Activity Accumulation and Cardiometabolic Risk in Youth: A Latent Profile Approach

SIMONE J. J. M. VERSWIJVEREN[1], KAREN E. LAMB[2,3], REBECCA M. LEECH[1], JO SALMON[1], ANNA TIMPERIO[1], ROHAN M. TELFORD[4], MELITTA A. MCNARRY[5], KELLY A. MACKINTOSH[5], ROBIN M. DALY[1], DAVID W. DUNSTAN[6,7], CLARE HUME[8], ESTER CERIN[7,9], LISA S. OLIVE[10,11,12], and NICOLA D. RIDGERS[1]

[1]Institute for Physical Activity and Nutrition (IPAN), School of Exercise and Nutrition Sciences, Deakin University, Geelong, Victoria, AUSTRALIA; [2]Murdoch Children's Research Institute, Royal Melbourne Hospital, Parkville, Victoria, AUSTRALIA; [3]Department of Paediatrics, University of Melbourne, Parkville, Victoria, AUSTRALIA; [4]Research Institute of Sport and Exercise, University of Canberra, Canberra, Australian Capital Territory, AUSTRALIA; [5]Applied Sports Science, Technology, Exercise and Medicine Research Centre, Swansea University, Swansea, Wales, UNITED KINGDOM; [6]Baker Heart and Diabetes Institute, Melbourne, Deakin, AUSTRALIA; [7]Mary MacKillop Institute for Health Research, Australian Catholic University, Melbourne, AUSTRALIA; [8]School of Public Health, University of Adelaide, Adelaide, South Australia, AUSTRALIA; [9]School of Public Health, The University of Hong Kong, Hong Kong, CHINA; [10]School of Psychology, Deakin University, Burwood, Victoria, AUSTRALIA; [11]IMPACT Research Institute, Deakin University, Burwood, Victoria, AUSTRALIA; and [12]ANU Medical School, Australian National University, Garran, Australian Capital Territory, AUSTRALIA

ABSTRACT

VERSWIJVEREN, S. J. J. M., K. E. LAMB, R. M. LEECH, J. SALMON, A. TIMPERIO, R. M. TELFORD, M. A. MCNARRY, K. A. MACKINTOSH, R. M. DALY, D. W. DUNSTAN, C. HUME, E. CERIN, L. S. OLIVE, and N. D. RIDGERS. Activity Accumulation and Cardiometabolic Risk in Youth: A Latent Profile Approach. *Med. Sci. Sports Exerc.*, Vol. 52, No. 7, pp. 1502–1510, 2020. **Introduction:** This cross-sectional study aimed to i) identify and characterize youth according to distinct physical activity (PA) and sedentary (SED) accumulation patterns, and ii) investigate associations of these derived patterns with cardiometabolic risk factors. **Methods:** ActiGraph accelerometer data from 7- to 13-yr-olds from two studies were pooled (n = 1219; 843 (69%) with valid accelerometry included in analysis). Time accumulated in ≥5- and ≥10-min SED bouts, ≥1- and ≥5-min bouts of light, and ≥1-min bouts of moderate and vigorous PA was calculated. Frequency of breaks in SED was also obtained. Latent profile analysis was used to identify groups of participants based on their distinct accumulation patterns. Linear and logistic regression models were used to test associations of group accumulation patterns with cardiometabolic risk factors, including adiposity indicators, blood pressure, and lipids. Total PA and SED time were also compared between groups. **Results:** Three distinct groups were identified: "prolonged sitters" had the most time in sustained SED bouts and the least time in vigorous PA bouts; "breakers" had the highest frequency of SED breaks and lowest engagement in sustained bouts across most PA intensities; and "prolonged movers" had the least time accumulated in SED bouts and the most in PA bouts across most intensities. Although breakers engaged in less time in PA bouts compared with other groups, they had the healthiest adiposity indicators. No associations with the remaining cardiometabolic risk factors were found. **Conclusion:** Youth accumulate their daily activity in three distinct patterns (prolonged sitters, breakers, and prolonger movers), with those breaking up sitting and least time in prolonged PA bouts across the day having a lower adiposity risk. No relationships with other cardiometabolic risk factors were identified. **Key Words:** PHYSICAL ACTIVITY, SEDENTARY BEHAVIOR, ACCUMULATION PATTERNS, ACCELEROMETRY, LATENT PROFILE ANALYSIS, CARDIOMETABOLIC HEALTH

Address for correspondence: Simone J. J. M. Verswijveren, M.Sc., Deakin University, Geelong, Australia, Institute for Physical Activity and Nutrition (IPAN), School of Exercise and Nutrition Sciences. Institutional address: 221 Burwood Highway, Burwood, Victoria, 3125, Australia; E-mail: sjverswi@deakin.edu.au.
Submitted for publication September 2019.
Accepted for publication January 2020.
Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Web site (www.acsm-msse.org).

0195-9131/20/5207-1502/0
MEDICINE & SCIENCE IN SPORTS & EXERCISE®

DOI: 10.1249/MSS.0000000000002275

To benefit health and reduce cardiometabolic risk factors, international guidelines state that youth age 5–17 yr should accumulate at least 60 min of moderate- to vigorous-intensity physical activity (MVPA) daily and minimize extended periods of sedentary (SED) behavior (1). Specifically, "accumulation" refers to the sum (i.e., total volume) of daily physical activity (PA) and SED activities engaged in across the activity spectrum (i.e., the movement continuum from SED to high-intensity vigorous PA (VPA) (2)), which can be composed of sporadic, short, or long bouts of activity across the day (1). Notably, there are no specific recommendations on how to accumulate PA (e.g., number of bouts and bout duration of different intensities) and SED (e.g., after how many minutes should youth break up their sitting).

One reason for the lack of specific accumulation recommendations is the dearth of evidence regarding associations between accumulation patterns (e.g., the timing, duration, and frequency of bouts and breaks [3]) and health outcomes in youth. Indeed, only a few studies in youth have investigated whether the manner in which such activities are accumulated is related to cardiometabolic health, and the evidence is inconsistent (4). In adults, evidence suggests that breaking up SED time and engagement in short and sustained activity bouts are beneficially associated with cardiometabolic risk factors (5,6). Given that cardiometabolic risk factors and activity behaviors track from childhood to adolescence and into adulthood (7,8), there is a need to better understand the underlying patterns of accumulated daily activity among youth. This information may help with understanding how specific patterns of activity may contribute to cardiometabolic health outcomes (9).

Previous research has focused solely on accumulation patterns of PA intensities (i.e., light PA (LPA), moderate PA (MPA), VPA, or MVPA) or SED in isolation, and how this is associated with children's cardiometabolic risk factors (4). This approach has limitations, as it fails to consider the fact that activity occurs across a spectrum and that all PA intensities and SED intermittently occur within a child's day (2). For example, youth with low levels of MVPA may also engage in high levels of prolonged sitting and thus have a distinct "accumulation pattern", which may have specific associations with certain health outcomes. If recommendations are to be developed regarding how accumulation of PA and SED should occur, consideration of distinct accumulation patterns among groups in the population needs to be explored.

Identification of groups of individuals who share similar characteristics or patterns of behaviors can be obtained through person-centered statistical approaches, which are conceptually different from the traditionally used variable-centered statistical approaches (10). An advantage of person-centered approaches, such as latent profile analysis, is that this approach can accommodate the investigation of combined accumulation patterns, whereas other approaches require adjustment for different intensities, thereby discounting the fact that accumulation patterns co-occur. Person-centered approaches have previously been used in youth to identify distinct groups according to total volumes of PA and/or SED (11), generally relying on self-reported lifestyle and activity-related behaviors (12). There is a scarcity of studies that have used objective measures of PA and SED to characterize accumulation patterns across the activity spectrum (4). To our knowledge, only one study has examined associations between objectively measured accumulation patterns (i.e., bouts) and cardiometabolic health outcomes in youth, using a data-driven, person-centered, statistical approach (13). This study concluded that children with a higher percentage of sustained (≥5 min) bouts across the day had lower body mass index (BMI) and waist circumference (WC) compared with children with a low percentage of those bouts, but only included MVPA and no other intensity bouts.

Another key limitation in studies to date is the almost exclusive focus on indicators of adiposity as the main cardiometabolic risk factor (4). Indeed, elevated blood pressure and dyslipidemia are established factors for cardiometabolic diseases, which can initially manifest during the early years of life and are subsequently maintained throughout the life course (14–16). Therefore, it is important to consider a range of biomarkers among youth. Yet, associations between accumulation patterns and other cardiometabolic risk indicators, such as lipoprotein-related biomarkers and blood pressure, have not been studied (4). Consequently, the aims of this study were to i) identify and characterize youth according to distinct PA and SED accumulation patterns, and ii) investigate associations of these derived patterns with cardiometabolic risk factors.

METHODS

Participant Information

This study utilized pooled cross-sectional data from two trials: "Lifestyle Of Our Kids" (LOOK; trial registration: ACTRN12615000066583 (23/01/2015)) and "Transform-Us!" (ACTRN12609000715279 (19/08/2009), ISRCTN83725066 (30/06/2010)). Both studies were school-based intervention studies; parents provided written informed consent for their children (n = 853 in LOOK; n = 599 in Transform-Us!) to participate in one or more assessment components. Baseline data (2010) from 581 Transform-Us! participants and time-point five data (2009; first time-point with accelerometry and blood collection) from 638 LOOK participants were provided for this study. Although more youth participated in the original trials, only data from those who provided data for at least one relevant variable (e.g., accelerometry or risk factors) were considered in this study. Supplemental Digital Table 1 shows the breakdown of participant numbers and key methodological characteristics of both studies (Supplemental Digital Content 1, Key methodological characteristics of the LOOK and Transform-Us! studies, http://links.lww.com/MSS/B906). The studies were approved by the Australian Capital Territory Health Human Research Ethics Committee (LOOK: ETH.9/05.687) and the Deakin University Human Research Ethics Committee (Transform-Us!: EC 2009-141), respectively. Further details of each study are reported elsewhere (17,18).

Accelerometry

Participants wore an ActiGraph accelerometer (GT1M in LOOK [18]; GT3X in Transform-Us! [17]) on their right hip during waking hours for at least seven consecutive days. These monitors have acceptable comparability (19). As LOOK collected data using 5-s epochs, ActiLife software (v5.1.5) was used to reintegrate these into 15-s epochs to be consistent with Transform-Us!. A customized Excel Macro was then used to further process the files. Nonwear time (≥20 min of consecutive zeroes) was subtracted from each day to determine wear time (20). Participants with ≥4 valid days (defined as 8 h of wear time on weekdays and 7 h on weekend days [20]) were included for further analysis (21). The different intensities across the activity spectrum were defined as per previously validated age-specific cut points: SED <100 counts per minute (20), and light PA (LPA), MPA (≥4 and <6 METs) (22) and VPA (≥6 METs) (23). Total time spent in each of these intensities was averaged over all valid days.

Accumulation patterns across the activity spectrum. Based on existing literature (4) and preliminary exploration of this sample's accumulation patterns, seven accumulation pattern variables of interest were identified: number of breaks in SED time (i.e., an interruption (≥25 counts per minute for ≥1 epoch) between SED epochs [21,24]) and time accumulated in ≥5-min SED, ≥10-min SED, ≥1-min LPA, ≥5-min LPA, ≥1-min MPA, and ≥1-min VPA bouts. Longer bout durations (e.g., ≥5- and ≥10-min MPA/VPA bouts) were not included, as a low proportion of the participants engaged in these patterns (i.e., a quarter of the sample or less). Based on previous recommendations for SED bouts (25), bouts did not include interruptions of any duration (i.e., no tolerance). Any interruption in intensity marked the end of a bout. Total time (in minutes per day) spent in bouts of each intensity and frequency of breaks in SED per day were averaged across all valid days. Variables that were highly correlated with wear time were adjusted using the residuals method (26). This method is commonly used within PA and SED research (26).

Cardiometabolic Risk Factors

Objective data on seven continuous cardiometabolic risk factors were collected using standardized procedures: BMI, WC, systolic (SBP) and diastolic blood pressure (DBP), HDL cholesterol (HDL-C) and LDL cholesterol (LDL-C), and triglycerides (TG; lipids). Standardized procedures were used to objectively measure stature, body mass, and WC in both studies (27). Continuous World Health Organization Child Growth Standards age- and sex-standardized z values (zBMI) were computed based on BMI (in kilograms per meter squared) (28). Then, a binary variable was created to classify participants as overweight/obese or healthy BMI (including those classified as underweight, $n = 1$) as per the international age-specific cut points for boys and girls (29). Australian percentile curves for WC were utilized to determine age- and sex-specific WC percentiles (30). WC was dichotomized as follows: ≥75th percentile (31) as being overweight (including obese participants ≥90th percentile [32]) or <75th percentile as being healthy weight (including those classified as underweight (i.e., ≤5th percentile); 3% of the sample). For both BMI and WC, a low proportion of participants were underweight, and these were therefore included in the healthy weight category. Blood pressure and blood samples taken from a forearm vein were measured in a seated posture after overnight fasting (17,18). A continuous cardiometabolic risk score (CMR-score) was calculated using the z values of WC, SBP, DBP, LDL-C, HDL-C, and TG (25). Higher CMR-scores indicate a higher risk. HDL-C was multiplied by −1 before inclusion in the score, as it is inversely related to cardiometabolic risk.

Participant Characteristics

Study (LOOK, Transform-Us!), school, self-reported age and sex, and socioeconomic status (SES) were included as covariates. Scores for SES were based on school locations using the Socio-Economic Indexes for Areas Score in Australia (SEIFA; https://www.abs.gov.au/websitedbs/censushome.nsf/home/seifa). These scores were grouped in quintiles of SEIFA score, and schools from the first, third, and fifth quintiles were categorized as low, mid, and high SEIFA strata, respectively (17).

Statistical Analyses

Latent profiles of accumulation patterns. Statistical analyses were performed using Stata Version 15.0 (StataCorp, College Station, TX). All participants with valid accelerometry data ($n = 843$; 69%), regardless of health data availability, were included in the latent profile analysis to identify distinct classes of youth who share similar accumulation patterns. Latent profile analysis is a statistical technique that describes similarities and differences among individuals and assumes that the population is heterogeneous with respect to the relationships between variables (10). The seven accumulation pattern variables of interest (i.e., breaks in SED time, and ≥5-min SED, ≥10-min SED, ≥1-min LPA, ≥5-min LPA, ≥1-min MPA, and ≥1-min VPA bouts) were used as observed variables in the latent profile models (10). Although these variables are not mutually exclusive, consistent with previous research (11,12), the decision was made to include all of them in the latent profile analysis, as they showed unique associations with cardiometabolic health (4). The variables were not treated as a subcomposition of waking hours, as the elements together are not "closed" so that they sum to 1 (33). This is due to the inclusion of frequency within SED breaks as a variable of interest, as well as different minimum bout lengths within SED and LPA.

Four different variance–covariance structures were compared to identify the best-fit model: 1) class-invariant, diagonal (most constrained; conditional independence is imposed and covariances between the indicators are fixed at zero within class, whereas the variances are constrained to be equal across classes); 2) class-varying, diagonal (conditional independence is imposed and covariances between the indicators are fixed at zero within class, whereas the variances are freely estimated and allowed to be different across classes); 3) class-invariant, unrestricted (all indicator variables are allowed to covary within class, and variances and covariances are constrained to be equal across classes); and 4) class-varying, unrestricted (least restrictive; all indicator variables are allowed to covary within class, and the variances and covariances are allowed to be different across classes) (10). The optimal number of classes was identified by analyzing one-class through to six-class models within each of the aforementioned variance–covariance structures using the Bayesian information criteria (BIC), Consistent Akaike's information criteria (CAIC), approximate weight of evidence criterion (AWE), log likelihood, class size (i.e., lowest proportion cutoff was set at 0.05 [34]), and the interpretation of classes (10). The "best" model was identified as the

EPIDEMIOLOGY

model with the fewest number of classes with a better relative fit than the initial "benchmark" one-class class-invariant, unrestricted model (10); the identified classes in that "best" model were the groups (i.e., with distinct accumulation patterns) used to represent accumulation patterns in further analyses.

Group characteristics and associations with cardiometabolic risk factors. Subsets of participants provided BMI and WC (n = 782 (93% of sample with valid accelerometry)), blood pressure (n = 637 (76%)), and/or lipids (n = 525 (62%)) data. Only participants with complete data on all variables were included in the CMR-score analysis (n = 404 (48%)). These smaller analytic samples were mostly due to participants opting out for consent for those assessments (17,18).

Linear regression models accounting for school clustering were conducted to determine whether there were any differences in age and SES across the derived distinct groups. Differences between groups according to sex were assessed using logistic regression models (also accounting for school clustering). For both types of regressions, *post hoc* multiple comparisons with Bonferroni correction were used to identify where the specific differences occurred between the groups. Total daily volumes of SED and different PA intensities were compared using descriptive statistics only, as they are highly correlated with the manifest (i.e., input) pattern variables used to create the distinct groups.

Linear regression models were conducted to analyze associations between the groups and each of the continuous cardiometabolic risk factors. Three incremental models were used: model 1 (minimally adjusted) adjusted for study involvement and accounted for school clustering, model 2 (partially adjusted) additionally adjusted for participants' age and sex, and model 3 (fully adjusted) further adjusted for SES. Logistic regression models estimated the odds ratio (OR) and 95% confidence intervals (CI) of the distinct groups for being overweight/obese (i.e., using the binary variables for BMI and WC, separately). Here, OR values >1 imply a higher chance for being overweight/obese relative to the distinct accumulation pattern reference group. All assumptions for linear and logistic regression models were met. For both linear and logistic regression models, the distinct group that was considered unhealthiest based on their accumulation patterns in comparison to current evidence was selected to be the referent group. Significance was assessed at the level of $P < 0.05$.

RESULTS

Participant characteristics. The characteristics of the sample are presented in Table 1. Participants were age between 7 and 13 yr. Three-quarters of the participants were not overweight or obese based on BMI and more than half based on WC classifications. The mean characteristics were similar across the different analytic samples (i.e., adiposity, blood pressure, lipids, and CMR-score). There was moderate agreement between the BMI and WC weight status categories ($\kappa = 0.60$, 82% agreement). The average times spent SED and in LPA, MPA, and VPA were 7 h and 20 min, 3 h and 50 min, 45 min, and 20 min, respectively.

Latent profiles of accumulation patterns. A comparison of fit indicators for the benchmark model and class-varying, unrestricted latent profile models are presented in Table 2. These models had the best fit compared with other models (i.e., class-invariant, unrestricted; class-invariant, diagonal; and class-varying, diagonal [10]). Of the 1–6 class models examined, the class-varying, unrestricted three-class model demonstrated the biggest drop in CAIC, BIC, and AWE values, when each solution was compared with the previous solution. The three-class model also had the lowest BIC overall. Although CAIC and AWE values were slightly better for the class-varying, unrestricted, five- and six-class models, compared with the class-varying, unrestricted three-class model, some classes identified in these two models were very small (i.e., n = 40 (5%) and n = 31 (4%), respectively) and below the recommended cutoff (<5%, [34]) for inclusion. Based on the model fit indices, interpretability of the models (i.e., particularly for the four-class model) and size of the extracted classes (i.e., particularly for the five- and six-class models), the

TABLE 1. Participant characteristics.

	N	
Original consented sample (*n*)	1452	
Potential sample at included time-point (*n*)[a]	1233	
Provided sample (*n*)[b]	1219	
Valid accelerometry, included in latent profile analysis (*n*)	843	
Subset adiposity (*n*)	782	
Subset blood pressure (*n*)	637	
Subset lipids (*n*)	525	
Subset CMR-score (*n*)	404	
Demographic characteristics[c]		
Age, mean ± SD, yr	806	10.5 ± 1.7
Sex, % female	823	54.7
SES (% high/mid/low SES)	824	3/36/61
Cardiometabolic risk factors[c]		
BMI, mean ± SD, $kg \cdot m^{-2}$	807	18.6 ± 3.3
BMI status, % overweight/obese[d]	804	25.0
WC, mean ± SD, cm	801	64.1 ± 8.9
WC status, % overweight/obese[d]	799	41.55
SBP, mean ± SD, mm Hg	660	106.7 ± 10.3
Diastolic blood pressure, mean ± SD, mm Hg	660	61.0 ± 7.5
HDL-C, mean ± SD, $mmol \cdot L^{-1}$	559	1.5 ± 0.3
LDL-C, mean ± SD, $mmol \cdot L^{-1}$	559	2.5 ± 0.7
TG, mean ± SD, $mmol \cdot L^{-1}$	559	0.9 ± 0.4
CMR-score, mean ± SD[e]	416	0.2 ± 3.5
Total daily volumes[c]		
SED, mean ± SD, $min \cdot d^{-1}$	843	439.4 ± 78.5
LPA, mean ± SD, $min \cdot d^{-1}$	843	229.9 ± 35.5
MPA, mean ± SD, $min \cdot d^{-1}$	843	45.5 ± 15.4
VPA, mean ± SD, $min \cdot d^{-1}$	843	20.3 ± 12.4
Accumulation patterns (included in latent profile analysis)[c]		
Breaks in SED time, mean ± SD, no. per day	843	310.7 ± 42.1
≥5-min SED bouts, mean ± SD, $min \cdot d^{-1}$	843	171.1 ± 66.7
≥10-min SED bouts, mean ± SD, $min \cdot d^{-1}$	843	81.9 ± 46.6
≥1-min LPA bouts, mean ± SD, $min \cdot d^{-1}$	843	104.3 ± 25.0
≥5-min LPA bouts, mean ± SD, $min \cdot d^{-1}$	843	2.5 ± 3.0
≥1-min MPA bouts, mean ± SD, $min \cdot d^{-1}$	843	8.7 ± 4.8
≥1-min VPA bouts, mean ± SD, $min \cdot d^{-1}$	843	5.7 ± 5.9

Data are presented as mean ± SD, unless otherwise indicated.
[a]The LOOK participants who were lost between time point 1 and time point 5 were mostly lost due to school relocation. In Transform-Us!, some participants from the original consented sample were lost before being allocated to the control group or intervention group.
[b]Participants who had raw data for one or more assessed variables relevant to this study.
[c]Participants included in the latent profile analysis (i.e., those who had valid accelerometry data).
[d]Overweight and obese BMI and WC categories were classified by international age specific cut points for boys and girls (28–30).
[e]A continuous combined CMR-score was derived using the *z* values of WC, SBP, DBP, LDL-C, HDL-C, and TG (20). Higher CMR-scores indicate a higher risk. HDL-C was multiplied by −1 before inclusion in the score, as it is inversely related to cardiometabolic risk.

TABLE 2. Comparison of best-fit indicators for benchmark model with class-varying, unrestricted latent profile models of one to six classes.

	Benchmark	1 Class	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes
BIC	44,503	44,503	43,734	**43,465**	43,475	43,562	43,767
CAIC	44,314	44,314	43,302	42,790	42,558	42,402	**42,365**
AWE	44,366	44,366	43,354	42,843	42,610	42,455	**42,417**
LL	−22,134	−22,134	−21,628	−21,372	−21,256	−21,178	**−21,159**
Cases per class (*n*)[a]	**843**	**843**	**673/170**	**268/463/112**	**222/208/308/105**	232/40/158/315/98	154/31/124/303/141/90

Bolded values indicate the value corresponding to the "best" model according to each fit indicator. Only class-varying, unrestricted latent profile models are presented in this table; these models had the best fit compared with other models (i.e., class-invariant, unrestricted; class-invariant, diagonal; and class-varying, diagonal (10)). The initial one-class class-invariant, unrestricted model was the "benchmark" model (10); this model has the same values as the one-class class-varying, unrestricted model. An overview of "best-fit" indicators of all other variance–covariance latent profile models can be found in Supplemental Digital Table 2 (Table, Supplemental Digital Content 2, Comparison of best-fit indicators for benchmark model all variance–covariance structures latent profile models of one to six classes, http://links.lww.com/MSS/B907).

[a]The cutoff for classes with too small proportion was set at 0.05 (34).

LL, log likelihood.

class-varying unrestricted three-class model was adopted for further analyses. An overview of "best-fit" indicators of all other variance–covariance latent profile models can be found in Supplemental Digital Table 2 (Supplemental Digital Content 2, Comparison of best-fit indicators for benchmark model all variance–covariance structures latent profile models of one to six classes, http://links.lww.com/MSS/B907).

Groups of participants with similar accumulation patterns were labeled according to their distinguishing features, as shown by high and low *z* values (Fig. 1) and means (SD) (Table 3) for the seven accumulation pattern variables relative to other patterns. Group 1 ("prolonged sitters") was characterized by the most time in sustained SED bouts and the least time in VPA bouts (*n* = 268; 32%). Youth in group 2 ("breakers") had the highest frequency of SED breaks and lowest engagement in sustained bouts across most PA intensities (*n* = 463; 55%). The smallest group (group 3; *n* = 112; 13%) had the least time accumulated in SED bouts and the most time accumulated in PA bouts across almost all intensities ("prolonged movers"). Prolonged sitters were selected as the referent group for the linear and logistic regression models, as breakers and prolonged movers were considered to be groups with healthier accumulation patterns.

Differences between groups. Breakers (~10 yr old) were, on average, approximately 1 yr younger compared with both prolonged sitters and prolonged movers (~11 yr old). Prolonged movers included the lowest proportion of girls (38%), followed by prolonged sitters (51%) and breakers (61%). No differences in SES across groups were observed.

Descriptive statistics showed that the total daily volumes of intensities were mostly in line with the accumulation pattern variables that were used in the latent profile analysis. Prolonged sitters engaged in the most SED time and the least VPA compared with both other groups. Although prolonged sitters spent a similar amount of time in sustained MPA bouts to that of prolonged movers, their total daily volume of MPA was lower. Prolonged movers spent the most amount of time in PA across intensities and the least amount in SED time. Although breakers spent the least amount of time in sustained bouts across PA intensities compared with both other groups, their total daily volume of PA was considerably higher than prolonged sitters and only slightly lower than prolonged movers.

Associations between groups with distinct accumulation patterns and cardiometabolic risk factors. Table 4 shows the associations between the distinct groups and cardiometabolic risk factors for the minimally (model 1) and fully adjusted models (model 3). The overall *P* value for group trend was significant for BMI and WC only. Pairwise comparisons showed that breakers had the healthiest zBMI and WC values; this remained after adjusting for confounders. After adjustment for confounders, breakers had a significantly lower zBMI (mean difference, −0.30; Table 3) compared with prolonged sitters. Similarly, breakers had an approximately 5 cm smaller WC compared with prolonged sitters (mean differences reported in Table 3). No associations between the distinct groups and the remaining cardiometabolic risk factors were found. The increment in the partially adjusted linear model 2 did not specifically influence the results and are therefore only reported in Supplemental Digital Table 3 (Supplemental Digital Content 3, Regression coefficients (β) and 95% CI for associations between distinct groups and cardiometabolic risk factors, http://links.lww.com/MSS/B908].

Breakers and prolonged movers had both significantly lower odds (59% for both groups) of being classified as overweight/obese based on their BMI compared with prolonged sitters, which remained after adjusting for confounders (Table 5). Although the odds for being overweight based on WC seemed lower for breakers and prolonged movers versus prolonged sitters, no consistent significant results were found for WC across

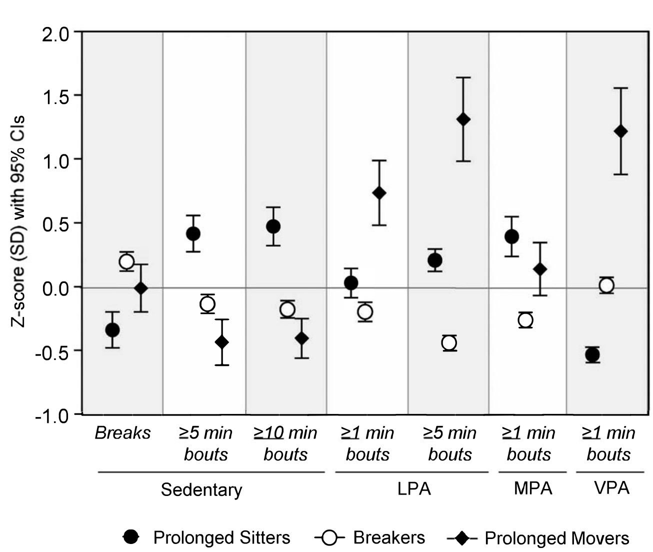

FIGURE 1—*Z* scores with 95% CI of the seven accumulation pattern variables among the three distinct groups of youth. *Z* score = (value − mean)/SD.

EPIDEMIOLOGY

TABLE 3. Participant characteristics for distinct groups.

	Prolonged Sitters, Mean ± SD	Breakers, Mean ± SD	Prolonged Movers, Mean ± SD	*P*
Class size (*n*)	268	463	112	
Demographic characteristics				
Age, yr	11.2 ± 1.5*	10.0 ± 1.6*,**	11.0 ± 1.6**	<0.0001
Sex, % female	51.2	60.9***	37.5***	<0.0001
SES (% high/mid/low SES)	3/36/62	4/35/61	1/34/65	0.6420
Cardiometabolic health outcomes				
BMI, kg·m^{-2a}	19.8 ± 3.8	18.0 ± 2.9	18.8 ± 2.8	
zBMI^{a}	0.7 ± 1.2	0.4 ± 1.1	0.5 ± 1.1	
BMI status, % overweight/obese^{a}	36.6	19.8	19.8	
WC, cm^{a}	67.0 ± 10.0	62.1 ± 7.7	65.8 ± 8.8	
WC status, % overweight/obese^{a}	48.8	36.7	45.0	
SBP, mm Hg^{b}	110.0 ± 10.1	104.8 ± 10.0	108.1 ± 10.0	
Diastolic blood pressure, mm Hg^{b}	61.4 ± 7.3	60.9 ± 7.7	60.7 ± 6.7	
HDL-C, mmol·L^{-1c}	1.4 ± 0.3	1.5 ± 0.3	1.4 ± 0.4	
LDL-C, mmol·L^{-1c}	2.6 ± 0.7	2.6 ± 0.7	2.5 ± 0.6	
TG, mmol·L^{-1c}	0.9 ± 0.4	0.8 ± 0.3	0.9 ± 0.4	
CMR-score^{d}	1.0 ± 3.6	−0.4 ± 3.3	0.8 ± 3.8	
Total daily volumes				
SED, min·d^{-1}	465.7 ± 92.8	428.8 ± 66.8	420.5 ± 70.8	
LPA, min·d^{-1}	225.2 ± 37.7	227.6 ± 31.1	250.4 ± 40.3	
MPA, min·d^{-1}	41.7 ± 15.4	46.9 ± 14.2	48.6 ± 18.3	
VPA, min·d^{-1}	13.3 ± 6.8	22.2 ± 10.9	29.5 ± 18.4	
Accumulation patterns (included in latent profile analysis)				
Breaks in SED time, no. per day	302.5 ± 48.2	314.6 ± 37.2	314.7 ± 42.7	
≥5-min SED bouts, min·d^{-1}	199.4 ± 82.1	158.9 ± 52.6	153.8 ± 56.7	
≥10-min SED bouts, min·d^{-1}	104.2 ± 60.8	71.8 ± 32.8	69.9 ± 36.9	
≥1-min LPA bouts, min·d^{-1}	106.2 ± 23.4	98.6 ± 21.0	123.2 ± 33.2	
≥5-min LPA bouts, min·d^{-1}	3.2 ± 2.2	1.1 ± 1.1	6.6 ± 5.3	
≥1-min MPA bouts, min·d^{-1}	10.6 ± 6.1	7.4 ± 3.0	9.4 ± 5.4	
≥1-min VPA bouts, min·d^{-1}	2.6 ± 1.8	5.8 ± 4.0	12.9 ± 10.7	

Data are presented as mean ± SD, unless otherwise indicated. Linear regression models accounted for school clustering were conducted to determine whether there were any differences in continuous demographic characteristics across the distinct groups. Differences according to demographic characteristics were assessed using logistic regression models accounted for school clustering. *Post hoc* Bonferroni tests were used to identify where the specific differences occurred between the groups. Significance was assessed at the level of $P < 0.05$. Symbols *, ***, ** denote pairwise significant differences between distinct groups.

*Significant difference between prolonged sitters and breakers.

**Significant difference between breakers and prolonged movers.

***Significant difference between prolonged sitters and prolonged movers.

[a]Adiposity subset, n = 782.

[b]Blood pressure subset, n = 637.

[c]Lipid subset, n = 525.

[d]CMR-score subset, n = 404.

the logistic models. The increment in the partially adjusted logistic model 2 did not specifically influence the results and are therefore only reported in Supplemental Digital Table 4 (Supplemental Digital Content 4, OR and 95% CI for overweight or obesity for the three identified distinct groups (n = 782), http://links.lww.com/MSS/B909).

DISCUSSION

To our knowledge, this is the first cross-sectional analysis to use objective data on SED and PA bouts and SED breaks to identify and characterize the complex accumulation patterns across the activity spectrum in youth. This study found three unique accumulation patterns among 7- to 13-yr-old youth: prolonged sitters, breakers, and prolonged movers. This analysis highlights the complexity of the relationships between intensities across the activity spectrum, and is consistent with previous research that has used exploratory data-driven techniques to investigate the clustering of total volumes and behaviors in this age group (9,12). The breakers group, characterized by the highest number of SED breaks and lowest engagement in sustained bouts across SED and most PA intensities, was inversely associated with indicators of adiposity (e.g., BMI: ß (95% CI) = −0.14 (−0.55 to −0.10); WC: −0.11 (−3.74 to −0.41)). Both breakers and prolonged movers had lower odds of being classified as overweight/obese based on their BMI compared with prolonged sitters. No associations were found between the distinct groups and the other cardiometabolic risk factors.

For most intensities, the total accumulated daily volumes across groups reflected the specific accumulation patterns. For example, prolonged sitters spent the most time in SED and least time in different PA intensities, and prolonged movers engaged in the highest daily volume of activity across intensities. Although breakers spent the least time in sustained PA bouts compared with the other groups, they engaged in more total daily PA across all intensities compared with prolonged sitters and comparable with prolonged movers. Previous evidence in this age group has shown that higher levels of PA, and in particular VPA, are important for cardiometabolic health in children (35). Consequently, the observed beneficial health outcomes in breakers and prolonged movers versus prolonged sitters may be explained by higher VPA levels in these groups.

Evidence regarding potential effects of sporadic versus prolonged behaviors on total daily volumes of activities is scarce, particularly in youth. Willis and colleagues (13) found that children aged 6–9 yr who accumulated a greater percentage of their MVPA in sustained bouts (defined as 5–10 and ≥10 min) and a lower percentage in sporadic MVPA (<5 min) had a higher total daily volume compared with children with a lower percentage of sustained

EPIDEMIOLOGY

TABLE 4. Regression coefficients (β) and 95% CI for associations between distinct groups and cardiometabolic risk factors.

Accumulation Pattern	Minimally Adjusted Model 1, *B* (95% CI)	Fully Adjusted Model 3, *B* (95% CI)
zBMI (*n* = 782)		
Prolonged sitters	Referent	Referent
Breakers	−0.15* (−0.57 to −0.12)	−0.14* (−0.55 to −0.10)
Prolonged movers	−0.06 (−0.47 to 0.06)	−0.07 (−0.49 to 0.02)
P for trend	0.0107	0.0169
WC (*n* = 782)		
Prolonged sitters	Referent	Referent
Breakers	−0.12* (−3.91 to −0.49)	−0.11* (−3.74 to −0.41)
Prolonged movers	−0.03 (−2.85 to 1.15)	−0.04 (−3.01 to 1.05)
P for trend	0.0188	0.0308
SBP (*n* = 637)		
Prolonged sitters	Referent	Referent
Breakers	−0.07 (−3.52 to 0.50)	−0.06 (−3.30 to 0.68)
Prolonged movers	−0.04 (−3.56 to 0.98)	−0.04 (−3.55 to 1.16)
P for trend	0.3183	0.3940
Diastolic blood pressure (*n* = 637)		
Prolonged sitters	Referent	Referent
Breakers	−0.01 (−2.08 to 1.64)	−0.01 (−2.06 to 1.65)
Prolonged movers	−0.03 (−2.54 to 1.36)	−0.02 (−2.41 to 1.51)
P for trend	0.8299	0.8996
HDL (*n* = 525)		
Prolonged sitters	Referent	Referent
Breakers	0.02 (−0.04 to 0.07)	0.03 (−0.03 to 0.07)
Prolonged movers	−0.03 (−0.10 to 0.05)	−0.05 (−0.12 to 0.03)
P for trend	0.5838	0.3223
LDL (*n* = 525)		
Prolonged sitters	Referent	Referent
Breakers	−0.01 (−0.14 to 0.10)	−0.01 (−0.14 to 0.10)
Prolonged movers	−0.03 (−0.23 to 0.11)	−0.03 (−0.23 to 0.11)
P for trend	0.7750	0.7982
TG (*n* = 525)		
Prolonged sitters	Referent	Referent
Breakers	−0.02 (−0.09 to 0.07)	−0.02 (−0.09 to 0.06)
Prolonged movers	0.04 (−0.06 to 0.16)	0.06 (−0.04 to 0.17)
P for trend	0.5988	0.3530
Cardiometabolic risk score (*n* = 404)		
Prolonged sitters	Referent	Referent
Breakers	−0.03 (−0.97 to 0.57)	−0.04 (−1.02 to 0.52)
Prolonged movers	0.02 (−0.85 to 1.28)	0.03 (−0.74 to 1.33)
P for trend	0.6247	0.4323

Significance was assessed at the level of $P < 0.05$. Linear regression models were conducted to analyze associations between the groups and each of the continuous cardiometabolic risk factors. The trend *P* values for overall group effect are presented. *Post hoc* Bonferroni tests were used to identify where specific differences occurred between the groups. Three incremental models were used: model 1 (minimally adjusted model), adjusted for study involvement, accounted for clustering within schools; model 2, additionally adjusted for participants' age and sex; and model 3 (fully adjusted model), further adjusted for SES. Results for model 2 can be found in Supplementary Table 3, http://links.lww.com/MSS/B908.
*Pairwise significant differences between prolonged sitters and breakers.

EPIDEMIOLOGY

bouts and a higher percentage of sporadic MVPA. Although this contrasts with findings from the present study, bouts were defined differently in that study, which makes it difficult to compare with the current study. This highlights the lack of consistency in the definition of bouts and suggests that the field would benefit from a consensus on bout definitions. This would then enable researchers to compare findings across studies and examine the contribution of these patterns to time-use compositions including total daily PA and SED.

Breakers had the healthiest indicators of adiposity when compared with both other groups, despite spending less total time being physically active compared with prolonged movers. Because most children were breakers, this is a promising finding for children's health, and suggests that youth may benefit health through accumulation patterns beyond total volumes. Based on consistent previous research that has shown the cardiometabolic benefits of engaging in high intensity activity levels, it was expected that prolonged movers (total MVPA: 78 min) would have similar or better health profiles, and in particular adiposity markers, than breakers (69 min). Yet, the opposite was observed. This suggests that activity accumulation patterns may be important for adiposity, and that the sporadic activity accumulation patterns of breakers, compared to the other groups, could lead to benefits beyond total volumes of physical activity. Although future research needs to further investigate the co-occurrence and codependence of these accumulation patterns (i.e., whether and why do these patterns occur alongside each other), our data suggest that breaking up SED time and sporadic engagement in PA is inversely related to overweight/obesity relative to engaging in sustained bouts of SED and PA.

Although breakers were younger (and thus may have had difficulties engaging in a particular behavior for a prolonged time [36)]) and had the highest proportion of girls compared with the other groups, our findings remained after adjusting for age and sex. Nevertheless, our study suggests that sporadic accumulation patterns may occur more often in girls than in boys, which is important information, as evidence to date has shown that girls are generally less active than boys (37). Although breakers—the group with the highest proportion of girls—were the healthiest group in our study, these findings suggest that interventions should target girls' patterns of accumulation to benefit health. Future studies should investigate differences in the accumulation patterns of boys and girls, as this will be critical information for the design of intervention strategies.

Because this is the first study in youth to examine accumulation patterns across the activity spectrum in this way, comparisons with prior research is difficult. Nonetheless, previous cross-sectional research in this age group found that sporadic MVPA (i.e., <5 min) and bouts of MVPA (i.e., ≥5 min) had similar relationships for both of these patterns with cardiometabolic risk factors (including WC and SBP) (38), and that bouts (defined as ≥4 s) were shorter and less intense in overweight versus nonoverweight boys (39). However, these studies investigated patterns of PA intensities separately (38,39) and not in combination with other intensities, which may explain the differences

TABLE 5. OR and 95% CI for overweight or obesity for the three identified distinct groups (*n* = 782).

	Minimally Adjusted Model 1		Fully Adjusted Model 3	
Accumulation Pattern	**OR (95% CI)**	***P***	**OR (95% CI)**	***P***
BMI				
Prolonged sitters	1.00		1.00	
Breakers	0.41* (0.29–0.59)	<0.01	0.41* (0.29–0.59)	<0.01
Prolonged movers	0.41* (0.26–0.65)	<0.01	0.41* (0.26–0.66)	<0.01
WC				
Prolonged sitters	1.00		1.00	
Breakers	0.71 (0.48–1.05)	0.09	0.71 (0.48–1.04)	0.08
Prolonged movers	0.88 (0.56–1.39)	0.58	0.89 (0.56–1.41)	0.61

Significance was assessed at the level of $P < 0.05$. Logistic regression models estimated the OR and 95% CI of the distinct groups for being overweight/obese (i.e., using the binary variables for BMI and WC, separately). Here, OR values >1 imply a higher chance for being overweight/obese relative to the accumulation pattern reference group. Three incremental models were used: model 1 (minimally adjusted model), adjusted for study involvement, accounted for clustering within schools; model 2, additionally adjusted for participants' age and sex; and model 3 (fully adjusted model), further adjusted for SES. Results for model 2 can be found in Supplementary Table 4, http://links.lww.com/MSS/B909.
*Significant results.

between those and our findings. There is also the potential of reverse causality where children who are overweight or obese may be less likely to engage in prolonged MPA or VPA. The explanations as to why accumulation patterns across the activity spectrum cluster in an unhealthy way in some groups, but not others, are underexplored, and the effect of these patterns on cardiometabolic health requires further investigation. Thus, there is a need for longitudinal research that will help with understanding the causal pathway of patterns of accumulation across the activity spectrum in relation to cardiometabolic health. This could inform recommendations around PA and SED-specific accumulation patterns that promote health and well-being.

The possible biological mechanisms by which sporadic, compared with sustained behaviors influence adiposity, and no other cardiometabolic risk factors, are unclear. Based on our findings, patterns seem to be important for adiposity, which may be the first indicator of an unhealthy profile in this age group (14–16). Some cross-sectional evidence in adults (40) and experimental studies in youth (40) have provided preliminary evidence that breaking up SED may provide beneficial metabolic effects on measures such as postprandial glucose and insulin levels. These indicators are closely linked to cardiometabolic pathways, such as adipocyte dysfunction and risk of obesity (14–16). Although no associations were found for the distinct accumulation patterns with blood pressure and lipids in the present study, this may be explained by the participant age range and their limited cumulative exposure to unhealthy lifestyle behaviors. In addition, evidence suggests that activity behaviors (i.e., total volumes) and cardiometabolic health parameters track across time (7). However, it is unclear if accumulation patterns also track over time. Longitudinal studies are therefore needed to assess whether long-term exposure to different accumulation patterns, independent of total volumes, predict cardiometabolic health later in life.

Strengths of this study included the use of a data-driven method to derive accumulation patterns and the novel application of these distinct patterns to identifying associations with a range of cardiometabolic risk factors in a large sample of youth. These patterns were derived from objective measures of PA and SED. Nevertheless, there were some limitations. First, data were not stratified based on age and sex, which may affect activity behaviors and adiposity. Although the models were adjusted for age, we were unable to adjust for puberty because of this not being collected in the Transform-Us! study. In addition, the chosen optimal three-class solution may have oversimplified activity patterns. This work needs to be replicated to understand if these accumulation patterns are consistent across youth (i.e., including other populations) and if this is influenced by maturity status. The use of accelerometers and the cut points made it impossible to collect postural information and isolated upper body activities (41). Because of the cross-sectional nature of this study, it is not possible to assess the temporal relationships. Although BMI is often used as a proxy for adiposity and results were mostly in line with the findings for WC, this is not a direct measure of fat mass, and thus, results should be interpreted cautiously (42). It is important to note that we classified participants categorized as underweight as being of healthy weight. Although the exclusion of these participants from the analyses did not change the findings, this should be acknowledged. In addition, despite not targeting activity patterns (i.e., breaking up sitting) and finding no intervention effect on PA during the school week, it is possible that the intervention delivered within the LOOK study may have influenced our findings. Finally, some of the cardiometabolic risk factors (e.g., lipids) were only collected between 43% and 52% of the original sample.

In summary, this study identified three distinct groups with unique activity patterns using latent profile analysis: prolonged sitters, breakers, and prolonged movers. In addition, sporadic PA and breaking up SED time were positively related to total daily PA and inversely associated with adiposity, but not other cardiometabolic risk factors including blood pressure or blood lipids. However, future research is needed to determine whether the identified accumulation patterns are replicable in other populations, discover why these patterns occur in some groups but not others, investigate biological processes and longitudinal effects in sporadic versus prolonged physical activities, and examine if these patterns can be changed to improve health in youth. The latter is particularly important to inform public health interventions and policies.

The authors thank Eoin O'Connell for the development of the customized Excel macro. The authors would like to thank the LOOK and Transform-Us! staff and participants, their parents, and the schools for their participation in this research. We specifically acknowledge LOOK and Transform-Us! chief investigators Professor Richard Telford, Professor David Crawford, Professor Kylie Ball, and Associate Professor Kylie Hesketh.

This research is secondary data analysis and did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The LOOK study received funding from The Commonwealth Education Trust and the Canberra Hospital Clinical Trials Unit. Transform-Us! was supported by a National Health and Medical Research Council Project Grant and a Diabetes Australia Research Trust grant. S. V. holds a Deakin University PhD scholarship. R. M. L. is supported by an Alfred Deakin Postdoctoral Fellowship and a National Heart Foundation Postdoctoral Research Fellowship (ID102109). J. S. was supported by a National Health and Medical Research Council (NHMRC) Principal Research Fellowship during the completion of this study (APP1026216). A. T. was supported by a Future Leader Fellowship from the National Heart Foundation of Australia (Award ID 100046) during the course of this work. J. S., A. T., and D. W. D. received funding support from the NHMRC Centre of Research Excellence (APP1057608). D. W. D. is supported by a NHMRC Senior Research Fellowship (NHMRC APP1078360) and in part by the Victorian Government's OIS Program. C. H. was supported by a National Heart Foundation of Australia postdoctoral fellowship during the completion of the study. E. C. is supported by an ARC Future Fellowship (FT140100085). L. S. O. is supported by an NHMRC Early Career Fellowship (APP1158487) and was supported by NHMRC/National Heart Foundation of Australia Postgraduate Fellowship during the LOOK Study (APP1056551). N. R. is supported by a Future Leader Fellowship from the National Heart Foundation of Australia (Award ID 101895).

The results of the present study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of the study do not constitute endorsement by the American College of Sports Medicine. All authors declare that they have no competing interests.

REFERENCES

1. World Health Organization. *Global Recommendations on Physical Activity for Health*. Geneva: WHO Press; 2010.
2. Tremblay MS, Colley RC, Saunders TJ, Healy GN, Owen N. Physiological and health implications of a sedentary lifestyle. *Appl Physiol Nutr Metab*. 2010;35(6):725–40.
3. Tremblay MS, Aubert S, Barnes JD, et al. Sedentary Behavior Research Network (SBRN)—terminology consensus project process and outcome. *Int J Behav Nutr Phys Act*. 2017;14(1):75.
4. Verswijveren SJJM, Lamb KE, Bell LA, Timperio A, Salmon J, Ridgers ND. Associations between activity patterns and cardio-metabolic risk factors in children and adolescents: a systematic review. *PLoS One*. 2018;13(8):e0201947.
5. Glazer NL, Lyass A, Esliger DW, et al. Sustained and shorter bouts of physical activity are related to cardiovascular health. *Med Sci Sports Exerc* [Internet]. 2013;45(1):109–15.
6. Chastin SF, Egerton T, Leask C, Stamatakis E. Meta-analysis of the relationship between breaks in sedentary behavior and cardiometabolic health. *Obesity (Silver Spring)*. 2015;23(9):1800–10.
7. Telama R. Tracking of physical activity from childhood to adulthood: a review. *Obes Facts*. 2009;2(3):187–95.
8. Camhi SM, Katzmarzyk PT. Tracking of cardiometabolic risk factor clustering from childhood to adulthood. *Int J Pediatr Obes*. 2010;5(2):122–9.
9. Heitzler C, Lytle L, Erickson D, Sirard J, Barr-Anderson D, Story M. Physical activity and sedentary activity patterns among children and adolescents: a latent class analysis approach. *J Phys Act Health*. 2011;8(4):457–67.
10. Masyn KE. 25 Latent class analysis and finite mixture modeling. In: Little TD, editor. *The Oxford Handbook of Quantitative Methods in Psychology: Vol 2: Statistical Analysis*. Oxford: Oxford University Press; 2013. pp. 1–123.
11. Leech RM, McNaughton SA, Timperio A. Clustering of children's obesity-related behaviours: associations with sociodemographic indicators. *Eur J Clin Nutr*. 2014;68(5):623–8.
12. Parker KE, Salmon J, Brown HL, Villanueva K, Timperio A. Typologies of adolescent activity related health behaviours. *J Sci Med Sport*. 2018;22(3):319–23.
13. Willis EA, Ptomey LT, Szabo-Reed AN, et al. Length of moderate-to-vigorous physical activity bouts and cardio-metabolic risk factors in elementary school children. *Prev Med*. 2015;73:76–80.
14. Balagopal PB, de Ferranti SD, Cook S, et al. Nontraditional risk factors and biomarkers for cardiovascular disease: mechanistic, research, and clinical considerations for youth: a scientific statement from the American Heart Association. *Circulation*. 2011;123(23):2749–69.
15. Canas JA, Sweeten S, Balagopal PB. Biomarkers for cardiovascular risk in children. *Curr Opin Cardiol*. 2013;28(2):103–14.
16. Rodrigues AN, Abreu GR, Resende RS, Goncalves WL, Gouvea SA. Cardiovascular risk factor investigation: a pediatric issue. *Int J Gen Med*. 2013;6:57–66.
17. Salmon J, Arundell L, Hume C, et al. A cluster-randomized controlled trial to reduce sedentary behavior and promote physical activity and health of 8–9 year olds: the Transform-Us! study. *BMC Public Health*. 2011;11:759.
18. Telford RM, Telford RD, Cunningham RB, Cochrane T, Davey R, Waddington G. Longitudinal patterns of physical activity in children age 8 to 12 years: the LOOK study. *Int J Behav Nutr Phys Act*. 2013;10(81):1–12.
19. Robusto KM, Trost SG. Comparison of three generations of ActiGraph activity monitors in children and adolescents. *J Sports Sci*. 2012;30(13):1429–35.
20. Cain KL, Sallis JF, Conway TL, Van Dyck D, Calhoon L. Using accelerometers in youth physical activity studies: a review of methods. *J Phys Act Health*. 2013;10(3):437–50.
21. Gabel L, Ridgers ND, Della Gatta PA, et al. Associations of sedentary time patterns and TV viewing time with inflammatory and endothelial function biomarkers in children. *Pediatr Obes*. 2016;11(3):194–201.
22. Ridley K, Ainsworth BE, Olds TS. Development of a compendium of energy expenditures for youth. *Int J Behav Nutr Phys Act*. 2008;5:45.
23. Freedson P, Pober D, Janz KF. Calibration of accelerometer output for children. *Med Sci Sports Exerc*. 2005;37(11 Suppl):S523–S30.
24. Healy GN, Dunstan DW, Salmon J, et al. Breaks in sedentary time: beneficial associations with metabolic risk. *Diabetes Care*. 2008;31(4):661–6.
25. Altenburg TM, de Niet M, Verloigne M, et al. Occurrence and duration of various operational definitions of sedentary bouts and cross-sectional associations with cardiometabolic health indicators: the ENERGY-project. *Prev Med*. 2015;71:101–6.
26. Carson V, Ridgers ND, Howard BJ, et al. Light-intensity physical activity and cardiometabolic biomarkers in US adolescents. *PLoS One*. 2013;8(8):e71417.
27. Garnett SP, Baur LA, Cowell CT. Waist-to-height ratio: a simple option for determining excess central adiposity in young people. *Int J Obes (Lond)*. 2008;32(6):1028–30.
28. WHO Multicentre Growth Reference study group. *WHO Child Growth Standards: Length/Height-for-Age, Weight-for-Age, Weight-for-Length, Weight-for-Height and Body Mass Index-for-Age: Methods and Development*. Geneva: WHO Press; 2006.
29. Cole TJ, Bellizzi MC, Flegal KM, Dietz WH. Establishing a standard definition for child overweight and obesity worldwide: international survey. *BMJ*. 2000;320(7244):1–6.
30. Eisenmann JC. Waist circumference percentiles for 7- to 15-year-old Australian children. *Acta Paediatr*. 2005;94(9):1182–5.
31. Savva SC, Tornaritis M, Savva ME, et al. Waist circumference and waist-to-height ratio are better predictors of cardiovascular disease risk factors in children than body mass index. *Int J Obes (Lond)*. 2000;24(11):1453–8.
32. Zimmet PZA, G, Kaufman F, Tajima N, et al. The metabolic syndrome in children and adolescents: the IDF consensus. *Lancet*. 2007;52(4):29–32.
33. Chastin SF, Palarea-Albaladejo J, Dontje ML, Skelton DA. Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: a novel compositional data analysis approach. *PLoS One*. 2015;10(10):e0139984.
34. Nasserinejad K, van Rosmalen J, de Kort W, Lesaffre E. Comparison of criteria for choosing the number of classes in Bayesian finite mixture models. *PLoS One*. 2017;12(1):e0168838.
35. Aadland E, Kvalheim OM, Anderssen SA, Resaland GK, Andersen LB. The multivariate physical activity signature associated with metabolic health in children. *Int J Behav Nutr Phys Act*. 2018;15(1):77.
36. Bailey RC, Olson J, Pepper SL, Porszasz J, Barstow TJ, Cooper DM. The level and tempo of children's physical activities: an observational study. *Med Sci Sports Exerc*. 1995;27(7):1033–41.
37. Hallal PC, Andersen LB, Bull FC, Guthold R, Haskell W, Ekelund U. Global physical activity levels: surveillance progress, pitfalls, and prospects. *Lancet*. 2012;380(9838):247–57.
38. Holman RM, Carson V, Janssen I. Does the fractionalization of daily physical activity (sporadic vs. bouts) impact cardiometabolic risk factors in children and youth? *PLoS One*. 2011;6(10):e25733.
39. Stone MR, Rowlands AV, Eston RG. Characteristics of the activity pattern in normal weight and overweight boys. *Prev Med*. 2009;49(2009):205–8.
40. Fletcher EA, Salmon J, McNaughton SA, et al. "Effects of breaking up sitting on adolescents" postprandial glucose after consuming meals varying in energy: a cross-over randomised trial. *J Sci Med Sport*. 2017;21(3):280–5.
41. Ridgers ND, Salmon J, Ridley K, O'Connell E, Arundell L, Timperio A. Agreement between activPAL and ActiGraph for assessing children's sedentary time. *Int J Behav Nutr Phys Act*. 2012;9:15.
42. Pietrobelli A, Faith M, Allison D, Gallagher D, Chiumello G, Heymsfield S. Body mass index as a measure of adiposity among children and adolescents: a validation study. *J Pediatr*. 1998;132(2).