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Original Article

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Dynamics of sleep, sedentary behavior, and moderate-to-vigorous physical activity on school versus nonschool days

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Abstract

Study Objectives: Studies examining time-use activity behaviors (sleep, sedentary behavior, and physical activity) on school days compared with nonschool days have examined these behaviors independently, ignoring their interrelated nature, limiting our ability to optimize the health benefits of these behaviors. This study examines the associations of school-day (vs. nonschool day) with time-use activity behaviors.

Methods: Time series data (6,642 days) from Fitbits (Charge-2) were collected (n = 196, 53% female, 5–10 years). We used a variable-centered dynamic structural equation modeling approach to estimate day-to-day associations of time-use activity behaviors on school days for each child. We then used person-centered cluster analyses to group individuals based on these estimates.

Results: Within-participant analysis showed that on school days (vs. nonschool days), children (1) slept less (β = −0.17, 95% CI = −0.21, −0.13), (2) were less sedentary (β = −0.05, 95% CI = −0.09, −0.02), and (3) had comparable moderate-to-vigorous physical activity (MVPA; β = −0.05, 95% CI = −0.11, 0.00). Between-participant analysis showed that, on school days, children with higher sleep carryover experienced greater decreases in sleep (β = 0.44, 95% CI = 0.08, 0.71), children with higher body mass index z-score decreased sedentary behavior more (β = −0.41, 95% CI = −0.64, −0.13), and children with lower MVPA increased MVPA more (β = −0.41, 95% CI −0.64, −0.13). Cluster analysis demonstrated four distinct patterns of connections between time-use activity behaviors and school (High Activity, Sleep Resilient, High Sedentary, and Dysregulated Sleep).

Conclusions: Using a combination of person-centered and more traditional variable-centered approaches, we identified patterns of interrelated behaviors that differed on school, and nonschool days. Findings can inform targeted intervention strategies tailored to children's specific behavior patterns.

Statement of Significance

Sleep, physical activity, and sedentary behavior exist on an interdependent movement continuum that mutually influences children's health. Using novel dynamic structural equation modeling, we simultaneously measured the bidirectional effects of sleep, sedentary behavior, and physical activity in order to establish "Granger causality"; systems where current behavior predicts future behavior. The utility of such research lies in the potential to intervene upon one behavior (i.e. sleep tonight) while simultaneously improving a related future behavior (i.e. sedentary tomorrow). Using cluster analyses, we identified four distinct interrelated patterns of sleep, sedentary behavior, and physical activity, both on school and nonschool days. Results can inform targeted interventions to simultaneously improve sleep, reduce sedentary behavior, increase physical activity, and ultimately prevent childhood obesity.

Key words: sleep; sedentary; physical activity; school; children; intensive longitudinal; person-centered

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Introduction

Sleep, sedentary behavior, and physical activity exist on a continuum of movement from sleep (i.e. no/low movement) to vigorous-intensity physical activity (i.e. high movement) and each have been independently linked with obesity and health outcomes [1–4]. Many studies regarding children's sleep and physical activity have examined these behaviors in isolation, which neglects their interconnected and nature. Although some work has begun to examine multiple time-use activity behaviors within a day, using techniques such as compositional analysis [5], there is a dearth of research examining the links between movement behavior patterns from one day to the following day, and across multiple days. While sleep and sedentary behavior are both low energy expenditure, low movement behaviors, sleep is uniquely characterized by distinct physiological and psychological phenomena [6]. Physical activity on the other hand is characterized by high energy expenditure and movement, but represents a proportionally smaller portion of children's time-use [7]. In line with the recently released 24-h movement guidelines for children and youth [8], there is growing interest in determining whether there is a virtuous/vicious cycle between children's nighttime sleep duration and daytime sedentary behavior and physical activity [9, 10].

Studies that examine the temporal connections between time spent in different time-use activity behaviors have shown inconsistent results. Some studies have reported higher physical activity levels during the day are predictive of shorter subsequent sleep duration [11, 12], while others have found the opposite [9], and still others have found no association [13]. A potential explanation for these mixed results is the failure to simultaneously examine bidirectional effects of multiple time-use activity behaviors, which limits our ability to establish "Granger causality"; systems where variable "x" predicts future variables of "y" [14]. Granger causality has been widely applied in economics literature, but only sparsely used in behavioral research [15]. Granger causal questions aim to compare the bidirectional nature of time-use activity behaviors (e.g. "does sleep predict sedentary behavior more than sedentary behavior predicts sleep?"). Though not true causality, comparing the relative strength of the cross-lagged associations can provide direction for future study and add clarity to theory [16]. Only recently has emerging literature begun to explore the temporal dynamics of time-use activity behaviors [9, 17]. The limited research that has examined Granger causality has found shorter sleep duration on a given night is followed by higher PA and increased sedentary levels the following day [11, 18]. The utility of such research lies in the potential to intervene upon one behavior (i.e. sleep tonight) while simultaneously improving a related future behavior (i.e. sedentary behavior tomorrow).

A limitation of this literature in its current form is the focus on "average" behavior on a typical day; with little attention to how individual behavior on a specific day might impact subsequent behavior [19]. This focus also implies that youth exhibit uniform patterns of the connection between sleep and activity [20]. It is plausible that the predictors of, and links between, time-use activity behaviors vary as a function of time and context *within* individuals and vary as a function of magnitude or intensity *between* individuals [19]. The identification of unique behavior patterns has the potential to inform improvements in planning and implementing effective behavioral interventions [20].

Time-use activity behavior patterns are influenced by both person-level factors (e.g. perceived competence) as well as external constraints (i.e. school) [21]. Children spend a majority of their waking time in school on school days [22] and as such, understanding its impact on multiple health behaviors holds significant public health relevance. There is mounting evidence that, compared with school days, on *nonschool* days children have poorer quality and delayed sleep, more sedentary behavior, and less physical activity [23, 24]. However, these findings are based on group mean averages and may not capture the heterogeneity of an individual child's behavioral response to attending versus not attending school on any specific day. This focus on "average" effects may partially explain the lackluster impact of school-based interventions on children's activity [25]. This is because findings from between-person associations may not be equivalent at the within-person level [26]. If the objective is to build more effective multiple health behavior change interventions, the results obtained at the within-participant level might be more informative as they represent dynamical processes (i.e. co-variations), and thus, contrast with the between-participant analyses that represent average associations over time.

A person-centered analysis approach that specifically incorporates variability within-individuals may reveal more targeted or flexible intervention opportunities and ultimately greater overall improvements in intervention effectiveness [20]. The current study takes a person-centered analytical approach to explore the impact of school on time-use activity behaviors by identifying patterns of behaviors based on Granger causal temporal associations between multiple time-use activity behaviors (i.e. sleep, sedentary, and physical activity) from day-to-day.

Methods

Setting and participants

This study utilized data from a larger longitudinal project [27, 28], which collected data from three schools in a single school district in South Carolina. One school followed a year-round schedule while the other two followed a traditional schedule and served similar student populations. Traditional schools followed a calendar that condensed the 180-day school year into 9 months, with a summer break between June 1 and August 17. The year-round school spread the 180 school days equally throughout the calendar year, taking a shorter more frequent breaks (i.e. summer break between June 12 and July 19). Table 1 presents the demographics of the participating schools and individual participants. The sample was 53.9% girls, mean age 7.0 ($SD = 1.2$). A majority of the sample was African American (64.6%) or White (28.9%), with 6.6% identifying as a different race. Nearly half of the sample had an annual household income of less than $30,000. Data were processed for 196 children over 6,642 days (median 22 days/child).

Procedures

All kindergarten through fourth grade students enrolled at the participating schools were invited to participate in the study in the Spring of 2018. A consent letter was sent home to the parents describing the study procedures. Consenting parents signed and returned the letter to research staff via school personnel. Of the 254 children whose parents consented, a total of 240 were randomly selected to participate in the study (160 traditional school, 80 year-round school). Participants in the study received a Fitbit Charge 2 to wear in the spring academic semester of 2018 (i.e. April) and wore the Fitbit for 20 consecutive weeks (i.e. August 2018). Children were instructed to wear the devices at all times including when they slept, showered/bathed, and swam (i.e. 24-h wear protocol). Participants were incentivized to sync, but not necessarily wear the devices. All protocols were approved by the lead author's University Institutional Review Board.

Measurement of physical activity and sleep

As described previously [28], physical activity and sleep were measured using a Fitbit Charge 2 (Fitbit Inc., San Francisco, California). Fitbit Charge devices have been shown to have good agreement with polysomnography (PSG) and electrocardiography when estimating sleep and heart rate [29, 30]. In a recent meta-analysis of multichannel Fitbit devices (those measuring both movement and heart rate), there were no significant differences between Fitbit and PSG estimation of wake after sleep onset (effect size = 0.16, 95% CI −0.12 to 0.44), total sleep time (effect size = −0.15, 95% CI −0.43 to 0.13), or sleep efficiency (effect size = −0.27, 95% CI −0.65 to 0.13) [31]. Furthermore, multichannel Fitbit devices have shown good agreement with wrist-worn scientific grade devices used to assess free-living sleep in school-age children [32]. Procedures for processing the Fitbit data have been described in detail elsewhere [28]. Data processing was informed by the ISCOLE data processing protocols [33].

Only days with at least 10 of valid awake "wear time" were included. Fitbit sleep data was exported to identify child sleep periods. A "sleep period" was defined as >160 consecutive minutes classified as "asleep" [34]. Based on previous parameterizations of nocturnal sleep [35], nocturnal *sleep onset* was defined as the first minute of a sleep period that started between 7:00 pm and 05:59 am. Nocturnal *sleep offset* was identified as the last minute of a sleep period between 05:00 am and 11:58 am. If nocturnal sleep periods were separated by less than 20 min, they were combined but only if the first sleep onset and last sleep offset were within the time windows specified above [33]. In the current study, sleep was quantified as the sum of minutes classified by the Fitbit device as asleep between sleep onset and sleep offset. The flow of participants and days of data as a result of these parameterizations is presented in Figure 1.

To distill the heart rate data into activity intensity levels, each child's resting heart rate was calculated each day of wear. Resting heart rate was defined as the average of the lowest 10-min beats-per-minute for each day [36–39]. Resting heart rates that were above the 95th (90 beats per minute [bpm]) or below the 5th (50 bpm) percentile were considered implausible and were replaced with the nearest day that the child had a plausible resting heart rate. Heart rates were distilled into activity intensity levels based on percent heart rate reserve (HRR). That is, 0.0%–19.9% of HRR equaled sedentary, and ≥50.0% equaled MVPA [40, 41]. As described in prior publications [28], percent HRR was calculated using the following formula: heart rate minus resting heart rate, divided by maximum heart rate minus resting heart rate. Since a maximal exercise test was not conducted, 197 bpm was used as the maximum heart rate for all children [42]. Additional details regarding processing of Fitbit Data can be found in Supplementary Material.

Sleep period data were removed from awake physical activity data which was then distilled into minutes of waking time children spent sedentary and in MVPA on each day. School days (n = 3,231) were defined as any day (Monday–Friday) when school was in session. Nonschool days (n = 3,411) included weekends, spring break, school holidays, and summer break.

Table 1. Demographics

Number of participants (*n*)	199
Male (%)	46.1
Mean age at baseline (*SD*)	7.0 (1.2)
Grade at baseline (%)	
Kindergarten	7.0
First	21.3
Second	29.3
Third	28.2
Fourth	14.3
Race (%)	
African American	64.6
White	28.9
Other	6.6
Income (%)	
<$30,000 annually	49.5
≥$30,000 annually	50.5
Mean BMI z-score (*SD*)	0.76 (1.15)
Mean days of data (*SD*)	39.4 (41.6)
Mean awake wear time/day (*SD*)	759.1 (225.3)
Mean sedentary minutes/day (*SD*)	312.7 (116.3)
Mean sleep minutes/day (*SD*)	468.1 (50.6)
Mean MVPA minutes/day (*SD*)	79.1 (39.9)

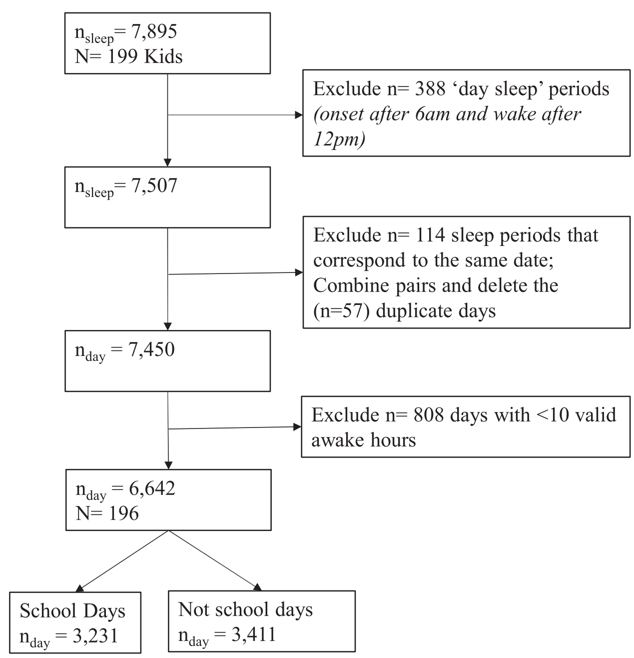

Figure 1. Flow of participants through data reduction.

Statistical analysis

Outliers on the outcomes of sleep, sedentary behavior or MVPA >3 *SD* from the mean were winsorized prior to analyses [43]. We used dynamic structural equation modeling (DSEM) in Mplus v. 8.2 to model the bidirectional dynamics of sleep and activity. DSEM is a framework that combines multilevel modeling, structural equation modeling, time-series modeling, and time-varying effects modeling [44]. Structural equation models can handle multiple-dependent variables, and thus are well suited for examining cross-lagged models and bidirectional effects.

The multilevel model used latent-centering to decompose the variance in sleep, MVPA and sedentary behavior into within-person and between-person components. The level 1 within-person model estimated autoregressive parameters or "carryover" (i.e. the association of yesterday's sleep with tonight's sleep) and cross-lagged or "spillover" parameters (i.e. the effect of tonight's sleep on tomorrow's MVPA). School day (whether an individual given day was a school day) was included as a dichotomous level-1 predictor of sleep, sedentary behavior, and MVPA. The level 2 between-person model estimated the person-level associations between "average" behaviors. Child body mass index z-score (zBMI) measured in spring 2018 was included as a between-person covariate as weight status has previously been linked to time-use activity behaviors among youth [4].

Average "carryover" (i.e. impact of one day on the following day) for sleep, sedentary behavior, and MVPA was estimated using an autoregressive lag-1 (AR-1) model which allows for estimation of the effect of a variable on itself from the preceding observation (i.e. lag 1). An autoregressive (or carryover) value close to *zero* implies a strong attraction dynamic; meaning, after a high or low score, the individual will quickly return to their equilibrium or "set point" on the following observation (i.e. typical level of sleep or activity). In contrast, an autoregressive value closer to *one* implies more carryover from one day to the next. A child with a high sedentary autoregressive value has high carryover and would be likely to have several consecutive days in a row with high or low sedentary behavior above or below their set-point/equilibrium. In other words, their high sedentary behavior would "carryover" onto the next day. Negative values of the autoregressive term have a different interpretation, because they imply reflexive back-and-forth shifting between scores above and below the equilibrium (called antipersistance) [45]. Antipersistance is a type of carryover that manifests as a "saw tooth pattern" where a night of short sleep is followed by a night of excessive sleep greater than that child's typical nighttime sleep. Additional details regarding fitting and interpretation of the DSEM model can be found in Supplementary Material.

After fitting the DESM model, within-person standardized model estimates (averaged over individual) were used in a cluster analysis to identify subgroups of behavior patterns within the sample. Model implied standardized estimates were used rather than measured variables because the focus of this analysis was on the associations *between* behaviors *across* individuals. Given the limited sample size, a Wards cluster analysis was conducted in SPSS v. 26. Means for all variables were calculated for each cluster. Then, for each case, the squared Euclidean distance to the cluster means was calculated and summed for all cases. At each step, the two clusters that merge were those that result in the smallest increase in the overall sum of the squared within-cluster distances. The coefficient in the agglomeration schedule was within-cluster sum of squares at that step, not the distance at which clusters were joined. Criterion validity was assessed by ANOVAs and Chi-squared tests to examine differences in clusters' zBMI and overall time-use activity behaviors (MVPA, sedentary behavior, and sleep) and demographics. Face validity was established using consensus of two experts in cluster profiling. This procedure was then further verified using a K-Means cluster approach to assess similarity in cluster profiling.

Results

Descriptive examination of individual DSEM patterns

The DSEM unstandardized estimates for the fixed and random parameters, and their 95% credible intervals (CI) are presented in Table 2 with corresponding paths represented in Figure 2. The within-person standardized model estimates are presented

Table 2. Unstandardized estimates and 95% credible intervals for fixed effects and random effects of DSEM

		Fixed effects (means)				Random effects (variances)		
Variable	Path symbol†	Estimate	Lower 2.5%	Upper 2.5%		Estimate	Lower 2.5%	Upper 2.5%
BMI z-score		0.747	0.556	0.941	*	1.595	1.265	2.038
Average sleep across all days	μ Sleep	469.132	461.252	476.859	*	2,031.694	1,462.111	2,822.006
Average sedentary across all days	μ Sedentary	306.361	288.691	323.887	*	12,652.785	9,669.310	16,632.932
Average MVPA across all days	μ MVPA	80.546	74.518	87.003	*	1,503.262	1,161.964	1,964.624
Effect of sedentary today on sedentary tomorrow‡	φ Sed→Sed	0.184	0.142	0.226	*	0.030	0.015	0.054
Effect of sleep tonight on sedentary tomorrow‡	φ Sleep→Sed	−0.166	−0.226	−0.103	*	0.054	0.029	0.098
Effect of sedentary today on sleep tomorrow night‡	φ Sed→Sleep	−0.086	−0.124	−0.047	*	0.021	0.010	0.039
Effect of sleep tonight on sleep tomorrow night‡	φ Sleep→Sleep	−0.060	−0.106	−0.010	*	0.030	0.016	0.053
Effect of MVPA today on MVPA tomorrow‡	φ MVPA→MVPA	0.128	0.083	0.175	*	0.036	0.021	0.058
Effect of sleep tonight on MVPA tomorrow‡	φ Sleep→MVPA	−0.053	−0.077	−0.028	*	0.006	0.003	0.012
Effect of MVPA today on sleep tonight‡	φ MVPA→Sleep	−0.084	−0.181	0.012		0.093	0.043	0.185
Effect of school today on sedentary today‡	φ School→Sed	−4.909	−9.484	−0.197	*	442.637	262.359	741.242
Effect of school today on sleep last night‡	φ School→Sleep	−10.541	−14.247	−7.074	*	308.960	196.984	475.679
Effect of school today on MVPA today‡	φ School→MVPA	−0.480	−2.277	1.320		50.863	27.064	89.796

*Significance based on 95% credibility intervals.
†Symbols correspond to paths presented in Figure 2.
‡Variables included in cluster analysis.

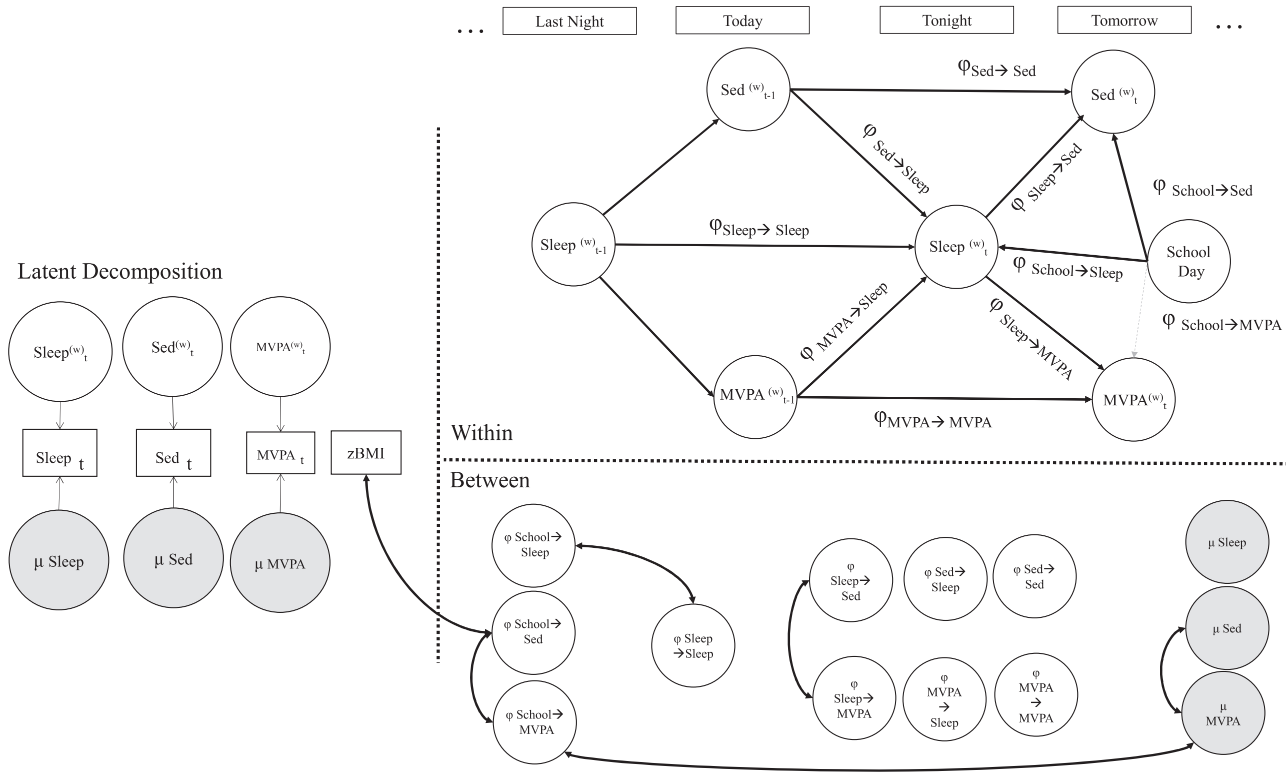

Figure 2. Multilevel DSEM examining bidirectional effects of sleep, sedentary behavior, and MVPA. Note: Unstandardized path estimates shown on Table 2. (W) indicates within-person estimates.

in-text. The current model explained 18.5% of the within-person variability in sleep and 15.2% of the within-person variance in sedentary behavior and 9.2% of the within-person variability in MVPA.

Autoregressive effects

We examined the within-person standardized cross-lagged coefficients (averaged over cluster) [16]. The autoregressive value for sleep was negative and significantly different from zero (standardized estimate = −0.058, 95% CI −0.098 to −0.017; see φSleep→ Sleep, Figure 1 and Table 2). The negative sign indicates antipersistance; if a child has a night of less than typical sleep, he/she is more likely to get relatively more than usual sleep the following night. Although statistically significantly different than zero, the autoregressive value is closer to zero than one, which indicates relatively low carryover; After a night of more or less sleep than typical (i.e. a perturbation to the system), a child will have a small amount of "compensatory" sleep the following night.

The autoregressive value for sedentary behavior, on the other hand was larger than the carryover for sleep, and was positive and significantly different from zero (standardized estimate = 0.184, 95% CI 0.150 to 0.219; see φSed→ Sed, Figure 1 and Table 2), indicating some carryover. This suggests that days of relatively high sedentary behavior are likely to be followed by days of relatively high sedentary behavior, and conversely, that relatively low sedentary behavior is likely to be followed by relatively low sedentary behavior.

Similarly, the autoregressive value for MVPA was positive and significantly different from zero (standardized estimate = 0.129, 95% CI 0.093 to 0.165; see φMVPA→ MVPA, Figure 1 and Table 2), indicating previous days MPVA positively predicted MVPA the following day.

Cross-lagged effects

In the current study, the standardized effect of sedentary behavior on nighttime sleep (standardized estimate = −0.127, 95% CI −0.173 to −0.080), indicated that days of higher sedentary behavior were followed by nights of reduced sleep. The standardized effect of nighttime sleep on sedentary behavior (standardized estimate = −0.109, 95% CI −0.145 to −0.075), similarly indicated that nights of shortened sleep were followed by higher sedentary behavior. Notably, the average within-person effect of sleep on sedentary behavior was stronger than the effect of sedentary behavior on sleep.

The standardized effect of MVPA on sleep was nonsignificant (standardized estimate = −0.056, 95% CI −0.112 to −0.000). The standardized effect of sleep on MVPA (standardized estimate = −0.076, 95% CI −0.106 to −0.044) showed that nights of shortened sleep were followed by days of relatively more MVPA.

School-day associations

Whether days were school or nonschool was included as a within-person (level-1) predictor of sleep, MVPA and sedentary behavior. Children slept relatively less on school nights (i.e. nights preceding a school day; standardized estimate = −0.170, 95% CI −0.209 to −0.130) compared with nonschool nights. Children also had less sedentary behavior on school days compared with nonschool days (standardized estimate = –0.054, 95% CI –0.092 to –0.015). Children's MVPA was not significantly different on school days compared to nonschool days (standardized estimate = –0.013, 95% CI –0.049 to 0.023).

Between-person associations

In addition to the averaged within-person standardized results, the between-person correlations between the random effects were included in the model. Between-person level association can be thought of as representing the average or trait-level of a behavior. Significant between-person correlation paths are shown on the bottom portion of Figure 2.

There was a significant correlation between overall MVPA and the association between MVPA and school such that children who had low MVPA compared to their peers, experienced greater change in their MVPA on school, versus nonschool days (standardized estimate = –0.410, 95% CI –0.635 to –0.131).

Children who had high sleep carryover experienced an even greater decrease in sleep on school days compared with children with low carryover (standardized estimate = 0.439, 95% CI 0.075 to 0.709). Children who had a strong connection between sleep and sedentary behavior, correspondingly had a weaker connection between sleep and MVPA (standardized estimate = –0.489, 95% CI –0.766 to –0.062) Similarly, children who had a strong connection between school and sedentary behavior, had a relatively weaker connection between school and MVPA (standardized estimate = –0.488, 95% CI –0.718 to –0.154). Children who had more sedentary behavior on average had less overall MVPA (standardized estimate = –0.496, 95% CI –0.623 to –0.342).

Lastly, there was a significant association between zBMI and the slope for school days and sedentary behavior. Specifically, children with a higher zBMI experienced a bigger decrease in sedentary behavior on school days compared to nonschool days (standardized estimate = 0.270, 95% CI 0.023 to 0.500).

Cluster analysis

Variables included in the cluster analysis are indicated in Table 2. Cluster analysis results are presented in Figures 3, A–C and 4, A–B. Four distinct clusters were identified. Children in cluster 1 (High Activity; $n = 71$) had significantly more MVPA compared with children in the other clusters $f(3,192) = 16.12$, $p < 0.01$ (see Figure 4, A) as well as the most MVPA carryover from one day to the next $f(3,192) = 35.46$, $p < 0.01$ (see Figure 3, A). For children in the High Activity cluster, sedentary behavior was a stronger predictor of subsequent night's sleep, compared to the reverse (see Figure 3, C).

Children in cluster 2 (Sleep Resilient; $n = 26$) had the lowest sleep carryover ($f(3,192) = 14.40$, $p < 0.01$; see Figure 3, A) and experienced the smallest reductions in sleep on school days compared with nonschool days ($f(3,192) = 60.75$, $p < 0.01$). Children in the Sleep Resilient cluster also had *less* sedentary behavior on school days compared with their nonschool days $f(3,192) = 48.86$, $p < 0.01$ (see Figure 3, B).

Children in cluster 3 (High Sedentary; $n = 60$) had significantly more sedentary behavior compared with children in other clusters $f(3,192) = 7.17$, $p < 0.01$ (see Figure 4, A). They also had *more* sedentary behavior on school days compared to their nonschool days ($f(3,192) = 48.86$, $p < 0.01$; see Figure 3, B).

Children in cluster 4 (Dysregulated Sleep; $n = 39$) had the most sleep carryover $f(3,192) = 14.40$, $p < 0.01$ (see Figure 3, A). Compared to children in other clusters, children in the Dysregulated Sleep cluster had significantly less sleep on school days compared to nonschool days $f(3,192) = 60.75$, $p < 0.01$ (see Figure 3, B).

Children in the Sleep Resilient cluster had significantly lower zBMI both at baseline $f(3,162)$, = 5.33, $p < 0.01$, and follow-up $f(3,156)$, = 4.19, $p < 0.01$ (see Figure 4, B). Children in the High Sedentary cluster were older compared to other clusters $f(3,192) = 2.90$, $p = 0.04$. Clusters did not differ with respect to average levels of sleep $f(3,192) = 2.50$, $p = 0.06$ (see Figure 4, A). There were no cluster differences in Fitbit wear time $f(3,192) = 0.72$, $p > 0.05$, or by demographics including sex, household composition, parent employment, income or school type (see Supplementary Table S1). Post hoc analyses revealed no significant cluster differences in sleep efficiency, sleep onset, or sleep offset (see Supplementary Table S2).

Discussion

The objective of the current study was to examine the bidirectional temporal associations between sleep, sedentary behavior, and MVPA among school age children and explore if these relationships differed on school days compared to nonschool days. In order to move beyond conventional assumptions about average participants, we used a within-person (DSEM) approach to identify individual level Granger causal links between time-use activity behaviors. We then used a person-centered (cluster analysis) approach to identify distinct patterns of behavioral associations across-days.

Results from the within-person analyses showed that on average, there was a significant bi-directional association between nighttime sleep and sedentary behavior. Nights of relatively shorter sleep were likely to be followed by days of relatively more sedentary behavior. Conversely if a child engaged in relatively more sedentary behavior during the day, that child would likely have relatively less sleep that night. Comparing the standardized estimates revealed that, for an average child in the sample, there was a stronger connection between sleep and sedentary behavior compared to sleep and MVPA.

These findings are consistent with previous studies that have explored the relationship between nighttime sleep and sedentary behavior [46]. This association may be driven causally (i.e. reduced sleep increases next day fatigue) or could perhaps be driven by other factors such as the use of electronic devices [47]. The use of more electronic devices (usually coinciding with sedentary behavior) can directly displace nighttime sleep and the light emitted from screens can impact circadian timing and physiological sleep [48]. Consistent with past research exploring the bidirectional relationship between nighttime sleep and sedentary behavior in young children [18], the effect of sleep on sedentary behavior was stronger than the effect of sedentary behavior on sleep. This finding might point to the effectiveness of sleep interventions to additionally reduce sedentary behavior [49].

Findings from this study also indicate a relationship between nighttime sleep and subsequent MVPA, where a night of relatively short sleep is likely to be followed by a day of relatively higher MVPA. Upon first inspection these results can

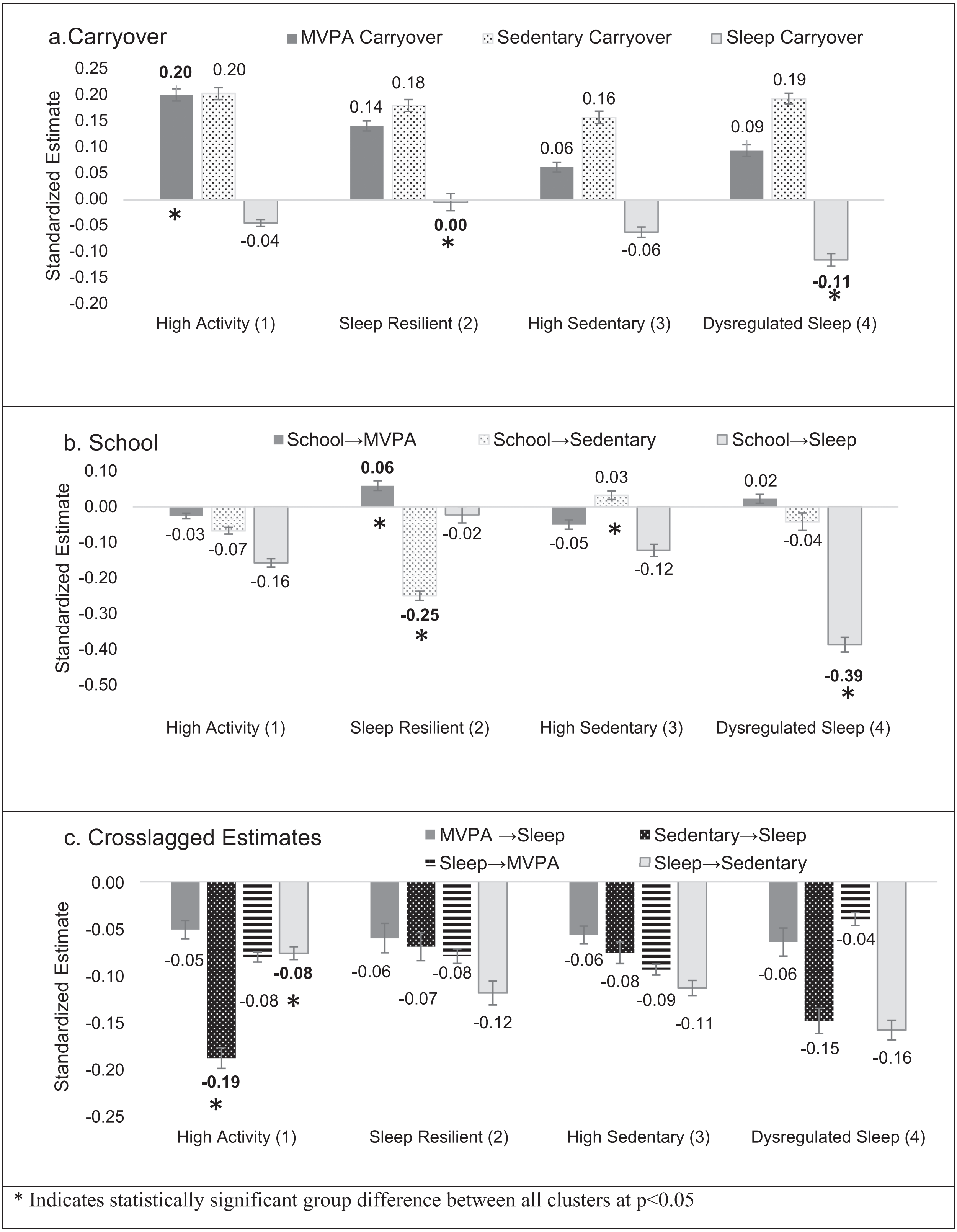

Figure 3. (A–C) Means of standardized estimates for clusters. Asterisk indicates statistically significant group difference between all clusters at $p < 0.05$.

appear counterintuitive. The mechanism for this relationship is unclear, as it might be expected that shorter sleep duration would predict lethargy (and thus less MVPA) the following day, as seen in experimental sleep restriction studies among adults [50]. However, these results are consistent with past research between nighttime sleep and MVPA in free-living children [11,

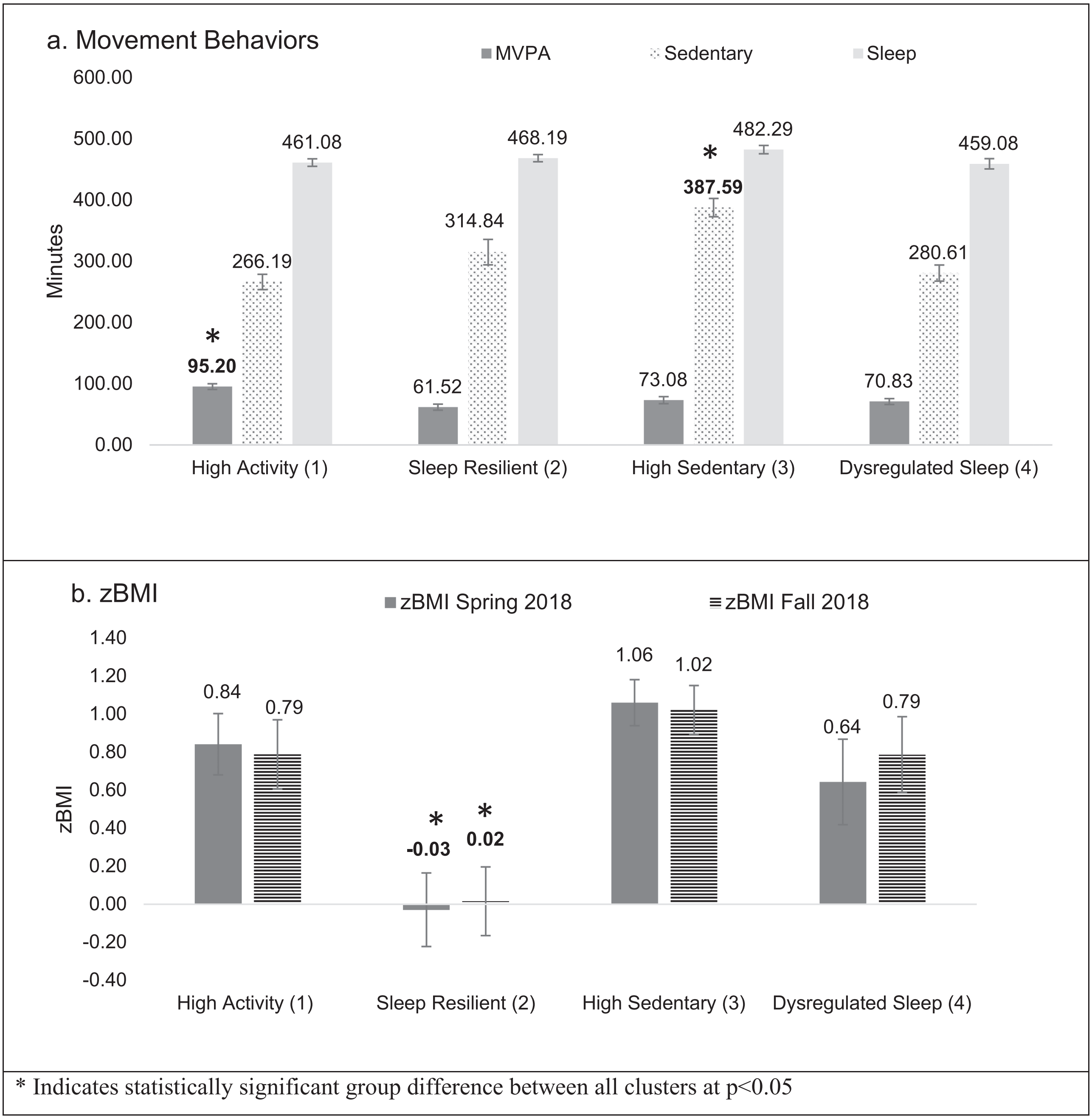

Figure 4. (A–B) Means of time-use activity behaviors and zBMI for clusters. Asterisk indicates statistically significant group difference between all clusters at $p < 0.05$.

12, 51]. It may be that this relationship exists as a function of bounded time. For instance, if a child sleeps less at night there are more hours in the day to engage in physical activity, consistent with a “filled time” perspective [52, 53]. Additionally, while MVPA did not appear to predict subsequent sleep duration, it is possible that aspects of sleep, such as sleep quality or sleep architecture (the cyclic pattern between different stages of sleep), may be influenced by daytime activity [54]. Future studies might explore these additional aspects of sleep, as well as their association with activity timing. Such research might examine if bouts of activity closer to bedtime have a greater impact on sleep than activity earlier in the day.

In this study both sedentary behavior and MVPA showed carryover from day-to-day within children. When children engaged in relatively high amounts of sedentary behavior or MVPA, they would engage in relatively higher amounts of MVPA on the following day as well. High values of carryover in MVPA and sedentary behavior might be indicators of habit formation, with low levels perhaps being indicative of a behavior maintenance framework [55]. Behavioral carryover might serve as an indicator of successful habit formation, and ultimately inform behavior maintenance interventions.

Sleep was characterized by antipersistance, a different form of carryover. The negative autoregressive carryover value indicated that children fluctuate around their average amount of nighttime sleep in a sawtooth pattern. For instance, a night of short sleep would be followed by a night of relatively longer sleep, and then a night of relatively short sleep and so on. This is consistent with past research examining children's sleep patterns [18], and is especially important given that inconsistent sleep patterns have been linked to increased risk for overweight and obesity [56, 57]. This finding reinforces the need for intervention strategies to stabilize children's sleep patterns in order to address overweight and obesity.

Between person associations

In addition to exploring the average (or nomothetic) associations between behaviors, this study aimed to capture the individual heterogeneity around these averages using a within-person approach, and then describe this heterogeneity using person-centered analyses. Consistent with past research using traditional modeling approaches, this study confirmed that children sleep less and engage in less sedentary behavior on school days [28, 52]. This work extends these findings by showing that children with higher zBMI experienced larger increases in sedentary behavior on nonschool days compared with children with lower zBMI. This finding is particularly relevant in the context of increasing evidence which points to children being at risk for accelerated weight gain during the summer break from school [28, 52]. Indeed, children who are overweight or obese have larger increases in zBMI during the summer when compared to their normal weight peers [58]. The current study results suggest that the disproportionate increases in summer zBMI observed among overweight or obese children, may be attributed to a differential impact of school structure on sedentary behavior. Thus, interventions that target reducing sedentary time during the summer may be particularly impactful for children who are already overweight or obese. Along similar lines, children who were less active on average, had relative increases in MVPA on school days, which may indicate that the regulated and consistent (i.e. structured) environment afforded by school can provide intentional (e.g. PE and recess), and unintentional (e.g. commute to school and classroom transitions) physical activity opportunities that benefit children who are not getting adequate physical activity [52], and are at the highest risk for overweight or obesity.

The finding that youth with high levels of sleep carryover experience greater decreases in sleep on school nights may indicate that such children require greater external support (such as parental rules or consistent family routines) for sleep hygiene behaviors in order to maintain stable sleep patterns. There is increasing recognition that sleep variability (above and beyond sleep duration) is uniquely associated with health outcomes including zBMI [59]. The ability to maintain consistent sleep might be conceptualized as sleep regulatory ability, or sleep resilience, and could be an indicator of broader self-regulatory ability, as has been observed in studies of mood stability [60]. Future research might continue to examine the concept of sleep resilience as a protective factor against negative health outcomes or indicator of treatment effectiveness.

Clusters

Cluster analysis based on standardized DSEM estimates revealed four heterogeneous groups (High Activity, Sleep Resilient, High Sedentary, and Dysregulated Sleep), which further demonstrate how typical (i.e. nomothetic) methods based on group means might obscure results. For example, overall results indicated that the "average" child in the sample showed some amount of sleep carryover. In contrast, individuals in the Sleep Resilient cluster 2, showed a greater degree of stability (sleep resilience) evidenced by a nonsignificant average autoregressive sleep parameter and more beneficial movement patterns on school days (i.e. less sedentary, more MVPA, and unchanged sleep). Individuals in the Sleep Resilient cluster 2 also had the lowest average zBMI across time.

In contrast, youth in the Dysregulated Sleep cluster showed the most dysregulated sleep (i.e. highest sleep carryover), and correspondingly greatest decrease in sleep on school nights, and no significant changes in MVPA or sedentary behavior on school days. Indeed, the Dysregulated Sleep cluster had over 10 times more carryover in sleep compared to the Sleep Resilient cluster. Thus, the Dysregulated Sleep cluster may represent children who have misaligned chronotypes or social jet lag. Social jet lag is the discrepancy between an individual's own biological rhythm and the daily timing determined by social constraints [61] such as school. Such children may benefit from later school start times [62] or interventions to improve sleep regularity. These children may require additional intervention to prevent weight gain during summer months, given that it appears that school structure is not associated with behavioral improvements compared to nonstructured days. It might be reasonable to speculate that children in the Sleep Resilient cluster would be most amenable to structure provided by school, whereas children in the Dysregulated Sleep cluster might require extra support given the variability in sleep and lack of benefit in movement patterns seen on school days.

While the overall (i.e. nomothetic) results indicated that sleep more strongly predicted subsequent sedentary behavior for the "average" child in the sample, children in the High Activity cluster 1 showed the opposite results. Children in the High Activity cluster 1 had significantly stronger effects for sedentary behavior predicting subsequent sleep compared with the reverse. Notably, these children also showed significantly higher MVPA compared to other clusters. Children with this behavior pattern might not benefit as much from interventions to improve sleep, as sleep appears to be a downstream effect of activity.

By using a combination of between person, within-person and person-centered approaches to examining interindividual day-to-day variability in time-use activity behaviors, researchers can examine the differences in movement patterns on school versus nonschool days across individuals. Such behavior patterns have the potential to inform targeted and personalized intervention efforts to prevent weight gain during summer months as well as during the school year.

Given the limited broad-based effectiveness of interventions to prevent and treat childhood obesity [63], the ability to identify behavioral subgroups based on links between behaviors presents the opportunity to leverage intensive longitudinal data to create behavioral phenotypes of dynamic behaviors. By using an idiopathic approach to examine the bidirectional effects between time-use activity behaviors, we can identify individualized behavioral targets that have maximum effectiveness and potential co-benefits.

An additional strength of the study is the representation of minority and low-income youth in the sample. Structural issues of race, SES, and racism underlie well documented health disparities in the United States [64] including those related to sleep [65] and physical activity [66]. Ensuring that individuals of diverse ethnic and racial backgrounds are represented in behavioral health research leads to better science and creates the potential to reduce health disparities in public health and medicine [67].

Limitations

This study is a step toward applying an idiographic approach to examine patterns of time-use activity behaviors across days both in and out of school. However, results should be interpreted in the context of the study limitations. Standardized comparison of cross-lagged effects shows that a parameter is statistically stronger, but not more important. Therefore, it is not clear from such a model that manipulation of nighttime sleep would necessarily *lead* to changes in sedentary behavior. It is worth noting that the VAR(1) model used in the current study assumes that the dynamics between variables remain stable over time [68]. This might be particularly relevant for sleep and activity given the potential effects of weekend/weekday cycles [62], as well as seasonality and developmental changes. The current study was not powered to detect cycles or trends, but future studies might make use of advanced time-varying-vector-autoregressive models to explore such trends [69] and cumulative effects of sleep on physical activity which could inform intervention timing.

An additional consideration with DSEM models is that the strength of lagged relationships depends on the interval between observations [70] meaning that future studies may reach different conclusions about the reciprocal nature and the “causal dominance” of sleep and sedentary behavior, depending on the interval of time selected. This phenomenon (known as the “lag problem”) implies that simply because we modeled MVPA, sedentary behavior and nighttime sleep at the level of a single day, does not mean that the variables necessarily exert an influence on each other only at this interval [71]. Indeed, use of different timescale strategies might reveal different patterns when examining the links between physical activity and sleep dynamics within a single day or across multiple days [15]. Aspects of sleep beyond duration such as sleep latency, sleep quality, and sleep fragmentation will be important to examine in future studies, along with the impact of activity behavior timing.

Conclusion

The current study revealed significant bidirectional links between sleep and time-use activity behaviors that varied in both magnitude and direction between individuals. Similarly, activity patterns were significantly different on school versus nonschool days, however the magnitude and direction of these effects differed across individuals. Methodologically, this study highlights the value of using an idiographic approach at a time when researchers are increasingly calling for individualized tailored approaches to prevention and intervention. Continued research using a person-centered perspective could inform novel and effective obesity prevention and intervention efforts.

Supplementary material

Supplementary material is available at *SLEEP* online.

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