ACTIVITY BEHAVIOR PROFILES AND SLEEP DURATION AMONG PHYSICALLY ACTIVE ADOLESCENTS: A PROSPECTIVE STUDY

by

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DISSERTATION ABSTRACT

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Title: **ACTIVITY BEHAVIOR PROFILES AND SLEEP DURATION AMONG PHYSICALLY ACTIVE ADOLESCENTS: A PROSPECTIVE STUDY**

Over 70% of US adolescents do not meet sleep recommendations despite the critical role of sleep in health and development. Increases in physical activity (PA) are associated with improved sleep among the general adolescent population. Among adolescents exceeding PA guidelines, less is known about how activity behaviors – moderate-to-vigorous intensity PA (MVPA), light-intensity PA (LIPA), sedentary behavior (SB), and phone-based screen time (ST) – cluster in association with sleep duration, and how nature exposure interacts with these associations. This study aimed to 1) identify distinct profiles of active adolescents characterized by activity behaviors, 2) examine demographic predictors of profile membership, 3) examine how profiles are associated with sleep duration, and 4) test nature exposure as a moderator.

An Oregon community sample of 326 adolescents (12-17y/o; 48.5% female) participated in a 7-day prospective study during summers 2022 and 2023. Seven days of MVPA, LIPA, SB, and sleep duration (via accelerometry) and nature exposure (via NatureDose™ phone-application) were collected; participants reported daily ST from phone data. Latent profile analyses were conducted, specifying four activity behavior indicators (MVPA, LIPA, SB, ST) using the three-step maximum likelihood approach to examine profile membership associations with demographic characteristics and sleep duration.

Four distinct profiles of active adolescents emerged: "Active Resters" (High-SB/ST;37.1%), "Active Screenies" (High-ST;6.1%), "Balanced Actives" (Moderate-High-MVPA/LIPA/SB;49.4%), and "Highly Actives" (High-MVPA/LIPA;7.4%), with age being the consistent predictor of profile membership in lesser active profiles. "Active Screenies" demonstrated significantly greater sleep duration (9.5hr±29.5 minutes) compared to all other profiles (p<.001). Nature exposure showed no significant moderating effect.

Despite exceeding physical activity guidelines, distinct activity profiles emerged with varying links to sleep. "Active Screenies", characterized by second lowest MVPA, least LIPA, least sedentary behavior, and highest screen time, demonstrated the longest sleep duration, and was the only profile that met sleep recommendations. Sleep interventions for active adolescents should consider interrelationships among activity behaviors, not only physical activity.

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DEDICATION

For my Family: The original Dr. Farley, who set an example of what it means to be a committed educator, researcher, and father; my mother, who always knows when I need some extra encouragement to get over the *hump*; my loving wife, without whom none of this would have been possible.

For my community, who I aim to serve, let's get connected – streets, resources, communities – to health, together.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Insufficient Sleep Among Adolescents: A Public Health Concern

The American Academy of Pediatrics' Adolescent Sleep Working Group has declared insufficient sleep an endemic issue greatly affecting the health and wellbeing of adolescents in the United States (Owens et al., 2014). According to the 2021 Youth Risk Behavior Surveillance System survey, almost 73% of US adolescents do not meet the national recommendation (Paruthi et al., 2016) of at least 8 hours of sleep per day, representing an increase of almost 5% since 2015 (CDC, 2024). This concerning trend highlights the growing magnitude of sleep insufficiency as a public health issue among the adolescent population whose developmental needs make adequate sleep especially crucial. The consequences of insufficient sleep among adolescents extend across multiple domains of functioning and health. Acute effects include impairment of attention, memory, and emotion regulation, increased risk-taking behaviors, and poor mental health outcomes (Owens et al., 2014). Chronically, insufficient sleep is associated with increased risk for anxiety and depression, impaired immune function, metabolic dysregulation, and, more distally, can contribute to the development of chronic conditions such as type II diabetes and cardiovascular disease (Owens et al., 2014; Sun et al., 2020). Widespread insufficient sleep – and the associated detrimental effects on development, health, and wellbeing – led the American Academy of Pediatrics to declare insufficient sleep among adolescents as an endemic issue, noting great need for additional and innovative research to promote sufficient sleep among adolescents (Owens et al., 2014).

Sleep also plays a crucial role in homeostasis – the body's maintenance of a balanced internal environment – which is especially important during adolescence due to rapid physical and neurological development occurring during this period (Carskadon, 2011). During adolescence, the brain undergoes significant remodeling, with processes of synaptic pruning and myelination requiring adequate sleep for optimal execution (Tarokh et al., 2016). Sleep also supports the regulation of hormonal processes central to adolescent development, including growth hormone secretion and pubertal maturation (Colrain & Baker, 2011). Furthermore, adolescents, particularly during puberty, can experience circadian phase delay – a natural shift towards delayed sleep onset by up to two hours – and altered sleep architecture influencing duration of sleep phases (e.g., slow-wave sleep, REM sleep, etc.; Colrain & Baker, 2011; Carkadon et al., 2011; Crowley et al., 2018). The combination of these developmental needs with biological shifts in sleep regulation during adolescence creates a *perfect storm* for sleep insufficiency (Carskadon et al., 2011; Crowley et al., 2018).

Physically Active Adolescents: A Unique Population

While physical activity engagement is often associated with improved sleep outcomes in the general adolescent population (Lang et al., 2016; Kredlow et al., 2015; Piercy et al., 2018), physically active adolescents – those consistently meeting or exceeding physical activity guidelines of 60+ minutes of daily moderate-to-vigorous intensity physical activity (MVPA; Piercy et al., 2018) – present a unique subpopulation that has received limited attention in sleep research and sleep promotion efforts. In a study of sleep among adolescent athletes, Suppiah and colleagues (2016) found that despite high training volumes (i.e., high amounts of MVPA), greater than half of the participants reported inadequate sleep duration. Similarly, among a sample of collegiate athletes, Mah et al. (2018) found that athletes exhibited lower sleep quality and report insufficient sleep at rates comparable to their less active peers.

This combination of high MVPA and insufficient sleep achievement challenges conventional assumptions about the relationship between physical activity and sleep and is concerning for several reasons. First, insufficient sleep places active adolescents at risk for the same poor health outcomes that affect their less active peers (Owens et al., 2014). Second, sleep insufficiency is linked directly to poorer athletic performance, decreased reaction time, impaired decision making, compromised recovery from exercise, and increased risk for injury (Charest & Grandner, 2020; Watson, 2017). Third, the combination of high physical activity demands with inadequate sleep may create a feedback loop that potentially deters sustained physical activity over time due to the accumulation of fatigue, perceived exertion, and diminished enjoyment of physical activities (Charest & Grandner, 2020; Antunes et al., 2017).

Physically active adolescents also face unique physiological challenges related to sleep. High amounts of high-intensity physical activity can trigger increased sympathetic nervous system activity, elevated core body temperature, and alterations in hormone levels that may persist into the evening hours, potentially disrupting sleep behaviors and outcomes (Fox et al., 2020; Lastella et al., 2016). Indeed, Roberts et al., (2019) found that adolescent athletes show distinct sleep-wake patterns compared to their less-active peers, with later bedtimes but similar wake times, resulting in shorter overall sleep duration despite higher physical activity levels.

Recently, the complex interplay between physical activity, sedentary behavior (sedentary behavior), and screen time (screen time) among physically active adolescents has garnered, although limited, attention. Physically active adolescents experience distinctive patterns of movement behaviors – MVPA, light-intensity physical activity (LIPA), and sedentary behavior – throughout the day, uniquely influencing their sleep outcomes. For instance, high training volumes may lead to overreaching or overtraining, potentially disrupting sleep quality and duration despite exceeding physical activity guidelines (Fox et al., 2020; Lastella et al., 2016; Roberts et al., 2019). Additionally, Whitworth-Turner et al. (2017) observed that physically active adolescents demonstrate different relationships between daytime behaviors and nighttime sleep compared to their less active counterparts, with factors such as training load, timing, and recovery practices playing critical roles. The unique constellations of daily activities, including movement behaviors, collectively influence sleep outcomes among physically active adolescents, warranting investigation into how movement behaviors cluster in their association with nightly sleep outcomes.

Movement Behaviors, Screen time, and Sleep

Moderate-to-Vigorous-Intensity Physical Activity. MVPA is characterized by activities requiring substantial energy expenditure at ≥3.0 metabolic equivalents, including structured sport participation and training, vigorous hiking, and other high-intensity recreational activities (Piercy et al., 2018). While the 2nd edition of the Physical Activity Guidelines for Americans recommends that adolescents engage in at least 60 minutes of MVPA daily (Piercy et al., 2018), physically active adolescents may often significantly exceed this threshold, with some engaging in several hours of MVPA daily (Lastella et al., 2016; Roberts et al., 2019). The relationship between MVPA and sleep appears more nuanced among physically active adolescents than the less active adolescent population.

While moderate levels of MVPA generally promote better sleep outcomes – including meeting sleep duration recommendations – evidence suggests a potential U-shaped relationship in which high volumes of MVPA may compromise sleep. For example, Master et al. (2019) found that timing, volume, and intensity of MVPA uniquely influence sleep outcomes among adolescent athletes, with moderate volumes showing more beneficial effects than extremely high volumes (i.e., ceiling effect). This non-linear relationship may be explained by the physiological stress response associated with high training load volumes, which can elevate evening cortisol levels and core body temperature, potentially interfering with sleep onset, leading to shortened sleep duration periods (Daaloul, Souissi, & Davenne., 2018; Roberts et al., 2019; Lastella et al., 2016).

Light-Intensity Physical Activity. LIPA is characterized by activities requiring energy expenditure between 1.5–3.0 metabolic equivalents, including activities such as walking slowly, light household chores, and casual play (Piercy et al., 2018). While often overlooked in research and physical activity recommendations in favor of MVPA, evidence suggests that LIPA plays a unique and potentially critical role in the sleep health of active adolescents. For example, Júdice et al. (2020) observed that adolescent athletes who engaged in more LIPA during recovery periods between bouts of higher-intensity physical activity experienced better sleep quality and longer sleep duration than those who were predominantly sedentary during recovery, despite similar levels of MVPA.

The benefits of LIPA for sleep among this active subgroup of adolescents may operate through several mechanisms. First, LIPA may help maintain metabolic activity and blood flow without triggering additional stress responses – observed in extended high intensity physical activity – that could interfere with sleep (Júdice et al., 2020). Second, LIPA can reduce/replace prolonged sedentary behavior, which has been independently associated with poorer sleep outcomes (Master et al., 2019). Third, LIPA may facilitate physiological and psychological recovery from intense training, potentially enhancing sleep readiness (Watson, 2017). Importantly, a finding by Roberts et al. (2019) indicated that the ratio of LIPA to sedentary behavior was more strongly associated with sleep quality among adolescent athletes than either behavior alone, highlighting the importance of considering the relative balance among movement behaviors. Ultimately, this finding suggests that active adolescents may benefit from strategies that promote LIPA over sedentary activities – or a balance between them – during non-MVPA or recovery periods.

Sedentary Behavior. Sedentary behaviors are characterized by activities requiring minimal energy expenditure (i.e., ≤1.5 metabolic equivalents) while sitting, reclining, or lying down, excluding while sleeping (Piercy et al., 2018). Despite high MVPA levels, active adolescents have been shown to be comparably or even more sedentary than their less-active peers (Franssen et al., 2021; Júdice et al., 2020) leading to the coining of the "active couch potato" phenomenon (Tremblay et al., 2010). For example, Júdice et al. (2020) found that young adult elite athletes spent an average of 8-10 hours per day in sedentary behavior, comparable to their less active peers despite significantly greater MVPA engagement. Furthermore, the effects of sedentary behavior on sleep appear to be largely independent from MVPA levels. For instance, Knufinke et al. (2017) found that adolescent athletes who engaged in prolonged sedentary behavior between training sessions experienced compromised sleep quality compared to those who disrupted sedentary behavior with LIPA, regardless of total MVPA.

Overall, the evidence on movement behaviors highlights the importance of considering the entire activity profile, beyond MVPA alone, to better understand and promote sufficient sleep and overall sleep health among active adolescents. Adolescents exceeding MVPA guidelines may benefit from strategies that promote a balance of MVPA, LIPA, and sedentary behavior to, in turn, promote longer sleep duration.

Phone-Based Screen Time. In recent years, screen time has emerged as a significant risk factor for adolescents' health and well-being, with phone-based screen time as a salient screen-based behavior (Carson et al., 2016a; Kandola et al., 2020). The prevalence of smartphone use among US adolescents makes phone-based screen time increasingly more relevant, where according to recent surveys, 95% of US teens (ages 13-17 years) report having access to a smartphone, with 46% reporting being on their electronic device 'almost constantly' (Anderson et al., 2023).

It is important to note that, although screen time is sometimes used as a proxy for or examined as a subcategory of sedentary behavior (Park et al., 2020; Rathod, 2023), not all screen time occurs while sedentary. For instance, an individual can watch videos on their phone while exercising (e.g., video-guided exercise routines) or engage with mobile applications during other physical activities (e.g., exergames like Pokémon-Go; Chaput & LeBlanc, 2017). Prior literature has identified links between screen time and sleep distinct from sedentary behavior, which highlights the importance of investigating the two behaviors separately (Carson et al., 2016b; Kandola et al., 2020; Zhang et al., 2021). Like sedentary behavior, screen time can negatively impact sleep patterns (e.g., timing and consistency) and sleep quality among adolescents, after adjusting for physical activity (Zhang et al., 2021).

Relevant to all adolescents, including active adolescents, excessive phone-based screen time may be especially detrimental, as it can interfere with both post-physical activity recovery processes and sleep through multiple pathways. First, exposure to blue light emitted by electronic devices suppresses melatonin production, potentially disrupting circadian rhythms and delaying sleep onset (Chang et al., 2014), which may compound circadian phase delay already experienced during adolescence (Crowley et al., 2018). Second, engagement with stimulating content (e.g., social media) can increase cognitive arousal and psychological stress, making it more difficult to transition to sleep (Hale, Hartstein, & LeBourgeois., 2019). Third, screen time can often displace other sleep-promoting activities and can lead to time misperception and delayed bedtimes (Turpin et al., 2024), ultimately leading to shortened sleep duration.

Among physically active adolescents specifically, these effects may interact with physical activity engagement-related factors in complex ways. MVPA, particularly in high volumes, can act to induce physiological activation, elevating body temperature and hormonal fluctuations (Kong et al., 2024) that, when combined with the stimulating effects of screen time, could potentially exacerbate sleep disruptions. For example, Xu et al. (2019) found that even when controlling for physical activity volume, high screen time engagement was associated with disrupted sleep among active adolescents, suggesting unique pathways of influence. Overall, the evidence regarding movement behaviors and screen time – collectively, ‘activity behaviors’ – and their associations with sleep outcomes, including sleep duration, point to the benefits of evaluating their collective effects on sleep over evaluation as independent variables in their associations.

The Integrated Evaluation of Activity Behaviors

While previous research has often examined activity behaviors – MVPA, LIPA, sedentary behavior, and screen time – in isolation, emerging evidence suggests the interrelationships between activity behaviors throughout the day may better explain sleep outcomes than any single behavior alone (Walsh et al., 2020; Tremblay et al., 2016). These behaviors interact in complex ways that together influence sleep achievement, which cannot be fully understood by examining each behavior separately. The concept of behavioral energy balance – encompassing both energy expenditure through physical activity and energy conservation through rest and sleep – provides a useful framework for understanding these interrelationships (Matricciani et al., 2018; Veronda et al., 2022). Physically active adolescents must navigate a balance between sufficient activity to support everyday functioning and athletic performance, adequate rest for recovery, and sufficient sleep for overall health and restoration.

Disruptions in any component of this balance can potentially influence the others, creating feedback loops that affect physical fitness, athletic performance, sustained physical activity, and overall health and wellbeing (Antunes et al., 2017; Matricciani et al., 2018; Veronda et al., 2022). Understanding and promoting optimal sleep health among physically active adolescents could benefit from an examination of the collective influence of activity behaviors, considering the integration of these behaviors across a given day in association with sleep duration (Watson, 2017).

Nature Exposure as a Potential Moderator

An emerging and particularly promising factor in the relationship between activity behaviors and sleep outcomes is nature exposure, or the time one spends in direct experience with natural environments and elements including green vegetation, landscapes, bodies of water, and wildlife (Browning et al., 2023). Nature exposure may moderate the relationship between activity behavior profiles and sleep outcomes among physically active adolescents. For physically active adolescents specifically, the environmental context in which they live and play – where physical activity occurs – appears to significantly influence not only the quality of the activity experience but also subsequent recovery and sleep outcomes. For instance, Noseworthy et al. (2023) found that adolescents who were physically active predominantly outdoors in natural settings reported better sleep quality and longer sleep duration compared to those training in indoor facilities, despite similar training volumes and intensities. This effect persisted even after controlling for potential confounders such as age, sex, and sport/activity-type, suggesting a robust relationship between nature-rich activity environments and sleep benefits.

These sleep-promoting effects of nature exposure have been hypothesized to operate through several potential pathways. First, natural environments may reduce feelings/perceptions of psychological stress and improve mood, potentially countering the physiological and psychological stress response associated with high-intensity physical activity engagement (Ulrich et al., 1991). For example, Argyriadis et al. (2024) found that adolescents engaging in physical activity in green spaces showed lower evening cortisol levels and reported lower perceptions of stress compared to those engaging in comparable physical activity in built-environment settings (e.g., a gym). Given that elevated evening cortisol is associated with sleep disturbances and reduced sleep duration (Daaloul et al., 2018, Roberts et al., 2019; Lastella et al., 2016), this stress-reduction pathway may be especially relevant for physically active youth.

Second, nature exposure has been shown to enhance cognitive and attention restoration (Kaplan, 1995), which may be particularly beneficial for physically active adolescents managing a plethora of social, academic, and athletic demands. For instance, research employing the use of mobile electroencephalography has demonstrated that physical activity performed in nature-rich settings is associated with greater improvements in cognition and neuronal activity in areas of the brain responsible for creativity, emotion regulation, and attention compared to indoor activity (Kimura et al., 2023; Bailey et al., 2018). Further, Boere et al. (2023) observed that these cognitive benefits translated to improved pre-sleep cognitive states among physically active adolescents, potentially facilitating the transition to sleep.

Third, natural light exposure during outdoor activities plays a crucial role in regulating circadian rhythms among adolescents, who naturally experience circadian phase delay during puberty (Colrain & Baker, 2011; Carskadon et al., 2011; Crowley et al., 2018). Lang et al. (2022) found that morning outdoor physical activity sessions were associated with dim light melatonin onset and shorter sleep latency (i.e., shorter time between going to bed and falling asleep) compared to morning indoor physical activity sessions among adolescents. For highly active adolescents, many of whom are involved in organized sports, their daily schedules may compound circadian challenges, but nature exposure may help maintain circadian alignment, potentially improving sleep timing, regularity, and duration (Gradisar, Smits, & Bjorvatn., 2014).

Beyond these mechanisms, nature exposure may also influence sleep through effects on other health behaviors. For instance, DeVille et al. (2021) observed that adolescents who spent more time in natural environments reported less screen time and more consistent bedtime routines (i.e., better sleep hygiene), suggesting that nature exposure may indirectly benefit sleep by promoting complementary health behaviors. Similarly, Li et al. (2018) found that nature exposure was associated with improved mood across diverse adolescent populations, which may reduce evening rumination and facilitate earlier sleep onset.

Importantly, not all nature exposure appears equally beneficial for sleep outcomes among adolescents. In other words, the quality, duration, and timing of nature exposure seem to matter. Browning et al. (2023) proposed a framework for measuring individual-level nature exposure that considers frequency, duration, and quality of exposure, suggesting that greater and deeper engagement with natural environments may yield greater benefits than brief or passive exposures. For physically active adolescents specifically, Pano-Rodriguez et al. (2024) found that adolescent athletes engaging in outdoor training environments reported significantly better perceived sleep quality than those engaging in indoor training environments. However, in that study, they operationalized natural context dichotomously (indoor and outdoor), not accounting for the quality, frequency, duration, and timing of nature exposure. These nuanced dimensions of nature exposure have been shown to be important to consider when examining the role of natural environmental context in association with health outcomes, including sleep (Jimenez et al., 2021; Browning et al., 2023). However, these dimensions of nature exposure have been difficult and expensive to explore objectively in community-based research under free-living conditions, leading to minimal evidence.

Despite prior measurement concerns, the potential moderating effect of nature exposure on the relationship between activity behaviors and sleep represents a promising area for intervention. If nature exposure can mitigate some of the negative effects of suboptimal activity patterns or enhance the benefits of more optimal patterns, it could provide a valuable additional strategy for improving sleep achievement among physically active adolescents. This possibility is particularly relevant considering evidence suggesting that nature-based interventions are generally feasible, cost-effective, and well-accepted by adolescent populations (Noseworthy et al., 2023).

The Summer Context

The summer months represent a distinct and potentially challenging period for adolescent sleep and activity patterns, with unique implications for physically active adolescents. While the structured schedules of the academic year can promote consistent sleep-wake patterns (Crowley et al., 2018), the summer break introduces greater flexibility and autonomy that may significantly alter both activity behavior patterns and sleep outcomes. During summer, adolescents typically experience substantial changes in their daily routines that can affect sleep timing and duration. The absence of early school start times often leads to delayed bedtimes and wake times, creating what has been termed "social jetlag" as adolescents shift toward their biologically preferred later sleep chronotype (Bei et al., 2013) outside of the school year schedule. This pattern is particularly pronounced among adolescents, who naturally experience delays to sleep timing preferences during puberty that predispose them toward later bedtime preferences and sleep onset (Crowley et al., 2018). Without the external constraint of school schedules, adolescents may adopt later and irregular sleep timing, potentially disrupting circadian alignment and reducing nightly sleep duration.

For physically active adolescents, the summer context presents both an opportunity and a challenge. On one hand, the absence of academic demands may reduce overall stress and provide more flexibility for training, recovery, and sleep (Whitworth-Turner et al., 2017). On the other hand, the lack of structure may lead to inconsistent sleep schedules, which has been associated with poorer sleep quality and duration (Bei et al., 2013; Johnson, Billings & Hale, 2018). Additionally, summer training schedules for active adolescents often differ substantially from those during the school year, and from those of their less active peers. For example, many adolescent athletes participate in intensive summer training programs, sports camps, or competitive seasons that may involve intense sport-specific conditioning, two-a-day practices, tournaments, or travel (Halson, 2019). These demanding schedules can lead to high training loads that, without the counterbalancing structure of school routines, may create imbalanced activity-behavior profiles (Halson, 2019; Antunes et al., 2017; Matricciani et al., 2018). For example, Killer et al. (2015) observed that adolescent athletes during summer training camps exhibited patterns of very high MVPA coupled with extended sedentary recovery periods between sessions, a pattern associated with compromised sleep outcomes compared to a more balanced activity distribution (Knufinke et al., 2017).

Summer environmental conditions may also influence sleep and activity behavior patterns. Increased environmental heat stress during outdoor training can elevate core body temperature and extend the time required for cooling before sleep, potentially delaying sleep onset (Fox et al., 2020; Lastella et al., 2016; Kong et al., 2024; Whitworth-Turner et al., 2017). Extended daylight hours in summer may also delay natural melatonin production and contribute to later bedtimes, particularly in regions at higher latitudes (Gradisar et al., 2014). However, the summer months also provide unique opportunities for nature exposure that may benefit sleep outcomes among active adolescents. For example, increased access to outdoor recreational spaces, nature-dense training environments, and nature-based summer programs may enhance the quality of physical activity experiences while providing exposure to natural light patterns that can support circadian regulation (Lang et al., 2022). Additionally, Li et al. (2018) found that adolescents reported significantly higher nature exposure during summer months compared to the school year, with this increased exposure associated with improved mood and sleep quality.

Screen time patterns also shift during summer months, with evidence suggesting that adolescents engage in significantly more screen-based activities during summer compared to the school year (Rideout et al., 2022). This increase may be particularly pronounced in the evening hours, potentially interfering with sleep onset. In summary, the combination of intensive summer training, summer environmental conditions, and increased screen time may create a particularly challenging profile for sleep health among adolescents engaging in extreme volumes of MVPA.

Despite the challenges of the summer context, it also provides opportunities for intervention and behavior change that may not be available during the structured school year. The flexibility of summer schedules allows for greater personalization of activity patterns and sleep timing to match individual chronotypes and preferences (Bei et al., 2013). Additionally, summer presents opportunities for integrating nature-based activities that may enhance both activity experiences and sleep outcomes (Noseworthy et al., 2023). Understanding how activity behavior profiles – distinct patterns of activity behaviors across a given day – manifest during summer months, and how these profiles relate to sleep outcomes among physically active adolescents is crucial for developing targeted interventions that address the unique challenges and opportunities during this critical period of development for this understudied group. Similarly, examining how nature exposure during the summer may moderate these relationships can provide valuable insights for optimizing summer activity behavior patterns to support sleep health in this population.

Person-Centered Approaches to Health Promotion

Given the complex interrelationships between activity behaviors and sleep outcomes among physically active adolescents, particularly during the summer months, a person-centered analytical approach using latent profile analysis offers distinct advantages over variable-centered methods. Latent variable mixture modeling (e.g., Latent Profile Analysis, Latent Class Analysis) is a statistical approach used to identify unobservable (latent) subgroups from observable (manifest or indicator) variables. These latent subgroups represent underlying patterns in the data that are not directly measured but can be inferred from the observed variables (Howard & Hoffman, 2018). This person-centered approach accounts for the reality that individuals do not exist in binary states (e.g., active or sedentary, on their phone or not), but rather exhibit unique constellations of behaviors and exposures across the course of a given period that collectively influence their health and wellbeing.

Unlike variable-centered approaches that examine relationships between variables across the entire sample, person-centered approaches identify more homogeneous subgroups of individuals sharing similar patterns across multiple indicator variables. This allows for the examination of how these distinct patterns relate to outcomes of interest. This distinction is particularly relevant when examining behaviors that are compositional – such as movement behaviors across a given day – where the relative balance and interaction between different behaviors may be more informative than their absolute levels in isolation (Matricciani et al., 2018; Tremblay et al., 2016).

Applications to Movement, Activity, and Screen Time Behaviors. Latent profile (continuous indicator variables) and latent class (categorical indicator variables) analyses have been increasingly applied to study patterns of movement behaviors among adolescents. Several studies have used this approach to identify distinct profiles based on device-measured or self-reported physical activity and screen time. For instance, Brown, Cairney, and Kwan (2021a) derived four distinct profiles among Canadian adolescents, ranging from a "healthy" profile characterized by high physical activity and low screen time to an "unhealthy" profile characterized by low physical activity and high screen time. Similarly, Brown, Kwan, Arbour-Nicitopoulos, and Cairney (2021b) identified four profiles in a US sample of adolescents, with the "healthiest" profile exhibiting high physical activity and low screen time. In both studies, sleep was originally included as an indicator of profile membership, but there were no distinct differences in sleep patterns across profiles, so sleep was removed as a profile indicator. In relation to sleep outcomes, Matricciani et al. (2024) observed that the day-to-day variation in activity composition was significantly associated with sleep parameters, such that days characterized by extreme imbalances showed the poorest sleep outcomes. Further, Whitworth-Turner et al. (2017) proposed that physically active adolescents may experience distinctive "behavioral phenotypes" characterized by specific patterns of activity, rest, and sleep behaviors that influence health and performance outcomes. Each pattern identified was associated with different sleep outcomes and recovery profiles, highlighting the importance of considering the overall configuration of behaviors rather than individual components in isolation.

Several studies have included screen time, instead of sedentary behavior, as a distinct behavior in latent analyses, recognizing its potentially unique influence on health outcomes beyond general sedentary behavior. Kim et al. (2016) applied latent class analysis to identify patterns of physical activity and different types of screen-based behaviors (television viewing, computer use, video gaming) among 3,828 adolescents. They identified four distinct classes, including one characterized by high physical activity combined with moderate-to-high screen time – a pattern that may be particularly relevant for physically active adolescents that engage in greater volumes of screen time during recovery periods. Carson et al. (2015) employed latent class analysis to examine patterns of physical activity, sedentary behavior, and screen time in a large sample of Canadian youth, identifying three distinct behavioral patterns. Notably, one pattern was characterized by high physical activity combined with high screen time, a combination they termed 'active screenies', like the term coined by Tremblay et al. (2010), "active couch potatoes", in reference to a profile with a similar pattern. This profile is particularly relevant to the current study, as it represents a pattern potentially common among physically active adolescents – those consistently meeting or exceeding physical activity guidelines – that may also engage in substantial screen time during non-training hours (Xu et al., 2019; Turpin et al., 2024). This, again, highlights the potential clustering effects of these behaviors that would not be adequately captured by variable-centered approaches.

Person-Centered Approaches to Sleep Outcomes. Patterns of activity behaviors and their relation to a variety of health outcomes or risks have begun to be explored. Although, none of the studies have examined how distinct profiles of activity and/or movement behaviors are associated with sleep outcomes, specifically sleep duration, among physically active adolescents.

There is only one study in which sleep duration was included as an indicator variable that led to distinct separation between latent groups. This study, by Carson et al. (2015), used latent class analysis to identify patterns of physical activity, screen time, and sleep among 19,831 adolescents in Canada, finding three distinct classes. The latent class of adolescents characterized by higher physical activity and lower screen time also had greater nightly sleep duration. Notably, the class characterized by high physical activity, but also high screen time, showed intermediate (i.e., second among identified classes) sleep outcomes, suggesting that screen time may partially attenuate the sleep benefits of physical activity. However, sleep duration was included as a profile indicator as opposed to being examined as an outcome of interest. This disallowed examination and discussion of any specific findings pertaining to differences in sleep duration based upon classes distinct in composition of movement and screen time behaviors.

Others have used variable-centered or different latent-variable approaches to examine how these behaviors may influence sleep outcomes among adolescents. These findings are best described in a recent scoping review by Hossian et al. (2025) examining a growing body of evidence regarding adherence to 24-hour movement guidelines among Australian adolescents. This review suggested that the reallocation of time from sedentary behavior to physical activity may improve fitness and cognitive performance, while increasing sedentary behavior may act to lower sleep efficiency. Conversely, as discussed, Brown et al. (2021a) and Brown et al. (2021b) examined associations between four distinct profiles of adolescents MVPA, recreational screen time, and sleep duration, with sleep duration remaining homogenous across profiles, despite significant separation between profile means for MVPA and screen time.

In summary, the utility of person-centered approaches for understanding how patterns of movement behaviors and screen time (i.e., activity behaviors) may relate to sleep outcomes is clear. This approach allows for the examination of the interrelatedness of physical activity, sedentary behavior, and screen time aligning with frameworks like the 24-hour Movement paradigm (Tremblay et al., 2016). Additionally, findings will provide insights into how activity behaviors cluster and are associated with sleep achievement among adolescents during the summer months, when sleep behaviors and patterns may be further disrupted. Additionally, most studies have focused on the general adolescent population rather than physically active adolescents specifically, leaving a gap in understanding as to how these relationships manifest in a population that regularly exceeds physical activity recommendations but still experience insufficient sleep achievement. Further, no studies having focused these analyses specifically among a sample of physically active adolescents, nor examined sleep duration as an outcome in association to latent profiles indicated by MVPA, LIPA, sedentary behavior, and screen time (i.e., activity behaviors).

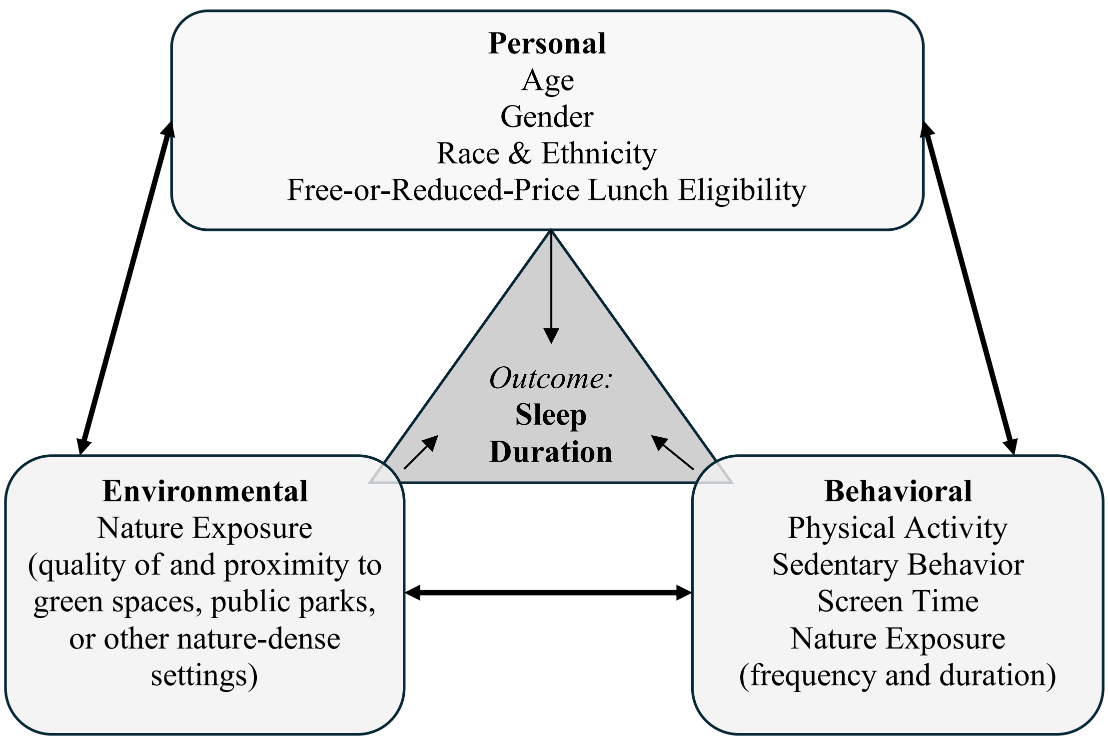
Nature Exposure in Person-Centered Approaches. While nature exposure has not been extensively incorporated into person-centered analyses of activity behaviors and sleep specifically, emerging research suggests its relevance. Some studies have begun to integrate environmental factors into latent profile analyses, providing frameworks that could be extended to include individual-level nature exposure. Borner et al. (2018) used latent profile analysis to characterize adolescents based on objectively measured physical activity across different environmental contexts, including parks and green spaces. Their analysis derived distinct profiles of where youth accumulated their activity, with some profiles engaging in high volumes of physical activity in natural environments while others engaged predominantly in indoor settings (e.g., gyms). Additionally, Adams et al. (2011) characterized profiles of adults by neighborhood environment characteristics, finding four distinct profiles from low walkability/transit and recreationally sparse to high walkability and recreationally dense. These profiles were associated with differences in physical activity levels and were associated with differential health outcomes and risks, suggesting that environmental context acts to shape activity behavior patterns in ways that influence health and wellbeing. Although not specifically focused on individual-level nature exposure, these studies demonstrate the feasibility and utility of incorporating environmental factors into person-centered analyses. Findings also point to the potential moderating role of nature exposure in the association between activity behaviors and sleep outcomes. More recently, Caetano et al. (2021) derived latent classes of Brazilian adolescents by perceptions of their neighborhood-built environment and examined the association with accelerometer-measured physical activity and sedentary behavior. They found that perceptions of neighborhood environments were associated with adolescents' physical activity and sedentary behavior engagement, again suggesting that the environmental context is important to consider in how activity profiles are composed.

While not using person-centered approaches, several studies have examined how nature exposure could serve as a moderator in the relationship between activity behaviors and sleep. Astell-Burt et al. (2019) found that higher levels of neighborhood greenspace buffered the negative association between physical inactivity and sleep, suggesting that nature exposure might compensate for suboptimal activity patterns and promote sleep despite differences in physical activity engagement. Similarly, Akpinar (2016) observed that the relationship between physical activity and mental health outcomes – including improved sleep quality – was stronger when activity occurred in natural environments compared to indoor or built environmental settings, suggesting the potential moderating effect of nature exposure. These findings, while not from latent profile or other latent variable analyses specifically, suggest that nature exposure could function as an important factor affecting the relationship between activity behavior profiles and sleep outcomes, potentially enhancing the benefits of favorable profiles or mitigating negative effects of less favorable profiles.

Theoretical Framework

Bandura's (2013) Social Cognitive Theory highlights the dynamic interplay among factors within personal, behavioral, and environmental domains, a concept referred to as reciprocal determinism. These three domains are interconnected, each influencing the other. In the context of the present study, personal factors include demographic characteristics like age, gender, race and ethnicity, and socioeconomic status. These personal factors may interact with environmental exposures, such as access to and the quality of nature (e.g., proximity to green spaces, community/neighborhood greenness), and may be associated with adolescents' activity behaviors and intentions, including physical activity, sedentary behavior, screen time, and frequency and duration of nature exposure (see Figure 1. Theoretical Model).

Figure 1: Theoretical Model Adapted from Social Cognitive Theory



In this theoretical framework, environmental factors, such as the quality of and proximity to natural spaces, can influence health behaviors. For example, adolescents with greater access to high-quality green spaces (environmental) may be more likely to spend time and engage in outdoor activities (behavioral), such as walking, playing sports, or engaging in free play (Borner et al., 2018; Browning et al., 2023). Further, the frequency and duration of nature exposure (behavioral) is shaped by both personal preferences and accessibility (environmental). Similarly, behavioral patterns of physical activity, sedentary behavior, and screen time are influenced by personal factors, and vice versa.

Moreover, factors within each of the domains may also interact with one another. Characteristics within the personal domain, such as age and gender, may interact in their relationship with activity behaviors. For instance, the decline in physical activity with increasing age tends to be steeper for girls than boys (Piercy et al., 2018), and gender differences in screen time often widen during middle to late adolescence (Anderson et al., 2023). Within the behavioral domain, different activity behaviors demonstrate complex relationships, where MVPA, LIPA, sedentary behavior, and screen time can displace one another – from a time-use perspective – or cluster in consistent and distinct patterns (Tremblay et al., 2016). Within the environmental domain, proximity to nature, access to recreational facilities, and neighborhood safety often interact to collectively influence opportunities for physical activity and nature exposure (Caetano et al., 2021). Importantly, nature exposure – conceptualized both as an environmental factor (quality and proximity) and as a behavioral factor (frequency and duration) – could play a critical role in shaping adolescents' health behaviors and outcomes. These complex, reciprocal interactions within and across personal, behavioral, and environmental domains align with the principles of SCT and underscore the importance of employing a holistic, person-centered approach to understand how the unique clustering of activity behaviors is associated with health outcomes, like sleep duration, while accounting for personal and environmental factors.

A person-centered approach (e.g., Latent Profile Analysis) could be especially helpful in grouping these factors to better understand their association with adolescents' sleep duration outcomes. Through this approach, this study aims to identify distinct latent patterns of activity behaviors to provide insights into how they cluster in free-living (i.e., real-world) contexts, and how they are associated with sleep duration among a physically active sample of adolescents during the summer months. In summary, Social Cognitive Theory (Bandura, 2013) provides a framework for conceptualizing the mechanisms through which unique constellations of activity behaviors are composed and how they may be differentially associated with sleep duration among physically active adolescents, while considering the potential interaction of nature exposure in these associations.

The Current Study: A Comprehensive Person-Centered Approach

The objectives of the current study are 1) to identify distinct profiles indicated by daily averages of MVPA, LIPA, sedentary behavior, and screen time among active adolescents, 2) assess likelihood of profile membership by participant demographic characteristics, 3) examine the association between profile membership and nightly average sleep duration, and 4) examine how these associations may be moderated by nature exposure, all within the context of the summer months. This study aims to advance the literature on sleep achievement among active adolescents in several ways.

First, by focusing on physically active adolescents – who regularly exceed physical activity guidelines – we can explore the more nuanced aspects of activity behavior patterns beyond simple achievement of MVPA targets or limiting sedentary behavior and screen time. Despite exceeding physical activity recommendations, these adolescents may still experience poor sleep achievement if their overall activity profile is imbalanced (Suppiah et al., 2016; Roberts et al., 2019; Antunes et al., 2017; Matricciani et al., 2018; Matricciani et al., 2024).

Second, by incorporating both LIPA and phone-based screen time as indicators of the activity profiles – alongside MVPA and sedentary behavior – we capture a more comprehensive picture of how different intensities of activity and subtypes of sedentary behavior might cluster together under free-living conditions. This would be the first study to examine profiles characterized by continuous and objectively measured activity behaviors, while also examining the potential moderating role of continuous and objectively measured, individual-level nature exposure. Objective measures enable us to derive person-centered profiles that more effectively capture the nuanced interplay between these health behaviors and exposures, and their influence on sleep duration. Using device-based measures of movement behaviors, screen time, and sleep duration, we reduce measurement error and provide more accurate characterization of activity profiles, addressing common limitations of self-reported measures – recall bias and social desirability (Adams et al., 2005; Hidding et al., 2018, Lubans et al., 2011).

Further, by examining demographic factors (e.g., age, gender, race and ethnicity, socioeconomic status) and nature exposure as to the likelihood of activity-behavior profile membership, we can effectively identify personal and environmental factors associated with adolescents' membership in distinct activity behavior profiles. This information is crucial for developing targeted interventions that address the unique needs and circumstances of distinct subgroups within the physically active adolescent population, which has received minimal attention in health promotion literature.

Additionally, by investigating the association between profile membership and sleep duration, we can determine which patterns of activity behaviors are most conducive to sleep achievement among physically active adolescents. This approach allows for the examination of the interrelatedness of physical activity, sedentary behavior, and screen time, aligning with frameworks like the 24-hour movement paradigm (Tremblay et al., 2016). Findings will provide insights into how activity behaviors cluster and are associated with sleep achievement among this population during the summer months, when sleep patterns may be disrupted due to increased flexibility and lack of routine (Bei et al., 2013).

Lastly, by examining nature exposure as a moderator in the relationship between profile membership and sleep duration, we introduce an innovative ecological perspective that acknowledges the potential role of the environment in how activity behaviors are associated with sleep duration. This recognizes that the benefits/detriments of certain activity behavior profiles may be enhanced or attenuated by individual-level nature exposure, providing insight for interventions that leverage both behavioral and environmental factors to promote sleep health. Ultimately, findings from this study could contribute to the development of more effective and holistic strategies for improving sleep health and overall well-being among adolescents, a population highlighted by the American Academy of Pediatrics as a group in need of additional research to improve sleep achievement (Owens et al., 2014). Study findings may also have policy implications regarding equitable access to natural environments and spaces, and in addressing demographic disparities in activity behaviors, nature exposure, and sleep health among adolescents.

By employing latent profile analysis with data from a community sample of active adolescents during the summer months, the current study will investigate the following research questions:

Research Question 1. How many distinct activity behavior profiles can be identified through latent profile analysis based upon participants' average daily MVPA, LIPA, sedentary behavior, and screen time in a sample of physically active adolescents during the summer months?

Hypothesis 1: Informed by prior research (Brown et al., 2021a; Brown et al., 2021b; Carson et al., 2015; Carson et al., 2016b; Evenson et al., 2016; Kim et al., 2016; Patnode et al., 2011), it is hypothesized that anywhere from three to five distinct latent profiles will emerge, characterizing adolescents' unique patterns of average daily MVPA, LIPA, sedentary behavior, and screen time. Hypothesizing for three to five profiles accounts for the possibility of mutually distinct profiles exhibiting varying combinations across the profile indicators.

Research Question 2. Are demographic characteristics (i.e., age, gender, race and ethnicity, FRPL-eligibility) and nature exposure associated with likelihood of profile membership in activity behavior profiles identified by latent profile analysis in a sample of physically active adolescents during the summer months?

Hypothesis 2: Informed by prior research (Dabke & Lynch, 2022; Piercy et al., 2018; Master et al., 2019; Lang et al., 2016; Jimenez et al., 2021; Caetano et al., 2021; Armstrong et al., 2018; Brown et al., 2021a; Brown et al., 2021b), it is hypothesized that older age, identifying as a girl, having a minoritized racial or ethnic identity, and FRPL-eligibility will be associated with greater likelihood of membership in profiles characterized by lesser MVPA and LIPA, and greater sedentary behavior and screen time, while greater nature exposure will be associated with greater likelihood of membership in profiles characterized by greater MVPA and LIPA, and lesser sedentary behavior and screen time.

Research Question 3. How are the activity behavior profiles associated with average nightly sleep duration in a sample of physically active adolescents during the summer months?

Hypothesis 3: Informed by prior research (Zhang et al., 2021; Kaur & Bhoday, 2017; Giddens et al., 2022; Whitworth-Turner et al., 2017; Carson et al., 2015; Carson et al., 2016b; Brown et al., 2021a; Brown et al., 2021b; Hossian et al., 2025), after controlling for demographic characteristics (age, gender, race and ethnicity, FRPL-eligibility) and nature exposure, it is hypothesized that membership in latent profiles characterized, generally, by greater daily MVPA and LIPA, and lesser sedentary behavior and screen time will be associated with longer average nightly sleep duration compared to latent profiles characterized by lesser MVPA and LIPA and greater sedentary behavior and screen time. Additionally, if a profile is characterized by a relative balance among activity behaviors – comparably, moderate-to-higher MVPA and LIPA, and moderate-to-lower sedentary behavior and screen time, the association between profile membership and sleep duration is hypothesized to be the strongest (Matricciani et al., 2024; Matricciani et al., 2018; Tremblay et al., 2016).

Research Question 4. Does daily average nature exposure moderate the association between activity behavior profile membership and average nightly sleep duration in a sample of physically active adolescents during the summer months?

Hypothesis 4: Informed by prior research indicating the restorative psychological and physiological benefits of nature exposure and the subsequent changes to sleep behaviors and outcomes (Ulrich, 1991; Kaplan, 1995; Caetano et al., 2021; Adams et al., 2011; Grigsby-Toussaint et al., 2015; Akpinar, 2016; Astell-Burt et al., 2019; Argyriadis et al., 2024), it is hypothesized that, across profiles, nature exposure will moderate the association between profile membership and average nightly sleep duration, such that as nature exposure increases, sleep duration increases.

CHAPTER II

METHODS

Data analyzed come from the Investigation of Nature Exposure, Health Behaviors, and Mental Health among Adolescents Study (MPIs: Dr. Elizabeth Budd and Dr. Nichole Kelly), a prospective study with adolescents (12-17 years) conducted in the greater Eugene/Springfield, Oregon area. Participation in this study included the completion of an initial survey, downloading an application (i.e., app) on their personal phone, and wearing an accelerometer on their wrist and responding to daily surveys for a 7-day data collection period. Data collection occurred in two bouts: August to October 2022 and June to September 2023. The work was supported by funding from the Innovation Fund from the University of Oregon's Office of the Vice President for Research and Innovation, and the University of Oregon's Sport and Wellness Initiative. Study protocols and procedures were approved by the University of Oregon's Institutional Review Board.

Study Procedure

Recruitment

Recruitment included (a) informational postcards mailed to households identified as having at least one youth between the ages of 12 and 17 years within the greater Eugene-Springfield, Oregon area; (b) flyers distributed via email, bulletin boards, social media, and in-person to staff of community-based organizations that serve youth; (c) an article in a local, University of Oregon-affiliated magazine about the ongoing research project (Callahan, 2023); and (d) word-of-mouth. Additionally, our primary community-based organization partner was a youth sports organization, KIDSPORTS. Their staff shared flyers via their network and allowed our study team to hold enrollment and study visits on their grounds. Research staff passed out flyers to families as they came and went from summer day camps and sports practices. Following the initial recruitment phase, adolescents were recruited and enrolled through a snowball effect of parents and youth sharing research information to friends and family, which also included some parents posting recruitment flyers to parent Facebook groups or sharing the information at their place of work.

Recruitment materials included a brief study description, eligibility and inclusion criteria, research team contact information, and a QR code that directed interested parents or guardians (henceforth referred to as, “parent”) to a Qualtrics screening survey that assessed eligibility and obtained parent contact information if eligible. Inclusion criteria included: being between the ages of 12 and 17 years old, having one’s own (or access to) smartphone that could be with them for the duration of the study (7 days), and the ability to read and understand English at least at a 5^{th} grade reading level. For those meeting inclusion criteria, the only exclusion criteria included not being able/available to meet research staff at KIDSPORTS for study visits. Once the eligibility screening was completed, only if deemed eligible, the research team would then contact the parent to schedule the initial enrollment. Parents were given the option to be emailed a Qualtrics link with the informed consent document to review, indicate their consent by typing their name and selecting a radio button that read, “I consent to have my teen participate in the study.” Research staff were available for questions via phone or email. Parents also had the option to complete the informed consent process at the enrollment visit via iPad using the same Qualtrics link or via paper copies. Research staff were present at the visit to answer questions. Research staff then reviewed the informed assent document via iPad with the eligible adolescent and solicited and answered any questions. The adolescent was then asked to indicate their informed assent by typing their name and cell phone number (used for sending daily surveys and study reminders throughout the 7-day data collection period), and selecting a radio button that read, “I agree to participate in the study”. Both the parent and adolescent were emailed or given paper copies of the consent/assent documents to keep. The following study activities occurred during the enrollment visit, after enrollment was complete.

One-time Survey

While meeting with research staff at KIDSPORTS, the adolescent participants were asked to complete a Qualtrics survey on an iPad. In some cases, when there were more than two participants scheduled at the same time (e.g., siblings), participants were given the Qualtrics survey link to complete the survey on their own mobile device. Participants were instructed to skip any question that they did not want to answer or did not feel comfortable answering. The survey included 77 questions (minutes to complete: Median = 12.58; M = 13.53, SD = 5.06) that assessed demographic characteristics and psychosocial constructs.

NatureDose™ Phone Application

A member of the research team then guided participants through the process of installing a free mobile app, NatureDose™, on their personal cell phone. The research team member reviewed and walked through the download and installation process with the participant, helped them to make an account using their own (or their parent's) email address, and ensured that the correct phone permissions were enabled to allow the collection of nature exposure continuously across the study period (e.g., enabled application-specific location services access). Participants were instructed that there was no need to open the NatureDose app during the study period, and that they should simply go about their days as they typically would.

Screen Time Tracking

Participants were then guided through the process of selecting the correct phone settings to track daily phone-based screen time and were instructed how to report phone-based screen time across the study period. Participants were sent a Qualtrics survey each evening of the study period (days 1-7) and were instructed to report their total phone-based screen time (hours:minutes) from the previous full day via the survey.

Accelerometry

In the last portion of the first study visit, participants were fitted with a wrist-worn accelerometer. For accelerometer initialization, participants were asked to self-report their height and weight, sex assigned at birth, and birthdate. Accelerometers were set to collect data at 100hz. A member of the research team provided participants with instructions on how the device should be worn – on their non-dominant wrist, firmly fitted, for 24-hours a day across the study period – and informed them that the accelerometer should only be removed for activities involving submersion in water (e.g., swimming, water sports, hot tubs). Participants were instructed to go about their days in the study as they normally would, while wearing the accelerometer. The device provides continuously collected frequency, duration, and intensity of activity, including physical activity (intensities), sedentary behavior, and sleep, across the study period. At the end of the first visit, the research team worked with the participant and their parent(s) to schedule the second study visit at a minimum of eight days later to allow for data to be collected for seven full days.

Study Period (Day 1 – Day 7)

Throughout the seven-day data collection period, participants were instructed to go about their day-to-day activities as they would when not participating in the study. Each evening between 5:00 PM and 7:00 PM of the study period, a member of the research team would send a text-message to the participant that included a personalized link to a brief (about five minutes) Qualtrics survey. These daily surveys assessed stress and body appreciation for that day, and total phone-based and application-specific screen time for the prior day. Participants reported total daily screen time and application specific screen time (hours: minutes) by navigating to their phone's screen time monitoring tool, within their phone settings. Survey links expired at the end of each respective day (11:59 PM) of the study period. A research team member sent a text message two days after the first visit to remind each participant of the correct way to wear the accelerometer, remind them to wear it continuously (including while sleeping), and ask if they had any questions or concerns about wearing it.

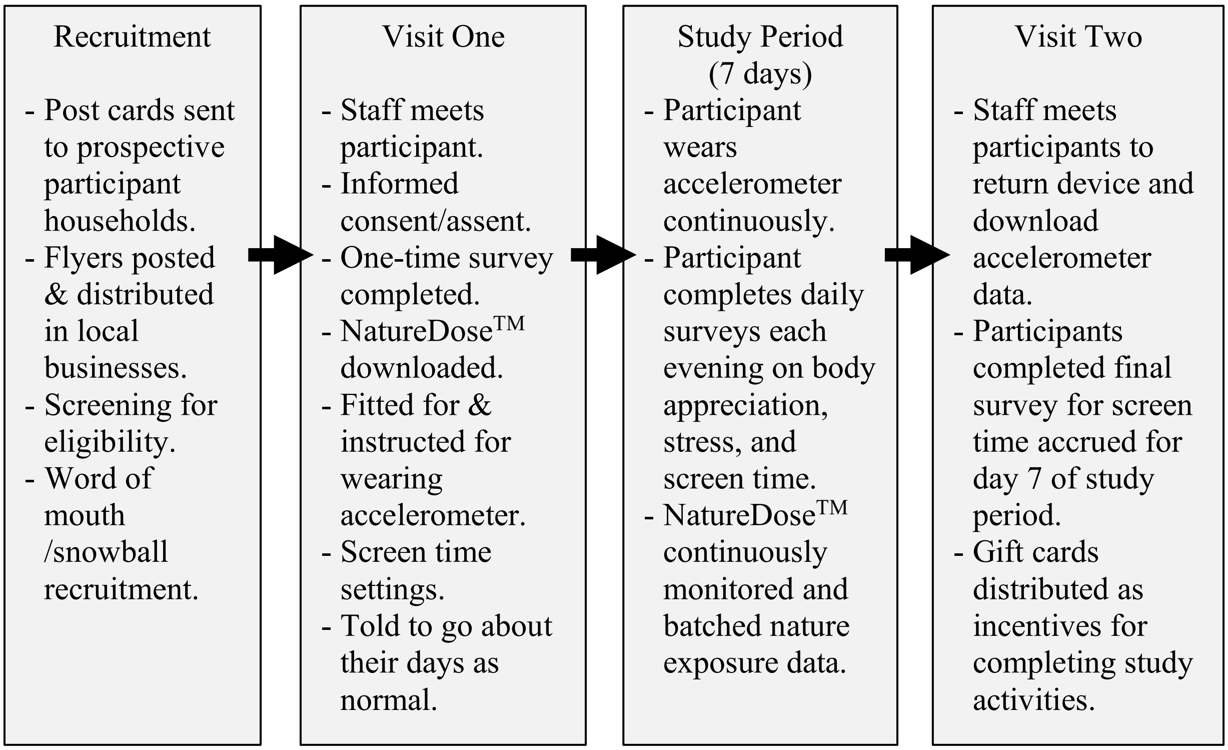
Visit Two

After the 7-day study period was complete, participants met research staff at KIDSPORTS again and returned the accelerometer. Staff downloaded the device data using the ActiLife software suite to both save the data for processing, and to compute valid wear-time percentage across the seven-day study period (for distribution of incentives). In the second bout of data collection, we had participants report their screen time from the previous day, as well. Not collecting screen time for the last day in the study period was an oversight during the first bout of data collection.

Incentives

During the enrollment visit, participants received a $30 VISA gift card for completing the one-time survey, being fitted for an accelerometer, and downloading the NatureDose application. At the end of visit two, participants received a $20 VISA gift card for completing at least five of the seven daily surveys; a $20 VISA gift card for returning the accelerometer; and a $30 VISA gift card for having worn the accelerometer at least 70% of the time across at least five of the seven days of the study period. Thus, if a participant fully enrolled in the study (completion of one-time survey and NatureDose download; $30), completed five of the seven daily surveys ($20), wore the accelerometer 70% of the time across at least five of the seven study days ($30), and returned the accelerometer at visit 2 ($20), they would earn a total of $100 in VISA gift cards for their participation. Figure 2 provides an overview of the study activities.

Figure 2: Overview of Study Activities



Measures

Demographic Characteristics

The one-time survey assessed demographic information about the participants including age (in years), gender identity, race and ethnicity, and free or reduced-price lunch (i.e., FRPL) eligibility. Participant age was obtained by asking participants to report their age in years, between 12 and 17 years old. Gender identity was obtained by asking participants to select the gender identity that best described them (i.e., cis-gender boy, cis-gender girl, transgender boy, transgender girl, agender), but were also given the option to provide an open-ended response describing their gender-identity. Race and ethnicity were obtained by asking participants to select all racial and ethnic identities they identify with from a list of options, but were also given the option to provide an open-ended response to describe their racial and ethnic identities. FRPL-eligibility was obtained by asking participants to report if they were eligible for FRPL, for which they could select ‘Yes’, ‘No’, or ‘I don’t know’. These demographic variables will be examined for likelihood of profile membership and will be included as covariates in the outcome analysis, as they have been shown to be associated with activity behaviors and sleep outcomes among adolescents (Dabke & Lynch, 2022; Piercy et al., 2018; Master et al., 2019; Lang et al., 2016).

Movement Behaviors and Sleep

Movement behaviors – MVPA, LIPA, and sedentary behavior – and sleep duration were objectively measured using ActiGraph GT3X+ accelerometers that were continuously worn on the non-dominant hand (like a watch) by participants throughout the study period. Sensors on these triaxial accelerometers are used to convert directional acceleration intensity (bodily movement) into counts that are summed over a given period (i.e., epochs) and converted to minutes/day that a participant spent at varied levels or intensities of activity (i.e., sedentary behavior, LIPA, MVPA). Wrist-worn ActiGraph GT3X+ accelerometers have been shown to provide valid estimates of activity among adolescent samples (Crouter, Flynn, & Bassett., 2014).

Accelerometer data were downloaded using the ActiLife software (Version 6) in 10-second epochs. Copies of the 10-second epoch files were saved in a separate file folder for future use. The 10-second epoch files were converted to 60-second epochs to permit processing with the Choi wear time validation algorithm (Choi et al., 2011) to assess if participants wore the accelerometer at least 70% of the time for at least 5 days across their respective 7-day study period(s). This algorithm incorporates zero-count thresholds to identify non-wear periods, a 90-minute window for consecutive zero and non-zero counts and allows a 2-minute interval of non-zero counts during a 30-minute consecutive zero count window to account for artificial movement (Choi et al., 2011). These 60-second epoch files were also saved in a separate file.

There are currently no agreed-upon cut-points to classify all intensities of physical activity (light, moderate, and vigorous) among our samples' age range (12-17 years old), but the Crouter et al. (2014) method has been shown to provide valid estimates among 8- to 15-year-olds. To use this method, the raw .AGD files were converted to 5-second epochs. Although Crouter et al. (2014) had participants wear accelerometers on their dominant wrist – as opposed to our use of non-dominant wrist – a recent review identified minimal differences for cut points calibrated for non-dominant and dominant wrists (Crotti et al., 2020; Clanchy et al., 2023). This calibration method only provides information for classifying sedentary behavior, LIPA, and MVPA. In other words, this method does not differentiate between moderate-intensity and vigorous-intensity physical activity levels, but simply combines them into an estimate of MVPA. For participants with at least four total valid collection days (valid day indicated by at least 70% wear time) of accelerometer data, daily average MVPA was computed by summing MVPA minutes from valid collection days and dividing by the number of valid collection days. The same method was used to calculate average daily sedentary behavior and average daily LIPA. All cases included in analyses had valid data for at least three weekdays and at least one weekend day. Decision-based criteria for a valid day (at least 70% wear time) and for a minimum of 4 valid days to compute daily averages of MVPA, LIPA, and sedentary behavior were informed by Troiano et al. (2008) to align with procedures applied in national data collection for the National Health and Nutritional Examination Survey (NHANES). These daily averages of MVPA, LIPA, and sedentary behavior were included as profile indicators for analyses.

Sleep periods were identified using the Sadeh (1994) sleep scoring algorithm. This algorithm uses a series of decision rules based on activity counts within a given epoch and the surrounding epochs to determine sleep and wake status. The algorithm considers activity levels in an 11-minute window centered around each epoch. It calculates several variables, including the mean activity level in a 5-minute window, the standard deviation of activity in a 6-minute window, and the number of epochs with activity levels between 50 and 100 counts. These variables are then used in a weighted equation to determine the probability of the epoch being scored as sleep or wake. In the Sadeh (1994) sleep algorithm, sleep onset is defined as the first of 15 consecutive minutes scored as sleep, and sleep offset as the last of 15 consecutive minutes scored as sleep.

Following estimation of sleep periods using the Sadeh (1994) sleep scoring algorithm, sleep duration for a single study night was calculated as the sum of all epochs scored as sleep between sleep onset and offset, excluding any wake episodes greater than 20-minutes, where only sleep periods starting between 7pm and 4am will be counted as nighttime sleep. Any sleep periods during that night's sleep separated by less than 20-minutes were collapsed into a single sleep period. Further, only data from participants with at least three valid weeknights and one valid weekend night of valid sleep data were used in these analyses (n = 295, 90.5%; Troiano et al., 2008; Short et al., 2018). Daily average nighttime sleep period (i.e., sleep duration) was calculated by summing total sleep time minutes for each valid study day and dividing by the total amount of valid collection days. This provided a nightly average across the study period, accounting for both weekday and weekend sleep. Average nightly sleep duration will be included as the outcome in analyses for research questions three and four.

Phone-Based Screen Time

Participants' phone-based screen time was assessed through nightly surveys sent to participants as a link via text message on each evening (between 5:00 PM and 7:00 PM) of the 7-day study period. Participants were instructed to navigate to their phone's internal screen time monitoring tool and report their total screen time and application-specific screen time (i.e., hours: minutes); any entry in the hours cell was converted to minutes and added to the minutes cell entry for the same day to return minutes of screen time for each study day. For participants who provided at least four survey responses for daily screen time, daily average phone-based screen time minutes were computed by summing the screen time minutes from each day and dividing by the number of survey responses. Average daily phone-based screen time will be included as a profile indicator for analyses.

Nature Exposure

The NatureDose phone app was used to measure participants' total minutes of nature exposure for each day of the study period. The NatureDose app, created by NatureQuant, LLC (n.d.), is a novel tool that measures nature exposure objectively, continuously, and at the individual-level (Browning et al., 2023**,** NatureQuant, n.d.). NatureDose runs in the background of participants' phones and uses smartphone sensors, geolocation (i.e., phone location services), and a proprietary algorithm (NatureScore^{TM}) to calculate an individual's exposure to natural elements shown to be associated with health benefits (e.g., open water, tree canopy, green spaces). The NatureScore algorithm analyzes and integrates various datasets (e.g., Normalized Difference Vegetation Index and other satellite imagery) and processed information within a 1km buffer of the phone's location, considering both the proximity to and quality of natural elements, as well as an estimation of duration of exposure to natural elements. The elements considered are then weighted to create the strongest correlation with the predictive health impacts – informed by empirical evidence – of given natural elements via a machine-learning process. In summary, NatureDose combines past measurement strategies, aggregate land-use and GPS data, and additional data and findings from extant literature to objectively estimate individual-level minutes of nature exposure.

The NatureDose phone app has been found to be a feasible monitoring tool for nature exposure (Vermeesch et al., 2022) and has been validated in comparison to the Normalized Difference Vegetation Index – commonly used for measurement of neighborhood proxies of nature exposure and/or access – a quantitative measure of the abundance of vegetation in a geographic buffer area (Huang et al., 2020). In the present study, participants' NatureDose minutes (i.e., nature exposure) for each valid day of the study period were summed and divided by total collection days – a minimum of 4 valid days, with at least 1008 minutes (70% of a day) of collected data – to provide average daily nature exposure minutes. The decision of 4 valid days was informed by alignment with decisions for movement behaviors and sleep. Like for the movement behaviors and sleep duration, all cases included in analyses had valid data for at least three weekdays and at least one weekend day. Nature exposure will be examined for likelihood of profile membership and as the moderator in the outcome analysis examining the association between profile membership and sleep duration.

Data Analysis Plan

Data Inspection

Data inspection was completed in Rstudio (R Core Team, 2021). First, data were examined for normality and univariate outliers through absolute values of skewness and kurtosis (i.e., +/- 2.0) and Z-scores >= 3 SD. Latent profile analysis was conducted using Mplus Version 8.8 (Muthén & Muthén, 2017) to identify distinct profiles based on four continuous indicators: average daily MVPA, LIPA, sedentary behavior, and screen time – all scaled in minutes/day.

A total of two, eight, one, eleven, and two extreme outliers (+/- 3 SD) were observed for LIPA, sedentary behavior, screen time, nature exposure, and sleep duration, respectively. Extreme outliers were windsorized, replacing values with the next highest or lowest value for the respective variable. After adjusting for extreme outliers, nature exposure was the only non-normally distributed variable, with extreme values of skewness and kurtosis. Nature exposure was log transformed to obtain normality. For the continuous outcome, average nightly sleep duration, a total of 31 (9.5%) of values were missing. Among the indicators, MVPA, LIPA and sedentary behavior each had a total of 10 (3.1%) values missing, and there was no missingness for phone-based screen time. Among the covariates, nature exposure had a total of 14 (4.3%) missing values, combined race and ethnicity had a total of 2 (<1%) missing values, and there were no missing values for age, gender, and FRPL-eligibility. In MPlus the manual three-step approach uses listwise deletion to handle missing data, thus the sample size was attenuated (n = 282, 86.5%) for analyses addressing research questions three and four.

RQ1: Latent Profile Enumeration

A series of models with increasing numbers of profiles (1-6) were estimated using robust maximum likelihood estimation to address research question 1. To avoid local maxima and ensure replication of the best (lowest) log likelihood value, each model was estimated with 500 random starts and 100 final stage optimizations. Model selection is based on statistical criteria, theoretical interpretability, and practical utility (Meyer & Morin, 2016). Following the suggestions by Nylund-Gibson & Choi (2018), statistical criteria included the Bayesian Information Criterion (BIC), Sample-Size Adjusted BIC (aBIC), adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and entropy. For AIC, BIC, and aBIC lower values indicate better model fit. For adjusted LMR-LRT, a significant p-value indicates that an estimated model is a better fit for the data than a model with one fewer profile (e.g., 4-profile vs. 3-profile solution). Lastly, entropy values – which range from 0 to 1 – closer to 1 indicate better classification precision, with a minimum value of 0.70 recommended (Nylund-Gibson & Choi, 2018). All fit indices used to evaluate model fit have been shown to have sufficient power in identifying the optimal profile solution with a sample size of >250, while LMR-LRT and aBIC have been shown to have the best power in selecting the optimal profile solution (Tien, Coxe & Cham, 2013). In addition to the fit indices discussed, the final class solution was also selected based upon interpretability, because quantitative fit indices can extract an excessive number of profiles that may include multiple small classes (e.g., <5% of the sample) that can be considered spurious (Meyer & Morin, 2016). Thus, final model selection will be informed by the fit indices (with preference to aBIC and LMR-LRT), based upon having >5% of the sample represented in each profile, and based upon interpretability of the profiles within the respective *k*-profile model being differentiated from one another theoretically.

Manual Three-Step Maximum Likelihood Approach

Following enumeration and identification of the final profile solution, the manual three-step maximum likelihood (ML) approach was employed to address research questions 2-4. This approach allows examination of the relationships between profile membership, predictors of profile membership (i.e., likelihood of profile membership), and the continuous outcome while accounting for profile classification error (Asparouhov & Muthén, 2014; Vermunt, 2010). The manual three-step ML approach is advantageous over single-step approaches as it prevents profile formation from being influenced by auxiliary variables, thus maintaining the theoretical integrity of the profiles based solely on the indicator variables (Nylund-Gibson, Grimm & Masyn, 2019), effectively balancing the need for profile stability with the accurate estimation of relationships between profile membership, likelihood of profile membership, and a continuous outcome.

Step 1 of Three-Step Approach. An unconditional model was estimated based on the enumeration results, incorporating auxiliary variables (i.e., age, gender, race and ethnicity, FRPL-eligibility, nature exposure, and sleep duration) without allowing them to influence profile formation. This unconditional model provided the profile-specific parameters and classification probabilities necessary for subsequent steps. Classification logits from this model were saved for use in subsequent steps to account for classification uncertainty (Asparouhov & Muthén, 2014).

RQ2: Likelihood of Profile Membership and Covariate Control

Step 2 of Three-Step Approach. The classification probabilities were used to fix the measurement parameters from Step 1, while examining predictors of profile membership. This approach maintains the integrity of the latent profiles while accurately estimating the effects of covariates on profile membership (i.e., likelihood of profile membership; Vermunt, 2010), addressing research question 2. To examine likelihood of profile membership based upon demographic characteristics and nature exposure, a multinomial logistic regression model was conducted, including age, gender, race and ethnicity, FRPL-eligibility, and nature exposure as predictors of profile membership. Odds ratios from the multinomial logistic regression were evaluated to examine differences in the likelihood of profile membership by each of the covariates.

RQ3 & RQ4: Outcome Analysis and Moderation

Step 3 of Three-Step Approach. To address research questions three and four, step 3 of the three-step approach was used to examine the relationship between profile membership and the outcome of interest (sleep duration) while also testing for the hypothesized moderation effect by nature exposure. To test whether the relationship between nature exposure and sleep duration varied across profiles, this step implemented the modified approach recommended by Bakk and Vermunt (2016), which has been shown to outperform alternative methods when examining continuous outcomes in the presence of covariates. This approach maintained the profile solution's stability and provided robust estimates of profile differences in outcomes while controlling for covariates (i.e., age, gender, race and ethnicity, FRPL-eligibility, and nature exposure), including tests of direct effects of profile membership on sleep duration, of all covariates on sleep duration, and differences in profile-specific effects of nature exposure on sleep duration (moderation). Class-specific intercepts and slopes were estimated to test for pairwise differences in the association between nature exposure and sleep duration across profiles; formal tests of mean differences (e.g., diff12-diff34) and slope differences (e.g., slope12-slope34) across profiles were specified using model constraints. Latent profile enumeration and the manual three-step ML approach was conducted in Mplus Version 8.8 (Muthén & Muthén, 2017) using robust maximum likelihood estimation.

CHAPTER III

RESULTS

Statistical Findings

Sample Descriptives

The sample included 326 adolescent participants (ages 12-17; M_{age} = 14.57, *SD* = 1.68). The largest proportion of participants identified as cis-gender girls (48.5%), followed by cis-gender boys (44.8%). Most participants identified as non-Hispanic White (73.9%), and approximately 30% of participants were eligible for free-or-reduced-price lunch (FRPL) at school. The average daily log-transformed nature exposure for the sample was 3.91 (87.92 minutes) with a standard deviation of 1.14 (108.28 minutes). Daily average MVPA was 283.7 minutes (SD = 71.17), daily average LIPA was 208.01 minutes (SD = 33.39), daily average sedentary behavior was 863.80 minutes (SD =126.96), daily average phone-based screen time was 279.45 minutes (SD = 144.12), and average nightly sleep duration was 416.88 minutes (6.95 hours; SD = 88.42 minutes). See Table 1 for full descriptives of the sample.

RQ1: Estimating Latent Profile Solution

LPA was conducted to identify distinct profiles based on four continuous indicators: daily averages of MVPA, LIPA, sedentary behavior, and screen time. A series of models ranging from one to six latent profiles were estimated using robust maximum likelihood estimation to determine the best class solution. Model selection was informed by statistical criteria, profile interpretability and separation, and theoretical considerations. The fit indices used to compare models include the AIC, BIC, aBIC, adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), and entropy.

The LMR-LRT suggested that the 4-profile solution provided significantly better fit ($p < 0.05$) than the 3-profile solution, while the 5-profile solution did not significantly improve fit ($p = 0.095$). The 4-profile solution also showed good entropy (0.802) and clear separation between profiles, with average latent class probabilities for most likely class membership ranging from 0.886 to 0.998 (see Table 2: Model fit indices for 1-6 profile solutions).

Table 1: Descriptives of the Sample (N=326)

Variable	n (valid %)	n missing	Mean (SD)	Min.,Max
MVPA	316 (96.9)	10	283.37 (71.17)	83.56, 488.69
LIPA	316 (96.9)	10	208.01 (33.39)	120.58, 304.99
Sedentary Behavior	316 (96.9)	10	863.80 (126.96)	471.37, 1112.51
Screen Time	326 (100)	0	279.45 (144.12)	10.20, 710.17
Nature Exposure	312 (95.7)	14	87.92 (108.28)	0.00, 464.00
Sleep Duration	295 (90.5)	31	416.88 (88.42)	218.00, 683.83
Age (Year)	326 (100)	0	14.57 (1.68)	12, 17
Variable	**n (valid %)**	**n missing**		
Gender	326 (100)	0		
Cis-Boy	146 (44.8)			
Cis-Girl	158 (48.5)			
Transgender*	11 (3.3)			
Agender*	11 (3.3)			
Race & Ethnicity	324 (99.4)	2		
Non-Hispanic White	241 (74.4)			
All Other	83 (25.6)			
Bi-/Multi-racial	53 (16.2)			
Hispanic/Latino/a	18 (5.5)			
Black/African American	6 (1.8)			
Asian	4 (1.2)			
Middle Eastern, North African	1 (<1)			
Native American, Hawaiian, Pacific Islander	1 (<1)			
Age	326 (100)	0		
12	46 (14.1)			
13	59 (18.1)			
14	53 (16.3)			
15	54 (16.6)			
16	59 (18.1)			
17	55 (16.9)			
FRPL-eligibility	326 (100)	0		
Yes	99 (30.4)			
No	163 (50.0)			
I Don't Know	64 (19.6)			

Note: MVPA = Moderate-to-vigorous-intensity physical activity; LIPA = Light-intensity physical activity; FRPL = Free-or-reduced-price lunch; PI = Pacific Islander

*Transgender includes both transgender boys and transgender girls; Agender refers to a gender identity that does not adhere with binary (i.e., boy/girl, man/woman) gender norms.

Table 2: Model Fit Indices for 1-6 Profile Solutions

Classes (est. parameters)	LL	AIC	BIC	aBIC	Entropy	LMR-LRT (p-value)
1 (8)	-7413.22	14842.44	14872.74	14847.36	-	-
2 (13)	-7363.48	14752.95	14802.18	14760.94	0.585	0.013
3 (18)	-7272.84	14581.68	14649.85	14592.75	0.802	0.001
4 (23)*	**-7246.53**	**14539.07**	**14626.16**	**14553.21**	**0.802**	**0.018**
5 (28)	-7223.55	14503.10	14609.14	14520.32	0.844	0.095
6 (33)	-7203.51	14473.02	14597.99	14493.32	0.851	0.137

Note: LL = Log-likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criteria; aBIC = sample size adjusted BIC; Entropy = indicator of classification precision; LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test
*The four-class row is bolded to indicate it as the best-fitting profile solution.

Cross-classification probabilities were generally low, with the most notable overlap between Profiles 1 and 3 (11.2% and 8.5% cross-classification probability, respectively) and for members of Profile 4 cross-classification probability for profile 3 (9.4%). Profile 2 showed particularly strong separation with a 0.998 probability of correct classification. The 4-Profile solution yielded reasonable profile sizes (i.e., all greater than 5% of the sample), with Profile 1 comprising 37.12% (n = 121), Profile 2 comprising 6.14% (n = 20), Profile 3 comprising 49.39% (n = 161), and Profile 4 comprising 7.36% (n = 24) of the sample based on most likely profile membership. The AIC, BIC, and aBIC continued a gradual decrease with profile solutions greater than the 4-profile solution – indicating slight improvements in model fit. However, the additional profiles in those profile-solutions could be considered spurious because they represent <5% of the sample and the LMR-LRT for the five-profile solution ($p = 0.095$) indicates a non-significant improvement from a 4-profile solution. Additionally, in evaluation of the five and six profile solution models, the additional profiles – past the four profile solution – were not theoretically distinguished from profile attributes observed in profiles from the 4-profile solution. Thus, the 4-profile solution was selected as the best-fitting model and was used for subsequent analytical steps.

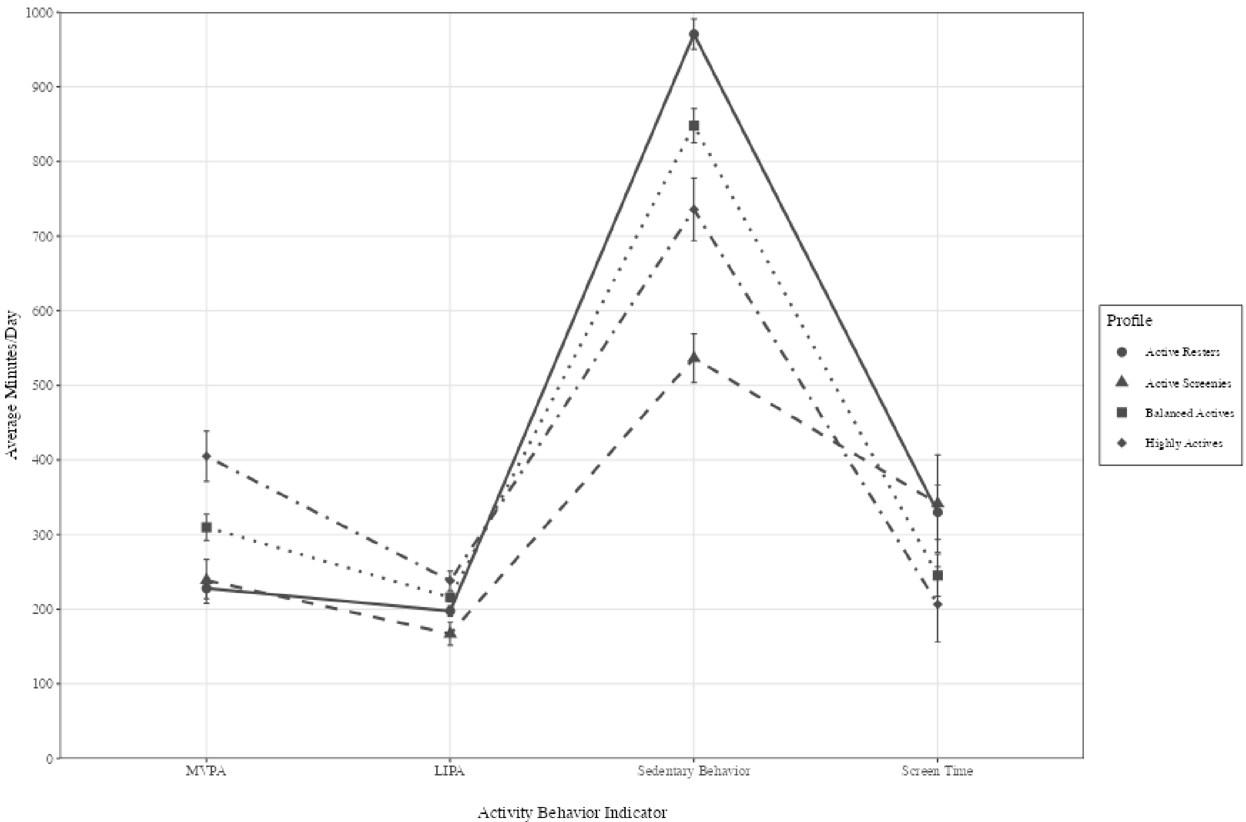
Latent Profiles of Selected Model. In reference to all profiles, Profile 1 (i.e., "Active Resters"; 37.12% of sample), ranked lowest in MVPA (228.05 ± 7.11 min/day), second lowest in LIPA (197.58 ± 3.55 min/day), highest in sedentary behavior (970.54 ± 10.34 min/day), and second highest in screen time (329.90 ± 18.60 min/day). Profile 2 (i.e., "Active Screenies"; 6.14%) ranked second lowest in MVPA (238.76 ± 15.81 min/day), lowest in LIPA (167.12 ± 7.89 min/day), lowest in sedentary behavior (536.39 ± 16.64 min/day), and highest in screen time (341.67 ± 33.33 min/day). Profile 3 (i.e., "Balanced Actives"; 49.39%), the largest group, ranked second highest in MVPA (309.92 ± 8.98 min/day), LIPA (216.00 ± 2.97 min/day), and sedentary behavior (848.09 ± 11.59 min/day), and second lowest in screen time (245.45 ± 14.39 min/day). Profile 4 (i.e., "Highly Actives"; 7.36%) ranked highest in MVPA (405.05 ± 17.16 min/day) and LIPA (238.30 ± 6.60 min/day), second lowest in sedentary behavior (735.71 ± 21.45 min/day), and had the least screen time (206.50 ± 25.64 min/day). The mean values for each activity behavior used as an indicator in the latent profile analysis are presented by profile-group in Table 3 and shown in Figure 3.

Table 3. Means and 95% confidence intervals of activity behaviors by profile.

Indicator min/day (Sample mean and standard deviation)	**Profile 1** ***Active Resters*** (37.12%) *M* (95% CI)	**Profile 2** ***Active Screenies*** (6.14%) *M* (95% CI)	**Profile 3** ***Balanced Actives*** (49.39%) *M* (95% CI)	**Profile 4** ***Highly Actives*** (7.36%) *M* (95% CI)
MVPA (283.7, 71.2)	**228.05 (214.11-241.99)**	**238.76 (207.77-266.75)**	**309.92 (292.33-327.51)**	**405.05 (371.42-438.68)**
LIPA (208.0, 33.4)	**197.58 (190.62-204.54)**	**167.12 (151.65-182.59)**	**216.00 (210.19-221.81)**	**238.30 (225.36-251.24)**
Sedentary Behavior (863.8, 126.9)	**970.54 (950.27, 990.81)**	**536.39 (503.77-569.01)**	**848.09 (825.37-870.81)**	**735.71 (693.67-777.75)**
Screen Time (279.5, 144.1)	**329.90 (293.44-366.36)**	**341.67 (276.34-407.00)**	**245.45 (217.25-273.65)**	**206.50 (156.24-256.76)**

Note: Percentages beneath each profile represent the proportion of the sample for that profile. Light Grey = Lowest; Second Lightest Grey = Second Lowest; Second Darkest Grey = Second Highest; Dark Grey = Highest. MVPA = moderate-to-vigorous-intensity physical activity; LIPA = light-intensity physical activity; CI = confidence interval.

Figure 3. Activity behavior indicator means and 95% confidence interval by profile.



RQ2: Likelihood of Profile Membership

Age was a significant predictor of profile membership, where for each unit increase in age, adolescents were 1.68 times more likely to be in the Active Resters profile compared to the Highly Actives profile ($b = 0.517$, SE = 0.246, $p < 0.05$, OR = 1.677, 95% CI [1.035, 2.715]). Similarly, older adolescents were 2.08 times more likely to be in the Active Screenies profile compared to the Highly Actives profile ($b = 0.734$, SE = 0.297, $p = 0.013$, OR = 2.084, 95% CI [1.165, 3.727]). FRPL-eligibility was a significant predictor of profile membership where, compared to those eligible for FRPL, those not eligible for FRPL or who did not know if they were eligible were 2.54 times more likely to be in the Balanced Actives profile than the Active Screenies profile ($b = 0.933$, SE = 0.440, $p = 0.034$, OR = 2.543, 95% CI [1.073, 6.023]). Both gender and race and ethnicity were not significantly associated with profile membership across any profile comparisons. Table 4 shows multinomial logistic regression results assessing likelihood of profile membership from step 2 of three-step approach.

Table 4. Multinomial logistic regression results predicting profile membership.

Predictor	Comparison	b	SE	p	OR [95% CI]
Nature Exposure (log)					
	1 vs. 4	-0.353	0.283	0.212	0.702 [0.403, 1.223]
	2 vs. 4	-0.064	0.375	0.865	0.938 [0.450, 1.957]
	3 vs. 4	-0.058	0.296	0.844	0.943 [0.528, 1.686]
	1 vs. 2	-0.289	0.265	0.275	0.749 [0.445, 1.259]
	1 vs. 3	-0.295	0.164	0.072	0.744 [0.540, 1.026]
	2 vs. 3	-0.006	0.268	0.983	0.994 [0.588, 1.680]
Race & Ethnicity (ref: Non-Hispanic White)					
	1 vs. 4	-0.450	0.642	0.483	0.637 [0.181, 2.243]
	2 vs. 4	-0.294	0.791	0.710	0.745 [0.158, 3.511]
	3 vs. 4	-1.040	0.721	0.149	0.354 [0.086, 1.453]
	1 vs. 2	-0.156	0.570	0.785	0.856 [0.280, 2.617]
	1 vs. 3	0.589	0.398	0.139	1.803 [0.826, 3.937]
	2 vs. 3	0.745	0.593	0.209	2.107 [0.659, 7.739]
Gender (ref: cis-boy)					
	1 vs. 4	-0.085	0.513	0.868	0.918 [0.336, 2.513]
	2 vs. 4	-0.061	0.567	0.914	0.941 [0.310, 2.856]
	3 vs. 4	-0.024	0.545	0.965	0.977 [0.335, 2.844]
	1 vs. 2	-0.024	0.311	0.939	0.976 [0.531, 1.795]
	1 vs. 3	-0.061	0.240	0.798	0.940 [0.588, 1.505]
	2 vs. 3	-0.038	0.312	0.904	0.963 [0.523, 1.775]
Age					
	1 vs. 4	0.517	0.246	**0.036***	1.677 [1.035, 2.715]
	2 vs. 4	0.734	0.297	**0.013***	2.084 [1.165, 3.727]
	3 vs. 4	0.416	0.257	0.105	1.516 [0.917, 2.507]
	1 vs. 2	-0.218	0.175	0.215	0.805 [0.571, 1.134]
	1 vs. 3	0.100	0.101	0.320	1.106 [0.907, 1.347]
	2 vs. 3	0.318	0.178	0.075·	1.374 [0.969, 1.949]
FRPL (ref: Yes)					
	1 vs. 4	0.220	0.636	0.544	1.247 [0.611, 2.542]
	2 vs. 4	-0.386	0.528	0.464	0.680 [0.241, 1.913]
	3 vs. 4	0.547	0.383	0.154	1.728 [0.185, 3.663]
	1 vs. 2	0.607	0.442	0.170	1.834 [0.771, 4.363]
	1 vs. 3	-0.326	0.261	0.211	0.722 [0.433, 1.203]
	2 vs. 3	-0.933	0.440	**0.034***	0.393 [0.166, 0.932]

Note: Profile 1 = Active Resters; Profile 2 = Active Screenies; Profile 3 = Balanced Actives; Profile 4 = Highly Actives; OR = odds ratio; CI = confidence interval; FRPL = free or reduced-price lunch eligibility.
*$p < 0.05$

RQ3: Sleep Duration with Covariates

Nightly Sleep Duration Means and Profile Differences. Members of the Active Screenies profile exhibited the longest average nightly sleep duration (*M* = 575.05min/9.58hrs, SE = 29.48min), followed by Active Resters (*M* = 421.04min/7.02hrs, SE = 19.97min), Balanced Actives (*M* = 413.02min/6.88hrs, SE = 18.84min), and Highly Actives (*M* = 412.72min/6.88hrs, SE = 26.08min) profiles. Pairwise comparisons confirmed significant mean differences in average nightly sleep duration between the Active Screenies and all other profiles (p<0.001). No significant differences in average nightly sleep duration were observed between the Active Resters, Balanced Actives, and Highly Actives profiles (p>0.05) (see Table 5. Nightly sleep duration profile means and mean differences (95% CI)).

Table 5. Nightly sleep duration profile means and mean differences (95% CI)

Profile	**Active Resters** (*M* = 421.04, SE = 19.97)	**Active Screenies** (*M* = 575.05, SE = 29.48)	**Balanced Actives** (*M* = 413.02, SE = 18.84)	**Highly Actives** (*M* = 412.72, SE = 26.08)
Active Resters	-	**154.01 (103.61, 204.41)****	-8.02 (-38.82, 22.28)	-8.31 (-47.94, 31.32)
Active Screenies	-	-	**-162.03 (-217.99, -106.07)****	**-162.32 (-222.77, -101.87)****
Balanced Actives	-	-	-	-0.29 (-43.66, 43.08)
Highly Actives	-	-	-	-

Note: Values within the matrix represent the mean sleep duration minutes of the profile in each column minus the mean sleep duration minutes of the profile in each row with a 95% confidence interval (CI) in parentheses. Higher values represent greater sleep duration minutes.
** p <0.001.

Direct Effects of Covariates on Nighttime Sleep Duration. Controlling for profile membership, gender was significantly associated with average nightly sleep duration (β = 21.51, SE = 6.69, *p* < .01), with cis-gender boys (ref) having significantly shorter average sleep duration when compared to cis-gender girls, transgender and agender identifying participants (Table 6). Age, race and ethnicity, and FRPL eligibility did not have significant direct effects on average nightly sleep duration after accounting for profile membership (all *p*s > 0.1).

Table 6. Covariate direct effects on sleep duration

Covariate	Estimate (SE)	p-value
Age	0.69 (3.24)	.830
Gender (ref: cis-boy)	21.51 (6.69)	**.001**
Race/Ethnicity (ref: NH-White Only)	-18.20 (11.61)	.117
FRPL eligibility (ref: Yes)	-1.03 (7.40)	.889

RQ4: Nature Exposure and Nighttime Sleep Duration

The relationship between nature exposure and average nightly sleep duration varied across profiles. For the Active Resters, nature exposure showed a significant positive association with average nighttime sleep duration (β = 21.10, SE = 8.86, *p* = .017), indicating that greater nature exposure is associated with longer average nightly sleep duration for members of this profile. The estimated effect was stronger but not statistically significant in the Active Screenies profile (β = 29.46, SE = 21.63, *p* = .173), and this association was not present for both the Balanced Actives (β = -0.36, SE = 9.73, *p* = .970) and Highly Actives (β = 6.06, SE = 17.52, *p* = .729) profiles (see Table 7, Panel A).

Moderation Effects. There were no significant slope differences in the nature exposure-sleep relationship between any pair of profiles (see Table 7, Panel B).

Table 7. Nature exposure effects on sleep duration and moderation analysis.

Panel A: Nature Exposure Effects Within Each Profile		
Profile	**Estimate (SE)**	**p-value**
Active Resters (Profile 1)	21.10 (8.86)	**.017**
Active Screenies (Profile 2)	29.46 (21.63)	.173
Balanced Actives (Profile 3)	-0.36 (9.73)	.970
Highly Actives (Profile 4)	6.06 (17.52)	.729
Panel B: Differences in Nature Exposure Effects Between Profiles (Moderation)		
Comparison	**Slope Difference (SE)**	**p-value**
Profile 1 vs. Profile 2	-8.36 (23.51)	.722
Profile 1 vs. Profile 3	21.46 (14.83)	.148
Profile 1 vs. Profile 4	15.04 (19.16)	.433
Profile 2 vs. Profile 3	29.82 (23.95)	.213
Profile 2 vs. Profile 4	23.39 (27.56)	.396
Profile 3 vs. Profile 4	-6.43 (22.31)	.773

Note: Panel A shows the effect of nature exposure (log-transformed and centered) on nightly sleep duration (in minutes) within each profile. A positive estimate indicates that higher nature exposure is associated with longer sleep duration. Panel B shows the differences in these effects between pairs of profiles. A negative slope difference indicates that the effect of nature exposure is stronger in the second profile compared to the first.

CHAPTER IV

DISCUSSION

Study Significance

This study advances understanding of health behaviors and their association with sleep duration among active adolescents, a population often overlooked in health promotion and sleep research, in several ways. Specifically, distinct activity behavior profiles were identified that challenge conventional assumptions about the physical activity-sleep relationship, with unexpected patterns between profile membership and sleep duration. Notably, nature exposure may provide compensatory sleep benefits for physically active adolescents with greater phone-based screen time and sedentary behavior. Findings also suggest potential pathways for targeted interventions through limiting or mitigating the effects of screen time through nature exposure. These findings highlight the advantages of using person-centered analysis with objective, device-based continuous measures to understand the integrated nature of 24-hour movement behaviors and their relationship with sleep duration among physically active adolescents.

Activity Behavior Profiles Among Physically Active Adolescents

The four identified activity behavior profiles, as hypothesized, highlight the heterogeneity that exists in how activity behaviors cluster, even among a sample of adolescents who all exceed physical activity guidelines. If a relative balance of activity behaviors was to be considered ideal, the Balanced Actives profile is named as such because it has no extremes across profile indicators. The Balanced Actives profile represents the largest estimated proportion of participants (49.4%) and demonstrated a pattern of second highest engagement across MVPA, LIPA, and sedentary behavior with second lowest screen time, relative to other profiles.

In contrast, the Active Resters profile (37.1%) exhibits characteristics of what Tremblay et al. (2010) termed the “active couch potato” phenomenon. These adolescents exceeded MVPA recommendations (although, exhibiting the lowest MVPA among profiles) but spent considerable time in sedentary behavior (highest sedentary behavior among profiles) and on screens (second highest screen time among profiles). This clustered pattern is concerning as high volumes of sedentary behavior are shown to have detrimental effects on health outcomes regardless of MVPA achievement (Tremblay et al., 2010; Knufinke et al., 2017).

The Active Screenies profile (6.1%) exhibited some positive attributes with its combination of relatively low sedentary behavior (lowest among profiles by ~200 minutes), while also showing a unique pattern of second lowest MVPA, lowest LIPA, yet the highest screen time. This profile demonstrates potential strengths in having the lowest sedentary behavior while still meeting MVPA recommendations. However, members of this profile also exhibited a potential weakness in having the greatest screen time, suggesting that rest/recovery periods between physical activity bouts were largely composed of screen use. The unexpected combination of lowest sedentary behavior with highest screen time could also reflect measurement considerations, as phone-based screen time can occur while simultaneously being active (e.g., walking while using the phone; engaging in exer-games, like Pokémon-Go; Chaput & LeBlanc, 2017) and was measured separately from accelerometer-assessed sedentary behavior. Further, certain applications may record screen time usage even during intense physical activities, like going for a run while having fitness apps open, which could also explain this seemingly contradictory pattern among profile indicators.

The Highly Actives profile (7.4%) demonstrated extremely high volumes of MVPA and LIPA (both highest among profiles) with second lowest sedentary behavior and lowest screen time. If a balance among activity behaviors is considered ideal, the Highly Actives may represent a less balanced group of adolescents who are over-engaging in physical activity and potentially not getting sufficient rest and recovery during non-active periods.

The finding of four distinct activity behavior profiles among an adolescent sample aligns with previous research using person-centered analyses having found three to four distinct profiles characterized by movement and/or activity behaviors among more general adolescent populations, with similar separation among indicator variable means between profiles, despite extreme differences in volume of engagement (Brown et al., 2021a; Brown et al., 2021b; Carson et al., 2015; Carson et al., 2016b; Patnode et al., 2011). The current study extends this work by 1) concentrating on physically active adolescents, 2) focusing examination on the summer months and, 3) including objective, continuous and individual-level measures of movement behaviors and phone-based screen time as separate indicators. These methods provide a more nuanced understanding of how these behaviors cluster under free-living conditions.

The identification of these distinct activity behavior profiles has important implications for how we may approach health promotion efforts for active adolescents. Our findings suggest that one-size-fits-all approaches to limiting sedentary behavior and screen time and promoting physical activity to support health and wellbeing may be insufficient, particularly among physically active adolescents. Future interventions may be more effective when tailored to target specific profile characteristics.

For example, if coaches or parents had information about the distribution of activity behaviors on their active adolescents, they could potentially identify specific behavior modifications to support more balanced or health-supporting activity patterns. For instance, they may guide the Active Screenies in reducing their screen time while maintaining their low sedentary behavior engagement. They may suggest that Active Resters replace sedentary behavior for LIPA or ensure the Highly Actives incorporate adequate rest and recovery periods between intense activity sessions. This targeted approach represents a form of precision health promotion, where specific behavioral recommendations are tailored to an individual's existing activity patterns rather than applying general guidelines universally (Ozemek & Arena, 2019).

The development and testing of such profile-specific intervention approaches represent an important next step. Beyond sleep outcomes examined in this study, a targeted approach could provide valuable insights for athletes, coaches, and parents regarding which activity behavior balances are linked to better short-term and sustained athletic performance, reduced risk for activity-related injuries, improved recovery, and sustained engagement in physical activity/sport. Future research examining these relationships could further enhance our understanding of optimal activity behavior patterns for physically active adolescents across various health, wellbeing, and athletic performance domains.

Factors Associated with Profile Membership

Our hypothesis, that demographic characteristics and nature exposure would be associated with profile membership was partially supported. Age and socioeconomic status (i.e., FRPL-eligibility) emerged as significant predictors of membership in some profiles, while gender, race and ethnicity, and nature exposure did not significantly distinguish between any profiles. Age and socioeconomic status, and to some degree, nature exposure, appear to interact with activity behavior patterns in ways that distinguish between activity behavior profiles among physically active adolescents. These findings reflect the importance of considering multiple levels when examining individual-level characteristics and exposures in association with activity behavior patterns for the development of targeted interventions for this population.

Age emerged as the strongest predictor of profile membership, with older adolescents being significantly more likely to belong to the Active Resters (OR = 1.68) and Active Screenies (OR = 2.08) profiles compared to the Highly Actives profile. This finding aligns with reports indicating increases in screen time as adolescents get older (Rideout et al., 2022), which may reflect the growing importance of digital communication and social media in older adolescents' lives. All adolescents in our sample exceeded physical activity recommendations that have been associated with health benefits (even those in the Active Resters profile averaged ~228 min/day of MVPA). Despite all exceeding recommendations, the age-related differences in screen time and sedentary behavior, where older adolescents gravitated toward activity behavior profiles characterized by greater screen time and sedentary behavior and lesser physical activity engagement, aligns with extant literature (van Sluijs et al., 2021; Piercy et al., 2018), and is particularly noteworthy.

This finding demonstrates how age relates to the integration of screen time alongside movement behaviors within an already active sample of adolescents. Rather than focusing on the clinical implications of MVPA differences, the more meaningful finding is how engagement in screen time and sedentary behavior increase with age, even among highly active adolescents. Longitudinal studies examining the stability of activity profiles across developmental periods (e.g., from late childhood to early and late adolescence) would enhance understanding of how these patterns evolve over time and potentially identify critical periods for intervention. Additionally, future research examining pubertal development would provide greater insight into the physiological mechanisms underlying these observed age-related patterns as opposed to chronological age.

FRPL-eligibility significantly predicted membership between certain profiles. Specifically, adolescents who reported “No” or “I don’t know” to FRPL-eligibility were 2.54 times more likely to be in the Balanced Actives profile than the Active Screenies profile compared to those reporting “Yes”. This finding requires nuanced interpretation, as one of the key distinctions between these profiles is that the Balanced Actives exhibited substantially greater sedentary behavior than the Active Screenies (848 vs. 536 min/day, respectively). This suggests that lower socioeconomic status adolescents may have fewer opportunities for undisturbed sedentary behavior. This is possibly due to housing conditions, shared living spaces, or responsibilities that require movement throughout the day (Stalsberg & Pedersen, 2018).

Conversely, higher socioeconomic status adolescents may have greater access to comfortable sedentary environments and fewer responsibilities during the summer, allowing for more extended periods of sedentary behavior, although these factors were not examined in the present study. These findings highlight the importance of considering socioeconomic context in research and addressing socioeconomic barriers when designing interventions aimed at promoting healthier activity behavior patterns.

Neither gender nor race and ethnicity were significant in differentiating likelihood of profile membership. These findings contrast with previous research (Kretschmer et al., 2023; Armstrong et al., 2018; Piercy et al., 2018) that have reported gender differences in screen time usage and physical activity patterns among general adolescent samples, with girls typically engaging in less MVPA and different patterns of screen use than boys (Kretschmer et al., 2023; Armstrong et al., 2018; Stalsberg & Pedersen, 2018). The lack of gender differences is particularly notable given our relatively gender-balanced sample (48.5% cis-girls, 44.8% cis-boys). While gender differences in activity behaviors are commonly observed among general adolescent populations (Kretschmer et al., 2023; Armstrong et al., 2018; Piercy et al., 2018), research specifically examining gender differences among physically active adolescents is sparse. Our findings suggest that, among adolescents already achieving high levels of physical activity, gender may play a less prominent role in determining patterns of activity behaviors. This contrasts with studies among general adolescent populations where gender is often strongly associated with physical activity, sedentary behavior, and screen time (Kretschmer et al., 2023; Armstrong et al., 2018; Piercy et al., 2018).

The relatively racial and ethnic homogeneity of our sample (74.4% non-Hispanic White) likely limited our ability to detect potential differences across diverse racial and ethnic groups. Despite a high degree of separation in profiles by activity engagement, all participants exceeded physical activity recommendations, which may have reduced variance in other activity behaviors as well, making it more difficult to detect significant demographic differences. Future research should employ more purposive sampling methods to ensure racial and ethnic heterogeneity, allowing for a more nuanced examination of how activity behavior profiles are distinguished across racial and ethnic identities as well as their varying relationships with health outcomes.

Although the relationship between nature exposure and activity behavior profile membership was non-significant, it appeared as though greater nature exposure could potentially be influential in observing a small yet notable increase in likelihood of membership in the Balanced Actives profile compared to the Active Resters profile. This aligns with research showing associations between nature exposure and more active lifestyles (Li et al., 2018; Jimenez et al., 2021). Studies incorporating detailed assessments of nature quality, engagement type, and timing would strengthen understanding of how exposures to natural elements and environments relate to activity behaviors and health outcomes (Jimenez et al., 2021; Browning et al., 2023). Researchers should explore how the quality of nature exposure – both objectively and subjectively – is associated with adolescents' activity patterns.

Activity Behavior Profiles and Nighttime Sleep Duration

As hypothesized, profile membership was associated with differences in sleep duration. However, these associations arose in unexpected ways. The Active Screenies profile, characterized by the highest screen time, yet the lowest sedentary behavior, was associated with significantly longer sleep duration (~9.58 hours) compared to all other profiles. The Active Resters, Balanced Actives, and Highly Actives profiles showed comparable sleep durations (~6.87-7.02 hours). Of clinical relevance, Active Screenies was the only profile meeting the recommendation of at least 8 hours of nightly sleep for adolescents (Paruthi et al., 2016), despite having the greatest screen time. On one hand, the finding that the Active Screenies profile achieves substantially longer sleep duration is consistent with some literature showing the association of sufficient physical activity, lower sedentary behavior engagement, and longer sleep duration (Knufinke et al., 2017), as this profile exhibited the lowest sedentary behavior among profiles while also exceeding physical activity recommendations. However, this finding is inconsistent with evidence suggesting that greater screen time is associated with poorer sleep outcomes, including lesser sleep duration (Zhang et al., 2021; Carson et al., 2015). This contradiction highlights the complexity of activity behavior-sleep relationships that our person-centered approach was able to reveal. Unlike variable-centered studies that examine isolated relationships between individual behaviors and outcomes across an entire sample, our approach captured how these behaviors cluster and are collectively associated with sleep duration among distinct profiles within the larger sample. This nuance would have been missed in traditional analyses examining only direct relationships between respective activity behaviors (MVPA, LIPA, sedentary behavior, screen time) and sleep duration.

Several explanations may account for these unexpected findings regarding differences in average sleep duration between activity-behavior profiles. First, considering a time allocation perspective, the Active Screenies profile, although exhibiting the greatest screen time, was also characterized by second least MVPA, least LIPA, and least sedentary behavior, potentially allowing more time for sleep within the 24-hour period (Tremblay et al., 2016). The behavioral energy balance framework, discussed in the context of energy expenditure (Matricciani et al., 2018) and the extension – to include circadian timing – presented by Veronda and colleagues (2022) suggest that daily behaviors involving physiological energy expenditure (i.e., physical activity) and energy conservation (i.e., rest, recovery, and sleep) must be balanced to support sustained physical activity engagement, physical/athletic performance, and sufficient sleep. The Active Screenies profile may represent a pattern where reduced overall movement behaviors engagement allows for extended sleep duration, regardless of extended screen time. This finding suggests that among active adolescents, the combination of ample MVPA and limited sedentary behavior may be more important for promoting sufficient sleep duration than screen time. Importantly, despite having the second-lowest MVPA and least LIPA across profiles, members of the Active Screenies profile far exceeded physical activity recommendations for youth of 60 min/day of MVPA (Piercy et al., 2018), which has been shown to improve overall sleep outcomes, including sleep quality and duration (Kline et al., 2022).

Second, the Balanced Actives and Highly Actives profiles demonstrated shorter sleep duration, despite greater physical activity volumes. This finding is contradictory to common conceptions about the association between physical activity and sleep, that engaging in greater volumes of physical activity will promote beneficial sleep outcomes. However, this finding aligns with Roberts et al. (2019) observations among adolescent athletes who showed later bedtimes, but similar wake times compared to less active peers, resulting in shorter overall sleep duration. Further, as described by Fox et al. (2020) and Lastella et al. (2016), high volumes of MVPA can trigger increased sympathetic nervous system activity, elevated core body temperature, and hormonal fluctuations that may persist into the evening hours, potentially disrupting sleep onset and shortening sleep duration. The Balanced Actives and Highly Actives profiles, with their extreme MVPA levels (~310 and 405 min/day, respectively) compared to the Active Resters (228 min/day), may also portray Master et al.'s (2019) observation of a U-shaped relationship between physical activity and sleep duration, where intermediate volumes of physical activity show more beneficial effects than volumes at the high extreme. This finding supports the call to examine activity behaviors collectively, as opposed to their direct associations with sleep outcomes (Walsh et al., 2020; Knufinke et al., 2017; Matricciani et al., 2018; Antunes et al., 2017; Watson, 2017; Tremblay et al., 2016), to reveal complex interactions that might otherwise remain unobserved when behaviors are studied in isolation. Doing so can ultimately lead to more effective, targeted sleep promotion strategies for physically active adolescents.

Third, while the Active Screenies profile had the highest screen time, their overall pattern of comparably (to other profiles) lesser physical activity engagement may reflect a preference for sedentary leisure coupled with potentially earlier bedtimes and later wake times during the lesser structured summer months. This was not assessed in the current study. Conversely, during the school year, adolescents must adhere to more rigid schedules, often requiring bed and wake times earlier than their biological preferences; early school start times (i.e., before 8:30 AM) have been associated with shortened and insufficient sleep duration in a national sample of US adolescents (Farley et al., 2024). Without the rigidity of school schedule restraints, these adolescents may have adopted sleep timing more aligned with biological preferences (circadian timing) for later bedtimes and waketimes (Yip et al., 2022; Crowley et al., 2018; Dunster et al., 2018).

Fourth, unmeasured factors such as sleep chronotype, parenting behaviors, or organized activity scheduling may affect (e.g., mediate and/or moderate) the relationship between activity behavior profiles and sleep duration (Bei et al., 2013; Crowley et al., 2018; Ewing et al., 2024; Richardson et al., 2021; Whitworth-Turner et al., 2017; Johnson, Billings & Hale, 2018). Sleep chronotype and timing preferences are closely aligned with adolescent development during puberty, specifically hormonal changes associated with puberty (Colrain & Baker, 2011), which should be considered in future studies. Further, in a meta-analytic review of parenting and sleep it was found that optimal parenting behaviors – being warm, autonomy-granting, and moderately controlling – as opposed to suboptimal behaviors – being hostile or over-controlling – support longer sleep duration, earlier bedtime, less daytime sleepiness, shorter sleep latency, and fewer sleep disturbances among adolescents (Ewing et al., 2024). Lastly, the scheduling of physical activity (i.e., timing) has been shown to influence sleep duration outcomes. For instance, MVPA performed earlier in the day has been associated with improved and lengthened nightly sleep, while MVPA in the evening time – closer to bedtime – has been associated with lower sleep quality, delayed sleep onset, and shortened sleep duration (Master et al., 2019; Whitworth-Turner et al., 2017). However, there is also the possibility that sports camps or sport-specific training occurring during the summer could restrict adolescent participants sleep-opportunity through early start times, like school start times during the school year (Farley et al., 2024). For example, in the present study, the Balanced Actives and Highly Actives profiles could have included more adolescents participating in sports camps or summer training sessions that occur early in the morning, necessitating earlier wake times despite more autonomy in bedtime behaviors during the summer (Carskadon et al., 2011).

The unexpectedly longer sleep duration in the Active Screenies profile challenges conventional assumptions about the relationship between activity behaviors and sleep, again suggesting that the overall pattern of activity behaviors across the day may be more important to consider than any single behavior. This aligns with the 24-hour movement behavior framework proposed by Tremblay et al. (2016), emphasizing the integrated nature of physical activity, sedentary behavior, screen time, and sleep. Future health promotion efforts should consider how these behaviors are distributed throughout and across the day and how different combinations and timing may optimize sleep and other health outcomes across both the summer months and the school year.

Further investigation of additional moderators and mediators of the activity-behavior profile-sleep relationship is warranted, including sleep chronotype, parental monitoring of sleep-related behaviors, and social factors. Additionally, future research should examine sleep quality and other dimensions beyond duration to provide a more comprehensive picture of sleep health among physically active adolescents. As suggested by Johnson et al. (2018), sleep consistency across weekdays and weekends represents an important dimension of sleep health that was not captured in the current study but could differ across profiles. Incorporating measures of sleep efficiency, timing, consistency, and subjective sleep quality in future studies would enhance understanding of how activity behavior profiles relate to multidimensional sleep health (Buysse, 2018; Matricciani et al., 2018; Veronda et al., 2022).

Regardless of profile membership, gender was significantly associated with sleep duration, with girls and gender-diverse adolescents demonstrating longer sleep duration than boys. This finding aligns with previous research on gender differences in adolescent sleep patterns (Kaur & Bhoday, 2017), potentially reflecting both biological (e.g., pubertal timing differences) and sociocultural factors (e.g., gender-based expectations for activities and schedules). These gender differences highlight the importance of considering gender-specific approaches to sleep promotion in future interventions, potentially addressing different barriers and facilitators to adequate sleep across genders. This might include tailoring sleep education messaging or developing gender- or sex-specific interventions that account for biological and/or social differences in sleep needs and patterns.

The observed sleep duration differences by gender could also reflect underlying physiological differences during pubertal development across sexes. Females typically begin puberty earlier than males, with accompanying hormonal changes that may influence sleep architecture and circadian timing preferences (Colrain & Baker, 2011). Specifically, the rise in estrogen and progesterone among females can affect sleep regulation, and potentially contribute to differences in sleep quality and duration compared to males (Crowley et al., 2018; Johnson et al., 2018). Males undergo different hormonal changes including testosterone increases that influence both physical activity behaviors and performance, and sleep patterns, but typically start and experience peak pubertal development later than their female counterparts (Crowley et al., 2018; Johnson et al., 2018). Future research and interventions may consider exploring the efficacy and effectiveness of targeted approaches specific to developmental stages rather than chronological age alone, in addition to socially constructed gender-based approaches.

The incorporation of objectively measured nature exposure (minutes/day) represents a methodological advancement in understanding environmental exposures and their associations with sleep health. Notably, we found a significant protective effect of nature exposure within the Active Resters profile, where each unit increase in nature exposure was associated with approximately 21 additional minutes of average nightly sleep duration. This profile-specific benefit suggests that nature exposure may serve as a buffer against the potential negative effects of high sedentary behavior and screen time on sleep duration. As noted by Chang et al. (2014), screen use can act to suppress melatonin production and disrupt circadian rhythms, while Hale et al. (2019) observed that engagement with screens can increase cognitive arousal, making the transition to sleep more difficult. Nature exposure may work to counteract these mechanisms. Specifically, among the Active Resters profile, stress reduction (Ulrich et al., 1991) or attention restoration (Kaplan, 1995) – benefits commonly associated with spending time exposed to natural elements – in addition to enhanced circadian alignment through exposure to natural light during the day could occur, promoting sleep health (Lang et al., 2022). This finding also supports Argyriadis et al.'s (2024) observation that adolescents engaging in activities in natural settings showed lower evening cortisol levels – a potential pathway to improved sleep outcomes for those otherwise engaged in predominantly sedentary, screen-based activities. However, this dimension of nature exposure and associated psychological effects was not examined in the present study.

For nature exposure, overall, findings suggest that promoting nature exposure may be a valuable complementary approach to improving sleep health, particularly for adolescents with higher sedentary behavior and screen time volumes. Programs that encourage outdoor activities, particularly for adolescents with otherwise more sedentary lifestyles, may offer dual benefits for reducing screen time and sedentary behavior and enhancing sleep duration. This is supported by DeVille et al.'s (2021) observation that nature exposure is associated with less screen time and more consistent bedtime routines, leading to beneficial sleep outcomes. Future investigation of physiological (e.g., cortisol patterns, core body temperature regulation) and psychological pathways (e.g., stress reduction, cognitive restoration) linking nature exposure to sleep outcomes would further elucidate these relationships and inform intervention design.

Nature Exposure as a Moderator

The relationship between nature exposure and sleep duration varied across profiles, though formal tests of moderation did not reach statistical significance. While the significant positive association between nature exposure and sleep duration in the Active Resters profile was discussed above, it is important to note that this relationship was stronger, though not statistically significant, in the Active Screenies profile, and essentially absent in the Balanced Actives and Highly Actives profiles. These differentiated associations suggest that nature exposure may have varying importance depending on an adolescent's activity behavior pattern. The beneficial association between nature exposure and sleep duration primarily among profiles characterized by higher screen time and/or sedentary behavior supports the hypothesis that nature exposure may be particularly valuable for adolescents with otherwise less optimal or imbalanced activity behavior patterns.

The mechanisms through which nature exposure might influence sleep likely differ by profile. For adolescents in the Active Resters profile, nature exposure may provide a counterbalance to extended periods of indoor sedentary behavior, offering exposure to natural light that supports circadian regulation (Gradisar et al., 2014), and natural elements shown to be associated with attention restoration and stress reduction (Ulrich, 1991; Kaplan, 1995). For those in the Active Screenies profile, who demonstrated the highest screen time yet the lowest sedentary behavior, and the longest sleep duration, nature exposure may enhance sleep quality in addition to sleep duration, though this sleep quality was not included in the current study.

The negligible relationship between nature exposure and sleep duration in the more physically active profiles (Balanced Actives and Highly Actives) suggests that these adolescents may already experience sleep-promoting benefits from their physical activity patterns, making nature exposure less impactful for sleep duration. Alternatively, as suggested by Noseworthy et al. (2023), the quality and context of nature exposure may matter more than quantity, with factors such as biodiversity, engagement type, and timing playing important roles. Those in the more active profiles are potentially engaging in more structured training activities or sports camps. Although they may be spending time outside during these activities or camps, they may not benefit from some of the effects of time outside and/or exposed to natural elements due to the context of their engagement (e.g., focused on sport performance and skills, lesser involuntary attention and greater directed attention).

While the profile-specific nature exposure effects did not translate into statistically significant moderation, this may be due to limited statistical power, particularly in the lesser-represented profiles. Although there are no specified power considerations for latent profile analyses with distal outcomes, it is recommended that profiles are represented by at least 5% of the sample (Meyer & Morin, 2016). All profiles in this 4-profile solution represented >5% of sample. However, small subgroup sample size estimates (i.e., ~20 for the Active Screenies and ~24 for the Highly Actives) could still have limited the ability to detect significant slope differences between profiles. Despite these power-related concerns, the pattern of stronger nature-sleep associations in less active profiles nonetheless suggests a potentially important ecological relationship warranting further investigation in larger samples with more refined measurement approaches and rigorous study designs. Future studies employing mixed methods approaches that incorporate qualitative data could provide deeper insights into adolescents' decision-making regarding time allocation across activities, factors influencing their behavioral patterns, and the qualitative and/or internalized experiences of nature exposure.

Limitations

Several limitations warrant consideration when interpreting findings of the present study. The cross-sectional design precludes any causal inferences about the relationships between activity profiles, nature exposure, and sleep duration. Future longitudinal studies examining the stability of activity profiles across seasons and developmental periods would enhance understanding of how these patterns may evolve over time and potentially identify critical periods for intervention. Following Killer et al.'s (2015) observation of distinct seasonal training patterns among adolescent athletes, research spanning both academic year and summer periods would provide valuable insights into how school structures and largely unstructured summer periods differentially influence activity behavior patterns and their relationship with nightly sleep duration.

The sample characteristics limit the generalizability of findings in several ways. Although not the intention of the current study, all participants were highly active and exceeded recommendations for daily MVPA. This occurred most likely because primary in-person recruitment and study visits took place at KIDSPORTS, a local youth sports community-based organization. Talking to and handing out study flyers on site to adolescents and families who were already coming to KIDSPORTS ended up being a more effective recruitment strategy than mass mailings and social media posts that may have reached adolescents with more variation in their activity behaviors. Additionally, the convenience sampling method was employed across the Eugene/Springfield, Oregon area, a region known for an abundance of natural spaces, expansive trail systems, and a strong culture supporting outdoor recreation (e.g., Eugene, Oregon is known as Track Town USA; Dubinsky, 2021).

There was also the possibility of selection bias, where adolescents who are active and/or enjoy physical activity or spending time in nature could be more inclined to sign up and participate in a study where recruitment materials indicated that the study was about physical activity and nature among adolescents. For example, in conversations with participants during study visits, research staff noted that many participants voluntarily mentioned that they would be participating in organized summer activities during their study periods, with some stating that this ‘would be great data [for the research team]’. These organized activities mentioned by participants to research staff included but were not limited to two-a-day football practices, full day soccer-training, sport-specific summer camps, and extended hiking/camping trips. However, participation in organized summer activities was not accounted for in the present study and could have influenced findings.

Our eligibility criteria included continuous access to a smartphone and the ability to meet at KIDSPORTS, both of which could be barriers to adolescents living in lower socioeconomic households, who are consistently reported to be disproportionately inactive (Dabke & Lynch, 2022; Piercy et al., 2018). That said, almost a third of the study sample indicated eligibility for FRPL. The relative racial and ethnic homogeneity of our sample presented additional limitations for analysis and generalizability. With a large majority of participants identifying as non-Hispanic White (74.4%), we dichotomized race and ethnicity into non-Hispanic White and All Other racial and ethnic identities to have enough participants for analytical purposes. This limited our ability to identify potential differences in likelihood of profile membership or in associations with sleep duration across lesser-represented racial and ethnic groups. However, the sample's racial and ethnic composition generally reflects that of the study's location, where approximately 75.4% of residents identify as non-Hispanic White, compared to just 58.4% nationally (U.S. Census Bureau, 2023). Future research should employ more purposive sampling methods and recruit adolescents from regions with more racial and ethnic diversity to allow a more nuanced examination of how activity behavior profiles and their relationship with sleep duration may vary by racial and ethnic identity.

Measurement limitations include the challenges of wrist-worn accelerometry for adolescents (ages 12-17), which may overestimate MVPA compared to hip-worn devices (Crouter et al., 2014) and cannot capture certain activities such as swimming or other water-based activities popular during the summer months. For instance, research staff recall at least one participant reporting that they would have to take off their accelerometer while training for competitive kayaking. Further, nature exposure measurement via the NatureDose phone application, while novel and superior to other measures of nature exposure in several ways (Browning et al., 2023), primarily captures time spent in areas algorithmically determined to be 'natural' without accounting for the quality of the individual-level experiences or engagement with natural elements. As discussed by Browning et al., (2023), subjective experiences (e.g., quality of the experience) – not just the quality of the natural elements – of nature exposure may play a unique and significant role in the effects of nature exposure. Future studies should incorporate repeated measures of subjective experiences of nature exposure (e.g., using momentary ecological assessment) to further elucidate the importance of considering quantity (frequency and duration), quality (subjective and objective), and timing of nature exposure in promoting health and wellbeing among active adolescents. Additionally, self-reported screen time, while assessed daily by having participants navigate to their phones internal monitoring tools to report screen time data, may still be subject to social desirability bias, potentially leading to under-reporting. This study also only specifically measured phone-based screen time, thus other types of screen-based activities – television, video games, and computers, for example – were not accounted for. As such, it is unknown how these different modalities of screen use could have differentially affected findings.

The patterns observed in the present study are unique to the summer context and may not generalize to other seasons, particularly when school schedules constrain sleep timing and duration (Farley et al., 2024). The summer context represents a specific period in adolescents' routines, characterized by reduced structure compared to the school year. As noted by Bei et al. (2013), adolescents often experience substantial changes to daily routines during summer that can significantly affect sleep timing and duration. The summer environmental context, particularly extended daylight hours and increased environmental heat stress during outdoor activities, likely influenced both activity behavior patterns and sleep outcomes in ways for which could not be fully accounted (Fox et al., 2020; Whitworth-Turner et al., 2017).

Lastly, our analyses focused on sleep duration as the primary outcome, without considering other dimensions of sleep such as sleep quality, timing, or consistency/regularity. Despite the call from the American Academy of Pediatrics focusing on sleep duration as the most salient sleep dimension to promote among children and adolescents (Owens, 2014), other dimensions are important to examine in the context of multidimensional sleep health (Buysse, 2018). Future studies should consider the multidimensionality of sleep due to differential effects across dimensions influenced by daily behaviors, including activity behaviors (Tremblay et al., 2016; Buysse, 2018; Matricciani et al., 2018; Matricciani et al., 2024). Additionally, there may be additional confounders such as sleep hygiene behaviors and parental influences that were not measured or assessed in the present study. Future studies should incorporate these additional sleep dimensions and consider additional confounders to provide a more comprehensive understanding of how activity behavior profiles relate to overall sleep health among active adolescents.

CHAPTER V

CONCLUSION

This study provides novel insight into the complex interrelationships between movement behaviors, screen time, nature exposure, and sleep duration among physically active adolescents during summer months. The identification of four distinct activity behavior profiles – indicated by continuously and objectively measured MVPA, LIPA, sedentary behavior, and screen time – demonstrates that even adolescents exceeding physical activity guidelines exhibit varied yet distinct activity behavior patterns that differentially relate to sleep duration. Unexpectedly, adolescents with the highest screen time but with lower physical activity – despite exceeding PA recommendations – than others in the sample exhibited the longest sleep duration. These finding challenge conventional assumptions about direct or bivariate physical activity-sleep relationships. In doing so, findings underscore the advantages of considering integrated 24-hour movement behavior patterns (Tremblay et al., 2016), and the value of person-centered approaches in understanding distinct activity behavior patterns under free-living conditions. The positive effect of nature exposure on the association between more sedentary profiles – greater sedentary behavior and screen time – and sleep duration suggests that nature exposure may play a compensatory role in supporting sleep health among adolescents who spend substantial time engaging in sedentary behavior and screen time. Study findings can inform intervention strategies that better support sleep achievement among active adolescents through consideration of the unique clustering of activity behaviors, their associations with sleep duration, and the potential role nature exposure plays in promoting increases in sleep duration among certain activity behavior subgroups of active adolescents.

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