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## Sleep Duration Mediates the Relationship Between Health Behavior Patterns and Obesity

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## Sleep Duration Mediates the Relationship Between Health Behavior Patterns and Obesity

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## Abstract

**Objective:** To examine associations between health behavior patterns and childhood obesity, and the mediating effect of sleep duration.

**Design:** Population-based survey.

**Participants:** Secondary analysis of data from the Infant Feeding Practices Study (age 6 years, n=1073).

**Measurements:** Mothers self-reported their child's health behaviors including physical activity (PA), screen time, sleep duration, and diet. Latent class analysis determined the child's patterns based on health behaviors. Sleep was examined as a mediator between the class membership variable and %BMI<sub>p95</sub>.

**Results:** A 3-class model fit the data best, with classes labeled as "Poorest eaters"(low fruit/vegetable consumption, high fast food), "Healthy"(low screen time, highest fruit/vegetable consumption) and "Active, super-eaters, highest screen time"(highest PA and screen time, ate the most). "Poorest eaters" had an increased %BMI<sub>p95</sub> ( $\beta=4.11$ ,  $p=0.006$ ) relative to the "Healthy" class. The "Poorest eaters" and "Active, super-eaters, highest screen time" classes had shorter sleep duration ( $\beta = -0.51$ ,  $p<0.001$ ;  $\beta= -0.38$ ,  $p<0.001$ ; respectively) relative to the "Healthy" class. Independent of class membership, each additional hour of sleep was associated with a %BMI<sub>p95</sub> that was 2.93 units lower ( $p<0.001$ ).

**Conclusions:** Our results indicate that health behavior patterns mediated by sleep duration may influence a child's %BMI<sub>p95</sub>. The bi-directionality of the relationship between health behaviors and sleep remains unclear. Our findings suggest the importance of a constellation of health behaviors on childhood obesity. Interventions should include a multitude of health behaviors and consider the possibility that improving diet and activity behaviors may facilitate improved sleep and lowered obesity risk among children.

Keywords: sleep, activity, pediatrics, obesity, diet

## Introduction

Pediatric obesity continues to be a public health crisis with one in three children classified as overweight or obese.<sup>1</sup> Given that children with obesity are more likely to become adults with obesity and its related adverse consequences,<sup>2</sup> there is an urgent need to better understand the pathways by which modifiable health behaviors influence obesity risk, as well as potential mediators of this pathway, such as sleep duration. Sleep problems are among the most common parental complaints to pediatricians,<sup>3</sup> and preschool-age children are more likely to be diagnosed with a sleep disorder than any other age group.<sup>4</sup> Recent evidence suggests that insufficient sleep is associated with greater risk for obesity.<sup>5</sup> However, how sleep interacts with health behaviors to influence obesity risk remains unclear. Insufficient sleep may negatively impact health behaviors (e.g., diet, physical activity, screen time) which in turn could lead to increased obesity risk. In a study of over 1,000 children aged 7 years, children who slept for longer durations were found to have a healthier diet and lower BMI z-score.<sup>6</sup> Similar findings in a cohort Canadian children found that parent reported longer sleep duration was associated with a better quality of diet as well as higher levels of physical activity.<sup>7</sup> Alternatively, it is possible that unhealthy behaviors could result in poorer sleep which in turn may influence obesity risk. The goal of this paper is to test the latter pathway to answer the question of whether sleep mediates the relationship between health behavior patterns and obesity risk in children. By better understanding this potential pathway, effective interventions to prevent and treat obesity early in life can be designed.

Health behaviors such as diet and activity have shown bivariate associations with sleep duration. Certain dietary behaviors, for example habitual snacking throughout the day and high caffeine consumption, have been associated with shorter sleep duration; conversely certain fruits and dairy products have been associated with improved sleep.<sup>8</sup> Physical activity (PA), particularly

moderate-vigorous PA, has been associated with improved sleep.<sup>9</sup> In contrast, screen time use has been consistently associated with shortened sleep duration.<sup>10</sup> Not only have health behaviors been associated with sleep duration, but sleep duration has been linked to obesity risk independent of these health behaviors.<sup>11-13</sup>

The underlying mechanism driving the sleep-obesity association, independent of diet and activity behaviors, appears to be through changes in metabolism. For example, in tightly controlled, laboratory-based sleep restriction studies among adults, shortened sleep duration had negative effects on hormones (i.e., leptin, glucose, insulin), which induced increases in weight.<sup>14</sup> Other adult studies also found significant decreases in body temperature following sleep restriction which could eventually lead to decreases in basal metabolic rate, thus impacting weight.<sup>14</sup> In pediatric populations, negative hormonal changes have occurred in individuals with circadian rhythm misalignment and sleep restriction (i.e., late bed times, early wake times).<sup>15,16</sup> However, whether insufficient sleep influences metabolism directly, or indirectly, through changes in diet and physical activity, is unknown, particularly in young children.

In understanding the pathway (Figure 1) by which sleep influences the association between health behaviors and obesity, it is important to capture health behaviors as they pattern together. For example, although there are a number of studies exploring the unique contribution of sleep, diet, screen time and physical activity behaviors individually on obesity, it remains unclear how these health behaviors together impact risk for obesity. To date, an underlying assumption has been that obesity risk is the same for a given “dose” of an exposure.<sup>17</sup> For example, while high sugar-sweetened beverage intake may increase obesity risk controlling for confounders, it is plausible that very active children may be protected against the effects of energy-dense nutrient poor quality diets whereas children with poor sleep duration or quality may respond even more strongly to

dietary risk factors. Thus it is critical to better understand how different health behavior clusters ultimately influence childhood obesity risk.

Health behaviors co-occur, and obese children most often report having two or more eating and activity risk behaviors.<sup>18</sup> It is possible that these health behaviors patterns may better predict obesity risk rather than focusing on single behaviors; unfortunately, few studies have examined behavior patterns,<sup>19-22</sup> only two of these in childhood.<sup>19,20</sup> Furthermore, no studies to our knowledge have used these patterns in understanding the pathway by which sleep mediates the association between health behaviors and obesity. Therefore, the objective of this analysis is to examine the mediating effect of sleep duration in the relationship between health behavior patterns and childhood obesity. We hypothesize that the association between health behavior patterns and obesity risk is at least partially mediated by sleep duration in children.

## Methods

### Participants

This was a secondary analysis using the nationally distributed Infant Feeding Practice Survey II (IFPS II) and Year 6 Follow—Up Study (Y6FU).<sup>23,24</sup> The IFPS II is a prospective, longitudinal cohort, funded by the Centers for Disease Control and Food and Drug Administration (CDC), that followed women in late pregnancy and their children through age 6 years. The sample for Y6FU was a subset of those who participated in IFPS II. Mothers who completed at least the first postnatal questionnaire for IFPS II were contacted to participate in Y6FU (n=2958 contacted). A total of 1542 mothers completed the mailed questionnaires.

### Measurements

Mailed questionnaires were completed by mothers. The 1-month Harvard Children's Nutrition

Food Frequency Questionnaire assessed the child's diet, and a study questionnaire queried their child's activity, screen time, and sleep behaviors.<sup>24</sup> These questionnaires were developed using previously published national surveys and pilot tested to ensure content validity as well as appropriate variation and range of responses. PA was assessed by asking "in a typical week, how many days is your 6-year old physically active for a total of at least 60 minutes per day". Screen time was assessed by asking "on average, about how many hours per day does your 6-year-old play video games and watch TV programs or videos (do not count school or homework time)". Sleep was assessed with the question "Over the past month, how many hours did your 6-year-old usually sleep each night on weekdays". Mothers were also asked to measure and self-report their child's height and weight (Y6FU) when the children were 6 years old. These data were used to calculate the BMI as % of the 95<sup>th</sup> percentile (%BMI<sub>p95</sub>) using the CDC SAS program for growth charts.<sup>25</sup> Social-demographic data for the family was also self-reported by the mothers. Complete information regarding this study has been previously published.<sup>23,24</sup>

### Statistical Analysis

Our analysis plan consisted of three steps. First, we created dichotomous versions of our seven health behavior indicator variables using the Youden index. Next we carried out a latent class analysis (LCA) to identify health behavior patterns using these seven indicators. Lastly, we conducted a series of regression models to examine sleep duration as a mediator of the association of health behavior patterns and obesity.

The seven health behavior indicator variables were constructed using the Youden index. By utilizing a data driven approach, the Youden index calculates the amount of a given behavior that is associated with the outcome, obesity. The threshold for each variable was chosen as the value which maximized the J statistic (sensitivity + specificity – 1) from a linear regression with



obesity ( $> \% \text{BMI}_{p95}$ ) as outcome and the specified indicator variable. The following variables were constructed; high physical activity ( $> 60$  min/day, 5 d/wk), high screen time ( $> 100$  min/day), high breakfast consumption ( $> 5$  d/wk), high fruit consumption (1+/d), high vegetable consumption (1+/d), high fast food consumption (1+/wk), and high sugar sweetened beverages (1+/d). These seven health behaviors were selected as they tend to be targets of childhood obesity treatment and prevention programs. Further a distinction of “high” was given to each behavior in order to guide interventionists in usable targets when developing such programs.

Next, we conducted latent class analysis (LCA) to identify children’s health behavior patterns. LCA is a commonly used approach to identify subpopulations (i.e., latent classes) by shared item response patterns. Using this approach, patterns (i.e., classes) of individuals are expected to be similar to one another with regards to the variables of interest, but different from individuals in other patterns. LCA was conducted using Mplus Version 7.1 to identify health behavior patterns using the above seven indicators of health behaviors.

For our LCA we started with a 1-class model and increased the number of classes until the best-fitting model was observed. Following current recommendations, we reported a constellation of various types of fit indices to offset advantages/limitations of any one index.<sup>26</sup> Relative fit indices based on information-heuristic criteria included Akaike’s Information Criterion (AIC), the Bayesian Information Criterion (BIC), Consistent Akaike’s Information Criterion (CAIC), and the Approximate Weight of Evidence Criterion (AWE). Additional fit statistics included the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), the Bayes Factor, and the Correct Model Probability (cmP). The LMR-LRT compares the k-class model under consideration to a k-1 class, where a significant p-value indicates that the estimated model fits the data significantly better than a model with one fewer class.<sup>27</sup> The Bayes Factor compares a k-class model to a k+1 class model

and assesses which of the two models is more likely to be the true model, assuming one of them is true (higher is better). The cmP assesses the probability of a given model being correct relative to a set of alternative models (i.e., all other models under consideration). The best fitting model was chosen based on the collective information provided by model fit indices (see Table 1). Specifically, we primary utilized the BIC and the LMR-LRT in choosing a best fitting model, and relied on additional fit indices as converging evidence for that model.<sup>28</sup>

Once a final model was chosen, each participant was assigned most likely class membership, resulting in each participant being assigned membership to a categorical observed variable representative of a health behavior pattern. Using this categorical variable, a series of regression models were estimated to address our hypothesis that sleep (hours per night) mediates the association between class membership and %BMI<sub>p95</sub>. Model 1 examined the effect of class membership on %BMI<sub>p95</sub>; model 2 examined the effect of class membership on sleep (hours); and model 3 examined the effect of sleep (hours) on %BMI<sub>p95</sub> while adjusting for class membership. This “classify/analyze” approach of generating an observed variable for most likely class membership and using that variable as input data in testing the regression relationships does not address classification uncertainty; therefore, sensitivity analysis confirmed model relationships under current best practices for examining the relationship of class membership to distal outcomes while accounting for classification uncertainty, and model conclusions were unchanged.<sup>29</sup> Due to the homogeneity of the cohort’s race and ethnicity, we did not address those variables further in the analyses; we did include gender as a covariate in the regression analyses, but model results were unchanged so we report the unadjusted results for simplicity.

## Results

Our complete cases for this analysis consisted of 1073 six-year-old children. Children without

complete data relevant for our analysis were excluded (n=469); missing due to sex (n=2), height/weight data (n=329), race (n=102), ethnicity (n=5), and income (n=31). There were no significant differences for SES indicators between the full cohort (n=1542) and our analysis sample (n=1073). The large number of missing height/weight data is thought to be attributed to additional burden of collecting this data as mothers were sent a measuring tape and instructed on how to measure the child's height and weight.

Mothers in the cohort were 89% White and 25% reported a household income below \$39,000 per year. Of the children, 49% were female and 13% of the children classified as obese (BMI above the 95<sup>th</sup> percentile). Further description of the cohort by latent class membership is provided in Table 2.

We estimated between 1-5 class models, using multiple random perturbations of start values for each model. All models converged, there were no negative indications with regard to model identification, and the log likelihood value was replicated for all solutions. The smallest class size in the 5-class solution was n=35 (3.26%), so we did not estimate beyond five classes. Model fit indices, shown in Table 1, supported the 3-class solution. As a measure of absolute fit, the likelihood ratio  $\chi^2$  test first becomes non-significant (good-fitting) under the 3-class solution. The AIC, BIC and CAIC supported the 3-class model; while the AWE supported a 2-class model, this index tends to under-extract classes and therefore provides a lower bound estimate for class enumeration. The LMR-LRT (p = 0.13), Bayes Factor (>10), and the cmP (>0.99) all supported the 3-class solution. The entropy value of the 3-class model was .58, with average posterior class probabilities of 0.84, 0.77, and 0.80 across the 3 classes, respectively.

Based on measures of absolute and relative fit, we proceeded to interpret the 3-class model results. Figure 1 depicts the model-estimated item response probabilities for each of the 7

indicators of the 3-class solution. The first class (n=233, 22%) was homogeneous with regard to low intake of fruits and vegetables and high fast food intake; we therefore labeled this class “Poorest eaters.” Class 2 (n=399, 37%) was homogeneous with respect to low rates of screen time and sugar-sweetened beverages and high rates of consuming fruits and vegetables, eating breakfast, and engaging in physical activity; we labeled this as the “Healthy” class. Class 3 (n=441, 41%) was homogeneous with high rates of physical activity, and fruit and vegetable intake but also high fast food consumption and the highest screen time of all three classes; we labeled this class “Active, super-eaters, highest screen time”. In summary, the 3-class model was supported as the best fitting model in relative and absolute terms and the observed class structure was theoretically interpretable.

Three regression models were estimated to test sleep duration as a mediator between class membership and %BMI<sub>p95</sub> (Table 3). First the effect of class membership on %BMI<sub>p95</sub> was examined. Compared to the “Healthy” class, the “Poorest eaters” class had an increased %BMI<sub>p95</sub> of 4.11 (p=0.006). The next model examined the effect of class membership on sleep (hours). Compared to the “Healthy” class, both other classes had significantly shorter amounts of sleep ( $\beta = -0.51$ , p<0.001 for “Poorest eaters”;  $\beta = -0.38$ , p<0.001 for “Active, super-eaters, highest screen time”). In the final model, the effect of sleep (hours) on BMI was examined adjusting for class membership. Independent of class membership, each additional hour of sleep was associated with a %BMI<sub>p95</sub> that was 2.93 units lower (p<0.001) and class membership was no longer significantly associated with %BMI<sub>p95</sub>. Thus, the effect of class variable on %BMI<sub>p95</sub> appears to be fully mediated by sleep.

## Discussion

The goal of this study was to explore the mediating role of sleep duration in the pathway between modifiable health behavior patterns and risk of obesity. We found that children with health behavior patterns consisting of low fruit and vegetable intake and high fast food consumption (“Poorest Eaters”) had higher %BMI<sub>p95</sub> compared to children with “Healthy” patterns. The “Poorest Eaters” and children classified as “Active, super-eaters, highest screen time” also had significantly reduced sleep duration compared to children classified with having a “Healthy” pattern. Finally, we found that sleep duration mediated the association of health behavior patterns and a child’s %BMI<sub>p95</sub>. Pediatric lifestyle management interventions should include a multitude of health behaviors and consider the possibility that improving diet and activity behaviors may facilitate improved sleep and obesity risk among children.

Our finding that poor health behavior patterns are associated with obesity risk are consistent with prior work. For example, two similar studies conducted in early childhood (4-6 years) found that unhealthy behaviors, in particular high screen time, are associated with obesity.<sup>19,20</sup> Our work, however, extends findings from the previous literature by implicating sleep duration in the pathway linking health behaviors with obesity. Although prior studies have not included sleep duration, they have examined individual behaviors (i.e., diet) and sleep duration in relation to obesity. Parent-reported sleep duration has been linked to diet and activity behaviors in a cohort of 10-11 year old Canadian children. A significant increase in both self-reported diet quality and physical activity were shown for every additional hour of sleep duration.<sup>7</sup> Further, longer sleep duration was associated with decreased odds of being classified as overweight or obese. The Project Viva cohort found that chronic insufficient sleep (defined as short sleep duration from infancy to age 7) was associated with poor diet quality.<sup>6</sup> However, after further testing, poor diet quality did not explain the association between sleep and childhood obesity. In the same cohort,

using data from the 7-year visit only, children with the highest sleep scores (defined as mean sleep duration) had the lowest BMI z-scores and higher self-reported diet quality scores. In a multiethnic cohort of 2-4 year old children, obese children with poor sleep duration (defined as less than 11 hours of sleep per night), had significantly higher intakes (g/d) of fat and saturated fat as well as a higher percentage of their overall dietary intake (% of kcal) from fat and significantly lower percent calories from carbohydrate during the weekdays.<sup>30</sup>

We found that the relationship between the health behaviors and obesity was no longer significant in our model 3 with the inclusion of sleep duration, suggesting that sleep may be an important mechanism linking health behaviors to obesity. Although these findings suggest that sleep mediates the relationship between health behaviors and obesity it is also possible that lack of sleep can have a negative impact on health behaviors which in turn impact obesity. Research has been conducted with the hypothesis that children with shorter sleep duration engage more often in obesity-related behaviors including lower levels of physical activity, higher screen time, lower consumption of fruits and vegetables and higher consumption of sugar sweetened beverages.<sup>31-</sup><sup>33</sup>Future work is needed to disentangle this relationship further to better understand where the cycle starts (Figure 1).

Moving forward, future studies should consider examining this question at a more mechanistic level to better understand how the cycle influences metabolism and specific hormones associated with poor health behaviors and sleep. Unfortunately, this cohort did not collect hormonal or metabolic data in this young sample, but our findings highlight the need for future studies to assess these factors when attempting to elucidate the mechanism behind the association between sleep, health behaviors, and obesity. Further, there may be other factors outside of diet and activity behaviors that impact sleep duration; including family routines and/or chaos.<sup>34,35</sup>

Recent evidence suggests that screen time in particular may play an important role on sleep through the effect of bright light in suppressing sleep promoting melatonin and delaying circadian rhythms,<sup>36-38</sup> although a causal association has not been confirmed.<sup>10,39</sup> Given that screens are becoming more ubiquitous in children's everyday life, future research should continue to tease out the impact of this behavior on sleep and obesity risk. Early evidence suggests that high family chaos plays a significant role in child sleep problems.<sup>35</sup> These and other health behaviors which were not able to be included in our analysis may also explain our findings and should be included in future research.

The results of this study provide preliminary evidence that specific health behavior patterns early in life are associated with obesity in children as young as six years. We utilized a novel approach on early health behavior patterns including diet, physical activity, and screen time in relation to indicators of obesity. Further, we were able to examine how multiple health behaviors may pattern together and then test how this association was influenced by sleep duration. To our knowledge, this is the first study to conduct this analysis. Our approach of strong quantitative analysis permitted us to examine multiple behaviors simultaneously compared to other approaches which focus only on one health behavior at a time while holding others constant. By exploring patterns of relevant obesity-related health behaviors and how they interrelate to influence weight status, our results can more efficiently guide future obesity prevention and treatment strategies by developing more effective and targeted interventions.

Our findings should be interpreted cautiously and may not be representative of all young children. The Infant Feeding Practices II cohort consists of predominantly White maternal-child dyads with higher incomes. Similar to other studies published to date, the measures of health behaviors, child height and weight, and sleep were obtained by parent-report and not verified by

medical records or objective measurements. The gold standard for sleep measurement is polysomnography, and actigraphy is able to objectively capture typical sleep across a longer duration in the home environment. Similarly, accelerometers can be used to objectively measure physical activity. Future research should evaluate relationships using these objective measures of health and health behaviors. Moreover, the current study only examined sleep duration yet sleep is a multidimensional construct and thus other variables such as sleep quality and variability should also be considered. Another limitation is the use of dichotomous health indicators for the pattern analysis. We utilized dichotomous cut-points for each of the health behaviors to improve public health relevance after initial modeling using continuous indicators resulted in difficulty with model estimation/interpretation, but recognize drawbacks of categorizing continuous measures. Finally, because these analyses used cross-sectional data, the directionality of these associations cannot be determined. However, given the robust research linking childhood health behaviors and childhood obesity risk, reverse causality is unlikely. This study also has a number of strengths including the large sample size, prospective design, use of extensively tested survey questions, and wealth of data collected related to childhood obesity risk. Further work should be conducted to replicate these findings in more diverse, longitudinal cohorts and if possible, with more objective measures of key study variables such as physical activity and sleep.

## Conclusion

In conclusion, we observed sleep duration as a potential pathway linking health behavior patterns and obesity in children. Future research should continue to explore the metabolic and behavioral pathways by which this occurs. In addition, future interventions may want to explore the improvement of health behavior patterns which in turn may improve a child's sleep duration and subsequently, BMI.



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Figure 1. Cyclic relationship of poor health behaviors worsening sleep

Figure 2. Model-estimated item response probabilities by class.

Table 1. Model fit indices for sample (n=1073).

Model	LL	npar	Adjusted $\chi^2$ LR (df), p-value	AIC	BIC	CAIC	AWE	Adjusted LMR-LRT p value	BF	cmP
1-class	-4156.50	7	440.86 (120), < .001	8327	8362	8369	8432	<.001	<.01	<.01
2-class	-4027.69	15	183.24 (112), < .001	8085	8160	8175	8310	<.001	<.01	<.01
3-class	-3987.83	23	103.53 (104), 0.49	8022	8136	8159	8366	0.13	>10	>.99
4-class	-3980.09	31	217.97 (220), 0.71	8022	8177	8208	8486	0.06	>10	<.01
5-class	-3972.65	39	110.44 (193), 0.87	8023	8217	8256	8607	--	--	<.01

LL = log likelihood value; npar = number of parameters estimated; LR=Likelihood ratio; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; CAIC = Consistent Akaike's Information Criterion; AWE = Approximate Weight of Evidence Criterion; LMR-LRT = Lo Mendall Rubin Likelihood Ratio Test; BF = Bayes Factor; cmP = Correct Model Probability.

Table 2. Description of cohort

	Class 1	Class 2	Class 3
	Poorest Eaters	Healthy	Active, super-eaters, highest screen time
Demographics (n (%))			
N	233 (22%)	399 (37%)	441 (41%)
Race			
White	198 (85%)	361 (90%)	394 (89%)
Black/AA	15 (6%)	9 (2%)	25 (6%)
Other	20 (9)	29 (7%)	22 (5%)
Hispanic origin (yes)	19 (8%)	14 (4%)	22 (5%)
Household Income			
< \$39K	62 (27%)	82 (21%)	125 (28%)
\$40-74999	78 (33%)	123 (31%)	145 (33%)
\$75-99999	37 (16%)	76 (19%)	80 (18%)
\$100-149000	39 (17%)	75 (19%)	66 (15%)
> \$150000	17 (7%)	43 (11%)	25 (6%)
Sex (female)	135 (58%)	188 (47%)	226 (51%)
Children with Obesity (BMI % > 95)	43 (18%)	39 (10%)	61 (14%)
Health Behaviors (means $\pm$ SD)			
Physical Activity (days active at least 60 minutes)	4.94 $\pm$ 1.74	5.49 $\pm$ 1.63	5.71 $\pm$ 1.46
Screen Time (minutes/day)	103.25 $\pm$ 74.18	43.73 $\pm$ 29.43	122.79 $\pm$ 70.99
Breakfast consumption (days/week)	6.42 $\pm$ 1.42	6.97 $\pm$ 0.17	6.59 $\pm$ 1.05
Fruit Intake (servings/day)	0.38 $\pm$ 0.30	1.84 $\pm$ 0.96	1.47 $\pm$ 1.06
Vegetable Intake (servings/day)	0.39 $\pm$ 0.28	1.85 $\pm$ 1.03	1.53 $\pm$ 1.23
Fast Food Intake (times/week)	1.20 $\pm$ 1.00	0.51 $\pm$ 0.73	1.02 $\pm$ 0.83
Sugar Sweetened Beverages (servings/day)	0.42 $\pm$ 0.68	0.15 $\pm$ 0.22	0.59 $\pm$ 0.88
Sleep (hours per night)	9.46 $\pm$ 1.10	9.97 $\pm$ 0.94	9.59 $\pm$ 1.09

Class (health behavior pattern) variables included: high physical activity (>60 min/day, 5 d/wk), high screen time (>100 min/day), high breakfast consumption (>5 d/wk), high fruit consumption (1+/d), high vegetable consumption (1+/d), high fast food consumption (1+/wk), and high sugar sweetened beverages (1+/d).

Table 3. Results from mediation analysis examining sleep duration as a mediator between class membership and BMI.

Model	Variable	$\beta$	95 <sup>th</sup> % Confidence Limits	p-value
Model 1. Examine the effect of class membership on BMI (%BMI <sub>p95</sub> )				
	Class 1: Poorest eaters	4.11	(1.21, 7.02)	0.006
	Class 2: Healthy		Reference	
	Class 3: Active, super-eaters, highest screen time	1.74	(-0.70, 4.17)	0.162
Model 2. Examine the effect of class membership on sleep (hours)				
	Class 1: Poorest eaters	-0.51	(-0.68, -0.34)	<0.001
	Class 2: Healthy		Reference	
	Class 3: Active, super-eaters, highest screen time	-0.38	(-0.53, -0.24)	<0.001
Model 3. Examine the effects of sleep (hours) on BMI (%BMI <sub>p95</sub> ) adjusting for class membership				
	Sleep	-2.93	(-3.96, -1.90)	<0.001
	Class 1: Poorest eaters	2.43	(-0.52, 5.38)	0.11
	Class 2: Healthy		Reference	
	Class 3: Active, super-eaters, highest screen time	0.62	(-1.83, 3.08)	0.62

