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Health-Related Quality of Life and Lifestyle Behavior Clusters in School-Aged Children from 12 Countries

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Objective To evaluate the relationship between children's lifestyles and health-related quality of life and to explore whether this relationship varies among children from different world regions.

Study design This study used cross-sectional data from the International Study of Childhood Obesity, Lifestyle and the Environment. Children (9-11 years) were recruited from sites in 12 nations (n = 5759). Clustering input variables were 24-hour accelerometry and self-reported diet and screen time. Health-related quality of life was self-reported with KIDSCREEN-10. Cluster analyses (using compositional analysis techniques) were performed on a site-wise basis. Lifestyle behavior cluster characteristics were compared between sites. The relationship between cluster membership and health-related quality of life was assessed with the use of linear models.

Results Lifestyle behavior clusters were similar across the 12 sites, with clusters commonly characterized by (1) high physical activity (actives); (2) high sedentary behavior (sitters); (3) high screen time/unhealthy eating pattern (junk-food screenies); and (4) low screen time/healthy eating pattern and moderate physical activity/sedentary behavior (all-rounders). Health-related quality of life was greatest in the all-rounders cluster.

Conclusions Children from different world regions clustered into groups of similar lifestyle behaviors. Cluster membership was related to differing health-related quality of life, with children from the all-rounders cluster consistently reporting greatest health-related quality of life at sites around the world. Findings support the importance of a healthy combination of lifestyle behaviors in childhood: low screen time, healthy eating pattern, and balanced daily activity behaviors (physical activity and sedentary behavior). *(J Pediatr 2017;183:178-83).*

Trial registration ClinicalTrials.gov: NCT01722500.

Health-related quality of life (HRQoL) is an important indicator of children's physical, mental, and social wellbeing.[1,2] Self-reported HRQoL is studied widely among children with chronic diseases or specific health conditions (eg, Law et al[3]). In addition, studies have begun to investigate the relationship between HRQoL and lifestyle behaviors, such as physical activity (PA) and diet.[4-8]

The HRQoL of children has been associated positively with PA, sleep, and healthy diet and negatively associated with screen time.[4-8] These studies have examined lifestyle behaviors as individual entities, without considering their interdependence.[9] The relationship between patterns of lifestyle behaviors and the HRQoL of children has, to our knowledge, only been investigated in 2 previous studies.[10,11] These studies suggest that HRQoL differs across lifestyle clusters, yet the results should be considered in the context of certain limitations. First, clusters were based on time use only and did not consider other lifestyle behaviors. Second, the closed nature and subsequent multicollinearity of time use was not accounted for in the statistical analyses.

BMI	Body mass index
FFQ	Food Frequency Questionnaire
HRQoL	Health-related quality of life
ISCOLE	International Study of Childhood Obesity, Lifestyle and the Environment
PA	Physical activity

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Notably, previous research on the HRQoL of children and lifestyle behaviors has been conducted almost exclusively in high-income nations. It generally is accepted that there are discrepancies in the way children from different cultures rate their own health and well-being.[12] Two recent multinational studies of children's subjective well-being found that although there tended to be a positive correlation between a country's socioeconomic status and subjective well-being, differences in well-being were most likely linked to individual-level factors (home situation) and area-level factors (school), rather than country-level factors (gross domestic product, Human Development Index).[12,13]

Observation of secular trends in children's PA, sedentary behavior, and diets has identified a progressive "Westernization" in many low-middle income nations, particularly in urban environments.[14-16] Specifically, a decline in PA, increase in screen time, and an increasing intake of "junk" foods have been reported widely in low-middle income nations.[15,17] An understanding of children's lifestyle behavior patterns and the links with HRQoL is crucial for policy development and proactive planning.

This study aims to (1) describe the HRQoL of children across sites in 12 different nations; (2) explore how school-aged children cluster in lifestyle behavior groups by the use of a comprehensive range of behaviors and by the application of compositional analysis techniques; and (3) explore the associations between HRQoL and membership of clusters.

Methods

Data from the cross-sectional International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE) were used (ClinicalTrials.gov: NCT01722500). A detailed description of the ISCOLE protocol can be found in the work of Katzmarzyk et al.[18]

Participants were recruited from schools in study sites spread across 12 countries (Australia, Brazil, Canada, China, Colombia, Finland, India, Kenya, Portugal, South Africa, England, and the US). From these schools, children aged 9-11 years were invited to participate.

A sex-balanced sample of approximately 500 children from each site contributed to the final sample of 7372. Participants were excluded if they had incomplete data for HRQoL (n = 74), as well as accelerometry (n = 1185), screen time (n = 2), eating pattern (n = 102), and sociodemographic covariate data (n = 250), yielding a final sample of 5759 children (3168 girls and 2591 boys). Excluded participants were more likely to be male ($P < .001$), have parents of lower education ($P < .001$), and have more siblings ($P < .001$) than included participants. Excluded participants also differed from included participants by greater screen time ($P < .001$), body mass index (BMI) z score ($P < .001$), and greater unhealthy eating pattern ($P < .001$).

Ethical approval was obtained from the institutional review board of the Pennington Biomedical Research Center in Baton Rouge, Louisiana, by the ISCOLE coordinators. Site-specific ethical approval also was received at each participating study site. Parental written informed consent and child assent were obtained as required by local review boards.

Child participants completed the KIDSCREEN-10[19] to provide a global measure of their HRQoL. The KIDSCREEN-10 is the brief form of a measure originally developed in Europe, using a participatory approach across 13 countries, with and for children aged 8-18 years. The KIDSCREEN instrument has been validated in numerous low- and middle-income countries and is used widely around the world.[20-23] The KIDSCREEN-10 is composed of 10 questions related to respondents' PA, energy and fitness, moods and emotions, social and leisure participation, social and family relationships, cognitive capacity, and school experience. Responses are recorded on a 5-point response scale and reversed where necessary to ensure that greater scores indicate better HRQoL. In countries in which the KIDSCREEN-10 had not been used previously, the questions were translated systematically to the local language following rigorous procedures outlined by Kidscreen.[24] Items for each participant were summed and used to calculate Rasch person-variables, which subsequently were transformed into T values with a mean of 50 and a SD of approximately 10.[19]

Daily activities (light, moderate, and vigorous PA; sedentary behavior; and sleep) were measured objectively by 24-hour, 7-day accelerometry. Participants were instructed to wear an ActiGraph GT3X+ accelerometer (ActiGraph LLC, Pensacola, Florida) on their right hip. The mean daily wear-time was 22.8 hours. To be included, participants were required to have ≥10 hours per day waking wear time (on at least 4 days, including at least 1 weekend day) and ≥160 minutes total sleep period for at least 3 nights (including 1 weekend night).[25] Activity was sampled at 80 Hz and downloaded in 1-second epochs, which were aggregated into 60-second epochs to estimate nocturnal sleep duration via a previously published algorithm.[26] Waking-wear time was processed in 15-second epochs to determine time vigorous, moderate, and light PA and sedentary behavior, as defined by Evenson et al.[27] Each component (sedentary behavior; light, moderate, and vigorous PA; and sleep) was weighted for weekdays:weekend days at 5:2.

Participants reported typical weekday and weekend day non-school time spent (1) watching television and (2) playing computer or video games in categories of none, <1, 1, 2, 3, 4, and ≥5 hours. Both television and video/computer time were combined to form a continuous variable representing "screen time." Typical weekday and weekend day screen time were weighted at 5:2 to create an average daily screen time score, which was then normalized by a square root transformation.

Child participants' responses to a Food Frequency Questionnaire (FFQ) of moderate reliability and low-to-moderate validity were used to assess eating patterns.[18,28] A total of 23 food categories were included in the FFQ, with examples of foods given for each category. Some food items were not available in some countries; therefore, examples were adapted according to the country's norm (for instance, under the "fried foods" category, "chicken wings" were given as one of the examples in the US and "empanadas" in Colombia). Principal component analyses that used FFQ food groups as input variables were interpreted to identify 2 factors: (1) a healthy eating pattern (positive loadings for vegetables, fruit, whole grains, etc), and (2) an unhealthy eating pattern (positive loadings for fast food, soft drinks, sweets, etc). Scores representing healthy eating pattern and unhealthy eating pattern were calculated for each participant.

Parents completed a questionnaire[18] that gathered details including the child's sex, family composition (number of siblings and number of parents), and highest level of education achieved by either parent (1 = less than high school and some high school; 2 = completed high school and some postsecondary [eg, vocational diploma or certificate]; and 3 = bachelor degree and postgraduate). BMI was calculated (BMI = weight [g]/height [m^2]) from objectively measured weight (TANITA Corporation, Tokyo, Japan[29]) and height (seca 213 portable stadiometer; seca, Hamburg, Germany), and then transformed to z scores by the use of age- and sex-specific World Health Organization reference data.[30]

Data Analyses

Data analysis consisted of (1) describing children's HRQoL by study site, (2) identifying site-specific lifestyle behavior clusters, and (3) examining the relationship between HRQoL and cluster membership on a site level.

Cluster analyses were performed with R (R Development Core Team, Vienna, Austria). Compositional data (24-hour accelerometry) were expressed as isometric log-ratio co-ordinates.[31] Isometric log-ratios are recommended for cluster analysis of compositional data because they are noncollinear and multivariate (ie, they carry information regarding the relative proportions of the components). Importantly, Euclidean distance between isometric log-ratio coordinates is a measure coherent with the relative nature of compositional data.[31,32]

Children's lifestyle behaviors were used to determine clusters on a by-site basis: z scores of 24-hour time use (ie, isometric log ratios); screen time; and healthy and unhealthy eating scores. Agglomerative hierarchical clustering was used to plot a dendrogram (using the method of Ward and squared Euclidean distances) for the interpretation of potential cluster structure and number.[33] Subsequently, a k-means partitioning cluster analysis was used. An optimal number of 4 clusters was identified in most sites based on analysis of the dendrograms and the interpretability of cluster solutions derived from the k-means procedures. To assess the invariance of the cluster solution, a random subsample from each site's cohort (n = half of each site's sample) was clustered via use of the same procedure. Agreement between solutions was substantial (Cohen kappa: range 0.71-0.95, median = 0.84). Components of 24-hour time use were described by the use of compositional means to represent the center of the compositional data points (geometric means adjusted to total 1440 minutes).[34,35] Screen time and eating pattern scores were described with arithmetic means and SDs.

Children's HRQoL was compared across lifestyle behavior clusters on a site-wise basis by the use of analysis of covariance (Stata/IC 14.0; StataCorp LP, College Station, Texas) with adjustment for BMI z score (due to the relationship between BMI z score and HRQoL reported in previous research[36]), sex, parental education and family structure, and the nested sampling design by use of the linearized variance estimation (svy).

Results

Participants were enrolled from September 2011 to December 2013, and their characteristics are presented in Table I. Children's self-reported HRQoL differed between sites (Table II). Children from higher-income countries tended to report greater HRQoL than children from low-to-middle income countries (correlation between HRQoL and world bank classification: r = 0.74, *P* = .01, and between HRQoL and human development index: r = 0.62, *P* = .03).

Three similar clusters were identified across most of the sites (Table III; available at www.jpeds.com),[37,38] with each of the 12 sites having; a high sedentary behavior/low PA cluster (sitters), a cluster characterized by high PA/low sedentary behavior (actives, retro-actives, or techno-actives; retro indicating low screen, and techno indicating high screen), and a cluster with a combination of high screen time and unhealthy eating pattern (labeled junk food screenies or junk food techno-actives). A fourth all-rounders cluster (low screen, healthy eating

Table I. Descriptive characteristics of participants

Characteristics	Included n = 5759	Excluded n = 1613	*P*
Sex, %			
Male	2591 (45)	831 (52)	<.001
Female	3168 (55)	782 (48)	
Highest parental education, %			
1	1133 (20)	267 (17) n = 1214	<.001
2	2434 (42)	541 (34)	
3	2192 (38)	406 (25)	
Number of parents, n (%)			
≤1	1056 (18)	323 (20)	.114
≥2	4703 (82)	1290 (80)	
Number of siblings, n (%)			
0	1034 (18)	207 (13)	<.001
1	2411 (42)	444 (28)	
2	1297 (23)	319 (20)	
3	538 (9)	155 (10)	
≥4	479 (8)	488 (30)	
BMI z score, mean (SD)	0.44 (1.25)	0.61 (1.29) n = 1582	<.001
HRQoL (T score), mean (SD)	50.12 (9.61)	49.58 (10.0) n = 1538	.05
Time use (min/d), compositional mean			
Sleep	539	536 n = 339	.08*
SB	525	524 n = 794	
LPA	320	322 n = 794	
MPA	41	42 n = 794	
VPA	15	15 n = 794	
Screen time (h/d), mean (SD)	2.5 (1.9)	2.8 (2.2) n = 1568	<.001
Eating pattern, mean (SD)			
Healthy	−0.00 (0.99)	0.00 (1.02) n = 1440	1.00
Unhealthy	−0.07 (0.93)	0.27 (1.12) n = 1440	<.001

SB, sedentary behavior; *LPA*, light intensity physical activity; *MPA*, moderate intensity physical activity; *VPA*, vigorous intensity physical activity.
No SDs presented for compositional means because univariate variability is irrelevant for compositional data.
Parent education levels are 1 = less than high school and some high school; 2 = completed high school and some post-secondary (eg, vocational diploma or certificate); 3 = bachelor degree and postgraduate.
*Daily time use compositions (transformed to isometric log ratio co-ordinates) were compared with the Hotelling T square test (multivariate ANOVA).

Table II. HRQoL of children by site and Human Development Index

Sites (cities)	HRQoL*	Human Development Index[37]	World Bank Classification[38]
Australia (Adelaide)	49.85 (8.54)	0.929 (Very High)	High income
Canada (Ottawa)	51.25 (9.29)	0.908 (Very High)	High income
Finland (Helsinki, Espoo, and Vantaa)	52.67 (8.67)	0.882 (Very High)	High income
Portugal (Porto)	52.91 (10.14)	0.809 (Very High)	High income
England (Bath and North East Somerset)	50.03 (8.77)	0.863 (Very High)	High income
United States (Baton Rouge)	50.63 (10.24)	0.910 (Very High)	High income
Brazil (São Paulo)	47.31 (7.80)	0.718 (High)	Upper-middle income
Colombia (Bogotá)	49.92 (8.15)	0.710 (High)	Upper-middle income
China (Tianjin)	51.21 (11.54)	0.687 (Medium)	Upper-middle income
India (Bangalore)	48.16 (9.21)	0.547 (Medium)	Lower-middle income
South Africa (Cape Town)	50.03 (11.41)	0.619 (Medium)	Upper-middle income
Kenya (Nairobi)	47.13 (9.95)	0.509 (Low)	Low income

*Values presented as arithmetic mean (SD).

pattern, and moderate PA/sedentary behavior) was identified in 9 of 12 sites. Sleep generally did not influence the determination of clusters.

Similar relationships between HRQoL and cluster membership were observed across sites, regardless of the country's Human Development Index (**Table III**). Children in the all-rounders cluster reported the greatest HRQoL in 7 of 9 sites in which this cluster was identified (Australia, Canada, China, Finland, India, Portugal, and England). The all-rounders' HRQoL was significantly greater than sitters' HRQoL in 7 of 9 sites and greater than actives' HRQoL in 5 of 9 sites. Effect sizes (Cohen) between clusters with highest and lowest HRQoL generally were moderate (**Table IV**).

Discussion

Remarkable commonality was observed in lifestyle behavior patterns throughout the world, with each country having a cluster characterized by (1) high sedentary behavior, (2) high PA, and (3) a combination of high screen time and unhealthy eating pattern. A fourth cluster, characterized by low screen/healthy eating and moderate PA (all-rounders), was absent in Kenya, South Africa, and Brazil, suggesting that this lifestyle behavior pattern may be more common in higher-income nations. Relationships between HRQoL and lifestyle behaviors were similar throughout the world, with all-rounders consistently reporting greater HRQoL than sitters and actives.

Sleep duration generally was unimportant in the determination of lifestyle behavior clusters, possibly because of parental influence mediating relative homogenous sleep durations in this age group. Previous cluster analyses rarely have included sleep duration, and none have used compositional analysis techniques; therefore, further research is required to explore the role of sleep in determining children's lifestyle clusters. Because clusters in this study were not differentiated by sleep duration, the contribution of sleep duration to the relationship between HRQoL and children's lifestyles cannot be determined.

The similarity of lifestyle behavior patterns identified in children across the world is striking. It could be expected, from a historical perspective, that children from lower-income countries would be more active and have healthier diets than children from greater-income countries.[17] In this study, however, clusters identified in low- and middle-income countries (eg, India) were comparable with those of some high-income countries (eg, England and Australia). The similarity in lifestyle behavior clusters may simply be the result of biological factors. Alternatively, it may reflect a cultural shift towards lower PA,

Table IV. Ranking of clusters at each site according to HRQoL (the effect size compares the groups with the highest and lowest HRQoL)

Clusters	Australia	Brazil	Canada	China	Colombia	England	Finland	India	Kenya	Portugal	RSA	US
All-rounders	1+		1+	1+	1	1+	1+	1+		1+		2+
Junk food screenies	3–		3–	2		3	2	2		2	1+	1+
Actives	2			4–		2	3–	4–		4–		3–
Sitters	4–	1	2–	3–	4	4–	4–	3–	4–	3–	2	4–
Junk food techno-actives		2	4–		3				2			
Lightly actives									1+			
Retro-actives		4							3		3	
Low food intake											4–	
Techno-actives		3										
Low sleep					2							
Effect size	0.59	0.22	0.83	0.61	0.17	0.50	0.41	0.66	0.44	0.39	0.44	0.48

RSA, Republic of South Africa; *US*, United States.
+ denotes significantly greater HRQoL than –, with values1-4 indicating highest to lowest HRQoL. Cohen effect size calculated between clusters with highest and lowest HRQoL, following adjustment for covariates.

greater screen time, and increased fast food consumption as low- and middle-income countries become increasingly Westernized.[17,39] Consistent with this finding, children recruited in ISCOLE were from urban and suburban centers, where a universal Western "monoculture" might exist. A transition in both PA[17] and nutrition behavior[39] has been documented in many low- and middle-income countries and attributed to economic development, global media and food distribution networks and increased reliance on motorized transport.[39]

Children identified as all-rounders (healthy eating pattern/low screen/moderate PA and sedentary behavior) reported the greatest HRQoL at all sites, except the US, where all-rounders reported the second highest HRQoL (however, at the US site, there was no significant difference between HRQoL in all-rounders and the cluster with the greatest HRQoL, ie, the junk food screenies). The favorable HRQoL reported by all-rounders is not surprising, given that both healthy diet[5] and low screen time[6] consistently have been linked to greater HRQoL in previous variable-centered studies. Notably, children with a largely opposite lifestyle behavior pattern (junk food screenies: unhealthy eating pattern/high screen/moderate PA) did not report the lowest HRQoL, except when unhealthy eating pattern and high screen were combined with high PA (Canada: the junk food techno-actives). The relationship between high PA and poor HRQoL is striking, considering PA previously has been consistently positively related to HRQoL.[4-6]

In contrast, we found actives generally reported lower HRQoL than all-rounders and tended to be on par with sitters. In exploring this unexpected finding, we noted that although all-rounders did not have the greatest PA, in the majority of cases (6 of 9) they nevertheless accumulated greater than 60 minutes of moderate-to-vigorous PA on an average day, in line with guidelines for this age group.[40] This finding suggests that 60 minutes per day may be a threshold above which additional moderate-to-vigorous PA has no further positive relationship with HRQoL; however, this should be confirmed by future studies. Furthermore, the all-rounders lifestyle represents a balance between the components of daily time use and so is possibly free from the stresses and pressures of high involvement in PA, eg, competitive sport (actives) or sedentary behavior, eg, study (sitters). It has been suggested previously that imbalances in time use imposes developmental and emotional costs on adolescents.[41] By considering the influence of combinations of behaviors rather than individual behavioral effects, our research moves beyond the majority of previous studies to consider behaviors in the context of a child's overall lifestyle.

This study had several important strengths. The results were based on a large multinational dataset encompassing many socioeconomic, cultural, and geographic contexts. Daily activities were measured objectively and analyzed with compositional techniques. Children's HRQoL was captured with a 10-item tool validated previously for school-aged children. Analyses adjusted for many potential confounders, including BMI z score.

A number of limitations should be considered. First, the study's cross-sectional design precludes determination of causation. Second, to ensure consistency in measurement protocols, the same HRQoL instrument (KIDSCREEN-10) was used at all study sites; however, this instrument has not been validated previously for children in all the nations included in the present study. Although the KIDSCREEN-10 tool has been used in many countries, it was developed for children in European countries and may reflect HRQoL differently for children from other regions. For this reason, our analyses were carried out on a by-site basis; however, caution must be exercised when comparing HRQoL across countries. Third, although activity was measured objectively, accelerometry may not differentiate between sitting and standing postures. Furthermore, sleep must be estimated. Other behaviors were self-reported; screen time did not include devices such as tablets or cell phones, and the FFQ had low-moderate validity and moderate reliability. Finally, the results cannot be generalized to other populations because of the exploratory, data-driven nature of cluster analysis. ISCOLE recruited entirely from urban and suburban centers, and results might be quite different for children in rural areas or smaller regional towns.

Interventions should focus on the combination of healthy diet and restricted screen time. Such interventions should be a priority in low- and middle-income countries, where there is evidence of lifestyle transition towards unhealthy behavior patterns.[17] Studies that examine HRQoL and its relationship with potentially modifiable contributors should be a priority of future research. Future studies also could investigate the relative importance of specific lifestyle behaviors (eg, diet or PA) in the relationship with HRQoL, using analytic methods such as partial least squares regression. ■

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Appendix

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Table III. Characteristics of lifestyle behavior clusters

Clusters	% (n)	Compositional mean: min/d Sleep	SB	LPA	MPA	VPA	Mean: h/d (SD) Screen time	Mean: z scores (SD) Healthy diet*	Unhealthy diet	Mean: T-score (sd) HRQoL
Australia										
Sitters	24 (105)	574	544	282	29	11	2.7 (1.6)	−0.33 (0.88)	−0.20 (0.68)	47.80[a] (7.08)
Actives	23 (98)	584	413	355	56	32	2.3 (1.3)	−0.34 (0.87)	−0.13 (0.68)	49.93 (8.42)
Junk food screenies	23 (99)	565	494	311	45	25	4.3 (1.6)	−0.13 (1.08)	0.99 (1.28)	48.52[b] (8.83)
All-rounders	30 (127)	571	488	312	44	24	1.4 (1.0)	0.64 (0.82)	−0.51 (0.55)	52.52[ab] (8.88)
Brazil										
Retro-actives	31 (134)	526	464	375	52	23	2.0 (1.3)	−0.03 (0.97)	−0.34 (0.58)	46.36 (8.34)
Sitters	29 (127)	528	569	310	25	8	3.0 (2.0)	−0.05 (0.94)	−0.35 (0.59)	48.08 (7.52)
Junk food techno-actives	13 (56)	513	482	369	51	24	4.9 (2.8)	0.28 (1.17)	2.05 (0.86)	47.59 (8.44)
Techno-active	27 (118)	515	521	338	46	20	5.6 (2.0)	−0.05 (1.00)	−0.22 (0.54)	47.42 (7.13)
Canada										
Junk food screenies	31 (152)	539	521	322	42	16	3.8 (2.1)	−0.82 (0.77)	0.17 (0.69)	48.61[a] (7.78)
Junk food techno-actives	4 (22)	561	480	326	52	21	3.6 (2.6)	−0.17 (1.20)	3.20 (1.50)	46.77[b] (8.61)
Sitters	27 (136)	546	580	274	30	10	1.7 (1.5)	0.26 (0.84)	−0.26 (0.67)	51.06[c] (9.17)
All-rounders	37 (185)	565	483	319	50	23	1.4 (1.1)	0.50 (0.81)	−0.33 (0.56)	54.09[abc] (9.78)
China										
Junk food screenies	10 (47)	537	522	326	39	16	3.1 (2.3)	0.50 (1.07)	2.24 (1.08)	50.73 (13.13)
All-rounders	23 (104)	535	548	310	35	12	0.9 (0.9)	0.95 (0.79)	−0.29 (0.63)	56.35[ab] (12.62)
Actives	36 (167)	526	546	314	38	16	2.3 (1.7)	−0.53 (0.66)	−0.21 (0.53)	49.27[a] (10.76)
Sitters	31 (140)	521	638	252	22	7	1.4 (1.3)	−0.24 (0.87)	−0.28 (0.62)	49.86[b] (9.91)
Colombia										
Low sleep	30 (244)	512	555	311	46	16	2.7 (1.4)	0.15 (1.04)	−0.35 (0.75)	50.10 (8.68)
Sitters	20 (161)	533	562	308	30	7	3.0 (1.6)	−0.18 (0.81)	−0.03 (0.81)	49.21 (8.04)
Junk food techno-actives	22 (180)	529	463	363	62	24	4.2 (1.5)	−0.38 (0.89)	0.97 (1.12)	49.47 (7.59)
All-rounders	29 (235)	539	452	363	62	24	1.7 (0.9)	0.26 (1.04)	−0.35 (0.73)	50.56 (8.10)
England										
Junk food screenies	25 (94)	553	504	310	48	25	4.6 (1.9)	−0.42 (0.89)	0.95 (1.25)	48.47 (9.13)
Actives	23 (87)	597	448	317	51	27	2.0 (1.0)	−0.32 (0.69)	−0.16 (0.58)	49.85 (7.31)
Sitters	23 (84)	584	561	254	30	11	2.9 (1.3)	−0.47 (0.82)	−0.03 (0.70)	48.43[a] (7.47)
All-rounders	29 (108)	572	516	285	46	21	2.0 (1.1)	0.99 (0.71)	−0.67 (0.46)	52.75[a] (9.86)
Finland										
Actives	35 (150)	515	506	325	61	33	2.9 (1.6)	−0.36 (0.68)	−0.01 (0.60)	51.77[a] (8.11)
All-rounders	28 (122)	529	542	298	48	24	1.5 (1.0)	1.00 (0.84)	−0.47 (0.52)	55.17[ab] (9.34)
Sitters	32 (139)	515	600	276	36	13	3.0 (1.7)	−0.51 (0.67)	−0.04 (0.65)	51.49[b] (8.56)
Junk food screenies	5 (21)	539	494	322	57	28	4.8 (1.9)	0.18 (1.33)	3.13 (1.63)	52.41 (6.68)
India										
All-rounders	23 (119)	519	524	349	35	12	0.9 (0.6)	1.12 (0.68)	−0.35 (0.76)	51.74[ab] (10.06)
Sitters	35 (183)	510	583	316	24	7	1.7 (1.2)	−0.32 (0.75)	−0.10 (0.81)	47.23[a] (8.74)
Junk food screenies	13 (59)	535	475	366	46	18	3.2 (2.2)	0.40 (1.01)	1.74 (1.16)	49.24 (10.04)
Actives	31 (165)	526	482	367	47	19	1.5 (0.9)	−0.60 (0.66)	−0.26 (0.58)	46.23[b] (8.00)
Kenya										
Retro-active	27 (123)	518	471	352	65	34	1.4 (1.4)	−0.77 (0.76)	−0.40 (0.57)	44.20 (10.12)
Lightly active	29 (130)	531	494	362	39	14	2.0 (1.3)	0.23 (0.82)	−0.40 (0.61)	50.03[a] (9.35)
Junk food techno-actives	22 (98)	516	481	350	62	31	3.3 (2.2)	0.66 (0.82)	1.30 (0.97)	47.77[b] (11.50)
Sitters	22 (99)	521	591	282	33	14	2.4 (1.4)	−0.01 (1.04)	−0.27 (0.75)	46.32[ab] (7.56)
Portugal										
All-rounders	29 (164)	511	555	312	42	19	1.8 (1.3)	1.02 (0.59)	−0.44 (0.54)	55.38[ab] (10.70)
Actives	30 (166)	497	541	332	48	22	1.8 (1.0)	−0.72 (0.58)	−0.13 (0.56)	51.57[a] (8.93)
Sitters	28 (158)	518	610	278	26	8	2.0 (1.4)	−0.21 (0.84)	−0.28 (0.54)	51.94[b] (9.85)
Junk food screenies	13 (74)	491	569	315	45	20	3.8 (2.0)	−0.21 (1.00)	1.86 (1.24)	52.53 (11.21)
South Africa										
Low food intake	27 (99)	558	511	310	43	18	3.2 (2.0)	−0.75 (0.72)	−0.26 (0.75)	47.31[a] (9.16)
Sitters	25 (92)	554	555	295	28	8	2.1 (1.6)	0.33 (0.97)	−0.56 (0.77)	50.76 (11.72)
Retro-actives	23 (81)	563	428	360	62	28	1.5 (1.4)	−0.07 (1.01)	−0.26 (0.76)	50.40 (12.36)
Junk food screenies	25 (89)	552	476	339	54	20	4.6 (2.3)	0.55 (0.75)	1.11 (0.79)	51.99[a] (12.07)
US										
Sitters	21 (88)	537	593	283	22	6	3.7 (2.3)	−0.07 (1.02)	0.19 (0.86)	48.27[ab] (8.66)
Actives	27 (113)	538	494	348	42	18	3.6 (2.4)	−0.77 (0.51)	−0.28 (0.59)	48.60[cd] (8.53)
All-rounders	36 (150)	550	532	306	34	17	1.4 (0.9)	0.31 (0.83)	−0.59 (0.51)	52.50[ac] (11.53)
Junk food screenies	16 (67)	520	502	354	44	20	5.0 (3.1)	0.70 (1.10)	1.54 (0.90)	52.94[bd] (10.58)

HRQoL, health-related quality of life; *SB*, sedentary behavior; *LPA*, light intensity physical activity; *MPA*, moderate intensity physical activity; *VPA*, vigorous intensity physical activity; *US*, United States.

No SDs presented for compositional means as univariate variability is irrelevant for compositional data.

*Diet refers to eating pattern score. Superscript letters denote statistically significant pairwise comparisons (following Bonferroni correction of $P < .008$). All linear models are adjusted for BMI z score, sex, parental education, number of parents, number of siblings, and potential clustering at school level.