remaining investigations were conducted in Spain, , Serbia, Thailand, Saudi Arabia, Pakistan, and Taiwan (Arshad et al., 2021; Grimaldi-Puyana et al., 2020; Lin et al., 2020; Penglee et al., 2019; Rafique et al., 2020; Randjelovic et al., 2019;). Sample sizes across the 12 investigations ranged from 21 to 1043 university students. Eight investigations had a greater percentage (≥51%) of female participants than males (Arshad et al., 2021; Barkley & Lepp, 2016; Barkley et al., 2016; Duraccio et al., 2021; Lepp & Barkley, 2019; Lepp et al., 2013; Penglee et al., 2019; Rafique et al., 2020). Grimaldi-Puyana et al. (2020) was the sole investigation to assess the relationship between smartphone screen time and all three components of the 24-HAC. Four investigations measured two 24-HAC behaviors (Barkley & Lepp, 2016; Barkley et al., 2016; Lepp & Barkley, 2019; Towne et al., 2017), and the remaining seven investigations measured one 24-HAC behavior (Arshad et al., 2021; Duraccio K.M., 2021; Lepp et al., 2013; Lin et al., 2020; Penglee et al., 2019; Rafique et al., 2020; Randjelovic et al., 2019).

Physical Activity

As outlined in Tables 2.1 and 2.2, eight investigations examined the relationship between smartphone screen time and physical activity in university students (Barkley & Lepp, 2016; Barkley et al., 2016; Grimaldi-Puyana et al., 2020;; Lepp & Barkley, 2019; Lepp et al., 2013; Lin et al., 2020; Penglee et al., 2019; Towne et al., 2017). A self-report measure was used in seven of the eight investigations to assess physical activity and screen time, but the questionnaires varied among single-item or two-item questionnaires, open ended questions, the Godin Leisure Time Questionnaire, and the International Physical Activity Questionnaire. The final investigation used smartphone applications to objectively measure smartphone screen (Grimaldi-Puyana et al., 2020). Specifically, iPhone users used the "Screen Time" feature on their device and Android users used the "Your Hour" feature on their device.

The eight investigations did not consistently report descriptive physical activity and screen time results. Three investigations (Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019; Lepp et al., 2013) reported means and standard deviations. Three investigations (Barkley & Lepp, 2016; Barkley et al., 2016; Lin et al., 2020) did not report physical activity results. Two investigations dichotomized physical activity based on country-specific physical activity recommendations (Penglee et al., 2019; Towne et al., 2017). Two investigations reported screen time in three or more groups (Barkley et al., 2016; Towne et al., 2017). One investigation reported differences in weekday and weekend screen time (Grimaldi-Puyana et al., 2020). One investigation reported screen time differences by sex (Lepp et al., 2013). One investigation reported median values only (Penglee et al., 2019).

Six investigations reported weak positive associations (β=-0.25 to β=0.03, r=0.02) between screen time and physical activity (Barkley & Lepp, 2016; Barkley et al., 2016; Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019; Lepp et al., 2013; Penglee et al., 2019). One investigation (Towne et al., 2017) found that screen time >7 hours per day and $\leq$8 hours per day (OR=2.3, 95%, CI: 1.1-4.8) or >8 hours per day (OR=3.4, 95% CI: 1.6, 7.5) significantly predicted the likelihood of meeting the aerobic portion of the physical activity guidelines ($\geq$150 min/week). The final investigation indicated that smartphone screen time was negatively correlated (r=-0.23) with physical activity (Lin et al., 2020).

Sedentary Behavior

As outlined in Tables 2.1 and 2.3, four investigations assessed the relationship between smartphone screen time and sedentary behavior in university students (Barkley & Lepp, 2016; Barkley et al., 2016; Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019;). All four investigations used the International Physical Activity Questionnaire to assess sedentary behavior. Three investigations used a single item questionnaire to examine total screen time exposure (Barkley & Lepp, 2016; Barkley et al., 2016; Lepp & Barkley, 2019) and one investigation used asmartphone application to measure screen time that was specific to the type of smartphone a participant used (iOS or Android).

All four investigations described sedentary behavior as mean and standard deviation values only. Two investigations reported total sedentary time as an average (Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019). Two investigations categorized sedentary time into tertiles (Barkley & Lepp, 2016; Barkley et al., 2016). The four investigations also did not consistently report total smartphone screen time. Two investigations reported screen time as mean and standard deviation values only (Barkley & Lepp, 2016; Lepp & Barkley, 2019). One investigation categorized screen time into three or more groups and examined sex differences (Barkley et al., 2016). One investigation reported weekday and weekend screen time differences (Grimaldi-Puyana et al., 2020). All of the investigations reported small positive relationships (β=0.12 to

0.30, r=0.31) between sedentary behavior and smartphone screen time (Barkley & Lepp, 2016; Barkley et al., 2016; Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019).

Sleep

As outlined in Tables 2.1 and 2.4, five investigations assessed the relationship between smartphone screen time and different sleep outcomes in university students (Arshad et al., 2021; Duraccio et al., 2021; Grimaldi-Puyana et al., 2020; Rafique et al., 2020; Randjelovic et al., 2019; Sohn et al., 2021). Four investigations used the Pittsburgh Sleep Quality Index to assess sleep quality (Arshad et al., 2021; Grimaldi-Puyana et al., 2020; Rafique et al., 2020; Randjelovic et al., 2019;). Of the four investigations, one investigation also used a consumer wearable device to estimate total sleep duration during weekdays and weekends and one investigation used the Epworth Sleepiness Scale (Randjelovic et al., 2019). The final investigation only used a wrist-worn Actigraph GT3X+ (Duraccio et al., 2021). Smartphone screen time was measured using different subjective and objective measures. One investigation used the Mobile Related Sleep Risk Factors Questionaire (Rafique et al., 2020). The remaining investigations used different objective measures. Three investigations used an Android application only (Arshad et al., 2021; Rafique et al., 2020; Randjelovic et al., 2019). One investigation used an iPhone application only (Duraccio et al., 2021). The final investigation used both Android and iPhone applications depending on the type of device a participant owned (iOS or Android) (Grimaldi-Puyana et al., 2020).

Four investigations provided mean and standard deviation sleep and screen time results. Of the four investigations, two investigations divided sleep and screen time into two or more groups. One investigation reported smartphone screen time during a 24-hour period and nighttime screen time usage (Randjelovic et al., 2019). One investigation reported screen time differences by weekday and weekend (Grimaldi-Puyana et al., 2020). One investigation reported screen time differences by sex (Arshad et al., 2021). The relationship between smartphone screen time and different sleep measures tended to be weak positive or have no relationship. Three investigations revealed a positive statistically significant relationship between smartphone screen time and overall sleep quality ($r=0.36$; $r= 0.65$, $\beta=0.076$) (Randjelovic et al., 2019, Arshad et al., 2021; Grimaldi-Puyana et al., 2020;). Of the four investigations, one investigation also found a weak negative relationship ($r=-0.23$) between smartphone screen time and daytime sleepiness (Randjelovic et al., 2019). The final investigation did not find a relationship among different smartphone screen time conditions (i.e., no phone usage, Apple No Night Shift mode, Apple Night Shift mode) and different sleep outcomes [e.g., total sleep duration: $\eta2=0.006$, $p=0.59$; sleep onset latency: $\eta2=0.002$, $p=0.85$; sleep efficiency: $\eta2=0.002$, $p=0.86$; and wake after sleep onset: $\eta2=0.003$, $p=0.81$) (Duraccio et al., 2021).

2.5 Discussion

This systematic review summarized the available evidence on the relationships between smartphone screen time and components of the 24-HAC in university student samples. The strength of the relationship between smartphone screen time and physical activity tended to be negative and weak. These findings indicate that smartphone screen time exposure has little to no association with university students' physical activity levels. The strength of the realtionship between smartphone screen time and sedentary behavior was positive and of modest strength. These findings indicate smartphone screen time exposure may have a small to moderate association with a university students' sedentary behaviors. The strength of the relationship between smartphone screen time and sleep quality was positive and strong. Other sleep outcomes such as total sleep duration, sleep onset latency, sleep efficiency, wake after sleep onset latency, and daytime sleepiness were not meaningfully associated with smartphone screen time.

One possible reason for the diverse relationships among the 12 investigations may be the different techniques used to measure smartphone screen time and the 24-HACcomponents. Physical activity and sedentary behavior were measured together in some investigations because of the type of instrument being administered. For example, the International Physical Activity Questionaire assesses moderate to vigorous physical activity and includes questions on total sitting time to provide an estimate of sedentary behavior (Craig et al., 2003). Interestingly, a single item question was repeatedly used in some investigations to estimate total smartphone screen time. The single item questionnaire asked participants the following: "As accurately as possible, please estimate the total amount of time (minutes) you spend using your mobile phone each day. Please consider all uses except listening to music. For example: consider calling, texting, sending photos, gaming, surfing, watching videos, Facebook, email, and all other uses driven by 'apps' and 'software.'" (Barkley & Lepp, 2016; Barkley et al., 2016; Lepp & Barkley, 2019; Lin et al., 2020; Penglee et al., 2019). Objective measures to assess the three different 24-HAC behaviors and smartphone screen time were also unvalidated. For example, investigations using smartphone applications to estimate total smartphone screen time were limited to either an iOS or Android platform, and thus the measurement approach varied between students using different platforms.

Because of measurement limitations and inconsistencies, researchers should proceed with caution when interpreting these relationships. Self-report was the most common approach used to assess all three behaviors of the 24-HAC, which can lead to substantial under- or over-estimations of these behaviors due to the cognitive challenges of recalling and quantifying these ubiquitous behaviors (Ainsworth et al., 2012; Altschuler et al., 2009; Lee et al., 2021; Castro et al., 2020; Cudney et al., 2022). For example, one meta-analysis found that self-report recalls of digital media use were rarely an accurate reflection of log-based estimates of media use (Parry et al., 2021). Additionally, administering a single item questionnaire that lacks established validity can create substantial measurement error (Ainsworth et al., 2012; Altschuler et al., 2009). Objective measures used in the different studies were limited due to a device's platform or capabilities. Sanudo et al. (2020), measured physical activity and total sleep duration with a consumer wearable device (i.e., Xiaomi Mi Band 2), but the validity of the algorithms used to classify the different behaviors of the 24-HAC from most consumer wearable devices are largely unknown (De Zambotti et al., 2019; Welk et al., 2019). The same consideration may also be applied towards the unknown validity of iOS and Android algorithms, and third party applications, used to calculate total smartphone screen time.

The present systematic review contains several strengths and limitations that should be noted. The strengths of this review include 1) the incorporation of all aspects of the 24-HAC (i.e., physical activity, sedentary behavior, and sleep related outcomes), and 2) the predominant types of instruments used to measure each behavior. Limitations of this systematic review include 1) the diverse instruments and methodical differences across the reviewed studies make it difficult to examine the consistency of findings and preclude the development of conclusive statements regarding the relationships examined, and 2) few of the identified investigations simultaneously measured all aspects of the 24-HAC, precluding an examination of the joint associations between smartphone screen time and all three inter-rrelated 24-HAC behaviors in a university student sample.

2.6 Conclusions

This systematic review summarized 12 investigations that reported on the relationship between smartphone screen time and at least one aspect of the 24-HAC in university students. This review provides insights into the types of instruments that have been used to measure smartphone screentime and the 24-HAC in studies examining associations between these behaviors. Self-report was the most common method used to assess smartphone screen time and the 24-HAC. If an objective measure of smartphone screen time was used, the approach was limited by the unknown validity of the algorithms used by consumer wearable devices and smartphone applications).

To address the identified gaps in this area of research, future investigations should measure all aspects of the 24-HAC to foster a better understanding of how smartphone screen time influences these behaviors. To address the limitations of self-report and consumer wearable devices, future investigations should consider using research-grade accelerometers that have well established validity and publicly available algorithms to classify the 24-HAC. Investigators should also become familiar with the different third party applications available for both iOS and Android platforms to measure smartphone screen time and strive to develop standardized tools and analytic approaches to quantify this behavior. Finally, future investigations should consider examining the long term, prospective associations between smartphone screen time and the 24-HAC.

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Figure 2.1

Prisma Flow Diagram of Research Study Inclusion and Exclusion Criteria

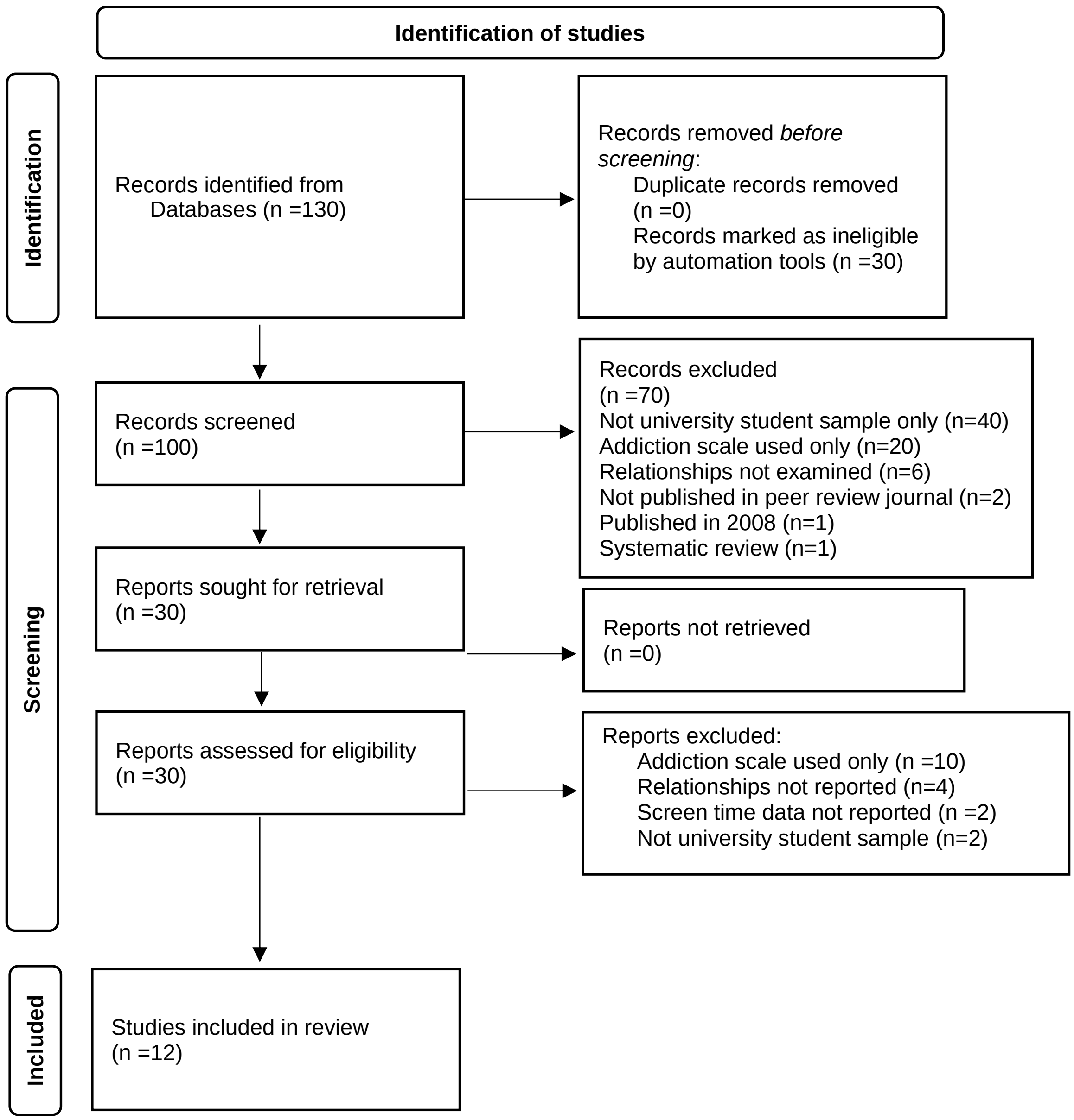

Table 2.1
Summary of Eligible Investigations Examining Smartphone Screen Time and 24-Hour Activity Cycle

Citation (year)	Country	Research Design	Sample Characteristics	PA, SED, Sleep Behaviors Measured [✓= Measured]
Lepp et al. (2013)	USA	Cross-Sectional	*Phase 1:* N=302, 55% female *Phase 2:* N=49, 55% female	PA ✓ SED Sleep
Barkley et al. (2016a)	USA	Cross-Sectional	N=226, 60% female	PA ✓ SED ✓ Sleep
Barkley et al. (2016b)	USA	Cross-Sectional	N=236, 54% female	PA ✓ SED ✓ Sleep
Towne et al. (2017)	USA	Cross-Sectional	N=490, 31% female	PA ✓ SED Sleep

Lepp et al. (2019)	USA	Cross-Sectional	N=228, 55% female	PA ✓ SED ✓ Sleep
Penglee et al. (2019)	Thailand/USA	Cross -Sectional	*USA:* N=242, 80% female *Thailand:* N=194, 75% female	PA✓ SED Sleep
Randjelovic (2019)	Serbia	Cross-Sectional	N=21, % female not reported	PA SED Sleep✓
Grimaldi-Puyana et al. (2020)	Spain	Cross-Sectional	N=306, 40% female	PA ✓ SED ✓ Sleep✓
Lin et al. (2020)	Taiwan	Cross-Sectional	N=975, % female not reported	PA✓ SED Sleep

Rafique et al. (2020)	Saudi Arabia	Cross-Sectional	N=1502, 77% female	PA SED Sleep✓
Arshad et al. (2021)	Pakistan	Cross-Sectional	N=159, 51% female	PA SED Sleep✓
Duraccio et al. (2021)	USA	Crossover Randomized Control Trial	N=167, 71% female	PA SED Sleep✓

Table 2.2
Summary of the Relationships between Smartphone Screen Time and Physical Activity

Citation	PA Measure	Screen Time Measure	PA Results	Screen Time Results	Relationship
Lepp et al. (2013)	Phase 1 *Self-Report:* 12 open-ended questions Phase 2 VO2 peak Testing on Treadmill	3 Open Ended Questions	Phase 1 Not reported Phase 2 *Males:* 45.6±9.0 $mL \cdot kg^{-1} \cdot min^{-1}$ *Females:* 36.7±10.2 $mL \cdot kg^{-1} \cdot min^{-1}$	*Males* 298.9±31.1 min/d (median 202.5 min/d) *Females* 313.0±252.1 min/d (median 240.0 min/d)	Phase 1 Not reported Phase 2 Negative relationship between smartphone screen time and VO2 Peak (β= -0.25, p=0.047)
Barkley et al. (2016a)	Godin Leisure Time Questionnaire (GLTEQ)	Single Item Questionnaire	Not Reported	380±316 min/d	Weak relationship between physical activity and screen time (β=0.03, p=0.70)

Barkley et al. (2016b)	Godin Leisure Time Questionnaire (GLTEQ)	Single Item Questionnaire	Not Reported	*High* [>66th percentile]: n=81 (595±201.7 min/d) *Moderate* [33rd-66th percentile]: n=77 (217.5±52.1 min/d) *Low* [<33rd percentile]: n=78 (81.8±35.1 min/d) *Females* (344.6±270.6 min/d) *Males* (252.1±217.1 min/d)	Weak relationship between screen time and physical activity (β= -0.02, p=0.90)
Towne et al. (2017)	Behavioral Risk Factor Surveillance System Questions	Two Item Questionnaire	Dichotomized Meeting Aerobic PA Guidelines (≥150 min/week) & Not Meeting Aerobic PA Guidelines (<149 min/week) N=417 Met PA Guidelines, N= 73 Did Not Meet PA Guidelines	Divided into 4 groups ≤6 hrs (n=155) >6 hrs and <8 hrs (n=94) >8 hrs and <12 hrs (n=110) ≥12 hrs (n=131)	Significant relationship between meeting PA guidelines and screen time >8 hrs/ and <12 hrs/d compared to ≤6 hrs/d (OR 2.3, 95% CI: 1.1,4.8) Significant relationship between meeting PA guidelines and screen time use ≥12h compared <6h per day. (OR 3.4, 95% CI: 1.6,7.5)

Lepp et al. (2019)	Godin Leisure Time Exercise Questionnaire (GLTEQ)	Single Item Question	43±34 Activity Leisure Score	302±248 min/d	Weak relationship between smartphone screen time and physical activity ($r=0.02$, $p=0.82$)
Penglee et al. (2019)	Self-Report: Three Item Questionnaire [assessing frequency (# of days), duration, and intensity during exercise]	Single Item Question	*USA* 3±1 days per week, 30±7 min per session at MVPA intensity; *Thailand* 2±1 days per week, 30±10 min per session at moderate intensity	Median values reported *USA* 180 min/d *Thailand* 240 min/d	*USA* weak relationship on # days per week of PA and hrs of screen time per day ($X^2(3)=2.39, p=0.496$) *Thailand* inverse relationship # days per week of PA and hrs of screen time per day (X^2(3)=10.55, p=0.06)
Lin et al. (2020)	International Physical Activity Questionnaire (IPAQ)	Single Item Question	IPAQ: Sufficient PA* (N=533) High PA* (N=182) *Values not defined	Divided into 5 different groups but only 2 groups reported 4 to 6 hrs/d (N=333) <2 hrs/d (N=34)	Negative correlation between screen time and total physical activity ($r=-0.23$)

Grimaldi-Puyana et al. (2020)	International Physical Activity Questionnaire (IPAQ) Apple Health or Google Fit applications	*iOS* "Screen Time" (smartphone feature) *Android* "Your Hour" (smartphone feature)	IPAQ *Walking:* (253±168 min/wk), *MOD:* (157±151 min/wk), *VIG:* (190±156 min/day) Objective *Weekday*: 7623±3606 steps/day, *Weekend*: 7486±3761 steps/day	*Weekday:* 254±99 min/day *Weekend:* 243±110 min/day	Total METS significantly predicted higher levels of smartphone screen time (β=-0.15; 95% CI= -0.27,-0.03) Total steps per day did not significantly predict higher levels of smartphone screen time (β=-0.08; 95% CI= -0.20,0.05)

Table 2.3
Summary of the Relationships between Smartphone Screen Time and Sedentary Behavior

Citation	SED Measure	Screen Time Measure	SED Results	Screen Time Results	Relationship
Barkley et al. (2016a)	International Physical Activity Questionnaire (IPAQ)	Single Item Question	<u>*High*</u>: 584±263min/d <u>*Moderate*</u>: 491±214min/d <u>*Low*</u>: 439±205min/d	380±316 min/d	Sitting time was positively associated with total cell phone usage (β=0.30, p<0.0001)
Barkley et al. (2016b)	International Physical Activity Questionnaire (IPAQ)	Single Item Question	<u>*High:*</u> 495.1+227.6 min/d <u>*Moderate:*</u> 417.1±208.3 min/d <u>*Low:*</u> 395.2±180.0min/d	High [>66th percentile]: n=81 (595±201.7min/d), Moderate [33rd-66th percentile]: n=77 (217.5±52.1min/d) Low [<33rd percentile]: n=78 (81.8±35.1min/d)	Cell phone usage positively related to sedentary behavior (β=0.23, p=0.05)
Lepp et al. (2019)	International Physical Activity Questionnaire (IPAQ)	Single Item Question	436±210 min/d	302+248min/d	Positive relationship between smartphone screen time and sedentary behavior (r=0.31, p<.001)
Grimaldi-Puyana et al. (2020)	International Physical Activity Questionnaire (IPAQ)	<u>*iOS*</u> "Screen Time" (smartphone feature) <u>*Android*</u> "Your Hour" application (smartphone feature)	306±156 min/d	<u>*Weekday:*</u> 254±99 min/d <u>*Weekend:*</u> 243±110 min/d	Total sitting time significantly predicted higher levels of screen time (β=0.12; 95% CI= 0.00,0.25)

Table 2.4

Summary of the Relationships between Smartphone Screen Time and Sleep

Citation	Sleep Measure	Screen Time Measure	Sleep Results	Screen Time Results	Relationship
Randjelovic (2019)	Epworth Sleepiness Scale (ESS) Pittsburgh Sleep Quality Index (PQSI)	Quality Time (Android Smartphone Application)	ESS: 7.78±3.55 PSQI: 5.62±2.59	24-hour Day Total: 234±130.7 min/d Night Time Screen Time (16:30-07:00): 132.6±80.0 min/d	Daytime Sleepiness and 24-Hour Total Screen Time (r=-0.23, p>.05) Daytime Sleepiness and Night Time Screen Time (r=-0.22, p>.05) Sleep quality and screen time during 24-Hour Day (r=0.65, p<.01) Sleep quality and Night Time Screen Time (r=0.61, p<.01)
Grimaldi-Puyana et al. (2020)	Xiaomi Mi Band 2 Pittsburgh Sleep Quality Index (PQSI)	*iOS "Screen Time"* (smartphone feature) *Android "Your Hour" application* (smartphone feature)	30.3% of sample reported poor sleep quality (PSQI score >5)	*Weekday:* 254±99 min/day *Weekend:* 243±110 min/day	Sleep quality (β=0.076; 95% CI=−0.06, 0.21) predicted smartphone use, with those reporting poor quality of sleep (PSQI index>5)
Rafique et al. (2020)	Pittsburgh Sleep Quality Index (PQSI)	Mobile Related Sleep Risk Factors Questionnaire	33% of male sample reported poor sleep quality	8.57±4.59 hrs/d	Screen usage of >8 hours was positive but weakly correlated with daytime

			37% of female sample reported poor sleep quality		sleepiness (r=-0.040), sleep disturbances (r=0.052), and sleep latency (r=0.033). Screen usage of >8 hours was negative but weakly correlated with sleep disturbances (r=0.052), total sleep duration (r=-0.054)
Arshad et al. (2021)	Pittsburgh Sleep Quality Index (PQSI)	Android Smartphone Application (Name Not Reported)	6.68±2.3, 72.4% men had poor sleep quality, 59.5% females reported poor sleep quality	*<u>Mean Screen Time over 30 days:</u>* 147.50±51.09 hrs *<u>Male Screen Time:</u>* 155.2±52.0 hrs *<u>Female Screen Time:</u>* 140.4±49.4 hrs	Screen time was positively associated with sleep quality (r=0.36, β=0.36 p<.001)
Duraccio et al. (2021)	Actigraph GT3X+	Moment (iPhone Smartphone Application)	Median values reported only *<u>Total sleep duration:</u>* 6.83±0.54 hrs/night *<u>Sleep latency:</u>* 11.84±6.9 min *<u>Sleep efficiency:</u>* 83.7±6.3	3 different conditions used for 60 minutes before bed time *<u>Condition 1:</u>* Night Shift mode enabled *<u>Condition 2:</u>* Night Shift mode disabled *<u>Condition 3:</u>* no phone usage	No relationship between three different conditions and sleep outcomes *<u>total sleep duration:</u>* η2=0.006, p=0.59 *<u>sleep onset latency:</u>* η2=0.002, p=0.85 *<u>sleep efficiency:</u>* η2=0.002, p=0.86 *<u>wake after sleep onset:</u>* η2=0.003, p=0.81

CHAPTER 3

DESCRIPTIVE CHARACTERISTICS OF THE 24-HOUR ACTIVITY CYCLE IN UNIVERISTY STUDENTS

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3.1 Abstract

Introduction: Measurement of the four components of the 24-Hour Activity Cycle (24-HAC) [Sleep, Sedentary Behavior (SED), Light Physical Activity (LPA), and Moderate to Vigorous Physical Activity (MVPA)] has gained popular interest; however, current approaches rely on self-reported measures that are subject to recall error or single wrist-worn acceleromters that are unable to equally capture all 24-HAC components. The present study aimed to describe the 24-HAC using three different research grade monitors by demographic, academic, and lifestyle characteristics in a sample of university students **Methods:** University students (n=108) wore three devices (ActiGraph GT3X on the right hip, ActiGraph GT9X on the non-dominant wrist, activPAL3 on the anterior aspect of thigh) between 7-10 days to capture habitual Sleep, SED, LPA, and MVPA. Each device was selected to measure different components of the 24-HAC (ActiGraph GT9X=Sleep, activPAL3=SED,ActiGraph GT3X=LPA, MVPA). All three data sources were merged and anlyzed in 1-minute epochs to classify each component. Weighted mean estimates from the four different components were generated and compared between groups using general linear models. **Results:** On average, university students spent 34% of their day sleeping, 41% sedentary, 21% in LPA, and 4% in MVPA. Three (Sleep, SED, MVPA) of the four components of the 24-HAC were similar by demographic, academic, and lifestyle characteristics. MVPA significantly differed by sex and race/ethnicity but did not by body mass index or by academic and lifestyle characteristics. **Conclusions:** The 24-HAC modestly differed by sex and race/ethnicity but not by body mass index, academic or lifestyle characteristics. Future studies should examine the 24-HAC with objective measures in diverse samples.

3.2 Introduction

Sleep, sedentary behavior (SED), light physical activity (LPA), and moderate to vigorous physical activity (MVPA) are four behaviors that can occur during a 24-hour day. Integrating all four of these daily behaviors into one model is the 24-Hour Activity Cycle (24-HAC) (Rosenberger et al., 2016; Rosenberger et al., 2019). Further, all behaviors that make up the 24-HAC are dynamic and can be influenced by individual, social, or environmental factors. (Rosenberger et al., 2016; Rosenberger et al., 2019).

Evidence consistently suggests that all four components are independently associated with health outcomes (Chastin et al., 2021). For example, short or long total sleep duration and high SED behavior have a moderate-to-strong relationship with several negative health outcomes including obesity, diabetes, hypertension, and early mortality (Jakicic et al., 2019; Katzmarzyk et al., 2019; Pescatello et al., 2019; Yin et al., 2017). In contrast, high LPA and MVPA have a moderate-to-strong relationship with many positive health outcomes including improved sleep quality, and reduced risks of anxiety, depression, type 2 diabetes, and cardiovascular disease (Jakicic et al., 2019; Katzmarzyk et al., 2019; Pescatello et al., 2019; Yin et al., 2017).

Traditional approaches to measure and classify the components of the 24-HAC include self-report and the use of a single objective measure (e.g., wrist-worn accelerometer), but two important limitations should be considered. First, self-report measures of the different components of the 24-HAC (e.g., International Physical Activity Questionnaire, Pittsburgh Sleep Quality Index) are subject to recall error or bias that may lead to substantial measurement error (Haskell, 2012; Cudney et al., 2022). Second, using a single objective wrist worn measure can result in substantially higher counts per minute (used to identify physical activity intensity), number of steps per day, or misclassifications of posture compared to a waist and/or thigh worn accelerometer (Marcotte et al., 2020). In contrast, integrating combined measures or simultaneously using more than one device may be beneficial for accurately measuring the 24-HAC (Rosenberger et al., 2016; Rosenberger et al., 2019). Simultaneous measurement of all components of the 24-HAC would also allow researchers to more fully examine both the direct and indirect associations of different 24-HAC profiles with important outcomes (Chaput, 2014; Rosenberger et al., 2016; Rosenberger et al., 2019).

One population that appears to have high day-to-day variation across all four components of the 24-HAC is university students (Chim et al., 2020). An investigation by Zhang et al. (2019) measured the 24-HAC with a wrist-worn ActiGraph GT9X Link in 278 university students, but estimates of each component were dichotomized [(Sleep: <7 hr/d, ≥7hr/d); (SED: <3hr/d, ≥3hr/d) (LPA: <50 percentile, ≥50 percentile); (MVPA: <60 min/d, ≥60 min/d)]. Another study by Kahlhofer et al (2015) assessed physical activity, SED, and sleep with two different accelerometers (i.e. activPAL and Actiwatch 2) in 132 university students. Although the study utilized simultaneous combined objective measurements, all components of the 24-HAC were not measured or reported in a suitable manner. For example, the study did not report LPA or MVPA and SED estimates from the activPAL inappropriately included sleep.

To our knowledge, no study has appropriately used simultaneous combined objective measures to classify all four components of the 24-HAC in a university student sample. In addition, no prior investigation has described the 24-HAC by demographic, academic or lifestyle characteristics in a university student sample. Previous studies have shown that 24-HAC profiles can vary in university students across demographic groups (i.e., females tend be less physically active compared to men) but these approaches have predominantly used self-report measures and have not measured all components of the 24-HAC (Edelmann et al., 2022; Mueller et al., 2022). It is important to address these limitations in order to determine the extent to which 24-HAC behaviors vary by demographic, academic or lifestyle characteristics during this important lifestage (Zhang & Gu, 2021).

To address these gaps, this study simultaneously used three different objective measures to estimate time spent in the different components of the 24-HAC. Further, the current study assessed associations between demographic, academic, and lifestyle characteristics and 24-HAC behaviors, including the probability of having a 24-Hour Activity Profile associated with high chronic disease risk, defined as having short (< 7 h) or long (>9 h) total sleep duration, high levels of SED (≥600 min/d), and low levels of daily MVPA (<30 min/d).

3.3 Methods

Participant Recruitment & Enrollment

Students enrolled at a large university were recruited via their university-provided email address during the spring and fall 2021 semesters. Email addresses were obtained from the Office of the Registrar. Prior to participation, prospective participants received an email that described the study's main purpose and an invitation to complete an online survey to assess their eligibility status. Prospective participants were classified as eligible if they met the following criteria: aged 18 to 24 years old, full-time student status, and fluent in written English. Participants were excluded by meeting one or more of the following criteria: enrolled as a student athlete, not owning a smartphone, having children or planning to become pregnant, having a diagnosis of an orthopedic injury in the past six months, or reporting a bipolar diagnosis reporting a bipolar diagnosis due to its impact on all components of the 24-HAC. If a prospective participant was deemed eligible, research staff emailed them confirmation of eligibility and scheduled their first visit. All study procedures were reviewed and approved by the university institutional review board and written informed consent was obtained during the participant's first in-person visit.

Research Design & Procedures

The study consisted of a cross-sectional design that ranged between seven to ten days with two in-person visits. During a participant's first visit, research staff briefly described the study's procedures, answered any research related inquiries, and obtained informed consent. Participants were then directed to a private quiet room and were instructed to complete several self-report questionnaires, including those assessing demographic characteristics. Next, a research team member asked the participant if he or she was prescribed any daily medication and then took the following body measurements: height (Hopkins Medical Products, Grand Rapids, MI, Model: Hopkins Road Rod Portable Stadiometer), weight and body fat percentage estimated from bioelectrical impedance (Tanita Corporation of America Inc, Arlington Heights, Illinois, Model: WB100, TBF-305), and waist circumference at the iliac crest. Participants were then fitted with three different research grade monitors: an ActiGraph GT3X+ worn on the right hip, an ActiGraph GT9X Link worn on the non-dominant wrist, and an activPAL3 worn on the anterior aspect of the non-dominant thigh. Participants were provided verbal and written instructions of how to wear the monitors during the next seven to ten days.

Prior to a participant's departure, a second in-person visit was scheduled.The second in-person visit occurred seven to ten days after the first in-person visit. Upon arrival, participants removed all monitors and returned their monitor log.

24 Hour Activity Cycle Measures

Light and Moderate to Vigorous Physical Activity

An ActiGraph GT3X+ (ActiGraph Corp, Pensacola, FL) was attached to an elastic belt and worn on the right hip during all waking hours to measure LPA and MVPA. Participants were instructed that the ActiGraph GT3X+ should not be worn during water-based activities or sleep. All devices were equipped with firmware version 3.2.1 and ActiLife software version 6.13.4 was used to initalize and download data in 1-minute epoch lengths to classify the different physical activity intensities. The low frequency extension was not used. LPA and MVPA were classified using the Freedson 2011 algorithm which incorporated an additional SED cut-point (Sedentary: 0-150 cpm, Light: 151-2689 cpm, Moderate: 2690-6166 cpm, Vigorous: 6167-9642 cpm, Very Vigorous: $\geq$9643 cpm) (Migueles et al., 2017; Sasaki et al., 2011). Non-wear periods were identified as periods with 60 consecutive minutes of 0 counts using the Choi algorithm (Choi et al., 2011). In addition, participants were provided with a monitor log to document periods when a device was removed.

Sedentary Behavior

The activPAL3 (PAL Technologies, Glasgow, UK) was used to measure sedentary behavior. A customized 1-minute epoch length was develped in the PAL Analysis Software to accurately classify the posture of different sedentary behaviors throughout the day. All were processed using PAL Analysis version 8.11.8.75 software with the CREA algorithm. The device provides valid estimates of sedentary behaviors (e.g., sitting time) during free living conditions in young adults compared to direct observation (Lyden et al. 2017). SED behavior metrics provided by the software include time spent sitting, in seated transport, and in primary (sleep-related) or secondary lying. ActivPAL3 estimates of times in and out of bed were derived from the primary lying times each day. As described by PAL Technologies, time in bed estimates are classifed by non-upright events lasting at least one hour and then expanding each event to adjacent non-upright events lasting at least one hour (allowing for bathroom breaks and other sleep interruptions), resulting in a container of a predominantly non-upright events. The longest container is classified as 'Primary Lying Time" and the shorter containers are classifed as 'Secondary Lying Time' variables (PAL Technologies, 2022).

Sleep

The ActiGraph GT9X Link was used as a measure of sleep times. Participants were instructed to wear the accelerometer on their non-dominant wrist during all 24 hours for a consecutive 7-10-day period, except for water-based activities (swimming or bathing). Devices were equipped with firmware version 1.7.1 and ActiLife software version 6.13.4 was used to initalize and download data in 1-minute epoch lengths.Participants were also provided a daily sleep log to report their times in bed and out of bed.

Estimated times in bed (Time in Bed [TIB]) and times out of bed (Time out of Bed, [TOB]) were derived by combining data from self-report sleep log, primary lying times detected by the activPAL3, and the sleep bouts detected by the GT9X using the automated algorithm included in the ActiLife software. Lacking a clear objective criterion measure, self-reported times were used when they approximated (within 60 min) the time provided by one or both objective measures, and when there was little agreement between estimates from the available objective measures (no pair of estimates within 60 min). However, activPAL3 estimates were used in the following situations: a) when the self-reported TIB was 1-60 min after the activPAL3 TIB, the activPAL3 TIB was used; and b) when the self-reported TOB was 1-60 min after the activPAL3 TOB, the activPAL3 TOB was used. These exceptions were made to avoid coding non-lying time detected by the activPAL3 as TIB and to avoid coding upright time detected by the activPAL3 as TIB. For sleep bouts where the above conditions were not met, a hierarchical decision tree was used to derive a best estimate of TIB and TOB (see Figure 3.1).

Data Processing

For this analysis, all three data sources (ActiGraph GT3X+, activPAL3, and ActiGraph GT9X Link) were processed using the previously noted software packages and then combined in 1-minute epochs. Each minute of monitored time was then classified as either sleep, SED, LPA, or MVPA. Briefly, non-sleep minutes were classified as 1) SED if the activPAL identified the participant as sitting for the entire minute or, absent activPAL data, the ActiGraph GT3X+ had a vector magnitude $\leq$ 150 counts per minute (cpm); 2) LPA if the activPAL registered upright posture for any portion of the minute or if the ActiGraph GT3X+ registered 151-2690 vector magnitude cpm; and 3) MVPA if the ActiGraph GT3X+ registered $\geq$ 2691 vector magnitude cpm. Only days in which a behavior could be assigned for $\geq$ 1380 minutes using the combined data sources were retained for analysis as “valid days”. Valid days with less than 1440 minutes of data, due to missing data or spring daylight savings, were standardized to a 1440 minute day by multiplying each 24-HAC estimate by 1440 / #valid minutes. Valid days with more than 1440 minutes of data, due to fall daylight savings, were standardized to a 1440 minute day by multiplying each 24-HAC estimate by #valid minutes / 1440. Mean estimates of 24-HAC behaviors were calculated separately for weekdays (a minimum of 4 valid days required) and weekend days (a minimum of 2 valid days required). Weekly 24-HAC behaviors were then derived as a weighted average of the weekday and weekend estimates.

Statistical Analysis

Descriptive statistics and histograms were obtained for all continuous variables at both the day and participant level to assess normality and to screen for data anomalies. Estimates from the ActiGraph GT3X+, activPAL3, ActiGraph GT9X are reported as mean, standard deviation (SD) values unless otherwise noted. General linear models were used to compare estimates of LPA, MVPA, SED, and total sleep duration across groups varying in demographic, academic and lifestyle characteristics. An indicator of having a poor 24-HAC profile was created and defined as meeting two or more of the following conditions: total sleep duration < 420 min/d or > 540 min/d, SED $\geq$ 600 min/d, MPVA $<$ 30 min/d. Cross tabulations were used to determine the percent of participants that met the poor profile criteria across demographic and lifestyle characteristics. Logistic regression was used to estimate the risk of having a poor 24-Hour Activity profile by demographic and lifestyle characteristics.

3.4 Results

A total of 695 participants completed the study's inital elgibility survey and 123 participants confirmed elgibility and consented to participate. After data processing and cleaning, 108 university students were included in the final analysis. As described in Table 3.1, the sample was primarily female (67%), identified as White Non-Hispanic (62.9%), and classifed as normal weight (62.0%). Different academic and lifestyle characteristics of the sample are summarized in Table 3.2.

Figure 3.2 depicts the average percent time spent in the four different components of the 24-HAC in university students. On average, university students spent 34% of their day sleeping, 41% of their day in SED behaviors, 21% of their day in LPA, and 4% in MVPA. Figure 3.3 shows that the time spent in the different components of the 24-HAC was similar on weekdays and weekends. As depicted in Figure 3.4, the amount of time spent in the different components of 24-HAC varied from day to day. Participants had the shortest total sleep duration on Fridays (459.5 min/d) and had the longest amount on Sundays (524.1 min/d). Participants had the lowest amount of SED time on Saturdays (545.7 min/d) and had the highest amount on Tuesdays (634.5 min/d). Participants had the lowest amount of LPA time on Thursdays (277.5 min/d) and the highest on Saturdays (361.7 min/d). Finally, participants had the lowest amount of MVPA time on Sundays (41.1 min/d) and the highest on Wednesdays (63.7min/d).

Sleep

University students slept an average of 486.0±62.4 minutes per day and slept significantly less on weekdays (482.6±73.5 min/d) compared to weekend days (494.5±99.5 min/d, $p<0.001$). Table 3.1 outlines total sleep duration differences by sex, race/ethnicity, and BMI classification. No total sleep duration differences were observed across these demographic characteristics. Differences in sleep duration by academic and lifestyle characteristics are displayed in Table 3.2. No significant differences were observed with the different academic and lifestyle characteristics. However, alcohol usage (non-drinkers: 476.7±60.2 min/d; drinkers: 499.5±60.5min/d, p=0.08) and medication usage (no: 477.8±67.8 min/d; yes: 497.9±52.1 min/d) approached statistical significance. Table 3.3 and Table 3.4 reveal weekday and weekend total sleep duration differences by demographic, academic, and lifestyle characteristics. No significant differences were found across the various characteristics.

Sedentary Behavior

University students engaged in 599.3±89.1 minutes of SED time per day. University students had significantly higher SED time on weekdays (611.7±100.2 min/d) compared to weekends (568.5±113.9 min/d, p<0.001). Table 3.1 displays SED time differences by sex, race/ethnicity, and BMI classification. No significant differences were observed across the different demographic characteristics. Table 3.2 describes the SED time values by academic and lifestyle characteristics; no significant differences were observed. Table 3.3 and Table 3.4 display total SED time on weekdays and weekends by demographic, academic, and lifestyle characteristics. On weekends, students that reported living on campus (598.2±94.9 min/d) had significantly higher SED time compared to students that lived off campus (552.3±120.5 min/d, p=0.04). No other statistically significant differences were observed.

Light Physical Activity

Overall, university students engaged in 298.9±76.9 minutes of LPA per day and accumulated significantly less LPA on weekdays (287.3±78.7 min/d) compared to weekend days (327.7±112.7 min/d, $p<0.001$). LPA estimates by demographic, academic and lifestyle characteristics are provided in Table 3.1 and Table 3.2. No significant differences were observed across the different characteristics. Table 3.3 displays weekday and weekend estimates of LPA by demographic characteristics. On weekend days, females (346.5±113.2 min/d) engaged in significantly more LPA than males (290.3±103.4 min/d, $p=0.01$). Table 3.4 describes weekday and weekend estimates of LPA by academic and lifestyle characteristics. On weekdays, LPA was significantly higher among Juniors (327.2±66.8 min/d) compared to Freshmen (272.6±77.9 min/d), Sophomores (269.9±73.2 min/d), Seniors (313.4±92.0 min/d), and Graduate Students (256.9±65.5 min/d).

Moderate to Vigorous Physical Activity

Overall, university students engaged in 55.8±33.3 minutes of MVPA per day. Students had significantly higher estimates of MVPA on weekdays (58.4±33.8 min/d) compared to weekend days (49.3±40.9 min/d, $p<0.001$). MVPA differences by sex, race, ethnicity, and body type are summarized in Table 3.1. Males engaged in significantly more MVPA (66.8±37.6min/d) compared to females (50.2±29.8 min/d, $p=0.01$). Participants that identified as White Non-Hispanic (60.8±33.5 min/d) obtained significantly higher MVPA per day compared to Asians (34.4±18.0 min/d) and Other racial backgrounds (53.0±44.1 min/d) but their MVPA was similar to Hispanics (60.2±28.8 min/d). MVPA estimates by academic and lifestyle characteristics are shown in Table 3.2; no significant differences in MVPA were observed. Table 3.3 and Table 3.4 display MVPA values on weekdays and weekends by demographic, academic, and lifestyle characteristics. On both weekdays and weekend days, males (Weekdays: 68.3±37.6 min/d; Weekends: 63.1±49.0 min/d) had significantly higher estimates of MVPA than females (Weekdays: 53.4±30.9 min/d, p=0.03; Weekends: 42.4±33.9 min/d, p=0.01). On weekdays, participants who identified as White Non-Hispanic obtained significantly more MVPA (63.2±33.8 min/d), p=0.03) than Asians (37.5±20.0 min/d) and those of Other racial backgrounds (55.3±44.5 min/d). Students that reported taking daily medication had significantly lower estimates of total MVPA on weekend days (39.5±30.1 min/d, p=0.03) compared to students that reported not taking daily medication (56.1±45.9 min/d).

Poor 24-HAC Profile

The percentages of students classified as having a poor 24-Hour Activity Profile by demographic, academic, and lifestyle characteristics are displayed in Table 3.5 along with odds ratios and 95% confidence intervals (CI) generated from univariable logistic regression models. Of the 108 participants, 19.4% had a poor Sleep profile, 48.1% had a poor SED profile, 29.6% had a poor MVPA profile, and 29.6% met our criteria defining a poor overall 24-Hour Activity Profile. No statistically significant differences were observed in the percentage of students having a poor 24-HAC profile across categories of the examined characteristics. However, poor 24-HAC profile prevalence was substantially higher among students classified as obese [57.1%; OR=3.13 (95% CI: 0.64, 15.30) compared to normal weight students], students living off campus [35.7%; OR=2.46 (95% CI: 0.95, 6.40) compared to living on campus], and students living with two roommates [53.8%; OR=2.00 (95% CI: 0.48, 8.40) compared to having no roommates].

3.5 Discussion

The aim of this study was to describe all individual components of the 24-HAC by demographic and lifestyle characteristics in university students. This study is the first of its kind to simultaneously use three different research grade monitors to measure all components of the 24-HAC in any group. This investigation also provides insights into how the components of the 24-HAC vary between weekdays and weekend days. Finally, this study developed a novel indicator of having a poor 24-Hour Activity profile from the different components of the 24-HAC. Based on our findings, students attending a large university in the southeastern United States spend about 34% of their day sleeping, 41% engaging in SED, 21% in LPA, and 4% engaging in MVPA. Finally, 30% of the 108 participants met our criteria for having a poor 24-Hour Activity Profile.

A study by Hargens et al (2021) also assessed MVPA, SED, and sleep with a single accelerometer in 81 university students. Specifically, participants in that study were required to wear the accelerometer on their waist during waking hours and wear the device on their wrist during periods of sleep. Compared to the current study, that study found that university students had similar MVPA (4%) but slept less (27% vs. 34%) and were more SED (46% vs. 41%). Hargens et al (2021) also reported estimates by sex (females: 57.7±24.5 min/d; males: 63.3±28.0 min/d). The present study also observed that males (66.8±37.6 min/d) had higher estimates of MVPA compared to females (50.2±29.8 min/d). Hargens et al. (2020) also reported that university students tend to sleep longer (404.1±66.7 min/d) and have lower MVPA (44.1±30.3 min/d) on weekend days compared to weekdays (Sleep: 378.9±60.4 min/d; MVPA: 65.7±28.0 min/d). In the current study, mean MVPA was about 17 minutes lower on Sundays (41.1 min/d) compared to Mondays (58.8 min/d) and mean sleep was about 36 minutes higher on Sundays (513.8 min/d) compared to Mondays (477.7 min/d). Finally, estimates of SED in the Hargens' study were higher on weekends (682.6±90.3 min/d) and lower on weekdays (637.4±130.9 min/d) while, in contrast, the present study found higher SED on weekdays (611.7±100.2 min/d) and lower SED on weekend days (568.5±113.9 min/d). However, two important study differences should be considered when comparing the results from the current study to the study by Hargens et al. (2021). First, LPA was not reported in the prior study. Second, only eight hours of accelerometer wear was required to be considered a valid day and the minimum number of valid days for inclusion was not reported. In this study, valid days were those in which a behavior could be assigned for >1380 minutes using the combined data sources and four or more valid weekdays, and two or

A study by Jones et al. (2020) examined sleep differences by race/ethnicity in a nationally represenative sample of 2119 university students living on campus and reported a higher prevalence of sleeping less than seven hours per night in university students that identified as Black/African American. In agreement with Jones et al., the current study found that those classified as Other race (i.e., Black Non-Hispanic and "other" races) had the shortest total sleep duration (463.3±52.8 min/d) compared to students identifying as White Non-Hispanic (489.4±65.7 min/d), Hispanic (495.4±50.7 min/d), or Asian (480.4±63.0 min/d). However, few studies have examined differences in total sleep duration by different lifestyle characteristics in university students. Reen et al

(2016) examined the association of alcohol usage and self-reported sleep patterns in first year university students. In that study total sleep duration was identical (7.2 hr/d) in students who reported drinking alcohol compared to students that did not drink alcohol. In contrast, the present study found that university students who reported drinking alcohol slept an additional 22.8 minutes per day compared to students that reported not drinking alcohol.

In this study, university students spent an average of 9.9 hours per day in different sedentary activies. These findings are in agreement with a recent systematic review by Castro et al. (2020) that reported college students are sedententary on average 9.8 hours per day based upon objective measures. However, SED time differences by demographic characteristics were dissimilar to results of previous investigations (Carpenter et al., 2021; Clemente et al., 2016; Juren et al., 2020) . For example, Juren et al (2020) reported that males (9.46 hrs) had similar estimates of sedentary time per week compared to females (9.64 hrs). The present study observed that females (596.1±87.9 min/d) and males (605.9±92.3 min/d) had similar total SED time estimates.

Estimates of LPA from the present study also shared some similarities and differences with exisiting studies (Arias-Palencia et al., 2015; Clemente et al., 2016;). As compared to Clemente et al. (2016), the present study had very similar weekday LPA estimates (287.3±78.7 min/d) but the current study observed estimates of LPA on weekend days that were 40.4 minutes higher. However, Arias-Palencia et al. (2015) reported substantially lower estimates of weekday (250.9 min/d) and weekend (259.1 min/d) estimates of LPA compared to the present study.

Because findings from the current study varied greatly compared to previous investigations, two important implications should be considered. First, not all prior investigations assessing 24-HAC behaviors were conducted in the United States; thus cultural factors may explain some of the observed differences. Second, prior investigations varied by the types of devices used to assess the 24-HAC, how the devices were worn, and the algorithms and accelerometer cut-points used to classify the components of the 24-HAC. In particular, of the use of different accelerometer cut-points can result in substantial differences in estimates of SED, LPA and MVPA, making it difficult to compare results across investigations. Finally, it should be noted that the observed day-to-day variations in the 24-HAC are likely caused by multiple factors that were not measured in the present study. For example, weather, including rain and extremes of heat and cold, are known to influence physical activity participation and weather was not considered in the present study (Chan et al., 2006).

A primary strength of this study was its use of three different research grade monitors to classify all four components of the 24-HAC. As suggested by Rosenberger et al. (2019), no single device has the capability to accurately classify all four components. The present study used three research grade monitors to classify the components of the 24-HAC. Specifically, an activPAL was worn on the thigh to assess SED, an ActiGraph GT3X+ was worn on the hip to measure LPA and MVPA, and an ActiGraph GT9X was worn on the wrist to measure sleep. Although many sleep investigations in free living conditions rely on self-report, the current study was able to utilize not only a self-reported log but also two objective measures (ActiGraph GT9X and activPAL) to derive estimates of TIB and TOB. Another strength of this study was the use of an innovative data processing procedure to use harness data from all three devices to determine the 24-HAC behavior being performed during each minute of the day. Finally, the present study utilized a strong wear time protocol which consisted of a minimum of 1380 minutes per included day and a minimum of four weekdays and two weekend days for each student. The present investigation also has several limitations that should be considered. First, the use of a cross-sectional design precludes examining prospective associations between demographic, academic, or lifestyle characteristics and 24-HAC behaviors. Second, this study measured 24-HAC behaviors over a one-week time period which may not reflect these behaviors over an entire semester or academic year. Third, females (66.6%) and students that identified as White-Non Hispanic (62.9%) primarily comprised of our student sample, limiting the study's generalizability to male students and students of different races and ethnicities. Fourth, measurement reactivity might have occurred with some participants due to the awareness of being monitored (Baumann et al., 2018). By being monitored, it is plausible some participants may have initally altered their daily sitting time or physical activity behaviors, thus influencing time spent in the components of the 24-HAC. Finally, no criterion measure was used to identify the times spent in and out of bed, leading to errors in our assignment of sleep times and, by extension, misclassification of time spent in the other components of the 24-HAC.

While this study classified all four individual components of the 24-HAC, further work in this area is still needed. Because the 24-HAC is still a new paradigm, future studies are needed to describe the 24-HAC in different samples, preferably using combined objective measures. In addition, future work should explore longer term changes in the components of the 24-HAC using combined objective measures and in diverse groups. However, researchers should consider the challenges (e.g., participant and investigator burden, research costs, device loss) of using multiple measurement devices if proceeding with this approach. Future studies should examine whether a single objective measurement device can provide similar estimates of the 24-HAC compared to those derived from multiple devices.

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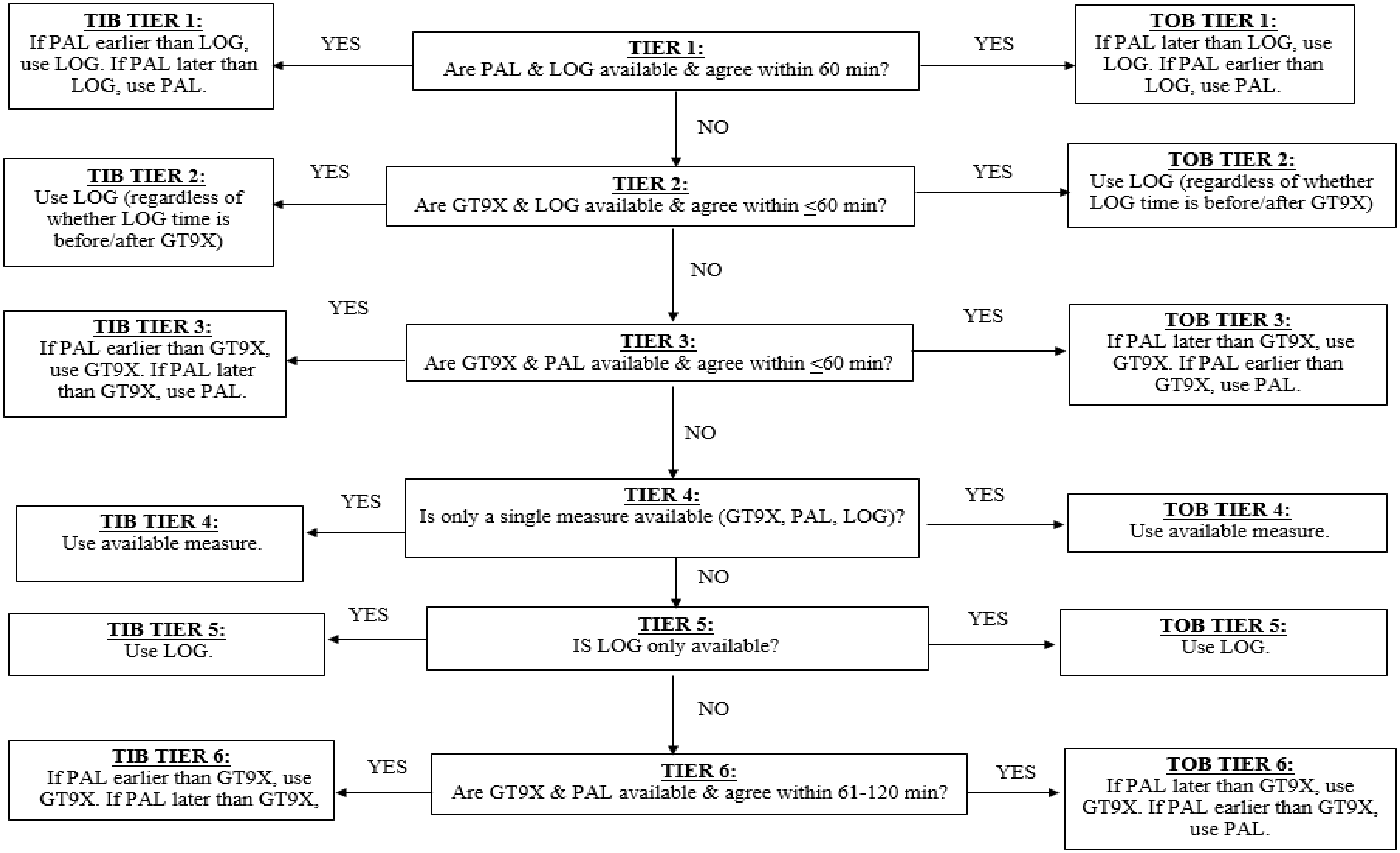
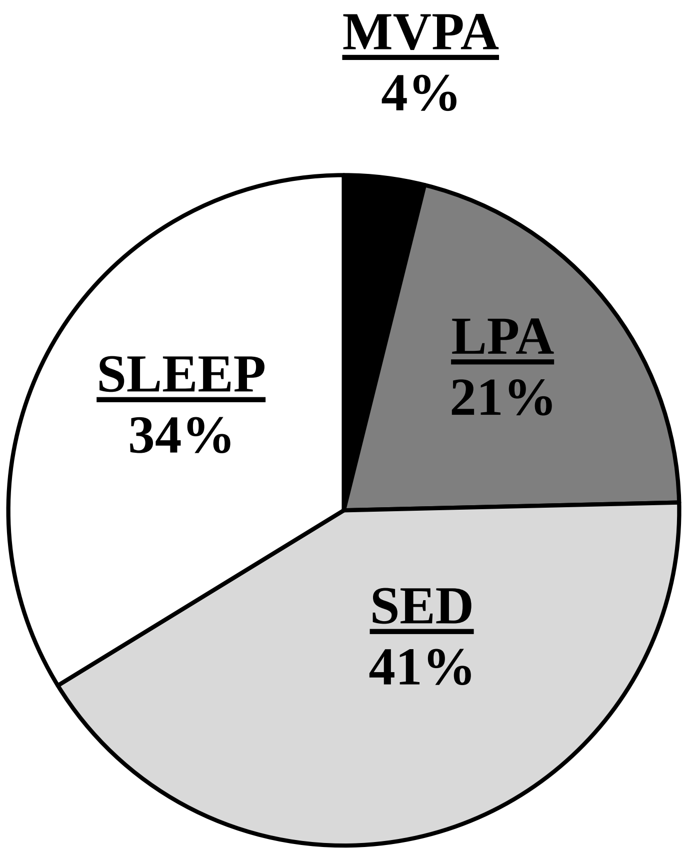
Figure 3.1 *Decision Tree for Classifying Times in Bed and Times out of Bed for Sleep*



*Note: GT9X=ActiGraph GT9X, PAL=activPAL3, LOG=Participant Sleep Diary

Figure 3.2
Average Percent Time Spent in Components of 24-Hour Activity Cycle in University Students



Note: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity

Table 3.1

Average Time Spent in Components of the 24-Hour Activity Cycle by Demographic Characteristics in University Students

Characteristic	**N**	**Sleep (min/d)** M±SD	**SED (min/d)** M±SD	**LPA (min/d)** M±SD	**MVPA (min/d)** M±SD
Sex					
Female	72	487.5±53.1	596.1±87.9	306.2±75.1	50.2±29.8
Male	36	483.0±78.5	605.9±92.3	284.3±79.6	66.8±37.6
		p=0.72	*p*=0.59	*p=0.16*	***p=0.01***
Race/Ethnicity					
White-Non-Hispanic	68	489.4±65.7	592.1±83.1	297.7±72.6	60.8±33.5
Asian	17	480.4±63.0	628.3±109.1	296.9±96.7	34.4±18.0
Hispanic	12	495.4±50.7	603.2±69.0	281.2±46.4	60.2±28.8
Other	11	463.3±52.8	595.4±112.2	328.3±96.7	53.0±44.1
		p=0.55	*p=0.50*	*p=0.51*	***p=0.02***
BMI Classification					
Underweight	10	479.2±49.7	627.0±109.0	282.9±90.4	50.9±32.2
Normal Weight	67	493.7±60.4	601.6±80.3	290.0±65.1	55.7±33.9
Overweight	24	478.5±69.8	583.4±106.4	318.7±94.4	59.4±34.4
Obese	7	447.9±65.1	592.7±83.5	348.3±80.6	51.1±30.8
		p=0.23	p=0.60	*p=0.09*	*p=0.89*

Notes: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity. “Other” Race/Ethnicity is comprised of Black Non-Hispanic (n=8) and Other race (n=3). The statistical significance of between group differences was assessed using Univariate General Linear Models.

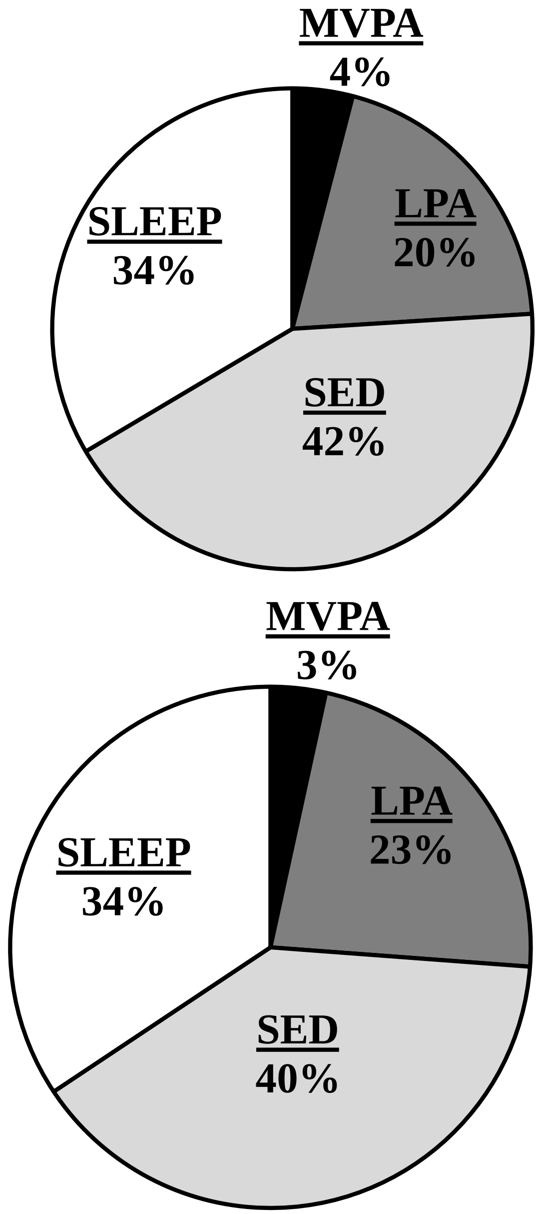
Table 3.2
Average Time Spent in Components of the 24-Hour Activity Cycle by Academic and Lifestyle Characteristics in University Students

Characteristic	**N**	**Sleep (min/d)** M±SD	**SED (min/d)** M±SD	**LPA (min/d)** M±SD	**MVPA (min/d)** M±SD
Academic Classification					
Freshman	27	484.0±66.7	605.7±76.7	284.5±61.2	65.8±39.1
Sophomore	28	499.0±57.7	605.0±84.6	279.3±65.1	56.7±31.6
Junior	20	480.6±84.0	568.8±96.7	331.6±74.8	59.0±36.8
Senior	26	473.7±41.3	609.0±104.0	313.4±92.0	44.0±25.8
Graduate	7	502.7±62.2	603.8±73.3	285.8±99.4	47.7±22.0
		p=0.55	*p=0.55*	*p=0.09*	*p=0.15*
Living Location					
On-Campus	38	479.6±60.3	615.1±78.7	283.9±59.5	61.4±35.9
Off-Campus	70	489.5±63.4	590.8±93.7	307.0±84.2	52.7±31.7
		p=0.43	*p=0.17*	*p=0.13*	*p=0.19*
# of Roommates					
None	19	477.9±50.7	624.5±115.9	289.9±93.3	47.7±29.9
1	40	485.8±54.4	591.8±84.7	299.1±59.5	63.4±36.7
2	13	508.8±64.6	556.7±67.3	326.7±99.7	47.8±34.2
3	36	482.3±74.9	609.8±81.3	293.4±76.8	54.4±30.1
		p=0.52	*p=0.13*	*p=0.53*	*p=0.24*
Greek Life					
Non-Member	90	484.1±63.7	601.9±90.0	299.0±79.2	54.9±32.4
Member	18	495.5±56.4	586.3±85.9	298.2±66.4	60.0±38.3
		p=0.48	*p=0.49*	*p=0.97*	*p=0.55*

Alcohol Usage					
Non-Drinker	59	476.7±60.2	606.4±99.3	303.0±78.9	53.9±32.7
Drinker	44	499.5±60.5	585.3±73.6	295.2±77.4	60.0±34.3
		p=0.08	*p=0.36*	*p=0.54*	*p=0.53*
Caffeine Drinker					
Non-Drinker	43	493.2±44.7	603.2±100.4	288.4±82.9	55.2±37.6
Drinker	65	481.3±71.7	596.8±81.4	305.8±72.6	56.1±30.5
		p=0.33	*p=0.71*	*p=0.24*	*p=0.90*
Medication Usage					
No	64	477.8±67.8	603.9±97.7	297.6±78.3	60.7±34.9
Yes	44	497.9±52.1	592.7±75.4	300.8±75.8	48.6±29.8
		p=0.09	*p=0.52*	*p=0.83*	*p=0.06*

Notes: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity. The statistical significance of between group values was assessed using Univariate General Linear Models.

Figure 3.2
Weekday and Weekend Percent Time Spent in Components of 24-Hour Activity Cycle in University Students



A. Weekday

B. Weekend

Note: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity.

Table 3.3

Weekday and Weekend Estimates of the 24-Hour Activity Cycle Components by Demographic Characteristics in University Students

Characteristic	N	Sleep (min/d) M±SD		SED (min/d) M±SD		LPA (min/d) M±SD		MVPA (min/d) M±SD	
		Weekday	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**
Sex									
Females	72	487.7±68.1	487.1±83.9	608.9±102.2	564.1±104.0	290.1±78.2	346.5±113.2	53.4±30.9	42.4±33.9
Males	36	472.5±83.5	509.2±125.0	617.3±97.2	577.3±132.5	281.9±80.7	290.3±103.4	68.3±37.6	63.1±49.9
		p=0.31	*p=0.27*	*p=0.68*	*p=0.57*	*p=0.61*	***p=0.01***	***p=0.03***	***p=0.01***
Race/Ethnicity									
White-Non-Hispanic	68	487.3±77.0	494.8±104.5	605.5±90.9	558.3±112.6	283.9±75.0	332.2±108.3	63.2±33.8	54.5±43.6
Asian	17	463.2±72.9	523.5±111.1	649.0±116.0	576.6±127.7	290.4±96.6	313.3±131.6	37.5±20.0	26.6±21.3
Hispanic	12	497.2±58.5	490.7±59.5	601.8±95.7	606.6±89.0	278.1±49.2	289.1±88.7	62.9±30.9	53.6±31.0
Other	11	468.1±67.6	*451.5*±75.1	602.8±132.8	*576.7*±128.1	313.7±100.5	364.6±133.6	55.3±44.5	47.2±47.8
		p=0.49	*p=0.30*	*p=0.41*	*p=0.55*	*p=0.66*	*p=0.38*	***p=0.03***	*p=0.07*
BMI Classification									
Underweight	10	461.9±66.3	522.2±84.3	653.6±127.3	560.4±93.8	276.3±109.9	299.6±86.7	48.2±29.9	57.8±41.8
Normal Weight	67	489.0±75.9	505.6±86.6	615.9±90.8	565.6±106.3	276.6±63.1	320.0±107.1	58.5±34.5	48.5±40.6
Overweight	24	481.7±69.7	470.6±125.6	585.5±108.6	578.2±149.9	310.5±99.9	339.1±127.6	62.3±34.1	52.1±46.4
Obese	7	454.8±73.5	430.5±114.3	601.0±112.8	572.1±83.2	326.5±71.1	402.9±132.9	57.7±35.5	34.5±21.4
		p=0.50	*p=0.10*	*p=0.29*	*p=0.97*	*p=0.13*	*p=0.21*	*p=0.74*	*p=0.68*

Notes: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity. "Other" Race/Ethnicity is comprised of Black Non-Hispanic (n=8) and Other race (n=3). The statistical significance of between group differences was assessed using Univariate General Linear Models.

Table 3.4
Weekday and Weekend Estimates of the 24-Hour Activity Cycle Components by Academic and Lifestyle Characteristics in University Students

Characteristic	N	Sleep (min/d) M±SD		SED (min/d) M±SD		LPA (min/d) M±SD		MVPA (min/d) M±SD	
		Weekday	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**
Academic Classification									
Freshman	27	486.1±93.0	479.0±91.4	612.8±99.9	587.9±99.5	272.6±77.9	314.5±89.2	68.5±37.4	59.0±54.6
Sophomore	28	494.4±72.2	510.6±76.7	615.1±98.2	579.6±100.4	269.9±73.2	302.8±89.6	60.6±32.1	57.0±37.2
Junior	20	473.7±74.4	498.0±147.8	578.6±99.2	544.3±134.1	327.2±66.8	342.5±122.7	60.5±36.3	55.2±43.3
Senior	26	469.5±56.0	484.1±70.6	626.0±113.6	566.5±116.9	299.0±88.3	349.3±117.3	45.5±28.6	40.1±28.4
Graduate	7	496.3±54.7	518.5±142.8	635.1±46.6	525.5±150.5	256.9±65.5	358.1±208.6	51.6±29.0	37.9±19.9
		p=0.70	*p=0.70*	*p=0.52*	*p=0.55*	***p=0.04***	*p=0.45*	*p=0.13*	*p=0.40*
Living Location									
On-Campus	38	480.2±85.1	478.1±75.4	621.9±100.1	598.2±94.9	273.5±77.3	309.7±82.2	64.4±34.6	54.0±49.1
Off-Campus	70	484.0±67.0	503.3±109.9	606.1±100.5	552.3±120.5	294.8±79.1	337.5±125.7	55.1±33.2	46.7±35.9
		p=0.80	*p=0.20*	*p=0.43*	***p=0.04***	*p=0.17*	*p=0.22*	*p=0.17*	*p=0.38*
# of Roommates									
None	19	466.4±61.2	506.6±66.8	653.1±114.8	553.1±145.1	271.7±92.5	335.3±127.7	48.8±31.3	45.0±30.7
1	40	484.1±70.6	489.8±89.4	601.2±101.1	568.3±93.9	289.0±69.9	324.2±90.3	65.6±34.9	57.7±51.2
2	13	508.3±59.5	510.0±107.2	564.8±75.5	536.5±117.5	320.2±104.5	342.8±138.1	46.7±32.0	50.7±44.5
3	36	480.2±86.3	487.8±121.9	618.4±92.9	588.3±115.5	281.8±69.3	322.3±121.1	59.5±33.5	41.6±29.7
		p=0.45	*p=0.83*	*p=0.07*	*p=0.47*	*p=0.34*	*p=0.93*	*p=0.16*	*p=0.35*
Greek Life									
Non-Member	90	479.2±72.6	496.5100.3	613.2±100.5	573.7±118.2	289.6±80.8	322.6±113.6	58.0±33.3	47.2±37.8
Member	18	499.9±78.0	484.4±97.2	604.0±101.3	542.3±87.0	276.1±68.3	353.4±107.5	60.1±37.3	59.9±54.1
		p=0.27	*p=0.64*	*p=0.72*	*p=0.28*	*p=0.29*	*p=0.51*	*p=0.81*	*p=0.22*

Alcohol Usage									
Non-Drinker	59	471.1±70.2	490.7±88.7	622.3±108.7	566.6±123.2	289.3±79.5	337.0±113.7	57.2±32.7	45.7±39.1
Drinker	44	502.7±70.8	491.3±111.8	590.5±85.6	572.4±105.7	285.4±81.7	319.6±114.7	61.4±35.5	56.7±43.7
		p=0.07	*p=0.67*	*p=0.22*	*p=0.85*	*p=0.96*	*p=0.34*	*p=0.70*	*p=0.31*
Caffeine Drinker									
Non-Drinker	43	484.5±57.3	515.0±72.1	616.2±111.0	570.8±123.6	282.3±90.4	303.4±105.9	57.0±37.5	50.7±46.3
Drinker	65	481.4±83.0	480.9±112.6	608.8±93.1	566.9±107.9	290.7±70.6	343.8±115.0	59.2±31.5	48.3±37.3
		p=0.83	*p=0.08*	*p=0.70*	*p=0.86*	*p=0.59*	*p=0.06*	*p=0.74*	*p=0.76*
Medication Usage									
No	64	475.5±82.9	483.6±96.8	612.8±110.2	581.6±115.5	289.1±81.0	318.7±110.8	62.6±34.3	56.1±45.9
Yes	44	493.0±56.6	510.3±96.8	610.1±84.7	549.4±109.9	284.7±76.3	340.9±115.4	52.2±32.5	39.5±30.1
		p=0.22	*p=0.17*	*p=0.89*	*p=0.14*	*p=0.77*	*p=0.31*	*p=0.11*	***p=0.03***

Notes: Sleep=Total Sleep Duration, SED=Total Sedentary Time, LPA=Light Physical Activity, MVPA=Moderate-to-Vigorous Physical Activity. The statistical significance of between group differences was assessed using Univariate General Linear Models.

Figure 3.3

Time (M±SE) Spent by in the Components of the 24-Hour Activity Cycle in University Students, by Days of the Week

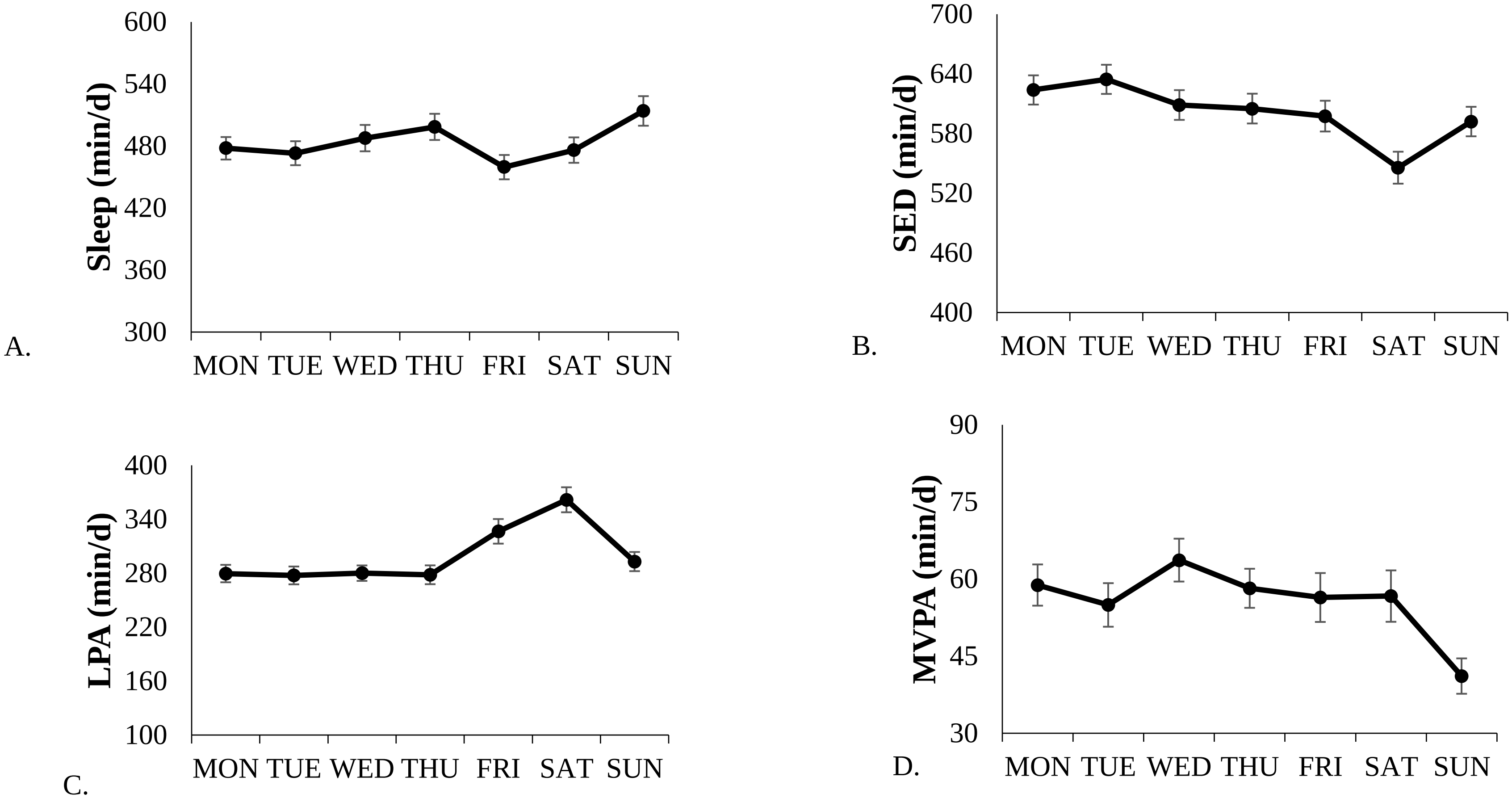


Table 3.5
Prevalence of having a Poor 24-Hour Activity Cycle Profile by Demographic, Academic, and Lifestyle Characteristics in University Students

Characteristic	% Poor Profile	Odds Ratio [95% CI]
Sex		
Females	30.6	0.87 [0.36, 2.12]
Males	27.8	REF
Race/Ethnicity		
White-Non-Hispanic	27.9	REF
Asian	29.4	1.08 [0.33, 3.46]
Hispanic	33.3	1.29 [0.35, 4.79]
Other	36.4	1.47 [0.39 ,5.62]
BMI Classification		
Underweight	20.0	0.59 [0.11, 3.02]
Normal Weight	29.9	REF
Overweight	25.0	0.78 [0.27, 2.27]
Obese	57.1	3.13 [0.64, 15.30]
Academic Classification		
Freshman	22.2	REF
Sophomore	32.1	1.66 [0.50, 5.53]
Junior	40.0	2.33 [0.65, 8.34]
Senior	23.1	1.05 [0.29, 3.80]
Graduate	42.9	2.63 [0.46, 15.11]
Living Location		
On-Campus	18.4	REF
Off-Campus	35.7	2.46 [0.95, 6.40]
# of Roommates		
None	36.8	REF
1	22.5	0.50 [0.15, 1.64]
2	53.8	2.00 [0.48, 8.40]
3	25.0	0.57 [0.17, 1.90]
Greek Life		
No Member	28.9	REF
Member	33.3	1.23 [0.42, 3.63]
Alcohol Usage		
No Drinker	30.5	REF
Drinker	28.6	0.91 [0.40, 2.09]

Caffeine Drinker		
No Drinker	25.6	REF
Drinker	32.3	1.39 [0.59, 3.28]
Medication Usage		
No	28.1	REF
Yes	31.8	1.19 [0.52, 2.75]

Odds ratios and 95% confidence intervals calculated using Bivariate Logistic Regression.

CHAPTER 4

RELATIONSHIP BETWEEN SMARTPHONE SCREEN TIME AND THE 24-HOUR ACTIVITY CYCLE IN UNIVERISTY STUDENTS[1]

[1]Boudreaux BD, O'Connor PJ, Evans EM, Frederick GM, Schmidt MD
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4.1 Abstract

Introduction: Relationships between smartphone screen time (SST) and the components [sleep, sedentary behavior (SED), light physical activity (LPA), moderate to vigorous physical activity (MVPA)] of the 24-Hour Activity Cycle (24-HAC) are poorly understood in university students. Smartphone ownership is prevalent among university students and the amount of time using a device may contribute to daily variations with the 24-HAC. This study examined relationships between SST and the 24-HAC in a sample of university students. **Methods**: University students (n=101) wore three devices (ActiGraph GT3X via right hip, ActiGraph GT9X via non-dominant wrist, activPAL3 via anterior aspect of thigh) and downloaded a smartphone application to capture habitual 24-HAC and SST. Pearson correaltions were used to examine the strength of the relationships between SST and the 24-HAC. Multiple linear regression was used to examine the relationshipsbetween SST and the 24-HAC adjusted for sex, race, living location, and other behaviors of the 24-HAC. **Results**: The relationships between SST and 24-HAC components were modest to weak in strength ($r=-0.21$ to $r=0.18$). LPA was the only 24-HAC behavior that maintained a statistically significant relationship with SST across all three adjusted models (Model 1: $\beta=-8.03$, Model 2: $\beta=-9.40$, Model 3: $\beta=-7.99$). After adjusting for demographic factors and select behaviors of the 24-HAC, SST had a positive statistically significant association with SED (Model 3: $\beta=7.99$). **Conclusions**: After adjusting for potential confounding factors, SED and LPA were the only components of the 24-HAC that maintained a statistically significant association with SST. Future studies should examine longer term relationships between SST and the 24-HAC in larger and more diverse samples.

4.2 Introduction

The four basic behaviors of a 24-hour day include sleep, sedentary behavior (SED), light physical activity (LPA), and moderate to vigorous physical activity (MVPA). Together, these behaviors are called the 24-Hour Activity Cycle (24-HAC). Growing evidence suggests that all four components are individually positively or negatively associated with long-term health outcomes (e.g., cardiovascular, diabetes, and mortality) (Chastin et al., 2021). Few prior studies have examined all four components of the 24-HAC simultaneously, with most researchers continuing to examine all four of these components individually (Chastin et al., 2021; Rosenberger et al., 2019). This is a limitation because outcomes of interest may be confounded or moderated by other behaviors that make up the 24-HAC (Chaput, 2014; Rosenberger et al., 2016; Rosenberger et al., 2019). Simultaneously considering all components of the 24-HAC would provide researchers with an opportunity to examine the potential joint and interactive associations that exist between the 24-HAC component behaviors and a range of health-related behaviors and outcomes (Chaput, 2014; Rosenberger et al., 2019).

Traditional approaches to measure and classify the components of the 24-HAC include self-report or the use of a single objective measure (e.g., wrist-worn accelerometer), but two important limitations should be considered. First, self-report measures of specific 24-HAC components (e.g., International Physical Activity Questionnaire, Pittsburgh Sleep Quality Index) are subject to recall error and potential bias depending upon health status. Substantial measurement error makes it harder to identify true associations between 24_HAC behaviors and health outcomes, while biased recall can lead to identifying erroneous associations (Haskell, 2012). Second, using a single wrist-worn accelerometer can result in substantially higher counts per minute (used to identify activity intensity), number of steps per day, or classifying posture compared to a waist and or thigh worn accelerometer (Marcotte et al., 2020). Based upon these reasons provided, integrating combined measurement approaches, or simultaneously using more than one wearable device may be needed to measure the 24-HAC behaviors with acceptable precision (Rosenberger et al., 2016; Rosenberger et al., 2019). Simultaneous measurement of all components of the 24-HAC would also allow researchers to more fully examine both the direct and indirect associations of different 24-HAC profiles with important outcomes (Chaput, 2014; Rosenberger et al., 2016; Rosenberger et al., 2019).

One behavior in particular, smartphone screen time, has emerged as a new behavior that was uncommon prior the introduction of the iPhone in 2007. Traditional screen time behaviors (i.e., watching television, playing video games, computer usage) are SED unless modified (i.e., stand up desk). In contrast, smartphone screen time is a dynamic behavior that can occur in any component of the 24-HAC except sleep. Although smartphone screen time does not occur during sleep, evidence suggests that interacting with a smartphone prior to bedtime can result in delayed sleep onset or poor sleep quality (Carter et al., 2016). It is estimated that the average adult uses their smartphone between five to eight hours per day (Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019), although the amount of time interacting with a smartphone screen may vary by characteristics such as age or race (Christensen et al., 2016).

Emerging evidence suggests that smartphone screen time is negatively associated with total physical activity and positively associated with sleep and SED in university students (Alshobaili & AlYousefi, 2019; Arshad et al., 2021; Barkley & Lepp, 2016; Barkley et al., 2016; Duraccio K.M., 2021; Grimaldi-Puyana et al., 2020;; Lepp & Barkley, 2019; Lepp et al., 2013; Lin et al., 2020; Penglee et al., 2019; Rafique et al., 2020; Randjelovic et al., 2019; Towne et al., 2017). However, the studies supporting these associations have used diverse approaches to measure both smartphone screen time and the components of the 24-HAC. For example, smartphone screen time has been assessed by predominantly by single item questionnaires while a few studies have used smartphone applications available for specific device platforms (i.e., iOS or Android). Likewise, the components of the 24-HAC have been measured by diverse methods including self-report questionnaires and consumer wearable devices (Alshobaili & AlYousefi, 2019; Arshad et al., 2021; Barkley & Lepp, 2016; Barkley et al., 2016; Duraccio K.M., 2021; Grimaldi-Puyana et al., 2020; Lepp & Barkley, 2019; Lepp et al., 2013; Lin et al., 2020; Penglee et al., 2019; Rafique et al., 2020; Randjelovic et al., 2019; Towne et al., 2017). In addition to the measurement inconsistencies, the approaches used to examine the relationship between smartphone screen time and components of the 24-HAC have varied greatly across the different investigations. For example, some investigations have explored if certain behavioral characteristics (e.g., meeting aerobic PA guidelines vs not meeting aerobic PA guidelines) predict smartphone screen time. Because of these inconsistencies and discrepancies, a standardized approach is needed to not only effectively measure smartphone screen time and the 24-AHC but also to examine the relationship between smartphone screen time and the 24-HAC behaviors.

To date, no study has simultaneously measured all components of the 24-HAC using multiple objective measures in a university student sample. Moreover, no prior study has standardized the approach to objectively measure smartphone screen time for both iOS and Android platforms in a university student sample. To address these gaps in the literature, this study was conducted to assess the relationships between smartphone screen time and components of the 24-HAC (SED, LPA, MVPA, and sleep) in university students before and after adjusting for plausible confounders as well as other components of the 24-HAC.

4.3 Methods

Participant Recruitment & Screening

Students enrolled at a large university were recruited via their university-provided email address during the spring and fall 2021 semesters. Email addresses were obtained from the Office of the Registrar. Prior to participation, prospective participants received an email that described the study's main purpose and an invitation to complete an online survey to assess their eligibility status. Prospective participants were classified as eligible if they met the following criteria: aged 18 to 24 years old, full-time student status, and fluent in written English. Participants were excluded if meeting one or more of the following criteria: enrolled as a student athlete, not owning a smartphone, having children or planning to become pregnant, had a diagnosis of an orthopedic injury in the past six months, or reporting a bipolar diagnosis. All study procedures were reviewed and approved by the university institutional review board and written informed consent was obtained during the participant's first in person visit.

Research Design and Procedures

The study consisted of a cross-sectional design that ranged between seven to ten days with two in-person visits. During a participant's first visit, research staff briefly described the study's procedures, answered any research related inquiries, and obtained informed consent from the participant. Participants were directed to a private quiet room and were instructed to complete a self-report questionnaire assessing demographic characteristics. Next, a research team member asked the participant if he or she was prescribed any daily medication and then took the following body measurements: height (Hopkins Medical Products, Grand Rapids, MI, Model: Hopkins Road Rod Portable Stadiometer), weight and body fat percentage estimated from bioelectrical impedance (Tanita Corporation of America Inc, Arlington Heights, Illinois, Model: WB100, TBF-305), and waist circumference at the iliac crest. Next, participants were fitted with three different research grade monitors: an ActiGraph GT3X+ worn on the right hip, an ActiGraph GT9X Link worn on the non-dominant wrist, and an activPAL3 worn on the anterior aspect of the non-dominant thigh. Participants were provided verbal and written instructions on how to wear the monitors over the next seven to ten days. After fitting all three monitors, participants were instructed to download the RescueTime application on their smartphone and log in with their researcher assigned username and password. After logging into the application, participants were instructed to continue using their smartphone as normal but to allow the application to have background refresh enabled. Prior to the participant's departure, a second in person-visit was scheduled.

The second in-person visit occurred seven to ten days after the first in-person visit. Upon arrival, participants removed all monitors and returned their monitor log to a research team member. Next, participants were instructed to open the RescueTime application for a final refresh before logging out and deleting the application on their smartphone. After the application was deleted, a research team member retrieved and downloaded the participant’s smartphone screen time data from RescueTime’s website for storage on the study’s secured server.

Smartphone Screen Time Measure

RescueTime is a third-party application compatible with both Apple and Android smartphones that objectively measures daily smartphone screen time. The application provides users different approaches to measure their daily smartphone screen time including a daily summary, 1-hour epochs, and 5-minute epochs. As provided by the developer, smartphone screen time is registered during times when the phone is unlocked and the screen is illuminated. Further, smartphone screen time is not registered during times a user is listening to music or making voice calls when the screen is in sleep mode. Because of the privacy restrictions by Apple Inc., the times spent in different categories of smartphone use (e.g., business, communication, design, entertainment, news, reference, shopping, social networking, software development, uncategorized, utilities, and miscellaneous) were not available for iPhone users but this feature was available and used for Android smartphone users. To prevent overestimation of smartphone screen time, participants smartphones were set to enter sleep mode after 30 seconds of nonuse. Participants were instructed to not change this assigned feature but were permitted to adjust the device’s brightness. Finally, if a participant accidently closed the application, they received a notification to re-open the application. A minimum of 4 weekdays and 2 weekend days of screentime data wasrequired for a student to be included in the final data analysis.

24 Hour Activity Cycle Measures

Light and Moderate to Vigorous Physical Activity

An ActiGraph GT3X+ (ActiGraph Corp, Pensacola, FL) was attached to an elastic belt and worn on the right hip during all waking hours to measure LPA and MVPA. Participants were instructed that the ActiGraph GT3X+ should not be worn during water-based activities or sleep. Devices were equipped with firmware v 3.2.1 and ActiLife software version 6.13.4 was used to initalize and download data in 1-minute epoch lengths. The low frequency extension was not used. LPA and MVPA were classified using the Freedson 2011 algorithm which incorporated an additional SED cut-point (Sedentary: 0-150 cpm, Light: 151-2689 cpm, Moderate: 2690-6166 cpm, Vigorous: 6167-9642 cpm, Very Vigorous: ≥9643 cpm) (Migueles et al., 2017; Sasaki et al., 2011). Non-wear periods were identified as periods with 60 consecutive minutes of 0 counts using the Choi algorithm (Choi et al., 2011). In addition, participants were also provided a log to document times of device non-wear.

Sedentary Behavior

The activPAL3 (PAL Technologies, Glasgow, UK) was used to measure sedentary behavior and estimates of times in and out of bed. Data in 1-minute epoch lengths processed by PAL Analysis Software (version 8.11.8.75 with the CREA algorithm) to classify participants' posture and ambulatory behaviors throughout the day. The device provides valid estimates of sedentary behaviors during free living conditions in young adults compared to direct observation (Lyden et al. 2017). SED behavior metrics provided by the software include time spent sitting, in seated transport, and in primary (sleep-related) or secondary lying. ActivPAL3 estimates of times in and out of bed were derived from the primary lying times each day. As described by PAL Technologies, time in bed estimates are derived from non-upright events lasting at least one hour and then expanding each event to adjacent non-upright events lasting at least one hour (thus allowing for bathroom breaks and other sleep interruptions), resulting in a container of predominantly non-upright events. The longest container is classified as 'Primary Lying Time" and the shorter is classifed as 'Secondary Lying Time'(PAL Technologies, 2022).

Data Processing

For this analysis, all three data sources (ActiGraph GT3X+, activPAL3, and ActiGraph GT9X Link) were processed using the previously noted software packages and then combined in 1-minute epochs. Each minute of monitored time was then classified as either sleep, SED, LPA, or MVPA. Briefly, non-sleep minutes were classified as 1) SED if the activPAL identified the participant as sitting for the entire minute or, absent activPAL data, the ActiGraph GT3X+ had a vector magnitude ≤ 150 counts per minute (cpm); 2) LPA if the activPAL registered upright posture for any portion of the minute or if the ActiGraph GT3X+ registered 151-2690 vector magnitude cpm; and 3) MVPA if the ActiGraph GT3X+ registered ≥ 2691 vector magnitude cpm. Only days in which a behavior could be assigned for ≥1380 minutes using the combined data sources were retained for analysis as "valid days". Valid days with less than 1440 minutes of data, due to missing data or spring daylight savings, were standardized to a 1440 minute day by multiplying each 24-HAC estimate by 1440 / #valid minutes. Valid days with more than 1440 minutes of data, due to fall daylight savings, were standardized to a 1440 minute day by multiplying each 24-HAC estimate by #valid minutes / 1440.

Mean estimates of 24-HAC behaviors were calculated separately for weekdays (a minimum of 4 valid days required) and weekend days (a minimum of 2 valid days required). Weekly 24-HAC behaviors and weekly smartphone screen time and were then derived as the weighted average of the weekday and weekend estimates.

Statistical Analysis

Descriptive statistics and histograms were obtained for all continuous variables at both the day and participant level to assess normality and to screen for data anomalies. Estimates for sleep, SED, LPA, and MVPA are reported as mean, standard deviation (SD) values unless otherwise noted. General linear models were used to compare smartphone screen time estimates across groups varying in demographic, academic and lifestyle characteristics. Pearson correlation coefficients were used to examine the strength of the relationships between smartphone screen time and each of the four components of the 24-HAC. Multiple linear regression was used to examine the relationship between smartphone screen time and each of the four components of the 24-HAC. The first model (Model 1) assessed the crude relationship between smartphone screen time and individual components of the 24-HAC. The second model (Model 2) adjusted for potential confounders (i.e., sex, race/ethnicity, living location). The final model (Model 3) adjusted for t not only sex, race/ethnicity, and living location but also select 24-HAC behaviors (Sleep=SED/MVPA, SED=Sleep/MVPA, LPA=Sleep/MVPA, MVPA=Sleep/SED). Statistical analyses were completed using SPSS (version 26.0) and SAS (version 9.4) and an alpha level <.05 indicated statisical significance.

4.4 Results

A total of 695 participants completed the study's inital elgibility survey. A total of 123 participants confirmed elgibility and consented to participate. After data processing and cleaning, 101 university students were included in the final analysis. Table 4.1 displays participant demographic characteristics. The sample was primarily female (67.3%) and identified as White Non-Hispanic (63.4%). On average, participant smartphone screen time was 318.3±117.4 min/d (or about 5.3hours/day). In addition, on average participants spent most of their day SED (600.3±87.6 min/d), followed by sleep (487.4±58.5 min/d), LPA (296.1±76.0 min/d), and MVPA (56.2±33.9 min/d).

As displayed in figure 4.2, university students had substantial day to day variability in smartphone screen time and all components of the 24-HAC. Interestingly, smartphone screen time trended downward over the course of the week (from Monday to Sunday). Total sleep duration was lowest on Fridays and highest on Sundays SED behavior was highest at the beginning of the week and gradually decreased over the course of the week, closely tracking changes in smartphone screen time. LPA remained consistent during week days but increased substantially on Fridays and Saturdays before decreasing again on Sundays. MVPA was relatively consistent over the course of the week but was substantially lower on Sundays.

Smartphone Screen Time

Table 4.2 provides estimates of screen time by demographic, academic, and lifestyle characteristics in university students. While there were no significant differences during weekdays, university students that identified as White-Non-Hispanic engaged in significantly less smartphone screen time on weekends (278.3±119.1 min/d) compared to

Asians (366.9±130.6 min/d), Hispanics (322.3±115.1 min/d), and those reporting other racial backgrounds (379.0±214.5 min/d). Overall, and on weekend days, university students that reported not consuming caffeine engaged in significantly higher smartphone screen time (Overall: 347.4±119.6 min/d, Weekends: 344.7±158.8 min/d) compared to university students that reported consuming caffeine (Overall: 299.1±112.9 min/d, Weekends: 283.4±117.2 min/d).

Sleep

Table 4.3 displays correlations between smartphone screen time and the components of the 24-HAC. The correlation between smartphone screen time and sleep was positive but weak (r=0.08) and non-significant. Correlations between sleep and the other components of the 24-HAC were negative and moderate to weak in strength (r=-0.38 to r=-0.15). Table 4.4 summarizes the associations between smartphone screen time and the components of the 24-HAC. The overall crude relationship between smartphone screen time and sleep was positve but small in magnitude [Model 1: β=2.34 (95% CI: -3.60, 8.28)]. After adjusting for demographic confounders and other components of the 24-HAC, the relationship increased in strength [Model 2: β=3.81 (95% CI: -2.36, 5.29)]; Model 3: β=5.29 (95% CI: -0.13, 10.70)] but remained non-significant. On weekdays and weekends, the relationships were similar and remained positive but small in magnitude.

Sedentary Behavior

The correlation between smartphone screen time and SED was positive but weak (r=0.18) and non-significant. The overall crude association between smartphone screen time and SED was moderate but non-significant [Model 1: β=8.23 (95% CI: -0.55, 17.01]. After adjusting for demographic confounders, these relationships remained consistent [Model 2: β=7.36 (95% CI: -1.75, 16.47)] and achieved statistical significance after further adjusting for other components of the 24-HAC [Model 3: β=7.99 (95% CI: 0.41, 15.58)]. The crude relationship between smartphone screen time and the 24-HAC was larger on weekends [Model 1: β=9.84 (95% CI: 0.33, 19.34)] compared to weekdays [Model 1: β=7.16 (95% CI: -2.92, 17.24)]. This result indicates that, on weekends, for each hour increase in smartphone screen time a 9.84-minute increase in SED occurred. After adjusting for confounders, these associations remained larger on weekends than weekdays but neither association achieved statistical significance.

Light Physical Activity

A statistically significant negative correlation was observed between smartphone screen time and LPA, although it was relatively weak in magnitude ($r=-0.21$, $p<.05$). LPA also had a strong negative correlation with SED ($r=-0.71$, $p<.01$) and a weaker negative correlation with sleep ($r=-0.26$, $p<.01$), but little correlation with MVPA ($r=0.05$, $p>.05$). The overall crude relationship between smartphone screen time and LPA was statistically significant and indicated that each hour increase in smartphone screen time was associated with an 8.03-minute decrease in LPA [Model 1: β=-8.03 (95% CI: -15.61, -0.46]. After adjusting for demographic confounders and other components of the 24-HAC, the relationships remained statistically significant and of similar magnitude [Model 2: β=-9.40 (95% CI: -17.08, -1.72); Model 3: β=-7.99 (95% CI: -15.58, -0.41)]. Across all 3 models, the beta values on weekend days (β=-9.83 to β=-9.36) had a larger magnitude compared to beta values on weekdays (β=-6.96 to β=-5.77).

Moderate to Vigorous Physical Activity

The correlation between smartphone screen time and MVPA was negative but weak ($r=0.15$) and non-significant. The correlations between MVPA and the other components of the 24-HAC were moderate to weak in magnitude ($r=-0.33$ to $r=0.05$; $p < .01$). The overall crude relationship between smartphone screen time and MVPA was negative but small in magnitude [Model 1: $\beta=-2.54$ (95% CI: -5.95, 0.88)]. After adjusting for demographic confounders and other components of the 24-HAC, the associations decreased [Model 2: $\beta=-1.78$ (95% CI: -5.15, 1.60)]; Model 3: $\beta=0.33$ (95% CI: -2.77, 3.43)]. Similar trends were observed on weekdays and weekend days.

4.5 Discussion

The aim of this investigation was to examine the relationship between smartphone screen time and the 24-HAC in university students. Findings indicate that total smartphone screen time decreased substantially during the week (from Monday to Sunday). Specifically, the largest screen time difference between days was about 110 minutes, with the highest amount of screen time on Monday (337.2 min/d) and the lowest on Sunday (226.2 min/d). The amount of time spent in the different components of the 24-HAC also varied substantially across days. As expected, smartphone screen time was positively associated with sleep and SED behaviors and negatively associated with active behaviors (e.g., LPA, MVPA). Overall, LPA was the only component of the 24-HAC that had a significant association with smartphone screen time after adjusting for potential confounders. After further adjusting for other components of the 24-HAC, smartphone screen time had a positive significant association with both LPA and SED. However, LPA and SED associations were identical in Model 3 which suggests collinearity problems exist for that particular model.

The present study is not the first investigation to measure smartphone screen time and the components of the 24-HAC. To date, Grimaldi-Puyana et al. (2020) is the sole study to examine the association between smartphone screen time and all components of the 24-HAC in university students. The study consisted of 306 Spanish university students and used the International Physical Activity Questionaire, Pittsburgh Sleep Quality Index Questionaire, and two different smartphone features depending on the participant's device platform (Android=”Your Hour”, iOS= “Screen Time”) to examine the different relationships. However, the study used smartphone screen time as the dependent variable and the 24-HAC behaviors as the independent variables. This approach prevents directly comparing this study’s results to the current study.

The smartphone is the most prevalent technology device in a university setting, as students rely on the device for both academic and leisure purposes. The present study examined the extent to which smartphone screen time varies across a range of demographic, lifestyle, and academic characteristics. In agreement with Christensen et al. (2016), higher estimates of smartphone screen time were observed in students who identified as Asian (+60.2 min/d), Hispanic (+42.8 mi/d), or other racial backgrounds (+66.7 min/d) compared to students that identified as White-Non Hispanic. Unexpectedly in the present study, students that reported not drinking a caffeinated beverage daily had significantly higher total smartphone screen time (+48.3 min/d) compared to students that reported drinking a caffeinated beverage daily. This finding warrents further research given that in large studies of younger adolescents in the United States (n=32,418) and

Korea (n=62,276), greater caffeine use was also associated with more smartphone use (Bradbury, 2019; Kim 2021). Smartphone screen time was not significantly associated with any other student characteristic in the current study.

The present study shares both similarities and differences of smartphone screen time by demographic or lifestyle characteristics when compared to previous investigations. However, two reasons may explain why these differences were observed. First, prior investigations were conducted in different countries which can lead to demographic differences in the population. Second, these investigations varied by the type of devices and algorithms used to measure the components of the 24-HAC. Specifically, there is a large number of accelerometer cut-points available to quantify LPA and MVPA which can greatly influence estimates of these behaviors, making it difficult to compare findings across studies.

Two primary reasons may explain the differences in smartphone screen time results observed in the present study compared to prior investigations. First, prior investigations were conducted in different countries which can lead to demographic differences in the population. Second, these investigations varied by the type of devices and algorithms used to measure the components of the 24-HAC. Specifically, there is a large number of accelerometer cut-points available to quantify LPA and MVPA which can greatly influence estimates of these behaviors, making it difficult to compare findings across studies.

This investigation also had several limitations that should be considered. First, the use of a cross-sectional design limits the ability to examine the associations with demographic, academic, or lifestyle characteristics as the temporal direction of these associations is unknown and causality cannot be inferred. Second, individuals' 24-HAC behaviors were assessed over a short measurement period which may not reflect changes that could occur during the semester. Having a longer-term measurement period (e.g., measurement during both spring and fall semesters) would better capture variations in 24-HAC behaviors over an academic year in university students and provide more stable estimates of habitual 24-HAC patterns. Third, the sample in the present study primarily consisted of females (66.6%) and students that identified as White-Non Hispanic (62.9%), thus potentially limiting the generalizability of these findings to student populations with different gender and race characteristics. Fourth, measurement reactivity might have occurred with some participants due to the awareness of being monitored (Baumann et al., 2018). By being monitored, it is plausible some participants may have altered their daily sitting time or physical activity behaviors, thus influencing our estimates of the time spent in the different components of the 24-HAC. Fifth, no criterion measure was used for identifying times in and out of bed, which may have lead to misclassification of time spent in the different components of the 24-HAC. Finally, the validity of the algorithm developed and used to derive the time spent in the components of the 24-HAC from multiple objective measures has not been established.

Based upon the study's findings, smartphone screen time had moderate to large associations with LPA (negative) and SED (positive) in university students. Smartphone screen time had little to no relationship with total sleep duration or MVPA . While these results contribute to addressing the current gaps and limitations in the literature on this topic, further work is needed. Specifically, future studies should explore how the amount of time spent in different types of smartphone activities interact with the 24-HAC.

Because smartphone screen time exposure varies throughout the day, future studies should also examine temporal relationships in more detail. For example, there is a need to better understand the relationship between smartphone screen time in the hour prior to bed time and different sleep outcomes (e.g., total sleep duration, sleep quality, sleep efficiency, wake after sleep onset). Finally, future studies should examine longer-term realtionships between smartphone screen time, the 24-HAC, and different health outcomes in university students.

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Table 4.1
Participant Demographic Characteristics

Characteristic	N (%)	M±SD	MIN	MAX
Age (years)		20.1±1.6	18	24
BMI (kg/m^2)		23.4±4.0	14.8	36.2
Sex				
Females	68 (67.3)			
Males	33 (32.7)			
Race/Ethnicity				
White-Non-Hispanic	64 (63.4)			
Asian	16 (15.8)			
Hispanic	10 (9.9)			
Other	11 (10.9)			
Smartphone Type				
iPhone	88 (87.1)			
Android	13 (12.9)			
24 Hour Activity Cycle Components, (min/d)				
Total Sleep Duration		487.4±58.5	344.4	662.0
Sedentary Behavior		600.3±87.6	373.7	812.6
Light Physical Activity		296.1±76.0	116.6	506.2
Moderate to Vigorous Physical Activity		56.2±33.9	0.0	155.6
Total Smartphone Screen Time, (min/d)		318.3±117.4	47.3	769.5

Table 4.2

Screen Time Differences by Demographic, Academic, and Lifestyle Characteristics in University Students

Characteristic	N	Overall (M±SD)	Weekday (M±SD)	Weekend (M±SD)
Sex				
Females	68	326.8±118.9	334.3±119.8	308.2±138.8
Males	33	300.6±114.2	298.2±110.9	306.7±137.8
		p=0.29	*p=0.14*	*p=0.96*
Race/Ethnicity				
White-Non-Hispanic	64	297.2±108.1	304.7±113.0	278.3±119.1
Asian	16	357.4±111.3	353.5±107.8	366.9±130.6
Hispanic	10	340.0±80.8	347.1±76.2	322.3±115.1
Other	11	363.9±178.3	357.9±172.2	379.0±214.5
		p=0.10	*p=0.24*	***p=0.02***
BMI Classification				
Underweight	9	351.1±178.7	357.3±159.8	299.5±120.4
Normal Weight	66	314.5±110.9	320.4±114.4	335.6±248.6
Overweight	19	323.6±112.6	327.2±111.9	314.6±138.2
Obese	7	297.2±116.8	284.1±116.2	329.9±129.6
		p=0.79	*p=0.65*	*p=0.84*
Academic Classification				
Freshman	26	322.1±98.3	322.0±97.1	322.5±117.0
Sophomore	25	343.5±98.0	354.3±106.2	316.6±108.7
Junior	18	293.9±120.9	304.2±126.1	268.3±124.1
Senior	25	301.6±138.9	303.1±128.6	297.8±179.9
Graduate	7	335.6±163.0	326.7±167.7	357.8±172.2
		p=0.61	*p=0.55*	*p=0.55*

Living Location				
On-Campus	36	337.2±126.6	337.6±123.4	336.3±154.2
Off-Campus	65	307.8±111.7	314.1±114.5	291.9±126.2
		p=0.22	*p=0.33*	*p=0.11*
# of Roommates				
None	19	320.1±150.1	314.9±140.8	333.0±185.6
1	37	320.9±108.8	322.3±106.9	317.5±127.6
2	12	284.7±77.0	294.7±75.9	259.5±93.3
3	33	326.5±120.7	337.2±129.3	299.7±131.1
		p=0.76	*p=0.73*	*p=0.48*
Greek Life				
Non-Member	83	319.0±121.9	322.3±119.7	310.7±147.1
Member	18	314.7±97.1	323.1±110.8	293.7±83.4
		p=0.89	*p=0.98*	*p=0.63*
Alcohol Usage				
Non-Drinker	55	327.8±125.9	331.6±124.6	318.5±148.7
Drinker	43	307.8±109.9	311.9±112.2	297.5±126.4
		p=0.40	*p=0.41*	*p=0.45*
Caffeine Drinker				
Non-Drinker	40	347.4±119.6	348.5±114.3	344.7±158.8
Drinker	61	299.1±112.9	305.4±117.6	283.4±117.2
		p=0.04	*p=0.07*	***p=0.02***
Medication Usage				
No	60	317.7±125.1	317.2±119.4	319.0±153.1
Yes	41	319.1±106.8	330.2±115.9	291.2±111.4
		p=0.95	*p=0.58*	*p=0.32*

Note: The statistical significance of between group values was assessed using Univariate General Linear Models

Table 4.3
Pearson Correlations between Smartphone Screen Time and 24-Hour Activity Cycle Components

24-HAC Component	**ST**	**Sleep**	**SED**	**LPA**	**MVPA**
ST	-				
SLEEP	.08	-			
SED	.18	-.38**	-		
LPA	-.21*	-.26**	-.71**	-	
MVPA	-.15	-.15	-.33**	.05	-

Note. *Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Table 4.4

Associations between Smartphone Screen Time and 24-Hour Activity Cycle Components

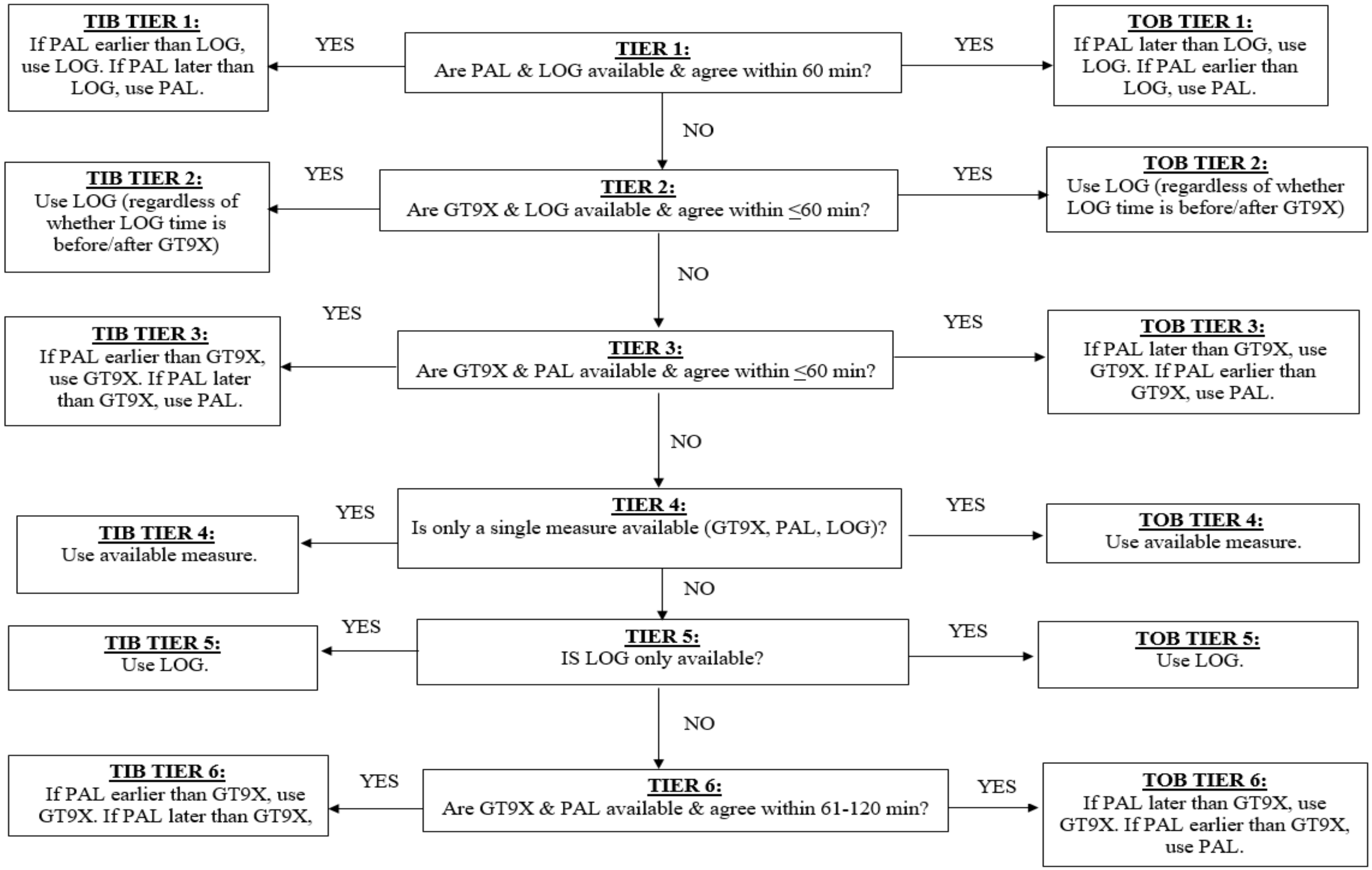
OVERALL SMARTPHONE SCREEN TIME (hrs/d)						
	Model 1*		**Model 2****		**Model 3*****	
24-HAC Component (min/d)	*β*	*95% CI*	*β*	*95% CI*	*β*	*95% CI*
Sleep	2.34	[-3.60, 8.28]	3.81	[-2.36, 9.98]	5.29	[-0.13, 10.70]
SED	8.23	[-0.55, 17.01]	7.36	[-1.75, 16.47]	**7.99**	**[0.41, 15.58]**
LPA	**-8.03**	**[-15.61, -0.46]**	**-9.40**	**[-17.08, -1.72]**	**-7.99**	**[-15.58, -0.41]**
MVPA	-2.54	[-5.95, 0.88]	-1.78	[-5.15, 1.60]	0.33	[-2.77, 3.43]
WEEKDAY SMARTPHONE SCREEN TIME (hrs/d)						
	Model 1*		**Model 2****		**Model 3*****	
24-HAC Component (min/d)	*β*	*95% CI*	*β*	*95% CI*	*β*	*95% CI*
Sleep	1.80	[-5.54, 9.13]	2.51	[-5.11, 10.13]	3.83	[-2.24, 9.90]
SED	7.16	[-2.92, 17.24]	6.96	[-3.45, 17.38]	5.89	[-2.03, 13.82]
LPA	-5.77	[-13.48, 1.95]	-6.96	[-14.90, 0.97]	-5.89	[-13.82, 2.03]
MVPA	-2.34	[-5.81, 1.13]	-2.44	[-5.81, 0.94]	-0.75	[-3.82, 2.31]
WEEKEND SMARTPHONE SCREEN TIME (hrs/d)						
	Model 1*		**Model 2****		**Model 3*****	
24-HAC Component (min/d)	*β*	*95% CI*	*β*	*95% CI*	*β*	*95% CI*
Sleep	1.05	[-7.04, 9.15]	2.27	[-6.03, 10.58]	4.30	[-3.59, 12.18]
SED	**9.84**	**[0.33, 19.34]**	8.14	[-1.90, 18.17]	8.08	[-0.81, 16.98]
LPA	-9.36	[-19.22, 0.51]	-9.83	[-19.83, 0.17]	-9.68	[-19.82, 0.45]
MVPA	-1.53	[-5.14, 2.08]	-0.96	[-4.64, 2.73]	1.33	[-1.64, 4.29]

***Model 1.** Crude relationship between smartphone screen time (hrs/d) and each component of the 24-Hour Activity Cycle (min/d).

****Model 2.** Relationship between smartphone screen time and 24-Hour Activity Cycle components after adjusting for potential demographic confounders (sex, race/ethnicity, living location).

*****Model 3**. Adjusted relationship between smartphone screen time and physical activity outcomes after adjusting for demographic confounders (sex, race/ethnicity, living location) and other components of the 24-Hour Activity Cycle (*Sleep*=SED/MVPA, *SED*=Sleep/MVPA, LPA=Sleep/MVPA, MVPA=Sleep/SED).

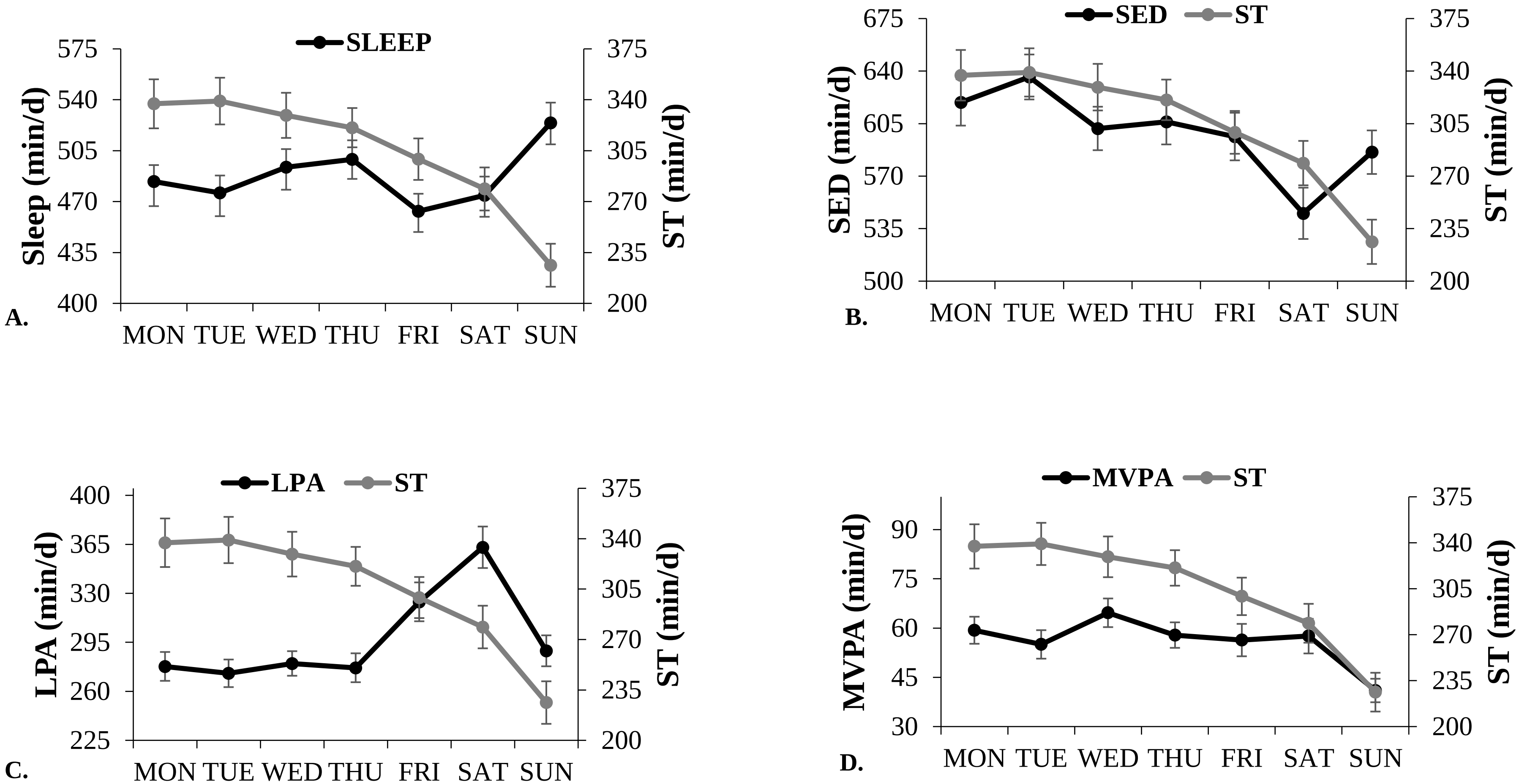
Figure 4.1 *Decision Tree for Classifying Times in Bed and Times out of Bed for Sleep*



*Note: GT9X=ActiGraph GT9X, PAL=activPAL3, LOG=Participant Sleep Diary

Figure 4.2

Time (M±SE) Spent in Smartphone Screen Time and Components of the 24-Hour Activity Cycle in University Students, by Days of the Week



CHAPTER 5

SUMMARY AND CONCLUSIONS

The purpose of this dissertation was to 1) simultaneously measure smartphone screen time and the different components of the 24-Hour Activity Cycle (24-HAC) with objective measures and to describe differences in 24-HAC and smartphone screen time behaviors by demographic, academic, and lifestyle characteristics in university students 2) describe the associations between smartphone screen time and the 24-HAC.

The first portion of this dissertation described time spent in all four components of the 24-HAC in university students and examined the extent to which these behaviors differed according to demographic and lifestyle characteristics. Overall, males engaged in significantly more MVPA compared to females but were similar in other 24-HAC behaviors. On weekends, females engaged in significantly more total LPA than males. Students that identified as Asian engaged in significantly less MVPA compared to students that identified as White-Non-Hispanic, Hispanic, or Other racial backgrounds. Finally, students that reported taking daily medication had significantly less MVPA compared to students that reported not taking daily medication.

The second portion of this dissertation examined associations between smartphone screen time and components of the 24-HAC in university students. An interesting finding revealed that screen time estimates tended to decrease during the week (Monday to Sunday). Smartphone screen time was positively associated with Sleep and SED behaviors and negatively associated with active behaviors (e.g., LPA, MVPA).

This dissertation incorporated several innovative features to help address important gaps and limitations in the literature about the 24-HAC and smartphone screen time. The main innovation involved the use of three different research grade monitors to classify the different components of the 24-HAC. By simultaneously using three different research grade monitors, the study was able to use synchronized data from all three devices to assign each minute to a 24-HAC component behavior. Another innovation was the development of an algorithm to identify participants having a "Poor 24-Hour Activity Profile". Specifically, this was defined as participants meeting two or more of the following criteria: a) sleeping less than six hours per night or sleeping longer than nine hours per night, b) having a total sedentary time greater than 10 hours per day, and c) engaging in less than 30 minutes per day of MVPA. Although the present investigation included several innovative methods, further work is needed to better understand the factors that influence 24-HAC behaviors, including the role of smartphone screen time.

The 24-HAC has gained popularity in recent years as a model to better understand the joint and interactive effects of Sleep, SED, LPA and MVPA on important health outcomes. This study has several implications that should be considered when designing a future study of a similar design. For example, the present study found frequent discrepancies between the time in bed and time out of bed reported in participants' logs and estimates from two research grade monitors. Without a clearly superior method of identifying times spent in bed for sleep, there is likely to be a substantial amount of error in sleep time estimates. This is likely, in turn, to introduce additional error into estimates of the other components of the 24-HAC, especially SED. Collaboration among researchers from diverse backgrounds is strongly recommended given the interdisciplinary nature of the 24-HAC and the breadth of the relevant areas of research. To address the various measurement challenges with the 24-HAC, future studies should: 1) examine whether a single objective measure can provide similar estimates of the 24-HAC compared to those derived from multiple devices, 2) explore the associations between smartphone screen time in the hour before bed and markers of sleep quality, 3) describe the 24-HAC behaviors in diverse populations, and 4) examine how interventions to change a single component of the 24-HAC alters the other 24-HAC components.