Int J Public Health (2015) 60:551–559
DOI 10.1007/s00038-015-0685-8

ORIGINAL ARTICLE

Patterns of movement behaviors and their association with overweight and obesity in youth

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Received: 18 July 2014 / Revised: 15 April 2015 / Accepted: 29 April 2015 / Published online: 19 May 2015

Abstract
Objectives To identify underlying subgroups based on patterns of physical activity, screen-based sedentary behavior, and sleep in a large sample of Canadian youth and to examine the associations between the identified subgroups and overweight and obesity.
Methods The study is based on 19,831 youth aged 13–18 years from across Ontario, Canada in the COMPASS study. Participants self-reported their movement behaviors (i.e., physical activity, sedentary behavior and sleep), height and weight, and demographics. Latent class analysis and logistic regression models were conducted.
Results Three underlying subgroups were identified in the total sample and male and female subsamples (i.e., unhealthiest movers, active screenies, healthiest movers). In the total sample, the active screenies subgroup was 1.19 (95 % CI 1.09–1.29) times and the unhealthiest movers subgroup was 1.24 (1.14–1.36) times more likely to be classified as overweight/obese compared to the healthiest movers subgroup. Similar associations were observed in the female subsample but not in the male subsample.
Conclusions Public health interventions targeting youth subgroups at increased risk of overweight and obesity through integrated approaches accounting for multiple movement behaviors should be considered, especially for females.

Keywords Adolescent · Obesity · Physical activity · Television · Computers · Sleep

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Introduction

Movement behaviors occur on an intensity continuum from sleep (i.e., no/low movement) to vigorous-intensity physical activity (i.e., high movement). Movement behaviors are distributed throughout a 24-h period, with varying proportions of physical activity of different intensities, sedentary behaviors, and sleep. Therefore, an increase in one movement behavior displaces the time spent in another (Buman et al. 2014). Movement behaviors and their association with overweight and obesity have traditionally been examined individually. There is consistent evidence of an inverse dose–response relationship between physical activity and obesity among youth, in particular for moderate-to vigorous-intensity physical activity (MVPA) (Janssen and Leblanc 2010). Conversely, excessive sedentary behavior, in particular screen-based sedentary behavior (e.g., television viewing and computer use), has unfavorable effects on adiposity (Tremblay et al. 2011). There is also substantial evidence linking insufficient sleep to overweight and obesity in youth (Chen et al. 2008).

While movement behaviors have individual associations with overweight and obesity, these behaviors do not occur in isolation and have intuitive and empirical interactions (Ferrar et al. 2013a; Leech et al. 2014).Therefore, patterns of multiple movement behaviors may have unique and potentially cumulative effects on overweight and obesity that are not explained by individual movement behaviors (Ferrar et al. 2013a; Leech et al. 2014). However, public health messaging related to movement has focused on promoting MVPA (i.e., one movement behavior), creating a misguided, and possibly harmful belief that a dose of MVPA protects from the potential consequences associated with other movement behaviors (e.g., excessive sedentary behavior and/or lack of sleep). Therefore, there is a need to understand the patterns of these movement behaviors and how these patterns relate to overweight and obesity.

Latent class analysis is an analytic technique that identifies mutually exclusive classes of individuals or underlying subgroups that have similar patterns of responses to a set of observed variables (Lanza et al. 2007). An advantage of latent class analysis over other types of analyses, such as cluster analysis, is the use of statistical criteria to determine the appropriate number of classes (Beets and Foley 2010). Using latent class analysis to segment youth into subgroups based on patterns of movement behaviors may help identify high-risk groups for targeted interventions that use integrated approaches accounting for multiple movement behaviors.

Two recent reviews have identified 11 studies that have used latent class or cluster analysis to identify patterns for two movement behaviors, physical activity and screen-based sedentary behavior in youth (Ferrar et al. 2013a; Leech et al. 2014). In addition to only including two movement behaviors, only five of the 11 studies examined associations with weight status. Three (Beets and Foley 2010; Patnode et al. 2011; te Velde et al. 2007) out of five studies (Beets and Foley 2010; Jago et al. 2010; Marshall et al. 2002; Patnode et al. 2011; te Velde et al. 2007) found patterns of low physical activity or high sedentary behavior were associated with being overweight. Subgroup-specific associations with overweight were not always consistent across sexes, with some studies observing stronger associations in males (te Velde et al. 2007) and others in females (Patnode et al. 2011).

To our knowledge, only two studies have used cluster analysis to look at the patterns of movement behaviors across the intensity continuum (i.e., physical activity, sedentary behavior and sleep) and how these patterns relate to weight status (Ferrar et al. 2013b; Olds et al. 2004). In a sample of 1429 South Australians aged 9–15 years, no differences in body mass index (BMI) were observed in the male subsample (Olds et al. 2004). However, for the female subsample, "screenies" (high screen time) had a higher BMI compared to the three other subgroups: "players" (high play time), "sporties" (high sport time), and "socialisers" (high inactive socializing time) (Olds et al. 2004). Similarly, in a sample of 679 New Zealanders aged 10–16 years, associations with weight status were not observed in the male subsample. For the female subsample, the "social sporty" (high sports and interaction) subgroup had the highest levels of overweight and obesity compared to the "screenie tasker" (high TV, computer, chores, work) and "super studious" (high reading, studying, and school-based activities) subgroups (Ferrar et al. 2013b). However, it is unclear if these patterns of movement behaviors and their associations with weight status are consistent in older samples of youth, where the prevalence of movement behaviors tends to differ (Colley et al. 2011).

The objectives of this study were to: (1) identify underlying subgroups based on patterns of physical activity, screen-based sedentary behavior, and sleep in a large sample of Canadian youth aged 13–18 years; (2) examine the associations between the identified subgroups and overweight and obesity; and (3) examine if the association between the identified subgroups and overweight and obesity is consistent across male and female subsamples.

Methods

Design

This cross-sectional study used self-reported data collected from grades 9–12 (aged 13–18 years) students attending 43 secondary schools in Ontario, Canada as part of the Year 1 sample for the COMPASS study (2012–2013). The data were collected using the COMPASS Student Questionnaire (C_q). Additional details on the COMPASS study are available elsewhere (http://www.compass.uwaterloo.ca) (Leatherdale et al. 2014a).

Data collection

All C_q surveys were completed in class time. Active information with passive consent was used to reduce demands on schools and to increase student participation rates. As described in detail elsewhere (Thompson-Haile et al. 2013), parents/guardians of eligible students were sent an information letter about the COMPASS study and asked to call a toll-free number (accessible 24 h a day) or e-mail the recruitment coordinator if they did not want their child to participate. Assent was obtained from all eligible participants on the day of the survey. The University of Waterloo Office of Research Ethics and

School Board and School committees approved all procedures.

Participants

A total of 39 out of 88 (44 %) purposefully sampled public schools agreed to participate. Primary reasons for declining participation were competing research demands and teacher labor issues. A total of 4 out of 23 (17 %) purposefully sampled private schools agreed to participate. Out of the 30,147 eligible students enrolled in the 43 purposefully sampled schools, 24,173 (80 %) students completed the student questionnaire. Missing respondents resulted from survey day absenteeism (19 %), student refusal (0.1 %), and parental refusal (0.9 %). This participation rate is consistent with previous passive consent studies (Leatherdale and Wong 2008). Further detail on sampling and recruitment can be found elsewhere (Leatherdale et al. 2014a).

Exposures (movement behaviors)

Physical activity was assessed by asking participants to record how many minutes of moderate (i.e., lower intensity activities such as walking, biking to school, and recreational swimming) and hard (i.e., jogging, team sports, fast dancing, jump-rope, and any other physical activities that increase your heart rate and make you breathe hard and sweat) physical activity they did on each of the last 7 days. Average min/day across the last 7 days was calculated for both moderate and hard physical activity. Screen-based sedentary behavior was assessed by asking participants how much time per day they usually spend: (1) watching/streaming TV shows or movies, (2) surfing the internet, and (3) playing video/computer games. Sleep was assessed by asking participants how much time per day they usually spend sleeping. Participants were classified into quartiles of min/day for each movement behavior variable to capture low health risk (highest quartile of physical activity, lowest quartile of screen-based sedentary behavior, and highest quartile of sleep) within the sample. Though a curvilinear relationship between sleep and overweight and obesity has been observed in adults, a linear relationship has been reported in children and adolescents; (Chen et al. 2008) therefore, the highest quartile of sleep was used to capture low health risk.

In a validation study with a sample of 139 grade 9 students in Ontario, Canada, 1-week test–retest reliability intraclass correlation coefficients (ICC) were 0.71 for moderate physical activity, 0.68 for hard physical activity, 0.71 for internet surfing, 0.65 for video/computer games, and 0.56 for television viewing. The criterion validity ICC coefficients of self-reported and accelerometer-measured physical activity were 0.18 for moderate and 0.22 for hard (Leatherdale et al. 2014b). These are consistent with other self-report measures (Mota et al. 2002; Wong et al. 2006).

Outcome (weight status)

Participants self-reported their weight and height and BMI (kg/m^2) was calculated. Participants were classified as non-overweight or overweight/obese based on World Health Organization growth standards (de Onis et al. 2007). In a validation study with a sample of 178 grade 9 students in Ontario, Canada, 1-week test–retest reliability ICC coefficients were 0.96 for height and 0.99 for weight. Concurrent validity ICC coefficients of self-reported and measured values were 0.88 for height, 0.95 for weight, and 0.84 for BMI (Leatherdale et al. 2014b).

Covariates

Age, sex, race/ethnicity (White, Black, Asian, Aboriginal, Latin American/Hispanic, and other), sugar-sweetened beverage consumption, and fruit and vegetable consumption were considered as covariates based on previous research examining the associations of different movement behaviors and weight status individually (Carson and Janssen 2011; Chen et al. 2008; Janssen and Leblanc 2010). Sugar-sweetened beverage consumption was assessed by asking participants how many days in a usual school week and usual weekend they drink sugar-sweetened beverages (i.e., soda pop, Kool-Aid, Gatorade, etc.). Participants were asked not to include diet/sugar-free drinks. Fruit and vegetable consumption was assessed by asking participants how many servings of fruit and vegetables they had yesterday from the time they woke up until the time they went to bed. Diagrams of Canada's Food Guide Serving Sizes were provided (Health Canada 2011).

Data analysis

Descriptive statistics were first calculated, including means, standard errors, and frequencies, for demographic and movement variables. ANOVAs were used to examine sex differences for the movement variable quartiles. Latent class analyses were conducted to identify underlying movement behavior subgroups within the sample (Lanza et al. 2007) based on quartiles of six indicators: moderate physical activity, hard physical activity, television viewing, internet surfing, video/computer game use, and sleep. Models with 1–6 latent classes were examined as recommended by Lanza et al. (2007). To select the model with the optimal number of latent classes, the model fit was compared using Akaike information criterion (AIC), Bayesian information criterion (BIC), consistent AIC

(CAIC), and adjusted BIC (a-BIC) (Lanza et al. 2007). Models with lower AIC, BIC, and, CAIC, a-BIC values were identified as better fitting models compared to models with higher values (Lanza et al. 2007). Participants were then placed into a latent class based on the highest probability of class membership (Goodman 2007; Lanza et al. 2007).

To examine the association between the latent classes (based on the highest probability of class membership) and weight status, separate logistic regression models were conducted that adjusted for potential confounders of age, sex, race/ethnicity, sugar-sweetened beverage consumption, and fruit and vegetable consumption (Pearson and Biddle 2011). The healthiest movement behaviors class (i.e., high physical activity, low screen-based sedentary behavior, and high sleep) was the reference group. Consistent with previous work (Ferrar et al. 2013a; Leech et al. 2014), the sample was stratified into male and female subsamples and the latent class analyses and logistic regression models were repeated to examine if the association between latent classes and weight status differed between sexes. Analyses were completed using SAS version 9.3 (SAS Institute Inc., Cary, NC). All analyses took into account the clustered nature of the data by including the school id number in the cluster statement of all SAS procedures. Statistical significance was set at $P < 0.05$ for all analyses.

Results

Out of the 24,173 participants that completed the baseline questionnaire, 19,831 (82 %) participants had complete data on the variables of interest for the latent class analyses. A total of 712 participants were missing at least one movement behavior data, and 1220 participants were missing covariate data. Additionally, 2410 participants had values for movement behavior variables that were considered outliers ($\geq \pm 3$ standard deviations). In comparison to the total sample, the final sample for the latent class analysis was younger (1.6 years) and included more males (10 %). A further 3752 participants were excluded for the logistic regression analyses due to missing weight status data. In comparison to the total sample, the final sample for the logistic regression was slightly younger (0.7 years) and included slightly more females (2 %).

Participant characteristics by sex are presented in Table 1. Overall, the average age was 16 years, approximately half of participants were female, 73 % were White, and 25 % were overweight/obese. Quartiles of movement behaviors in the total sample and sex-stratified samples are presented in Table 2. Sex differences in some movement behaviors were observed. For instance, males in quartile 4 reported participating in 6 more min/day of moderate and 9 more min/day of hard physical activity compared to females in quartile 4. Conversely, females in quartile 4 reported engaging in 6 more min/day of internet surfing compared to males in quartile 4.

The model fit information for the latent class models with 1–6 latent classes is presented in Table 3. Large decreases were observed in model fit information for models with 1–3 latent classes. For instance, model fit values were approximately 1700–1900 lower for the 2 latent class model compared to the 1 latent class model and approximately 1000–1200 lower for the 3 latent class model compared to the 2 latent class model. Smaller decreases

Table 1 Participant characteristics from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

Variable	Total (n = 19,831)	Males (n = 9660)	Females (n = 10,171)
Age (years)	15.7 (0.03)	15.7 (0.03)	15.7 (0.03)
Sex (%)			
Male	48.7	–	–
Female	51.3	–	–
Race/ethnicity (%)			
White	72.8	71.7	73.9
Black	4.6	5.2	4.0
Asian	7.1	7.2	7.0
Aboriginal	4.7	4.6	4.8
Latin American/Hispanic	3.2	3.5	2.8
Other	7.6	7.8	7.5
Weight status (%)	(n = 16,079)	(n = 7988)	(n = 8091)
Non-overweight	74.9	68.7	81.0
Overweight/obese	25.1	31.3	19.0

Data presented as mean (standard error) for continuous variables and percentage for categorical variables

Table 2 Quartiles (Q) of movement behaviors in the total sample and the sex-stratified samples from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

Variable	Total ($n = 19,831$)	Males ($n = 9660$)	Females ($n = 10,171$)
Physical activity (min/day)			
Moderate			
Q1 (low)	9.8 (0.1)	8.9 (0.2)[a]	10.5 (0.1)[a]
Q2	31.7 (0.1)	31.7 (0.1)	31.7 (0.1)
Q3	57.7 (0.1)	58.2 (0.2)[a]	57.3 (0.1)[a]
Q4 (high)	124.3 (0.7)	127.2 (1.0)[a]	120.9 (0.8)[a]
Hard			
Q1 (low)	9.7 (0.2)	9.7 (0.2)	9.7 (0.2)
Q2	42.3 (0.2)	42.6 (0.2)	42.2 (0.2)
Q3	74.4 (0.2)	74.6 (0.2)	74.2 (0.2)
Q4 (high)	139.6 (0.7)	143.1 (0.9)[a]	133.7 (1.0)[a]
Screen time (min/day)			
Television viewing			
Q1 (low)	19.4 (0.4)	20.0 (0.4)[a]	18.7 (0.5)[a]
Q2	67.9 (0.2)	68.1 (0.3)	67.8 (0.3)
Q3	126.3 (0.2)	126.4 (0.3)	126.3 (0.3)
Q4 (high)	218.1 (0.8)	218.9 (1.2)	217.2 (0.8)
Internet surfing			
Q1 (low)	19.2 (0.3)	19.3 (0.4)	19.0 (0.3)
Q2	65.3 (0.2)	64.8 (0.2)[a]	65.8 (0.3)[a]
Q3	124.6 (0.2)	124.5 (0.3)	124.5 (0.2)
Q4 (high)	248.9 (1.3)	245.2 (1.6)[a]	251.3 (1.6)[a]
Video/computer games			
Q1 (low)	0	0	0
Q2	22.9 (0.2)	24.3 (0.2)[a]	21.9 (0.2)[a]
Q3	81.7 (0.4)	83.9 (0.5)[a]	77.5 (0.7)[a]
Q4 (high)	232.4 (1.2)	233.1 (1.4)	229.3 (2.7)
Sleep (min/day)			
Q1 (low)	304. 2 (2.1)	295.7 (2.4)[a]	311.5 (2.3)[a]
Q2	428.4 (0.2)	428.8 (0.3)[a]	428.0 (0.2)[a]
Q3	479.4 (0.1)	479.4 (0.1)	479.4 (0.1)
Q4 (high)	537.8 (0.4)	538. 8 (0.5)[a]	536.7 (0.7)[a]

Data presented as mean (standard error)

[a] Significant sex differences in movement behaviors by quartile ($P < 0.05$)

were observed for models with 4–6 latent classes. For instance, model fit values were only approximately 100–300 lower for the 4 latent class model compared to the 3 latent class model. Differences became even smaller when moving from the 4 latent class to 6 latent class model. A similar pattern was observed for the male and female subsamples (data not shown). As a result, the 3 latent class model was chosen as the best model for further analyses (Lanza et al. 2007).

The item-response proportions for the 3 latent classes in the total sample are presented in Fig. 1. The first latent class (healthiest movers) represents 31 % of participants. This subgroup had the highest proportion of participants in quartile 1 of television viewing (27 %), internet surfing (49 %), and video/computer games (43 %) as well as the highest proportion of participants in quartile 4 of sleep (28 %). It also had a quarter or more of participants in quartile 4 for moderate (25 %) and hard (34 %) physical activity. The second latent class (active screenies) represents 25 % of participants. This subgroup had the highest proportion of participants in quartile 4 of moderate physical activity (54 %) and hard physical activity (53 %). It also had the lowest proportion of participants in quartile 1 of television viewing (9 %), internet surfing (12 %) and video/computer games (27 %). The third latent class (unhealthiest movers) represents 44 % of participants. This subgroup had the lowest percentage of participants in quartile 4 of moderate physical activity (10 %), hard physical activity (3 %), and sleep (18 %). It also had less than 20 % of participants in the bottom quartile for television (17 %) and internet surfing (14 %). Similar patterns were observed when the latent class analysis was repeated

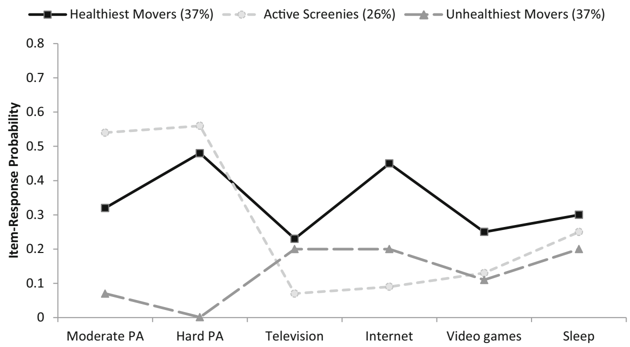

Fig. 1 Item probability for high physical activity (Quartile 4), low screen time (Quartile 1), and high sleep (Quartile four) in the total sample ($n = 19{,}831$) from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

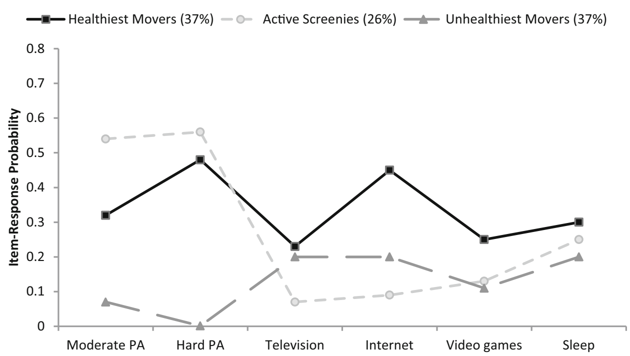

Fig. 2 Item probability for high physical activity (Quartile 4), low screen time (Quartile 1), and high sleep (Quartile 4) in the male subsample ($n = 9660$) from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

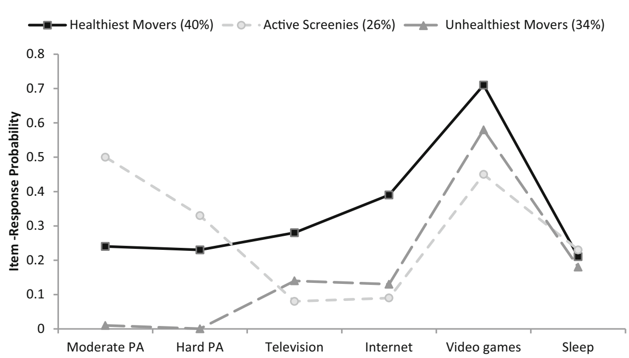

Fig. 3 Item probability for high physical activity (Quartile 4), low screen time (Quartile 1), and high sleep (Quartile 4) in the female subsample ($n = 10{,}171$) from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

in male and female subsamples (Figs. 2, 3). However, the proportion of participants in quartile 1 for video games in the female sample was much higher for all three classes (45–71 %) compared to the total sample (27–43 %) and the male subsample (11–25 %).

The associations between the latent class groups and weight status are presented in Table 4. In the total sample, participants in the active screenies subgroup were 1.19 (95 % CI 1.09–1.29) times and participants in the unhealthiest movers subgroup were 1.24 (1.14–1.36) times more likely to be classified as overweight/obese compared to the healthiest movers subgroup. In sex-stratified analyses, females in the active screenies subgroup were 1.37 (1.18–1.59) and females in the unhealthiest movers subgroup were 1.49 (1.29–1.71) times more likely to be classified as overweight/obese compared to the healthiest movers subgroup. No associations were observed with the male subsample.

Discussion

In this study, a latent class analysis was used to examine the patterns of movement behaviors across the intensity continuum (i.e., physical activity, sedentary behavior, sleep), and the association of these patterns with overweight and obesity in a large sample of Canadian youth. Three underlying subgroups (i.e., healthiest movers, active screenies, unhealthiest movers) were identified and the active screenies and unhealthiest movers subgroups were more likely to be categorized as overweight/obese compared to the healthiest movers subgroup, especially among females.

Only two studies to our knowledge have examined the patterns of movement behaviors across the intensity continuum and the relationships between these patterns and weight status (Ferrar et al. 2013b; Olds et al. 2004). In these studies, three or four subgroups were identified based on patterns of sport, play, light-intensity activity, inactive socializing, screen time, and sleep (Olds et al. 2004) or patterns of 17 activities in a 24-h period (Ferrar et al. 2013b). Though the specific movement behaviors examined differed with the present study, the sex-specific associations with overweight and obesity were consistent with the present study (Olds et al. 2004; Ferrar et al. 2013b). Specifically, females in the “screenie” subgroup, which was characterized by above average screen time and below average sleep, light-intensity activity and sport, were more likely to be overweight and obese compared to all other subgroups (Olds et al. 2004). Similarly, females in the “social sporty” subgroup, which was characterized by high values of social interaction and sports, had a higher prevalence of overweight and obesity compared to all other subgroups (Ferrar et al. 2013b). In both studies, no associations were observed with weight status in the male subsample (Ferrar et al. 2013b; Olds et al. 2004). In the present study, males had higher min/day of moderate physical activity, hard physical activity, and sleep and

Table 3 Model fit information for the latent class models with 1–6 latent classes (n = 19,831) from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

Classes	AIC	BIC	CAIC	a-BIC
1	10,076.76	10,218.81	10,236.81	10,161.61
2	7466.87	7758.98	7795.98	7641.40
3	**5858.02**	**6300.14**	**6356.14**	**6122.17**
4	5536.61	6128.73	6203.73	5890.39
5	5250.87	5993.00	6087.00	5694.24
6	5029.82	5921.96	6034.96	5562.85

The latent class model that was chosen is highlighed in bold

AIC Akaike information criterion, *BIC* Bayesian information criterion, *CAIC* consistent Akaike information criterion and *a-BIC* adjusted Bayesian information criterion

Table 4 Overweight/obesity according to latent class for the total sample and male and female subsamples from Year 1 (2012–2013) of the COMPASS study in Ontario, Canada

	Total (n = 16,079)	Male (n = 7988)	Female (n = 8091)
Latent classes	OR (95 % CI)	OR (95 % CI)	OR (95 % CI)
Healthiest movers	1.00	1.00	1.00
Active screenies	1.19 (1.09–1.29)*	1.09 (0.97–1.23)	1.37 (1.18–1.59)*
Unhealthiest movers	1.24 (1.14–1.36)*	1.12 (0.99–1.27)	1.49 (1.29–1.71)*

Models were adjusted for age, sex (total sample only), race/ethnicity, soft drink consumption, fruit and vegetable consumption

* $P < 0.05$

lower min/day for internet surfing compared to females. The combination of healthier levels of movement behaviors among males may have been protective against overweight and obesity. Combined, these findings suggest that females may be an important focus in future interventions targeting multiple movement behaviors.

While there is a dearth of information on the patterns of behaviors across the intensity continuum among youth, existing studies employing similar analytical methods to examine patterns of physical activity and screen-based sedentary behavior were identified in two recent systematic reviews (Ferrar et al. 2013a; Leech et al. 2014). The number and combinations of subgroups observed varied widely across studies (Ferrar et al. 2013a; Leech et al. 2014), which is likely due to the variation in how physical activity and sedentary behavior have been operationalized. Despite the variation in the variables included across studies, a healthier pattern characterized by high physical activity and low sedentary behavior (Jago et al. 2010; Liu et al. 2010; te Velde et al. 2007) or an unhealthier pattern characterized by low physical activity and high sedentary behavior (Patnode et al. 2011; te Velde et al. 2007) has been generally reported. Similar to the findings of the present study, a pattern of high physical activity and high sedentary behavior has also been reported (Jago et al. 2010; Marshall et al. 2002; te Velde et al. 2007). Combined these findings indicate it is possible for unhealthy movement behaviors (e.g., television viewing) to not only co-occur with other unhealthy movement behaviors (e.g., surfing the internet) but also with other healthy movement behaviors (e.g., moderate physical activity). In the present study, the high levels of physical activity in the active screenies subgroup were not associated with reduced overweight and obesity risk likely due to co-occurring unhealthy levels of screen time, in particular for females. This supports the notion that it is problematic to consider the health impacts of movement behaviors in isolation.

A novel aspect of the present study, which builds on previous research conducted in this area, is the consideration of the lowest end of the intensity continuum. Unlike other movement behaviors, sleep has received less attention in obesity prevention research (Chen et al. 2008). Sleep has intuitive interactions with other movement behaviors. For instance, it is thought that tiredness from sleep loss is associated with lower physical activity levels (Taheri 2006). Furthermore, it is thought that exposure to bright screen light before bed may disrupt sleep cycles (Cain and Gradisar 2010). The finding that participants with the unhealthiest levels of physical activity, sedentary behavior, and sleep had the greatest likelihood of being classified as overweight/obesity supports the concept that movement behaviors may have a cumulative effect on overweight and obesity (Leech et al. 2014).

While sleep was captured in the present study, light-intensity physical activity was not. Research examining the association between physical activity and overweight and obesity has traditionally focused on MVPA (Janssen and Leblanc 2010). Emerging research indicates light-intensity physical activity may also be important for health (Carson et al. 2013). It is difficult to measure light-intensity physical activity without an objective measure. Motion sensors such as accelerometers can accurately capture different intensities of activity from sleep to vigorous-intensity physical activity. Therefore, future research using objective measures of movement behaviors that capture the entire 24-h period is needed to confirm and build upon the findings of the present study. Studies should combine objective measures with a 24-h log or diary so that valuable contextual information can still be captured.

Strengths of this study include the large sample of youth, which enabled the examination of sex-specific associations and multiple behaviors. A limitation of the study was the cross-sectional design, which precludes making causal inferences about the associations observed. Another limitation is the self-report data which are prone to information bias. However, for a sample of this size, objective measurement poses feasibility challenges in terms of both cost and time. Selection bias may have also occurred due to the exclusion of participants based on missing data and outlier data. Information and selection biases may have resulted in the under- or overestimation of the true associations (Rothman et al. 2008). Additionally, though we adjusted for confounders identified in previous research (Carson and Janssen 2011; Chen et al. 2008; Janssen and Leblanc 2010), residual confounding may have occurred due to unmeasured confounders (e.g., other components of dietary intake) or due to measurement error of measured confounders. Further, though participants were placed into a latent class based on the highest probability of class membership, the probability needs to be equal to 1 for there to be no uncertainty with the class memberships (Lanza et al. 2007). Finally, as previously mentioned, this study did not capture data on all movement behaviors because light-intensity physical activity and non-screen-based sedentary behavior were not measured.

Despite the limitations, the findings have important public health implications. Specifically, public health messaging around movement in the prevention of overweight and obesity among youth should be cautious of just focusing on MVPA and not considering the entire intensity continuum. Consistent with findings of this study, an integrated approach has been found to be more effective in behavior change compared to an approach that only focuses on individual behaviors (Prochaska 2008). Furthermore, messaging as well as interventions aimed at preventing overweight and obesity should consider targeting specific groups of youth. In particular, youth with clustering of several unhealthy movement behaviors and youth who engage in high levels of both physical activity and sedentary behavior may be important targets. This is supported by literature that indicates tailored approaches are more effective than global approaches (Kreuter and Wray 2003; Noar et al. 2007).

Conclusion

Based on patterns of physical activity, sedentary behavior, and sleep, three subgroups of participants were identified in a large sample of youth. Notably, the largest subgroup was characterized by the unhealthiest patterns. Participants with the unhealthiest patterns of movement behaviors and participants classified as active screenies were more likely to be categorized as overweight and obesity compared to participants with the healthiest patterns, particularly females. Public health messaging, interventions, and initiatives targeting these subgroups with integrated movement approaches may be an effective strategy for overweight and obesity prevention. Future research is needed to confirm and build upon these findings with objective measures of movement behaviors in large representative samples of youth.

Acknowledgments The authors would like to thank Chad Bredin (COMPASS study project manager), Dr. Dana Church (COMPASS study recruitment coordinator), and Audra Thompson-Haile (COMPASS school coordinator) for their assistance with this project. The COMPASS study was supported by a bridge grant from the Canadian Institutes of Health Research (CIHR) Institute of Nutrition, Metabolism and Diabetes (INMD) through the "Obesity—Interventions to Prevent or Treat" priority funding awards (OOP-110788; Grant awarded to ST. Leatherdale) and an operating grant from the Canadian Institutes of Health Research (CIHR) Institute of Population and Public Health (IPPH) (MOP-114875; Grant awarded to ST. Leatherdale).

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