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Original Research Article

Temporal Associations Between Sleep and Physical Activity Among Overweight/Obese Youth

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Abstract

Objective Examine average interindividual and temporal intraindividual associations between time of sleep onset (sleep onset), total sleep time (TST), and minutes in moderate-to-very-vigorous physical activity per hour (MVPA/h) among overweight/obese youth. **Methods** Overweight/obese youth ($n = 134$; 7–12 years) wore an accelerometer for 16+ hr/day, 5–7 days, which provided daily objective estimates of MVPA/h, TST, and sleep onset. **Results** Multilevel models revealed an intraindividual effect of TST, such that nights with longer TST preceded less MVPA/h during the midnight-to-midnight monitoring period; a significant random effect qualified this relationship. Average interindividual TST did not predict mean MVPA/h, whereas sleep onset significantly predicted mean MVPA/h. **Conclusions** Later time of sleep onset (as opposed to TST) was the strongest predictor of group-level decreased physical activity. At the individual level, longer TST than usual predicted *less* MVPA/h than usual. Results suggest the need for more person-centered research and a greater focus on sleep timing among youth.

Key words: child; exercise; pediatric; physical activity; sleep; temporal.

Introduction

Overweight and obesity is the most prevalent chronic condition of childhood (Ogden, Carroll, Kit, & Flegal, 2014), and is associated with various negative physical and psychosocial outcomes. Sleep morbidities are common in overweight and obese children, and include higher rates of sleep disordered breathing and obstructive sleep apnea (OSA; Beebe et al., 2007), more frequent nighttime awakenings, and less efficient sleep (Cappuccio, Taggart, Kandala, & Currie, 2008). Overweight and obese youth also demonstrate higher rates of problematic bedtime behaviors, such as later bedtimes (Cappuccio et al., 2008), variable sleep schedules (Spruyt, Molfese, & Gozal, 2011), and screen time directly before bed (Sekine et al., 2002).

A well-supported body of literature details the interindividual associations between sleep duration (referred to as "total sleep time" herein) and weight across youth; four epidemiological studies find that shorter total sleep time (TST) predicts overweight status broadly across American 10–19-year-olds (Gupta, Mueller, Chan, & Meininger, 2002; Knutson, 2005; Knutson & Lauderdale, 2007; Seicean et al., 2007). Short TST in preschool predicts overweight status at 5- and 9-year follow-ups in prospective studies (Agras, Hammer, McNicholas, & Kraemer, 2004; Landhuis, Poulton, Welch, & Hancox, 2008), even after controlling for preschool weight (Snell, Adam, & Duncan, 2007). Meta-analyses find that children who sleep less than the recommended daily amount confer 58%

increased risk for being overweight or obese (Chen, Beydoun, & Wang, 2008). Conversely, overweight or obese youth are 60–80% more likely to sleep less than the recommended nightly amount compared with healthy-weight peers (Cappuccio et al., 2008).

A commonly held hypothesis is that sleep exerts its effect on weight partially by altering weight-related behaviors influencing energy intake and expenditure. Mechanistic studies have thus attempted to identify specific behaviors that mediate or moderate the relationship between sleep and obesity in children. For the purposes of this article, we will review only the pertinent literature on sleep and energy expenditure among youth. Studies find that youth with later bedtimes and shorter TST are more sedentary and spend more time in front of televisions, video games, or computers (Drescher, Goodwin, Silva, & Quan, 2011), particularly in the late evening before bed (Sekine et al., 2002). When considering nonsedentary activity (e.g., moderate-to-vigorous physical activity; MVPA), results are somewhat conflicted. For example, Ortega and colleagues found that any positive associations between child-reported TST and physical activity (measured via activity monitor) were fully explained after controlling for demographic variables (Ortega et al., 2011). A similarly designed study that used pedometers and self-reported sleep in adolescents also found no associations between TST and daytime physical activity (Olds, Maher, & Matricciani, 2011). Interestingly, in this study, late-night chronotype adolescents (preferring later bed and waketimes) spent less time in daytime moderate-to-vigorous physical activity (MVPA) than their early-type counterparts, despite similar measured TST. Findings imply that sleep timing may play an important role in physical activity, over and above TST. In contrast, Stone and colleagues (2013) found that children who obtained >10 hr of TST (measured via parent-report) spent more minutes in MVPA, as measured by accelerometer, than those who obtained <9 hr per night. Two studies which used a wrist-mounted actigraph and the arm-mounted Sensewear Armband accelerometer to measure both sleep and physical activity found no associations between average TST and MVPA in youth (Ekstedt, Nyberg, Ingre, Ekblom, & Marcus, 2013; Soric et al., 2015).

In sum, one study to date indicates that shorter TST predicts less physical activity among youth. On first consideration, one may deduce that sleep must act primarily on some other system (e.g., dietary intake) to influence weight gain in youth. However, inconsistent findings must be taken in the context of a relatively new field of inquiry that relies on varying assessment instruments. Measurement methods span single-question subjective reports from children or parents (e.g., *How many hours does your child typically sleep?*) to objective devices worn on the wrist, arm, waist, or ankle. Within objective devices, each uses varying sensors and algorithms that vary in sleep/wake estimation, average activity counts, or intensity of physical activity. Within studies, each uses different measurement periods (e.g., 1 day vs. 3 days vs. 7 days). However, few studies investigate how these constructs relate at the individual level. Thus, inconsistent methodology and potential systematic differences between sleep and physical activity assessment devices may obscure group-level comparisons. Studies may also simply lack the temporal sensitivity to detect nuanced intraindividual (within a person) associations that may "wash out" at the interindividual (between subjects) level. Further, it is notable that traditional statistical methods (e.g., analysis of variance [ANOVA], regression) assume that the mean-level trajectory is representative of the entire group response, and necessarily treats deviations from that trajectory as error, rather than potential individual differences (Kristjansson, Kircher, & Webb, 2007). This assumption of fixed effects may be particularly concerning when assessing physical activity levels, as physical activity levels may naturalistically vary by person (Mâsse, Dassa, Gauvin, Giles-Corti, & Motl, 2002).

The study of person-level day-to-day fluctuations in sleep (i.e., intraindividual variability) has gained recent popularity among adult sleep researchers. For example, night-to-night sleep variability has been identified as a common symptom of adult insomnia (Buysse et al., 2010). Bei and colleagues (2015) posit that although biological bases of sleep (e.g., homeostatic sleep pressure and circadian drive) that underlie stable sleep patterns across humans are well-studied, external (i.e., environment, life stressors) and internal (i.e., personality, psychopathology) factors that drive intraindividual variability are understudied, especially in children. The study of intraindividual sleep variability may be especially important among overweight youth, as they are at heightened risk for "biologically driven" sleep problems (e.g., OSA) that may predispose them to behavioral problems. Overweight or obese children rate themselves as experiencing greater psychosocial stress than healthy-weight children (Gundersen, Mahatmya, Garasky, & Lohman, 2011) and often have less structured and cohesive families (Zeller et al., 2007), two environmental factors that may promote greater night-to-night sleep variability. Interestingly, among adults, greater night-to-night TST variability (measured via the standard deviation of TST) is associated with increased odds of being obese, even after accounting for mean TST (Patel et al., 2014). Thus, measuring and characterizing intraindividual trajectories in child sleep patterns may be one way to categorize associations with heightened weight status.

Among youth, several studies find associations (albeit conflicted) between intraindividual sleep variability and altered energy expenditure among youth. For example, Spruyt and colleagues (2011) find that night-to-night TST variability is highly associated with metabolic dysfunction among 4–10-year-olds. Three pediatric studies to date investigate temporal associations between objectively measured TST and MVPA at the intraindividual level. In the earliest study, Pesonen and colleagues (2011) measured sleep and physical activity via the wrist-mounted Actiwatch AW4 within a group of Finnish 8-year-olds. They found that nights with longer TST predicted *fewer* minutes of next-day MVPA and that greater sleep fragmentation at night predicted *more* minutes in next-day MVPA. Interestingly, a 2013 study that used the same Actiwatch AW4 found that TST and sleep fragmentation were unrelated to next-day MVPA among Swedish 6–12-year-olds (Ekstedt et al., 2013). In a more recent study, Soric et al. (2015) measured sleep and physical activity over 2–6 days via an upper-arm-mounted accelerometer (the Sensewear Armband) among American, Croatian, and Slovenian 11-year-olds. Although TST and sleep efficiency were unrelated to MVPA at the interindividual level, significant temporal intraindividual effects revealed that each hour longer a child spent in bed corresponded to a 16-min decrease in next-day MVPA. Further, girls in this sample exhibited a negative intraindividual temporal relationship between TST and MVPA. Given the contradictory nature of their results with previous findings, authors urged interpretative caution and called for study replication of these studies, as well as longer periods of monitoring with both schooldays and weekends.

Study Purpose

Studies support a link between sleep and weight among youth, but have not yet isolated physical activity as a reliable mediator in this relationship. Several methodological and conceptual gaps remain to be addressed, as many previous studies are cross-sectional, do not objectively operationalize sleep, exclusively use TST as their measure of sleep, and disregard intraindividual covariation in sleep and physical activity. Further, despite citing clinical implications for the pediatric obesity epidemic, no studies to date have investigated the unique relationship between sleep and physical activity among currently overweight or obese children.

Thus, this study sought to replicate three previous studies examining the average inter- and temporal intraindividual relationships between TST and moderate-to-very-vigorous physical activity (MVPA) in a novel sample of currently overweight and obese 7–12-year-olds. It sought to also extend the literature by investigating the role of sleep timing in this relationship. Daily objective estimates of TST, time of sleep onset (sleep onset), and minutes spent in moderate-to-very-vigorous physical activity per hour (MVPA/h) were derived over seven consecutive days from the Sensewear Armband, an arm-mounted accelerometer. This study design permitted fixed interindividual estimations, which addressed the question “Is TST or sleep onset associated with MVPA/h broadly across all participants?” Consistent with previous literature in youth spanning the weight continuum (Olds et al., 2011), researchers hypothesized that sleep onset would negatively predict MVPA/h at the fixed interindividual level; researchers also hypothesized that TST would not predict MVPA/h at the fixed interindividual level, in line with three previous findings (Ortega et al., 2011; Ekstedt et al., 2013; Soric et al., 2015). The study design also allowed for fixed temporal intraindividual estimates, which addressed the question “Does TST or sleep onset predict MVPA/h the next day within an individual?” At this intraindividual level, researchers hypothesized that time of sleep onset during the night would negatively predict next-day MVPA/h. Consistent with two previous temporal studies (Pesonen et al., 2011; Soric et al., 2015), researchers also hypothesized that nightly TST would negatively predict next-day MVPA/h at the individual level. Finally, this design also allowed for random temporal effects, which addressed the question “Are there individual differences in the extent to which TST or sleep onset exerts its effect on MVPA day-to-day?”

Method

Participants

Participants were 134 treatment-seeking overweight or obese 7–12-year-olds ($n = 64$ males) who lived in a rural county in North Central Florida. Participants were part of a larger pool of participants ($n = 250$ children) beginning a behavioral weight intervention. See the section “Data inclusion criteria” below for further information on participants who did ($n = 134$) and did not ($n = 116$) meet data inclusion criteria. See Table I for participant demographics.

Procedure

The University of Florida institutional review board approved all study protocols. Participants in this study were part of a larger randomized-controlled clinical trial evaluating the efficacy of a behavioral lifestyle intervention on child weight status in overweight and obese children. See Janicke et al., 2011 for a full review of the intervention design and methods. All data used in this study were collected at the intervention baseline assessment only.

Table I. Participant Demographics

Demographic characteristic	*N*	%	*M*	*SD*
Child age			9.86	1.4
7 years	7	5.20		
8 years	18	13.40		
9 years	26	19.40		
10 years	38	28.40		
11 years	26	19.40		
12 years	19	14.20		
Child BMI z-score			2.19	0.38
1.20–1.59	10	7.00		
1.60–1.99	29	22		
2.00–2.39	54	40		
2.40–2.79	35	26		
2.80+	6	4		
Child gender				
Female	70	52.20		
Male	64	47.80		
Child race/ethnicity				
Caucasian	93	69.40		
African American	19	14.20		
Asian	3	2.20		
Native Hawaiian	1	0.70		
Biracial	15	11.20		
No response	6	4.50		
Family income				
Below $19,000	22	16.00		
$20,000–$39,999	44	32.50		
$40,000–$59,999	30	22.00		
$60,000–$79,999	16	12.00		
$80,000–$99,999	10	7.50		
Above $100,000	10	7.50		
Parent marital status				
Never married	14	10.50		
Divorced/separated	19	14.00		
Widowed	3	2.00		
Presently married	92	68.00		
Living in marriage-like relationship	6	4.50		

Researchers recruited families through community outreach efforts. Interested families completed an in-person screening following the initial phone screen, where researchers collected child height and weight while parents completed demographic questionnaires. Families met eligibility criteria if the child was 8–12 years old at the date of intervention initiation (as such, some children were 7 years old during completion of the baseline assessment), the child's body mass index (BMI) was $\geq$>=85th percentile for CDC-published age and gender norms, and the parent or legal guardian was under the age of 75 and living with the child. Families were excluded for parent or child contraindicated medical conditions (e.g., hypertension) or participation in another weight management program, child contraindicated medications (e.g., antipsychotic agents), or extreme child oppositional behaviors or cognitive/developmental delays. Roughly 2 weeks before intervention start, eligible families attended a baseline assessment visit where researchers recorded height and weight again and instructed the children on accelerometer procedures; all study data were taken from this baseline assessment.

Measures

Height, Weight, and BMI Z-Score

At the baseline visit, a trained health technician or nurse collected height and weight while children wore light clothes and no shoes. BMI was calculated as kilograms per meters squared; BMI z-scores were calculated using age and gender norms from the Centers for Disease Control and Prevention (Kuczmarski et al., 2002).

Demographic Information

Researchers considered child age, gender, and race/ethnicity (Caucasian = 0, Minority = 1) as potential covariates, which were provided via a parent self-report questionnaire during the initial screening visit.

Weekend Versus Weekday

To test whether potential associations between sleep and physical activity varied by weekday versus weekend, researchers created a binary variable that was coded: weekday (Monday–Friday) = 0, weekend (Saturday and Sunday) = 1.

Season

To test whether physical activity varied by school season, researchers created a binary variable that was coded: in-school = 0, out of school during summer season = 1.

Objective Measure of Child Sleep and Physical Activity. Researchers obtained objective estimates of child sleep and physical activity via the Sensewear Pro3 Armband Accelerometer (SWA; Bodymedia, Inc., Pittsburg, PA) at a 32 Hz sampling rate. Researchers programmed the armbands with demographic information (gender, age, handedness, and objectively measured height and weight) and downloaded data using the Sensewear Professional Software (version 7.0; Body-Media Inc.) in 1-min epochs, as is limited by the software (Soric et al., 2013). Researchers instructed the children to wear the device in standardized fashion; for 24 hr/day (with the exception of swimming or bathing) on the upper back of the right arm for seven consecutive days (Arvidsson, Slinde, & Hulthén, 2009; Arvidsson, Slinde, Larsson, & Hulthen, 2007).

Sensewear Armband Algorithms. The Sensewear Armband is a multisensor device that incorporates demographic, motion/positionality (measured via a biaxial accelerometer), Galvanic skin response, skin temperature, and heat dissipation information into independent algorithms that estimate sleep and physical activity (Soric et al., 2013; Van Wouwe, Valk, &

Veenstra, 2011). The proprietary algorithms were independently developed for sleep and physical activity measurement in children ages ≥7 years (Arvidsson et al., 2009). Physical activity algorithms are continually updated by the software manufacturers (InnerView®) and tailored to provide activity-specific (e.g., resting, walking, riding a stationary bike, running, and weight-lifting) estimates of physical activity (Arvidsson et al., 2009). Sleep/wake detection algorithms were developed using overnight polysomnography (PSG) data among healthy and sleep-disordered individuals, whereby epoch-by-epoch PSG estimates were compared with raw Sensewear Armband sensor data, and sleep prediction algorithms were created via an artificial neural network (Soric et al., 2015).

Validity and Sensitivity in Pediatric Sleep and Physical Activity Measurement. Given that "gold standard" objective methods for sleep and physical activity assessment (e.g., PSG for detecting sleep disorders, indirect/direct calorimetry, or the doubly labeled water method for physical activity; (Arvidsson et al., 2007) are expensive and inconvenient for naturalistic use, the Sensewear Armband represents an attractive ambulatory alternative for use in the free-living environment. The Sensewear Armband is not limited by only incorporating information about one bodily process (unlike pedometers, heart rate monitors, and Actigraphy) (Arvidsson et al., 2007). It is currently the only validated device for estimation of both energy expenditure (Arvidsson et al., 2009; Calabró, Welk, & Eisenmann, 2009) and sleep (Roane, Van Reen, Hart, Wing, & Carskadon, 2015; Soric et al., 2015) among children and teens. Validation studies in children comparing the Sensewear Armband with PSG find no systematic biases in overnight sleep detection (reliability = 0.94, $SD = \pm 0.05$), but note the Sensewear Armband estimates more overnight wake minutes than PSG (reliability for wake detection = 0.39, $SD = \pm 0.28$; Roane et al., 2015). Further, Roane and colleagues (2015) note that "accuracy, which is dependent on the device's ability to act both as a proxy for sleep while also adequately identifying wake, was high... (armband = 0.88)" (p. 4). Of note, both validation studies of the Sensewear Armband note its superior sleep estimation at the group level compared with the individual level among children and teens.

Sleep Variables. Predictor variables included TST and time of sleep onset (sleep onset). Sleep variables were hand-computed by one researcher and were derived from device-estimated positionality (standing upright = 0, lying down = 1) and sleep/wake status (awake = 0, asleep = 1) in the exported Sensewear Excel file. Although the device has an "event marker" capability to denote time, the child began trying to initiate and terminate sleep; these data were unavailable in the current study. Thus, researchers began computing sleep variables once it was clear the child began attempting to initiate sleep. This determination was made once after at least three consecutive positionality epochs were scored as lying down *and* epochs directly following were either scored as lying down but still awake *or* lying down and asleep. Sleep onset was defined as the clock time after which at least three consecutive epochs were scored as lying down and asleep. Time of sleep offset was defined as the clock time after which at least five consecutive epochs were scored as awake with no other sleep periods following. These scoring cutoffs (three epochs of scored sleep to determine sleep onset and five epochs of scored wake to determine sleep offset) are consistent with methods used by Graef and colleagues (2014), and are the most commonly used thresholds for scoring pediatric actigraphy variables (Meltzer, Montgomery-Downs, Insana, & Walsh, 2012). TST was defined as the total number of scored sleep epochs between sleep onset and sleep offset.

Physical Activity Variable. The outcome variable of interest was the average number of minutes per hour spent in MVPA/h. The Sensewear Armband automatically estimated the number of minutes the child engaged in MVPA over 24 hr (from midnight to midnight). Physical activity intensity levels were operationalized as minutes spent in activity requiring specific metabolic equivalents. Specifically, moderate activity = 3–5.9 metabolic equivalents (METs), vigorous activity = 6–8.9 METs, and very vigorous activity ≥ 9 METs. To control for varying amounts of device wear time, researchers divided the total number of minutes spent in MVPA by the total number of hours the child wore the device during that 24-hr period. The final variable was expressed as minutes of MVPA/h.

Statistical Analyses

Data Inclusion Criteria

To provide adequate intraindividual temporal data, researchers included participants in the present analyses only if they wore the SWA for 16+ hr/day (consistent with data inclusion criteria outlined by Graef et al., 2014) for 5–7 days, including at least 1 weekend day. Although there are no published recommendations for adequate number of accelerometer days for intraindividual analyses, three previous temporal studies of sleep and physical activity in youth have used varying numbers of days of data (from 2 to 6 days to 7 consecutive days; (Ekstedt et al., 2013; Pesonen et al., 2011; Soric et al., 2015). Of the 250 children who completed baseline measures (including the 7-day accelerometer reading) and were ultimately randomized to intervention, 53% ($n = 134$) met data inclusion criteria for these analyses. Independent t tests revealed that children who met data-inclusion criteria did not differ significantly from those who did not meet criteria across child BMI z-score, family income, and child age; a two-way chi-squared test revealed no group differences across binary demographic variables, including child race/ethnicity, child gender, and season when child was completing the study (summer vs. school year).

Multilevel Modeling

Researchers conducted analyses using the hierarchical mixed model approach (Singer & Willett, 2003) within IBM SPSS (version 22) using maximum likelihood estimations. Unlike traditional casewise deletion in ANOVA, maximum likelihood estimations use all available data from all occasions. Mixed modeling is an ideal method for assessing nested hierarchical data where multiple occasions (days) are nested within one participant. In the current analyses, seven potential days of TST/sleep onset data and MVPA/h data were nested within 134 participants, with up to two "missing data" days. Mixed models are advantageous in this context because they do not require independent samples (which is impossible in this "repeated measures" design), and test both Level 1 (intraindividual) and Level 2 (interindividual) fixed and random estimates. In the current study, Level 1 analyses at the fixed level answered the question "When a child experiences more TST/earlier sleep onset than is usual for her, does she engage in more 24-hour MVPA/h during the following midnight-to-midnight monitoring period?" Level 1 random-level analyses answered the question "Does the intra-individual relationship between TST/sleep onset and MVPA/h vary by person, based on some other factor?" Level 2 analyses tested whether predictor and outcome means covary together across all participants, and does not differ from ordinary least squares regression. Thus, Level 2 analyses in this study addressed questions such as "On average, is more TST/earlier sleep onset associated with greater MVPA/h across all subjects?"

Researchers computed a within-person mean value across the week for TST and sleep onset to include in Level 2 interindividual fixed effects. To prepare for Level 1 temporal fixed models, researchers centered and reverse-lagged each subject's daily TST and sleep onset values on that person's unique within-person mean, such that nighttime sleep variables fell on the same row as midnight-to-midnight MVPA/h values. Thus, each centered value represented that individual's daily deviation from his or her average predictor value. Researchers conducted a bivariate correlation between within-person mean TST and sleep onset to ensure that the predictor variables could be conceptualized as independent predictors. TST and sleep onset were weakly (but significantly) correlated ($r = .26$, $p = .01$), and were therefore conceptualized as independent predictors.

The final model was built over several steps. In the first step (the null model), researchers added no predictors; this model established the amount of interindividual and intraindividual variance to be accounted for by future predictors. In the second step (unconditional growth model), researchers estimated both the random and fixed effects of a time variable (coded 0 through 6, 0 = day 1 of wearing the device) to establish whether MVPA/h varied systematically as a function of time; time was to be retained in future models if it was confirmed as a significant predictor of MVPA/h. In the third step (demographic model), researchers entered all potential intraindividual (group-level) covariates to estimate their fixed effects, and then removed all nonsignificant predictors to maximize model parsimony. Finally, in the fourth step (conditional random intercept model), researchers entered the four variants of the predictor variables into one final model. Within-person mean values for TST and sleep onset were entered to estimate the fixed interindividual effects; reverse-lagged person-centered values for TST and sleep onset were entered to estimate the fixed and random intraindividual effects.

Results

See Table I for a display of demographic variables. Sample means and standard deviations for the outcome and predictor variables are presented in Table II.

Initial Model

Results from the null model revealed significant random effects for both the intercept and residual, indicating a significant amount of inter- and intraindividual variance to be accounted for in future models. Adding time to the unconditional growth model did not significantly predict MVPA/h at the fixed or random level, indicating that children did not differ systematically in their MVPA/h as a function of the day; time was therefore excluded from both fixed and random estimates as a predictor in subsequent models. The demographic model tested for significant covariates, including child gender, BMI z-score, child age, child race, weekday/weekend, and season (school vs. not in school). This model revealed BMI z-score as the only significant predictor of MVPA/h (B = 2.044, $p = .007$; data not shown); therefore, all other covariates were dropped from future models, to maximize parsimony. Building on this model, the conditional random intercept model included all relevant predictors, including BMI z-score, within-person mean TST, and sleep onset in the fixed effects, as well as person-centered TST and sleep onset in the random effects. This model resulted in model nonconvergence, indicating that sleep onset and MVPA/h did not differ between participants. Nonsignificant random effects of sleep onset were therefore not included in the final model.

Table II. Descriptive Characteristics of Independent and Dependent Variables

Measure	Minimum	Maximum	*M*	*SD*
Total sleep time	136 min (2 hr 16 min)	805 min (13 hr 25 min)	412 min (6 hr 52 min)	84 min
Time of sleep onset	7:18 pm	6:14 am	10:58 pm	98 min
Time of sleep offset	3:22 am	3:49 pm	7:27am	111 min
Moderate-to-very-vigorous physical activity/hour	0 min	28 min	5 min	4 min

Note. Minimum and maximum values represent values for individual children on one measurement day, rather than within-person means. Mean values reported represent averages across all participants across all days of measurement.

Table III. Interindividual and Intraindividual Associations Between Sleep Variables and Minutes Spent in Moderate-to-Very-Vigorous Physical Activity Per Hour

	Initial model			Model removing outliers		
	B	*SE*	*p*	*B*	*SE*	*p*
			Fixed effects			
Independent variable predictors						
Interindividual estimates						
BMI z-score	−1.633	0.750	.03*	−1.632	0.580	.006**
Mean total sleep time	−0.002	0.006	.76	−0.001	0.004	.861
Mean sleep onset	−0.012	0.004	<.01**	−0.010	0.003	.001**
Intraindividual estimates						
Person-centered total sleep time	−0.005	0.002	.03*	−0.005	0.002	.006**
Person-centered sleep onset	−0.001	0.002	.45	−0.002	0.002	.115
			Random effects			
Intraindividual estimates Person-centered total sleep time	0.0001	0.000006	.03*	0.00004	0.00003	.113
	Interindividual pseudo $R^2 = 0.05$			Interindividual pseudo $R^2 = 0.28$		
	Intraindividual pseudo $R^2 = 0.09$			Intraindividual pseudo $R^2 = 0.10$		

$^{*}p < .05$; $^{**}p < .01$.

Results of the final conditional random intercept model, including the fixed and random predictors of interest and significant covariate, are presented in Table III. In this final model, BMI z-score was related to MVPA/h, such that youth with higher BMI z-scores engaged in less physical activity (B = −1.632 *p* = .031). Fixed interindividual analyses revealed that TST was not significantly related to MVPA/h; thus, TST had no bearing on MVPA/h at the group level. Conversely, mean sleep onset was negatively related to MVPA/h, such that later bedtimes were associated with less MVPA/h at the group level (B = −0.012, *p* = .001), independent of any effect of TST. Fixed intraindividual temporal analyses indicated that TST was negatively related to MVPA/h within an individual; for each 60 min more sleep a child obtained over his/her personal average, he/she engaged in 0.27 fewer min of MVPA/h than was usual for them during the subsequent midnight-to-midnight monitoring period (B = −0.005, *p* = .028). This finding was qualified by a significant random effect for TST; thus, the strength that TST exerted on MVPA/h varied by person. Intraindividual fluctuations in sleep onset time were not related to next-day MVPA/h. Pseudo R^2 measures indicated that the final model explained 5% of the interindividual variance in MVPA/h and 9% of the intraindividual variance in MVPA/h.

Model Removing Outliers

Given the extensive range of sleep values (TST range = 136–805 min, sleep onset range = 7:18 pm–6:14 am, sleep offset range = 3:22 am–3:29 pm), the study authors also conducted follow-up analyses excluding outliers on both independent and dependent variables. This was done to explore whether extreme values (which could have potentially represented device error) might be driving effects found in the initial model.

Independent variable outliers (TST and sleep onset) were identified via the Mahalanobis Distance (D^2), a statistical method for detecting multivariate outliers (Nussbaum, 2014). D^2 represents the distance from a single case to the multidimensional mean (centroid) of the distribution, taking into account covariance between the predictor variables. Mahalanobis D^2 is the multivariate version of the standardized z-score and follows a chi-square of distribution. Outlier cases are identified when the probability of a case's D^2 is <0.001 (Nussbaum, 2014). Following this procedure resulted in the elimination of 12 cases; nonoutlier participant data points remained in the database if they continued to have at least 5 days of data (including 1 weekend day). Outlier cases were not replaced with any values and were simply treated as "missing." Outlier dependent variable (MVPA/h) values were operationalized as any case value that was 3 standard deviations above the grand mean; there were no values 3 SDs below the mean. This resulted in the identification and removal of 13 data points. Within-person means and centered values were recomputed with the new data set, and all analyses were rerun.

Results of the final conditional random intercept model that excluded extreme outliers resulted in a similar pattern of findings compared with the initial model, and can be found in Table III. In this final model removing outliers, BMI z-score continued to be significantly negatively related to MVPA/h ($B = -1.632$ $p = .006$), as did the fixed interindividual sleep onset ($B = -0.010$, $p = .001$) and the fixed intraindividual temporal analyses ($B = -0.005$, $p = .028$). However, the previous random intraindividual effect of TST was no longer significant ($B = 0.00004$, $p = .113$). Pseudo R^2 measures indicated that the final model that excluded extreme outliers explained 28% of the interindividual variance in MVPA/h and 10% of the intraindividual variance in MVPA/h.

Discussion

This is the first study to objectively document average and temporal relationships between TST, sleep onset, and minutes spent in MVPA/h among a sample of currently overweight or obese youth. Findings indicate that sleep and physical activity are related among this population; effects, however, were small and varied based on whether inter- or intraindividual relationships are considered. Follow-up analyses excluding outliers revealed similar findings to initial models; therefore, all discussion points herein will be based on findings from initial analyses.

Fixed Interindividual Associations Between Sleep and Physical Activity

Time of Sleep Onset

Time of sleep onset significantly predicted MPVA/h over and above any effect of TST, which supported the study hypothesis. Although effect sizes were small, children who were consistently late to bed were also less physical active, on average, across the week. Specifically, for each 60 min later to bed, children engaged in 0.72 less minutes of MVPA/h. These findings are consistent with previous findings that children with later bedtimes are more sedentary (Drescher et al., 2011) and that evening-type adolescents (who prefer to go to bed and wake up late) engage in less physical activity than their morning-type counterparts (who prefer to go to bed and wake up early (Golley, Maher, Matricciani, & Olds, 2013), even after controlling for TST. Although pediatric studies typically use TST as the sole predictor of physical activity, these findings collectively indicate that sleep timing may be a particularly salient predictor of physical activity among overweight and obese youth. Taken in the context of other research suggesting that overweight children tend to go to bed later (Ekstedt et al., 2013) and spend more time engaging with technology late in the evening before bed (Sekine et al., 2002), sleep timing should become a significant target of future studies and clinical application.

Total Sleep Time

Study results did not support a significant interindividual relationship between TST and MVPA/h; that is, in general, how long children slept did not predict how physically active they were across the week. These findings support the study hypothesis and are consistent with multiple earlier studies using objective methods for measuring sleep and physical activity in children spanning the weight continuum (Ekstedt et al., 2013; Pesonen et al., 2011; Soric et al., 2015). Thus, this study lends support to the notion that either (1) TST has no bearing on physical activity among overweight or obese children, or that (2) potential effects of TST on physical activity can only be detected at the individual level. It should be noted that the current sample of overweight and obese youth were particularly short sleepers; 0 of the 134 participants met the average recommended amount of sleep for their age range (>10 hr). Mean TST was just under 7 hr, which is notably lower than self-report population norms for this age range (Galland, Taylor, Elder, & Herbison, 2012). Although this could reflect that overweight or obese children in this age range who reside in this rural are particularly short sleepers, we cannot rule out the possibility that device malfunctioning or loss of contact with skin during the night could contribute to the particularly low TSTs.

Fixed Intraindividual Temporal Associations Between Sleep and Physical Activity

Time of Sleep Onset

Despite a significant interindividual association, physical activity captured during the standard midnight-to-midnight measurement period was not related to earlier time of sleep onset. Rather, it appears TST was more predictive of physical activity during the midnight-to-midnight measurement period. This is a new finding in the literature, and taken in context with the other findings reported here, may indicate that time of sleep onset is the strongest predictor of activity patterns of overweight and obese children at the broad group level, whereas TST is most important at the daily level.

Total Sleep Time

In this sample of overweight and obese youth, intraindividual nightly TST significantly predicted physical activity in the subsequent midnight-to-midnight monitoring period. Specifically, for each 60 additional minutes of TST above their personal weekly average, overweight and obese children engaged in 0.3 *fewer* minutes of next-day physical activity per hour. Although seemingly paradoxical, these results supported our hypothesis and are consistent with a previous temporal study of sleep and physical activity in boys and girls (Pesonen et al., 2011), as well as a study that also used the Sensewear Armband with 11-year-old girls (Soric et al., 2015). Of note, Soric and colleagues (2015) also noted their sample as exhibiting significantly less TST than developmental standards. Thus, as previously noted, it is not possible to rule-out the possibility of measurement artifact. Further, results from each of these studies reflect relatively small effect sizes in the temporal relationships between intraindividual fluctuations in TST and MVPA. Thus, it is possible that daily fluctuations in physical activity do not produce clinically significant alterations in energy expenditure for some children. However, given that this effect was qualified by a random effect (discussed further below), it is also possible that there are other children for whom this differs.

Random Intraindividual Temporal Effect Between TST and Physical Activity

The daily, intraindividual association between TST and MVPA/h was also qualified by a significant random effect in this study. Thus, the strength of the association between TST and physical activity captured in the subsequent midnight-to-midnight monitoring period differed among the sample, and could be further explained by another "unknown" variable. Although gender was not a significant predictor of MVPA/h in our study sample, Soric et al. (2015) found that physical activity differed for girls and boys in their sample; gender represents one such possible moderating factor that could explain individual trajectories in the intraindividual temporal relationship between TST and MVPA/h. One other potential interesting factor that may explain individual trajectories is the paradoxical effect of insufficient sleep increasing hyperactivity. It is well-documented that sleep deprivation can present similarly to attention-deficit/hyperactivity disorder in youth (Paavonen et al., 2009), although most studies focus primarily on inattention. No studies to date have documented an association between short sleep and hyperactivity. However, children with OSA who are successfully treated with surgical tonsillectomy and adenoidectomy have shown weight gain after surgery (Barr & Osborne, 1988; Soultan, Wadowski, Rao, & Kravath, 1999), which has been partially attributed to decreases in fidgeting and daytime and nighttime motor activity (Roemmich et al., 2006). Thus, although speculative, it is possible a similar phenomenon occurs when overweight or obese children obtain more sleep than is usual for them.

Study Strengths, Limitations, and Future Directions

This study's methodology represents a significant study strength, as the study design allowed for day-to-day measurement of intraindividual sleep and physical activity variability over 7 days, rather than collapsing all days into one value. Children are likely more variable than constant in their sleep (Spruyt et al., 2011); thus, it is crucial to use statistical methods that accurately capture these relationships, as well as explore the role of sleep variability in overall child functioning. Sleep and physical activity were both objectively measured using the Sensewear Armband, a promising new device for dual measurement of sleep and physical activity in youth. However, sleep is a complex construct that is best studied by assessing both subjective (e.g., sleep diary-report) and objective (e.g., accelerometer) parameterization, and future studies would benefit from examining if and how daily subjective and objective methods differ in predicting physical activity among youth. Although findings reported here are seemingly paradoxical, they are consistent with two previously published pediatric studies among youth spanning the weight continuum. Replication is clearly necessary among children spanning the weight and sleep deprivation/sufficiency continuum. Further exploration among more diverse populations and varying time trends (e.g., curvilinear) may better elucidate mechanisms (e.g., changes in circadian drive or sleep pressure) by which sleep variability influences daytime behavior.

This study also points to the importance of building more person-centered research. Given that behavioral weight interventions are only moderately effective in reducing and maintaining weight status among youth (Janicke et al., 2014), researchers must begin to focus on more specific and individualized person-level factors that influence weight-related behaviors. This study found that the temporal intraindividual relationship between TST and next-day physical activity varied by person. Future studies exploring potential individual moderating factors in this relationship are warranted; such studies may examine individual trajectories of sleep, physical activity, and dietary intake concurrently to deconstruct potential subtypes of children who gain weight secondary to decreased physical activity, increased dietary intake, or a combination. At the group intraindividual level, this is one of the first studies to suggest that sleep onset timing impacts physical activity, over and above obtained TST. These findings point to the need for future research that explores the role of sleep timing in daytime activity levels, particularly because sleep and wake activities follow a diurnal rhythm, and disruptions in one rhythm might impact the other.

When considering clinical implications, these findings suggest that utility of promoting consistent and earlier bedtimes (although not necessarily longer TST) among overweight and obese youth as a potential method for increasing physical activity. Although many clinicians are aware of the heightened risk for OSA among overweight and obese youth, relationships between modifiable sleep habits (e.g., sleep duration, bedtime) and weight are relatively less known. Behavioral interventions to move bedtime earlier, decrease nighttime technology use, and increase consistency may be a relatively cost-effective way to improve sleep, and potentially, weight-related behaviors such as physical activity.

Despite study strengths, results should be interpreted in light of several limitations. Although researchers found no significant sociodemographic differences between groups, nearly half of the full sample ($N = 116$, 46.4%) did not meet data inclusion criteria. Further, at time of data collection, there were no published recommendations for sleep parameterization or data exclusion thresholds (e.g., how many hours of armband data should be required to be included in analyses); therefore, it is possible that study results are impacted by overly liberal data inclusion criteria with too few days of data collection for reliable intraindividual variability calculations. In addition, statistical methods involved using a centered and reverse-lagged within-person mean for sleep variables, which potentially could have confounded outcomes.

Use of the Sensewear Armband represents both a study strength and limitation. In this study, researchers did not use sleep diary data to anchor times that the child attempted sleep onset and offset; therefore, it is possible that sleep parameters could have captured periods of restful nonsleep, such as reading or watching television. Further, there is risk of the Sensewear Armband losing skin contact (and subsequent inaccurate measurement of sleep or physical activity) during wear. Internal validity may be somewhat limited for several reasons. Despite independent algorithms for estimating sleep and physical activity, multiple predictor variables and the dependent variable were inferred from the Sensewear Armband. Further, measurement periods from predictor variables (sleep onset, TST) could have overlapped with physical activity measurement periods, as this was computed automatically by the device algorithm from midnight-to-midnight. The Sensewear is also unable to identify or account for reasons for sleep disruption, such as sleep disordered breathing. Given the high prevalence of sleep disordered breathing in overweight/obese children (Wing et al., 2003) and adolescents (Beebe et al., 2007), future studies should attempt to parse apart the role of sleep disordered breathing versus behavioral sleep problems in the influence on physical activity.

Finally, although the Sensewear Armband shows potential as an adequately sensitive and valid device for estimating TST, sleep onset latency, and sleep efficiency, previous studies have noted the superior nature of the Sensewear in estimating sleep at the group level compared with the individual level among children and teens (Roane et al., 2015; Soric et al., 2013). Therefore, the intraindividual associations documented here should be interpreted with caution. However, it should be noted that this pattern of superior sensitivity for measuring sleep and poor specificity for wake is similar to patterns found in use of Actigraphy in children and adolescents (Meltzer, Walsh, Traylor, & Westin, 2012). Given the variety of assessment methods used in the literature for measuring child sleep and physical activity, standardized methods and procedures for assessing, cleaning, and reporting data are clearly warranted. Standardized procedures for acceptable device wear time, computing sleep parameters, and handling missing data owing to loss of skin contact, similar to those for actigraphy outlined by Meltzer and colleagues (2012), would be particularly helpful.

There also remain a variety of unmeasured variables that often occur in parallel with sleep problems (e.g., stressful home environment, internalizing symptoms) or that impact sleep processes (e.g., medications, caffeine usage) that were unaccounted for and may explain variability in both sleep and physical activity. Final limitations pertain to study generalizability, as the current sample included only treatment-seeking overweight and obese youth who resided in a rural setting. Rural families presenting for treatment may have varied in their distress about and severity of weight-related problems (potentially including sleep problems) than the general overweight/obese population. For example, rural youth are generally less active than urban-residing counterparts (Joens-Matre et al., 2008). Further, this population exhibited particularly short sleep duration, therefore limiting generalizability to non-treatment-seeking overweight/obese youth residing in other geographical regions.

Conclusions

In sum, results from this study support a previously existing literature that fails to identify TST as a reliable predictor of child physical activity levels at the group, interindividual level. Rather, it appears that TST only influences physical activity levels at the day-to-day, intraindividual level. Further, effect sizes are small, and increases in nightly TST appear to be linked to *decreases* in next-day physical activity. Taken together, these findings suggest that more research is needed to determine whether this relationship holds across varying levels of the sleep deprivation/sleep sufficiency continuum. If similar patterns are documented, this may support the notion that short sleep duration primarily acts through other mediating behaviors (e.g., dietary intake) to favor energy imbalance and weight gain. Conversely, time of sleep onset appears to be the strongest predictor of group-level daytime physical activity in this sample of overweight and obese youth, with later bedtimes predicting less physical activity, independent of any effect of TST. Results of this study suggest that future studies should begin to prioritize more research on the role of sleep timing in physical activity.

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