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ORIGINAL ARTICLE

Clusters of non-dietary obesogenic behaviors among adolescents in Brazil: a latent profile analysis

Rafael M. Tassitano[1] · Robert G. Weaver[2] · Maria Cecília M. Tenório[1] · Keith Brazendale[3] · Michael W. Beets[2]

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Abstract

Objectives To identify patterns of non-dietary obesogenic behaviors, and social and environmental factors associated with overweight and obesity (OWOB).

Methods A representative sample (n = 5520) of high school students (55.4% girls, 16.3 ± 1.0 years) from Pernambuco State, Brazil. Latent profile analyses were performed using self-reported daily sleep duration, television use, computer use, videogame use, seated time during the week and weekend days, physical activity, and active commuting to school during the week. Social and environmental factors and body mass index were included to identify classes. Multinomial analysis explored differences in social, environmental factors, and BMI by classes.

Results Five patterns were identified [Computer users (C1), Short sleepers (C2), Typical behaviors (C3), Techno-active-gamers (C4), and Lower screen engagement (C5)]. Three groups (C1, C3 and C4) included students from better social conditions and a more urbanized environments. The prevalence of OWOB was higher in C1 (34.5%; 95% CI 31.1–38.0) and in C2 (29.7%; 95% CI 26.1–33.5) compared to C5 (23.3% 95% CI 21.3–25.3).

Conclusions In one of the poorest regions of Brazil, different groups of social/environmental factors and behavior patterns emerged associated with OWOB.

Keywords Behavior · Obesity · Public health · Socioeconomic risk factors · Adolescent

Introduction

Over the last decade, special attention has been given to the rising prevalence of overweight and obesity (OWOB) among youth in developing countries (Swinburn et al. 2011; Afshin et al. 2017; Ng et al. 2014; Abarca-Gómez et al. 2017; Finucane et al. 2011; CSDH 2008; Popkin et al. 2012; Prentice 2006; Ford et al. 2017; Hruby and Hu 2015; Rivera et al. 2014; Popkin et al. 2006). It is estimated that 1-in-4 youth in Latin America is OWOB, representing 16.5–21.1 million adolescents and 22.5–25.9 million school-age children (Rivera et al. 2014).

OWOB is the result of a complex web of interrelated obesogenic behaviors, as well as social and environmental factors. Urbanization (i.e., changing in lifestyle and living conditions from rural to urban) has been highlighted as a major driver for changes in global food systems (e.g., reductions in the time–cost of food, quality, and price) and the built environment (Swinburn et al. 2011; Monteiro et al. 2007), and this shift has facilitated the growth of a more obesogenic environment. In contrast to developed countries, urbanization in developing countries, especially middle-income countries, is occurring rapidly and, in some cases, there is differential reach of urbanization across the population (Chen et al. 2014). This differential reach has led to inequities in the social determinants of health disparities related to unhealthy weight. In Brazil, for example, rates of OWOB are accelerating faster in lower-income

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✉ Rafael M. Tassitano
rafael.tassitano@ufrpe.br

1 Department of Physical Education, Federal Rural University of Pernambuco, SN Dom Manoel de Medeiros St., Recife, PE 50630-610, Brazil

2 University of South Carolina, Columbia, SC, USA

3 University of Central Florida, Orlando, FL, USA

populations and in youth compared to high-income populations and adults. In addition, between 1974/1975 and 2008/2009, the prevalence of overweight has increased six-fold for boys (3.7–21.7%) and three-fold for girls (7.6–19.4%) (IBGE 2010). Data from the Brazilian National School Health Survey indicated a high prevalence of ultra-processed food consumption and physical inactivity, but that remained stable between 2009 and 2015 (Levy et al. 2010; Azeredo et al. 2015; Costa et al. 2018; Ferreira et al. 2018). However, considering the rapid and recent rise of access to screen-based media in Brazil, little is known about the impact of these additional drivers on the rate of obesity.

It is well recognized that behaviors can co-occur with one another through several pathways (Prochaska et al. 2008; Ottevaere et al. 2011; Leech et al. 2014; Fleary 2017), and often behaviors do not occur in isolation (Laxer et al. 2017). Based on the framework by Prochaska et al. (2008), identifying multiple health behaviors can help create an integrative approach to effective interventions. Currently, there are few studies that examine the co-occurring patterns of obesogenic behaviors, and social and environmental factors in relation to obesity, especially in middle-income countries (Ferrar et al. 2013; Leech et al. 2014). The purpose of this study was to: (1) identify different classes of adolescents based on non-dietary obesogenic behaviors in a middle-income country, Brazil; (2) verify the difference of social and environmental factors associated with the classes; (3) verify the variation in the prevalence of OWOB among the classes.

Methods

Sample and procedures

All data for this cross-sectional study were part of the 2016 data collection of the *Physical Activity and Health Risk Behaviors in High School Students of Pernambuco State (Brazil) study*. The Ethics Committee of Pernambuco State University approved this study (CAAE: 56341416.9.0000.5192). Pernambuco State (Gross Domestic Product (GDP) per capita in 2016 -U$ 5097) is located in the Northeast of Brazil (poor region by GDP/per capita in 2016-U$ 4502) with 9,473,266 inhabitants across 185 cities (57.8% classified as low Human Development Index). The capital (i.e., Recife) and metropolitan region comprises 45.5% of the inhabitants (95% in urban area), and 62% (n = 115) of the cities have less than 30,000 inhabitants.

The population of this study was high school students attending state funding public schools. In 2016, 288,770 students were enrolled in 740 public schools across 16 State Education Boards (SEB). Since 2011, there has been a transition in educational policy and as a result, the distinction of three different attendance times for public schools was formed: ‘regular’, ‘semi-integral’ and ‘integral’. In a regular school, the adolescents could attend classes from 7:30 am to 12:00 pm, 1:30 pm–6:00 pm, or 6:40 pm–10:00 pm. Adolescents from a semi-integral school attend classes from either 7:30 am–12:00 pm or 1:00 pm–5:30 pm, and in addition spend two or three weekdays attending school during the other shift. In the integral schedule they attend classes all weekdays from 7:30 am to 5:00 pm. Schools differed in student population size (< 200 students, 200–499 students, and > 500 students).

The sample size criteria were: population of 288,770 students, 95% confidence interval; 2% points of margin of error; estimated prevalence was set to 50%; design effect established at 2.0, and 20% increase in the minimum sample size due to dropouts and students who declined to participate. The minimum required sample size was 5,668 subjects. The sample was selected using a two-stage cluster sampling process. For the first stage, schools were randomly selected using probability proportionate to size sampling (PPS) based on SEB’s, school attendance and school size. The second stage incorporated PPS for youth in each classroom. The sampling of schools and classrooms were performed using a research randomizer program (www.randomizer.org).

Measurement

Data were collected between September and December 2016. Adolescents reported their city, sex (male or female), age (years), race (white or non-white), employment status (yes or no), home location (urban or rural), mother‘s education (< high school, high school or > high school), television at home (yes or no), computer at home (yes or no) and computer with internet at home (yes or no). School attendance (regular, semi-integral or integral) was obtained from the SEB. After data collection, the following information for each city was retrieved from the official site of Brazilian Institute of Geography and Statistics database: population (range: 5648–1,537,704), population density (ranged: 5.29–9603.0 Hab/km^2), GDP per capita (ranged: U$1647–U$10,778), external funding dependency (ranged 97.5–47.1%) and sanitation (ranged: 9.8–81.3%). These variables were transformed into z-scores, summed and classified into tertiles with tertile 1 representing a less urbanized environment and tertile 3 representing the most urbanized environment.

Information on the non-dietary obesogenic behaviors was obtained through an interview using an adapted version of the Global School-Based Student Health Survey (GSHS) developed by the World Health Organization. The non-dietary obesogenic behaviors assessed were sleep duration, television time, computer time, videogame time, sitting during leisure time during weekdays and weekend days, and moderate-to-vigorous physical activity, and active commuting to school.

Sleep duration “During the weekdays, on average, how many hours do you sleep per day?” and “During the weekend days, on average, how many hours do you sleep per day?”. The answers were expressed in hours/per day.

Television time “During weekdays, how much time do you spend per day watching television? and “During weekend days, how much time do you spend per day watching television?”. The answers were expressed in minutes/per day.

Computer time “During weekdays, how much time do you spend per day using computer? and “During weekend days, how much time do you spend per day using computer?”. The answers were expressed in minutes/per day.

Videogame time “During weekdays, how much time do you spend per day playing videogame? and “During weekend days, how much time do you spend per day playing videogame?”. The answers were expressed in minutes/per day.

Sitting during leisure time “During weekdays, how much time do you spend per day sitting talking with friends, playing cards, speaking on phone, reading, studying (do not consider the time on television, videogame, computer, smartphone or tablet)?” and “During weekend days, how much time do you spend per day sitting talking with friends, playing cards, speaking on phone, reading, studying (do not consider the time on television, videogame, computer, smartphone or tablet)?”. The answers were expressed in hours and minutes/per day.

Moderate-to-vigorous physical activity Total time was computed in minutes/per week from the combination of two questions: During a typical or usual week, on how many days do you practice moderate-to-vigorous physical activity? (0–7 days) and “In the days that you practice moderate-to-vigorous physical activity, how long time you spend?”. Answers were expressed in minutes, and a final variable was created by multiplying both questions presented in minutes/per week.

Active commuting to school The following two questions measured active commuting to school: “During a week, on how many days do you walk or ride a bicycle to and from school?”, answers ranged from 0 to 5 days. The second question asked, “During a week, on average, how much time per day do you spend commuting to and from school (consider the total time of the round-trip to and from school)?”, and the answers were expressed in minutes/per day. A final variable was created by multiplying the answers of both questions presented in minutes/per weekdays.

OWOB Weight and height were measured by trained research staff using a digital scale (Beurer, Beurer, Ulm, Germany) and portable stadiometer (Wiso E210, Wiso, Florianópolis, Brazil). Each height was estimated to the nearest 0.1 cm and all weights were estimated to the nearest 0.1 kg. Students were measured in light clothes and without shoes. Body mass index (BMI) was calculated as [weight (kg)/height (m^2)]. International sex-and age-specific cut points (IOTF) were used to define nutritional status (Cole and Lobstein 2012).

Statistical analyses

A latent profile analyses (LPA) was used to identify the number of groups (*k*-classes) and class membership based on non-dietary obesogenic behaviors as indicator variables. All other categorical (e.g., sex, race, mother scholarship, occupational status, living zone, television at home, computer with internet at home, school type and city index) and continuous (e.g., age) variables were used as covariates in the model. For all analyses, categorical variables were dummy coded as 0 or 1. The procedure to determine the number of classes and class membership followed three steps (Beets and Foley 2010; Muthén and Muthén 2012): (a) Model fit based on Bayesian information criteria (BIC), Akaike Information Criterion (AIC) and loglikelihood value (b) the Lo–Mendell–Rubin value that compares a model of k minus 1 ($k - 1$) classes with significant p values representing that the $k - 1$ is rejected (c) the entropy value (0.0–1.0) as criterion of the quality of class membership classification, which higher value is better. One-way analyses of variance (ANOVA) with Tukey Post hoc analysis was performed for all non-dietary obesogenic behavior to compare the differences between classes. Non-dietary obesogenic behaviors were transformed into *z-scores* to interpret the variation across class. Multinomial logistic regression was performed with group (i.e., class) as the dependent variable with individual, school, and environmental information predicting group membership. Finally, a binary logistic regression was performed using OWOB as an outcome and class membership as the primary exposure, adjusted for covariates. Significance was set at $p < 0.05$. All analyses were performed using Mplus version 7.1 (Muthen & Muthen, Los Angeles, California).

Results

A total of 5514 adolescents were interviewed and 5250 (95.2%) had complete data for all variables. The LPA identified 5 classes as the best solution (Table 1) Fig. 1 presents the means *z-score* of non-dietary obesogenic behaviors for each class, where *z*-score-based positive

Table 1 Model fit estimates for K class solutions for latent profile analysis, Brazil, 2016 (n = 5250)

Classes	Loglikelihood[a]	AIC[b]	BIC[c]	Entropy[d]	aLMR P for $K-1$[e]
2	− 325,753.94	651,707.91	651,935.81	0.97	< 0.001
3	− 325,734.36	651,668.73	646,818.09	0.94	< 0.001
4	− 323,221.41	646,642.85	643,708.75	0.96	< 0.001
5	− 320,343.74	640,887.56	641,731.64	0.95	< 0.001
6	− 325,136.27	650,472.58	651,522.10	0.94	0.50
7	− 325,757.67	651,715.33	652,970.34	0.91	0.24
8	− 323,092.35	646,384.71	647,845.03	0.89	0.23
9	− 322,558.10	645,316.28	646,981.90	0.88	0.21

[a]The larger Loglikelihood value represents the better model

[b]The smaller or lower Bayesian information criteria (BIC) value represents the better fit model

[c]The smaller or lower Akaike Information Criterion (AIC) value represents the better fit model

[d]Entropy is a measure of correct classification and range 0.0–1.0. High values are desirable

[e]Adjusted Vuong–Lo–Mendell–Rubin likelihood ratio test adjusted (aLMR) for $k-1$ class indicates that the value is significant than the current model fits the data better than a model specified with $k-1$ class

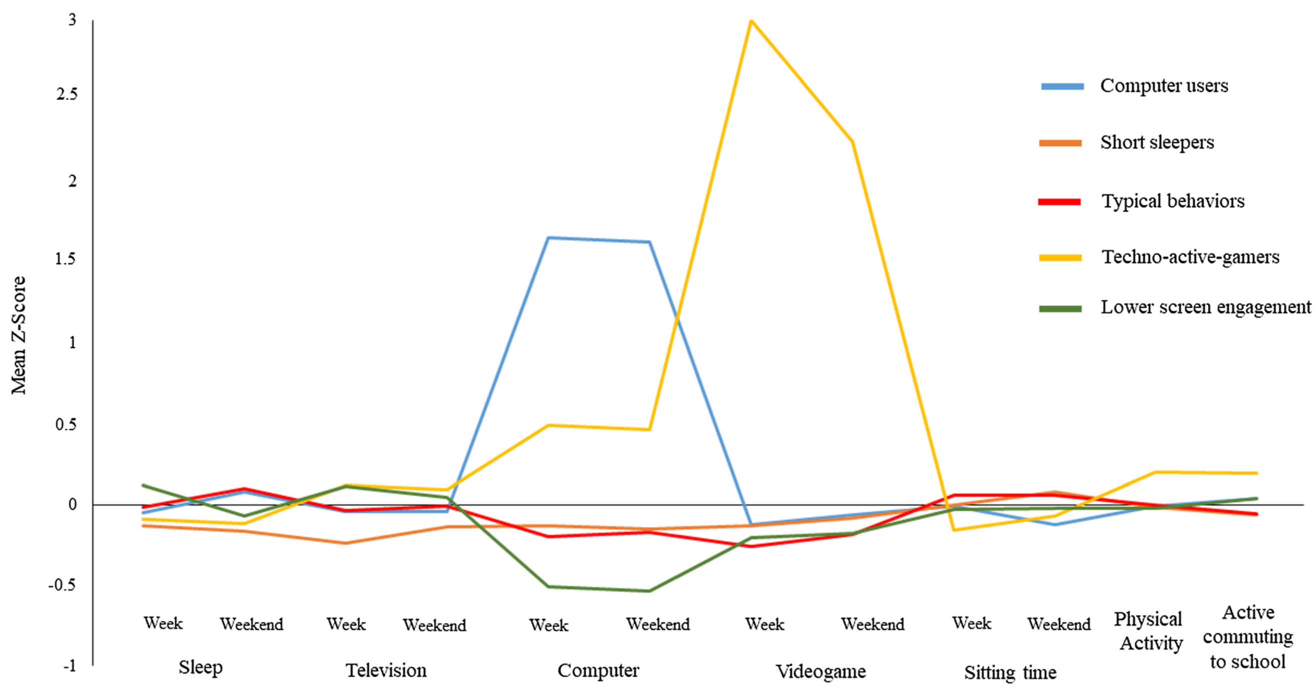

Fig. 1 Mean Z-score of all non-dietary obesogenic behaviors by week and weekend days and classes membership, Brazil, 2016

values indicate spending time on a given behavior above the average, while negative values indicate spending time on a given behavior below the average.

Table 2 summarizes characteristics of the total sample and differences between classes. Class 1 (n = 713;13.6%) was characterized by adolescents who had higher time using computers (labeled as "Computers users"), and spent a relatively average amount of time on others behaviors; Class 2 (n = 592;11.3%) were adolescents with shorter sleep duration on average who were also employed, labeled as "Short sleepers"; Class 3 (n = 1872; 35.7%) comprised adolescents who spent an average amount of time on most behaviors, labeled as "Typical behaviors", and represented the largest class and set as the reference for analyses; Class 4 (n = 335;6.4%) included adolescents who had higher time playing videogames, greater screen time, MVPA and active commuting to school, labeled as "Techno-active-gamers"; Class 5 (n = 1738; 33.1%) consisted of

Table 2 Descriptive characteristics of each cluster, Brazil, 2016 (n = 5250)

	Computer users (C1) n = 713 13.6%	Short sleepers (C2) n = 592 11.3%	Typical behaviors (C3) n = 1872 35.7%	Techno-active-gamers (C4) n = 335 6.4%	Lower screen engagement (C5) n = 1738 33.1%	Total sample n = 5250
Sex						
Boys	58.4[b,c,d]	59.1[e,f,g]	37.4[b,e,h,i]	86.3[c,f,h,j]	33.8[d,g,i,j]	44.6
Girls	41.6	40.9	62.6	13.7	66.2	55.4
Age						
14	3.8[a]	0.7[a,e,f,g]	4.2[e]	4.2[f]	3.5 [g]	3.5
15	23.2	10.8	24.3	20.3	18.6	20.5
16	33.1	23.8	34.0	31.9	31.5	31.8
17	28.0	37.3	27.2	30.4	31.1	30.0
18	11.9	27.4	10.3	13.1	15.4	14.3
Skin color						
White	25.2[a,d]	20.4[a]	23.3[i]	20.0[c]	18.3[d,i]	21.4
Non-white	74.8	79.6	76.7	80.0	81.7	78.6
Occupational status						
No	98.5[a]	0[a,e,f,g]	100[e]	92.2[f]	100 [g]	88.0
Yes	1.5	100	0	7.8	0	12.0
Zone						
Urban	87.0[a,d]	78.9[a,e,f,g]	86.8[e,i]	87.2[f,j]	68.9[d,g,i,j]	80.0
Rural	13.0	21.1	13.2	12.8	31.1	20.0
Mother education						
< High school	31.3[a,d]	54.5[a,e,f,g]	33.1[e,i]	34.8[f,j]	62.5[d,g,i,j]	44.9
High school	43.6	30.2	42.3	48.8	30.5	37.9
> High school	25.1	12.4	24.6	16.4	7.0	17.3
Television at home						
Yes	98.3	98.3	99.4	100	98.8	99.0
No	1.7	1.7	0.6	0.0	1.2	1.0
Computer at home						
Yes	97.5[a,d]	54.7[a,e,f,g]	100[b,e,h,i]	79.7[c,f,h,j]	0[d,g,i,j]	60.2
No	2.5	45.3	0	20.3	100	39.8
Computer with internet at home						
Yes	94.5[a,b,c,d]	52.5[a,e,f,g]	87.8[b,e,h,i]	75.5[c,f,h,j]	0[d,g,i,j]	56.2
No	5.5	47.5	12.2	24.5	100	43.8
School type						
Regular	41.0[a,d]	86.5[a,e,f,g]	40.7[e,i]	48.1[f,j]	56.7[d,g,i,j]	51.7
Semi-integral	25.5	8.3	25.3	24.8	23.5	22.7
Integral	33.6	5.2	34.0	27.2	19.8	25.6
City index						
1st tertile	38.0[a,d]	34.8[a,e,f,g]	38.1[e,i]	36.4[f,j]	45.7[d,g,i,j]	40.1
2nd tertile	21.8	38.2	25.4	26.3	33.0	28.9

Table 2 (continued)

	Computer users (C1) n = 713 13.6%	Short sleepers (C2) n = 592 11.3%	Typical behaviors (C3) n = 1872 35.7%	Techno-active-gamers (C4) n = 335 6.4%	Lower screen engagement (C5) n = 1738 33.1%	Total sample n = 5250
3rd tertile	40.2	27.0	36.5	37.3	21.3	31.0

[a]Difference between C1 and C2
[b]Difference between C1 and C3
[c]Difference between C1 and C4
[d]Difference between C1 and C5
[e]Difference between C2 and C3
[f]Difference between C2 and C4
[g]Difference between C2 and C5
[h]Difference between C3 and C4
[i]Difference between C3 and C5
[j]Difference between C4 and C5

adolescents who predominantly spent less time on computers and videogames, and was labeled as "Lower screen engagement". Adolescents from Computer users, Typical behaviors, and Techno-active-gamers classes were typically from urban areas, with mothers had who have more than a high school education, lived in an area with a higher city profile index, and had access to a computer with internet at home, compared to adolescents from Short sleepers and Lower screen engagement classes ($p < 0.05$).

In Table 3 the mean values of non-dietary obesogenic behaviors by class membership are presented. Regardless of class membership (except for videogame use in Techno-active-gamers class), adolescents reported more time sleeping, watching television, using computers and videogames, and sitting during leisure time, during the weekend days compared to weekdays. Computer users (34.5% 95% CI 31.1–38.0) and Short sleepers (29.7% 95% CI 26.1–33.5) had a statistically significant higher rate of OWOB compared to the Lower screen engagement class (23.3% 95% CI 21.3–25.3).

The hierarchical multinomial analyses indicated that the odds of boys were at least two times greater to be in classes with higher computer and videogame time, and in a class with lower time spent sleeping, compared to girls in relation to the typical behaviors class (Table 4). Younger adolescents who reported a lower levels of maternal education, living in a more urbanized city, and were from an integral school had lower odds to be in Short sleepers and Lower screen engagement classes compared to the reference.

Finally, adjusted regression analysis indicated that adolescents from Computer users are more likely to be OWOB [1.52 (CI 95% 1.25–1.86)] compared to the reference.

Discussion

This study identified five distinct non-dietary obesogenic behavior classes associated with social and environmental factors in adolescents from a single state in a middle-income country. While similar patterns of some non-dietary obesogenic behaviors (i.e., sitting during leisure time and television time) and daily variation (weekdays vs weekend days) were observed across the classes, differences among classes that carry important implications for the prevention and treatment of childhood obesity emerged. Specifically, some behaviors were more prevalent in computer users, typical behaviors and techno-active-gamers classes. Adolescents in these classes typically had better social conditions and lived in a more urbanized environment. The behaviors that distinguished these groups were computer and videogame use, more engagement in MVPA, and active commuting to school. Sleep duration seemed to be more related with environmental (i.e., city-dependent factors like access to internet in a low city index) than social conditions (i.e., income-driven factors like mother education). Findings also indicate differences in OWOB by classes and ranged between 23.3% (21.3–25.3) and 34.5% (31.1–38.0).

The findings of this study have important implications for public health efforts seeking to address OWOB in adolescents living in middle-income countries. Low- and middle-income countries are undergoing social and economic transitions (Chen et al. 2014). These transitions are characterized by increased access to screens, unhealthy processed foods, and motorized transportation (Swinburn et al. 2011; Popkin et al. 2012;Prentice 2006; Ford et al. 2017; Hruby and Hu 2015; Monteiro et al. 2013). Thus,

Table 3 Mean values of each cluster solutions and results of ANOVA and Tukey post hoc test, Brazil, 2016 (n = 5250)

Variables	Computer users (C1) 713 (13.6%) Mean (95% CI)	Short sleepers (C2) 592 (11.3%) Mean (95% CI)	Typical behaviors class (C3) 1872 (35.7%) Mean (95% CI)	Techno-active-gamers (C4) 335 (6.4%) Mean (95% CI)	Lower screen engagement (C5) 1738 (33.1%) Mean (95% CI)	F
Sleep duration (h/week day)	7.11 (7.00–7.22)^{d}	6.97 (6.86–7.09)^{g}	7.15 (7.08–7.22)^{i}	7.04 (6.88–7.20)^{j}	7.37 (7.30–7.45)^{d,g,i,j}	10.8
Sleep duration (h/weekend day)	8.26 (8.13–8.38)^{a,d}	7.85 (7.71–7.98)^{a,e}	8.29 (8.21–8.36)^{e,i}	8.11 (7.92–8.30)	8.00 (7.91–8.08)^{d,i}	12.0
Television (min/week day)	111.4 (104.1–118.3)^{a,d}	92.6 (86.2–99.1)^{a,e,f,g}	111.2 (107–115.2)^{e,h,i}	126.0 (115.6–136.0)^{f,h}	125.8 (121.5–130.1)^{d,g,i}	17.3
Television (min/weekend day)	139.5 (131.4–147.8)^{c}	128.2 (119.7–136.6)^{e,f,g}	143.0 (138.1–147.8)^{e,h}	165.3 (153.3–176.9)^{c,f,h,j}	148.1 (143.3 –153.0)^{g,j}	57.4
Computer (min/week day)	202.5 (195.5–209.4)^{a,b,c,d}	48.0 (42.0–53.9)^{a,f,g}	41.1 (38.9–43.3)^{b,h,i}	101.2 (89.9–112.5)^{c,f,h,j}	14.6 (12.6–16.5)^{d,g,i,j}	1216.6
Computer (min/weekend day)	243.5 (236.9–250.8)^{a,b,c,d}	57.7(50.6–64.9)^{a,f,g}	54.0 (51.1–56.9)^{b,h,i}	121.5 (109.7–134.6)^{c,f,h,j}	17.4 (15.0–19.9)^{d,g,i,j}	1270.9
Videogame (min/week day)	13.9 (11.4–16.5)^{b,c}	14.0 (11.0–17.0)^{e,f}	6.6 (5.7–7.5)^{b,e,h,i}	192.4 (184.3–200.5)^{c,f,h,j}	9.8 (8.4–11.5)^{i,j}	2278.7
Videogame (min/weekend day)	23.2 (19.4–27.8)^{b,c,d}	22.0 (17.5–26.4)^{e},^{f}	15.0 (13.1–17.0)^{b,e,h}	181.9(169.3–194.4)^{c,f,h,j}	15.5 (13.3–17.8)^{d,j}	702.9
Sitting (min/week day)	165.5 (159.3–171.7)	165.4 (158.4–172.4)	171.2 (167.4–175.0)^{h}	152.8 (144.1–161.4)^{h}	164.3 (160.4–168.2)	4.10
Sitting (min/weekend day)	180.9 (174.6–187.7)^{a,b}	197.3 (190.1–204.5)^{a}	195.8 (191.9–199.7)^{b}	183.1 (174.1–192.0)	189.2 (185.1–193.4)	5.80
Moderate-to-vigorous Physical Activity (min/week)	331.4 (309.7– 353.2)^{c}	329.3 (304.8–353.8)^{f}	332.8 (319.5–346.1)^{h}	386.4 (354.0–418.1)^{c,f,h,j}	328.2 (315.0–341.4)^{j}	2.9
Active commuting to school (min/week)	188.1 (173.8–202.3)	170.2 (155.4–184.9)^{f}	170.7 (162.6–178.8)^{h,i}	214.0 (192.6–235.3)^{f,h}	188.6 (179.8–197.3)^{i}	5.6
Overweight	25.5 (22.4–28.8)^{j}	22.0 (18.8–25.4)	19.3 (17.5–21.1)	20.3 (16.3–24.9)	17.3 (15.5–19.1)	< 0.05
Obesity	9.0 (7.1–11.3)	7.7 (5.8–10.2)	7.4 (6.2–8.6)	6.3 (4.1–9.3)	6.0 (5.0–7.2)	ns
Overweight/obesity	34.5 (31.1–38.0)^{b,d}	29.7 (26.1–33.5)^{g}	26.7 (24.7–28.7)	26.6 (22.1–31.5)	23.3 (21.3–25.3)	< 0.001

[a] Difference between C1 and C2

[b] Difference between C1 and C3

[c] Difference between C1 and C4

[d] Difference between C1 and C5

[e] Difference between C2 and C3

[f] Difference between C2 and C4

[g] Difference between C2 and C5

[h] Difference between C3 and C4

[i] Difference between C3 and C5

[j] Difference between C4 and C5

Table 4 Adjusted multinomial logistic regression and relative risk ratio (95% CI) for background variables in cluster solutions, Brazil, 2016 (n = 5250)

Variables	Computer users (C1)		Short sleepers (C2)		Techno-active-gamers (C4)		Lower screen engagement (C5)	
	713 (13.6%)		592 (11.3%)		334 (6.4%)		1738 (33.1%)	
	RRR (95% CI)	p	RRR (95% CI)	p	RRR (95% CI)	p	RRR (95% CI)	p
Boys	2.38 (1.97–2.87)	< 0.01	2.44 (1.98–3.00)	< 0.01	10.37 (7.35–14.62)	< 0.01	0.93 (0.80–1.10)	0.39
14–16 years	0.94 (0.78–1.13)	0.52	0.37 (0.30–0.47)	< 0.01	1.01 (0.77–1.31)	0.95	0.79 (0.67–0.91)	0.01
White	1.03 (0.83–1.28)	0.77	0.81 (0.63–1.05)	0.11	0.88 (0.63–1.09)	0.49	0.74 (0.62–0.89)	0.01
Mother scholarship								
High school	1.03 (0.80–1.33)	0.78	0.51 (0.36–0.73)	< 0.01	1.02 (0.76–1.37)	0.88	0.39 (0.33–0.46)	< 0.01
≥ High school	1.05 (0.85–1.31)	0.31	0.53 (0.41–0.74)	< 0.01	0.57 (0.38–0.83)	0.01	0.16 (0.12–0.50)	< 0.01
School type								
Semi-integral	0.97 (0.78–1.21)	0.84	0.13 (0.09–0.18)	< 0.01	0.81 (0.60–1.10)	0.17	0.61 (0.51–0.72)	< 0.01
Integral	0.99 (0.80–1.24)	0.97	0.05 (0.04–0.08)	< 0.01	0.65 (0.48–0.88)	0.01	0.37 (0.31–0.44)	< 0.01
Urban	0.99 (0.76–1.28)	0.94	0.89 (0.68–1.15)	0.37	1.10 (0.76–1.57)	0.61	0.45 (0.37–0.53)	< 0.01
City index								
2nd tertile	1.16 (0.91–1.48)	0.21	1.33 (1.04–1.70)	0.02	1.20 (0.70–2.06)	0.49	1.18 (0.99–1.41)	0.06
3rd tertile	1.28 (1.02–1.61)	0.03	0.51 (0.40–0.65)	< 0.01	1.33 (0.81–2.20)	0.26	0.51 (0.43–0.61)	< 0.01

Typical behaviors class (n = 1872) was used as a reference class; Intraclass correlation coefficient ICC class level = 5.48e−31; ICC School level = .0019575, and ICC School Education Board level = 2.77e−32; RRR = Relative risk ratio

subpopulations of adolescents in the midst of these transitions may be at risk for adopting unhealthy behaviors.

One potential reason for differences in obesogenic behaviors and OWOB rates across classes could be the urbanization process. Studies have reported a positive relationship between urbanization and rising OWOB rates in middle-income countries (Popkin et al. 2012; Prentice 2006; Ford et al. 2017; Monteiro et al. 2007), especially in youth (Popkin et al. 2006). Social and environmental inequity is also well documented between and within Brazilian regions, states, and cities. These inequities affect the availability and accessibility of goods (e.g., computer) and services (e.g., internet, leisure physical activity facilities) associated with obesogenic behaviors (PNAD 2016). Even though previous research has reported disparities in obesogenic behaviors and OWOB by comparing groups based on socioeconomic status or region in Brazil (IBGE 2010; Ferreira et al. 2018; Bloch et al. 2016), little is known about the behaviors and OWOB in subpopulations. The current evidence indicates that adolescents of a higher socioeconomic status (e.g., income, parent scholarship, private school *vs* public school) in a more urbanized regions (i.e., South and Southeast) are more likely to be physically active in leisure time and less active during commuting to school and have higher prevalence of OWOB (IBGE 2010; Ferreira et al. 2018; Bloch et al. 2016). In addition, a recent systematic review indicated a positive association between socioeconomic status (i.e., income and parent scholarship) and total screen time, computer and videogame time, but not television time, in adolescents from low-middle-income countries (most data from Brazil) (Mielke et al. 2017). Our results support this evidence and the urbanization process related to availability and accessibility of goods and services. As seen in the majority of Brazilian households, TV is widespread regardless of social status; however, the access to computer with internet at home is not yet commonplace.

Extending upon previous findings, our study shows that even in a state located in the poorest region of Brazil, social and environmental disparities exist in adolescents from public schools. Further, there are distinct patterns of behaviors and OWOB rates that differ by socioeconomic status. Three classes demonstrated social and environmental factors that were comparatively better than the other two classes. These classes were Computer users, Typical behaviors and Techno-active-gamers. For example, in these three classes mother's completion of high school and access to a computer with internet at home were higher than expected for students enrolled in public schools from Northeast (PNAD 2016; Ferreira et al. 2018). This indicates that theses adolescent's families had higher income than the others two classes. In other words, they have more access to goods and services, and, thus, differential patterns related to screen time use is expected across adolescents from different social and environmental conditions.

Additionally, the present study identified different patterns of screen time use, MVPA and active commuting to school among adolescents in these three classes. This is an important finding since the prevalence of OWOB of adolescents from Computer users were significantly higher compared to those in the Typical behaviors class. Put simply, excessive time on the computer could be an important factor that is related to increased risk for OWOB. It is also important to note that no significant differences between prevalence of OWOB and sex were observed among adolescents in the same class (data not shown). Moreover, the Techno-active-gamers had similar duration of total screen time compared to Computer users, but the prevalence of OWOB was lower ($p = 0.07$) and similar to the Typical behaviors class. This result could be interpreted in two ways. High computer usage could be a more important risk factor for OWOB than the total screen time, or is it the distribution of time across screen time devices? In this case higher screen time with a large proportion of time spent playing videogames was related to higher MVPA and active commuting to school. This is an important finding since we did not expect to find different patterns of MVPA and active commuting to school in these students. The authors of the present study speculate that videogame use could have influenced active choices, such as commuting to school and engagement in more MVPA. However, the majority ($\sim$ 80%) of adolescents in this class were male, therefore this finding may be a function of sex rather than the other characteristics. This class is similar to other classes of children that report high activity and video game use in previous studies. For example, a recent, systematic review reported that their "technoactives" cluster/class were identified by eight of 18 studies of obesogenic behaviors which employed latent class analysis or cluster analysis (Ferrar et al. 2013). Our study reinforces the global monoculture associated with technology in youth worldwide.

Short sleep duration in adolescents has been associated with increased risk for OWOB (Sluggett et al. 2019), and our study shows that the environment plays a larger role in sleep duration compared to social factors of adolescents in lower social conditions. Our findings both confirm and extend previous evidence by considering the environment for youth in middle-income countries. All adolescents in the Short sleepers class are workers and the observed higher association with OWOB could be related to occupational factors. For example, adolescents of this class have the same school start time as the other classes, therefore may have late bedtimes due to work commitments and the quality of sleep may be worse than the other classes given laboral activity and/or the workplace environment that they are exposed.

It is difficult to directly compare the results of this study to other studies due to the methodological differences (Ferrar et al. 2013). Additionally, most previous studies have been conducted in high-income countries. For example, Iannotti and Wang (2013) using the same statistical approach in a nationally representative sample of U.S adolescents and found differences in obesity between the identified classes, although these differences were smaller when compared to our results. This could be due to the prevalence of obesity being higher and the trajectory of OWOB becoming more 'stable' in developed countries as reported in recent time series studies (Ng et al. 2014; Abarca-Gómez et al. 2017; Finucane et al. 2011), or on the other hand, this may be explained by the improved 'access' to goods and services (i.e., becoming more urbanized) for the total population and, thus, differences are less likely to be identified in these rapidly-changing countries. In addition, findings from two systematic reviews of co-occurrence behavioral patterns indicated that the identified subpopulations are specific to the cultures and population (Leech et al. 2014; Ferrar et al. 2013).

Our findings provide more evidence of adolescents' behavioral patterns related to OWOB and have implications for targeted health interventions to adolescents from different social conditions and environments. Interventions for classes with better social conditions could target schools' extra-curricular programs since the majority of time is spent at school. In that case, expand and/or extend opportunities of physical activity during the school time to replace sedentary time (Beets et al. 2016). Moreover, intervention efforts should also focus on weekend days, particularly youth characterized as computer users and techno-active-gamers, due to the high levels of observed screen time. For working adolescents, a comprehensive approach should be considered due to the various they attend during the day. This study has several strengths. First, BMI was measured in a representative sample of adolescents from a state in the poorest region in a middle-income country. Second, this study used a latent profile analysis, allowing for the input of simultaneous covariates in the model to identify classes, and thereby, has demonstrated different patterns associated to OWOB. Third, a broad number of non-dietary obesogenic behaviors were measured on weekdays and weekends, compared to previous studies. However, there are limitations that must be considered when interpreting the results. First, even though a large and representative sample of adolescents from public schools were used, the results cannot be generalized to adolescents from the same region or other regions, or adolescents enrolled in private schools in the same state. Second, all behaviors were self-reported, and it could be representing a bias. Third, data on dietary behaviors were not collected. Fourth, we used demography, economic and environmental indicators as a proxy for urbanization. While these are commonly reported metrics from the Brazilian government there is no universally accepted measure of urbanization. Thus, the findings of this study related to urbanization may only apply to Brazil.

Future studies should investigate the attitudes and behaviors related to specific screen devices to determine when and how it could affect other risk behaviors related to OWOB (e.g., MVPA and diet). In addition, longitudinal studies are crucial to better understand how social and environmental factors are associated with non-dietary obesogenic behaviors patterns over time and how this impacts OWOB in youth.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

Ethical Statement All procedures performed were in accordance with ethical standards of the Ethics Committee Research of Pernambuco State University and with 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants involved in the study.

References

Abarca-Gómez L, Abdeen ZA, Hamid ZA, NCD Risk Factor Collaboration (NCD-RisC) (2017) Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 1289 million children, adolescents, and adults. Lancet 390:2627–2642. https://doi.org/10.1016/S0140-6736(17)32129-3

Afshin A, Forouzanfar MH, Reitsma MB, GBD 2015 Obesity Collaborators (2017) (2017) Health effects of overweight and obesity in 195 countries over 25 years. N Engl J Med 377:13–27. https://doi.org/10.1056/NEJMoa1614362

Azeredo CM, Rezende LFM, Canella DS, Claro RM, Castro IRR, Carmo Luiz O et al (2015) Dietary intake of Brazilian adolescents. Public Health Nutr 18:1215–1224

Beets MW, Foley JT (2010) Comparison of3 different analytic approaches for determining risk-related active and sedentary behavioral patterns in adolescents. J Phys Act Health 7:381–392

Beets MW, Okely A, Weaver RG, Webster C, Lubans D, Brusseau T et al (2016) The theory of expanded, extended, and enhanced opportunities for youth physical activity promotion. Int J Nutr Phys Act 13:120. https://doi.org/10.1186/s12966-016-0442-2

Bloch KV, Klein CH, Szklo M, Kuschnir MCC, Abreu GA, Barufaldi LA et al (2016) ERICA: prevalências de hipertensão arterial e obesidade em adolescentes brasileiros. Rev Saúde Pública 50:1–13. https://doi.org/10.1590/s01518-8787.201605000supl1ap

Chen M, Zhang H, Liu W, Zhang W (2014) The global pattern of urbanization and economic growth: evidence from the last three decades. PloS ONE 9:e103799. https://doi.org/10.1371/journal.pone.0103799

Cole TJ, Lobstein T (2012) Extended International (IOTF) body mass index cut-offs for thinness, overweight and obesity. Pediatric Obesity 7:284–294. https://doi.org/10.1111/j.2047-6310.2012.00064.x

Costa CSC, Flores TR, Wendt A, Neves RG, Assuncao MCF, Santos IS (2018) Sedentary behavior and consumption of ultra-processed foods by Brazilian adolescents: Brazilina National School Health Survey (PeNSE), 2015. Cad Saude Publica 34(3):e00021017. https://doi.org/10.1590/0102-311X00021017

CSDH (2008) Closing the gap in a generation: health equity through action on the social determinants of health. Final Report of the Commission on Social Determinants of Health, Geneva, World Health Organization

Ferrar K, Chang C, Li M, Olds TS (2013) Adolescent time use cluster: a systematic review. J Adoles Health 52:259–270

Ferreira RW, Varela AR, Monteiro LZ, Hafele CA, Santos SJ, Wendt A et al (2018) Desigualdades sociodemográficas na prática de atividade física de lazer e deslocamento ativo para a escola em adolescentes: Pesquisa Nacional de Saúde do Escolar (PeNSE 2009, 2012 e 2015). Cad Saúde Pública 34:e00037917. https://doi.org/10.1590/0102-311x00037917

Finucane MM, Stevens GA, Cowan MJ, Danaei G, Kin JK, Paciorek CJ et al (2011) National, regional, and global trends in body-mass index since 1980: systematic analysis of health examination surveys and epidemiological studies with 960 country-years and 91 million participants. Lancet 377:557–567. https://doi.org/10.1016/s0140-6736(10)62037-5

Fleary SA (2017) Combined patterns of risk for problem and obesogenic behaviors in adolescents: a latent class analysis approach. J Sch Health 87:182–193. https://doi.org/10.1111/josh.12481

Ford ND, Patel SA, Narayan KM (2017) Obesity in low- and middle-income countries: burden, drivers, and emerging challenges. Annu Rev Public Health 38:145–164. https://doi.org/10.1146/annurev-publhealth-031816-044604

Hruby A, Hu F (2015) The epidemiology of obesity: a big picture. Pharmacoeconomics 33:673–689. https://doi.org/10.1007/s40273-014-0243-x

Iannotti RJ, Wang J (2013) Patterns of physical activity, sedentary behavior, and diet in U.S. adolescents. J Adolesc Health 53:280–286. https://doi.org/10.1016/j.jadohealth.2013.03.007

Instituto Brasileiro de Geografia e Estatística (IBGE) (2010) Pesquisa de orçamentos familiares 2008–2009: Antropometria e Estado Nutricional de Crianças, Adolescentes e Adultos no Brasil. Rio de Janeiro: IBGE; http://www.ibge.gov.br/home/estatistica/populacao/condicaodevida/pof/2008_2009_encaa/pof_20082009_encaa.pdf

Laxer RE, Brownson RC, Dubin JA, Cooke M, Chaurasia A, Leatherdale ST (2017) Clustering of risk-related modifiable behaviours and their association with overweight and obesity among a large sample of youth in the COMPASS study. BMC Public Health 17:102. https://doi.org/10.1186/s12889-017-4034-0

Leech RM, McNaughton SA, Timperio A (2014) The clustering of diet, physical activity and sedentary behavior in children and adolescents: a review. Int J Nutr Phys Act 11:4. https://doi.org/10.1186/1479-5868-11-4

Levy RB, Castro IRR, Cardoso LO, Tavares LF, Sardinha LMV, Gomes FS et al (2010) Consumo ecomportamento alimentar entre adolescents brasileiros: Pesquisa Nacional de Saúde do Escolar (PeNSE)2009. Ciênc Saúde Coletiva 15(2):3085–3097
Mielke GI, Brown WJ, Nunes BP, Silva ICM, Hallal PC (2017) Socieconomic correlates of sedentary behavior in adolescents: systematic review and meta-analysis. Sports Med 47:61–75
Monteiro CA, Conde WL, Popkin BM (2007) Income-specific trends in obesity in Brazil: 1975–2003. Am J Public Health 97:1808–1812
Monteiro CA, Moubarac JC, Cannon G, Ng SW, Popkin B (2013) Ultra-processed products are becoming dominant in the global food system. Obes Rev 2:21–28. https://doi.org/10.1111/obr.12107
Muthén LK, Muthén BO (2012) Mplus user's guide: statistical analysis with latent variables, 7th ed. Author, Los Angeles, CA
Ng M, Fleming T, Robinson M, Thomson B, Graetz N, Margono C et al (2014) Global, regional, and national prevalence of overweight and obesity in children and adults during 1980–2013: a systematic analysis for the Global Burden of Disease Study 2013. Lancet 30:766–781. https://doi.org/10.1016/s0140-6736(14)60460-8
Ottevaere C, Huybrechts I, Benser J, Bourdeaudhuij ID, Cuenca-Garcia M, Dallongeville J et al (2011) Clustering patterns of physical activity, sedentary and dietary behavior among European adolescents: The HELENA study. BMC Public Health 11:328. https://doi.org/10.1186/1471-2458-11-328
Pesquisa Nacional por amostra de Domicílios (PNAD) (2016) Contínua. A internet e a televisão e posse de telefone móvel celular para uso pessoal em 2016. Instituto Brasileiro de Geografia e Estatística. Pesquisa Nacional de Saúde. ISBN 978-85-240-4445-8
Popkin BM, Conde W, Hou N, Monteiro C (2006) Is there a lag globally in overweight trends for children compared with adults? Obesity (Silver Spring) 2006:1846–1853
Popkin BM, Adair LS, Ng SW (2012) Global nutrition transition and the pandemic of obesity in developing countries. Nutr Rev 70:3–21. https://doi.org/10.1111/j.1753-4887.2011.00456.x
Prentice AM (2006) The emerging epidemic of obesity in developing countries. Int J Epidemiol 35:93–99
Prochaska JJ, Spring B, Nigg CR (2008) Multiple health behavior change research: An introduction and overview. Prev Med 46:181–188. https://doi.org/10.1016/j.ypmed.2008.02.001
Rivera JA, de Cossío TG, Pedraza LS, Aburto TC, Sánchez TG, Martorell R (2014) Childhood and adolescent overweight and obesity in Latin America: a systematic review. Lancet Diabetes Endocrinol 2:321–332. https://doi.org/10.1016/s2213-8587(13)70173-6
Sluggett L, Wagner SL, Harris L (2019) Sleep duration and obesity in children and adolescents. Can J Diabetes 43:146–152
Swinburn BA, Sacks G, Hall KD, McPherson K, Finegood DT, Moodie ML et al (2011) The global obesity pandemic: shaped by global drivers and local environments. Lancet 27:804–814. https://doi.org/10.1016/s0140-6736(11)60813-1

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