Activity accumulation and cardiometabolic risk in youth: A latent profile approach

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ABSTRACT

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 7-13 year olds from two studies were pooled (n=1,219; 843 [69%] with valid accelerometry included in analysis). Time accumulated in ≥5-min and ≥10-min SED bouts, ≥1-min and ≥5-min bouts of light (LPA), and ≥1-min bouts of moderate (MPA) and vigorous (VPA) PA were calculated. Frequency of breaks in SED were 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 prolonged SED bouts and the least time in VPA bouts; ‘Breakers’ had the highest frequency of SED breaks and lowest engagement in sustained bouts across most PA intensities; ‘Prolonged movers’ had the least time accumulated in SED bouts and the most in PA bouts across most intensities. ‘Prolonged movers’ and ‘Breakers’ had lower odds of being classified as overweight/obese based on body mass index compared to ‘Prolonged sitters’. Whilst ‘Breakers’ engaged in less time in PA bouts compared to other groups, they had the healthiest adiposity indicators. No associations with the remaining cardiometabolic risk factors were found.

Conclusion: The current results suggest that youth accumulate their daily activity in three distinct patterns (‘Prolonged sitters’, ‘Breakers’ and ‘Prolonger movers’), with those breaking up sitting and most time in sporadic PA 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.

INTRODUCTION

To benefit health and reduce cardiometabolic risk factors, international guidelines state that youth aged 5-17 years should accumulate at least 60 minutes of moderate- to vigorous-intensity physical activity (MVPA) daily and minimize extended periods of sedentary behavior (SED) (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 comprised 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 (4), and the evidence is inconsistent (4). In adults, evidence suggests breaking up SED time and that engagement in short and sustained activity bouts are associated with a reduction in 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 daily accumulation of PA intensities (i.e., moderate [MPA], VPA, or MVPA) or total SED in isolation, and how this is associated with children’s cardiometabolic risk factors. 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 use 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 to children with a low percentage of those bouts, nevertheless, 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. Whilst 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) was considered in this study. Supplemental Digital Table 1 shows the breakdown of participant numbers and key methodological characteristics of both studies. 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 second epochs, ActiLife software (v5.1.5) was used to reintegrate these into 15-second epochs to be consistent with Transform-Us! a customized Excel Macro was then used to further process the files. Non-wear time (≥20 minutes of consecutive zeroes) was subtracted from each day to determine wear time (20). Participants with ≥4 valid days (defined as 8 hours of wear time on weekdays and 7 hours 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/min (20); and, light PA (LPA), MPA (≥4 and <6 METs; (22)) and VPA (≥6 METs) (23). Total time spent in each of these intensities 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 cpm for ≥1 epoch] between sedentary 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-min 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 (min/day) spent in bouts at 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), high-density lipoprotein (HDL-C) and low-density lipoprotein (LDL-C) cholesterol, 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 (kg/m^2) (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: ≥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 following 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, USA). 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 regarding how observed continuous variables relate to each other 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). Whilst 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 sub-composition of waking hours, as the elements together are not 'closed' so that they sum to one (33). This is partially due to the inclusion of frequency of SED breaks as a variable of interest, as well as different minimum bout lengths for SED and LPA and multiple variables within the same intensity.

Four different variance-covariance structures were compared in order 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, while 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, while 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 were identified by analyzing 1-class through to 6-class models within each of the above 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 cut-off was set at 0.05 (34)) and the interpretation of classes (10). The 'best' model was identified as the model with the fewest number of classes with a better relative fit than the initial 'benchmark' 1-class class-invariant, unrestricted model (10); the identified classes in that 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.

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 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 (ORs) and 95% confidence intervals of the distinct groups for being overweight/obese (i.e., using the binary variables for BMI and WC, separately). Here, ORs >1 imply a higher chance for being overweight/obese relative to the 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 aged between 7 and 13 years. 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% percent agreement). The average time spent SED and in LPA, MPA and VPA was 7 hours and 20 minutes, 3 hours and 50 minutes, 45 minutes, and 20 minutes, respectively.

***** Table 1 here *****

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 to 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 3-class model demonstrated the biggest drop in CAIC, BIC and AWE values, when each solution was compared to the previous solution. The 3-class model also had the lowest BIC overall. Whilst CAIC and AWE values were slightly better for the class-varying unrestricted, 5- and 6-class models, compared to the class-varying unrestricted 3-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 cut-off (<5%, (34)) for inclusion. Based on the model fit indices, interpretability of the models (i.e., particularly for the 4-class model), and size of the extracted classes (i.e., particularly for the 5- and 6-class models), the class-varying unrestricted 3-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.

***** Table 2 here *****

Groups of participants with similar accumulation patterns were labelled according to their distinguishing features, as shown by high and low Z-values (Figure 1) and means (SD) for the seven accumulation pattern variables relative to other patterns (Table 3). Group 1 (‘Prolonged sitters’) was characterized by the most time in prolonged 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.

***** Figure 1 here *****

***** Table 3 here *****

Differences between groups

‘Breakers’ (~10 years old) were, on average, approximately one year younger compared to both ‘Prolonged sitters’ and ‘Prolonged movers’ (~11 years 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 to both other groups. Whilst 'Prolonged sitters' spent a similar amount of time in prolonged MPA bouts as '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. Whilst 'Breakers' spent the least amount of time in sustained bouts across PA intensities compared to both other groups, their total daily volume in all PA intensities was higher than 'Prolonged sitters'.

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, see Table 3) compared to 'Prolonged sitters'. Similarly, 'Breakers' had an approximately five cm smaller WC compared to '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 results and are therefore only reported in Supplemental Digital Table 3.

***** Table 4 here *****

'Breakers' and 'Prolonged movers' had both significantly lower odds (59%) of being classified as overweight/obese based on their BMI compared to 'Prolonged sitters', which remained after adjusting for confounders (Table 5). Whilst the odds for being overweight based on WC seemed lower for 'Prolonged movers' versus 'Prolonged sitters', no consistent significant results were found for WC across the logistic models. 'Breakers' did have significantly lowers odds of being classified as overweight/obese compared to the 'Prolonged sitters'. The increment in the partially-adjusted logistic Model 2 did not specifically influence results and are therefore only reported in Supplemental Digital Table 4.

***** Table 5 here *****

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 7-13 year 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). '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, -0.10]; WC: -0.11 [-3.74, -0.41]). Both 'Breakers' and 'Prolonged movers' had lower odds of being classified as overweight/obese based on their BMI compared to '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. Whilst ‘Breakers’ spent the least time in prolonged PA bouts compared to the other groups, they engaged in more total daily PA across all intensities compared to ‘Prolonged sitters’. This suggests that sporadic activity accumulation (i.e., <5-min bouts of LPA and <1-min bouts of MPA and VPA) and breaking up sitting throughout the day may be typical in active lifestyles. Previous evidence in this age group has shown that higher levels of physical activity, and in particular VPA, are important for the 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 years who accumulated a greater percentage of their MVPA in prolonged MVPA bouts (defined as 5–10 min and ≥10 min) and a lower percentage in sporadic MVPA (<5 min) had a higher total daily volume compared to children with a lower percentage of prolonged MVPA bouts and a higher percentage of sporadic MVPA. Whilst 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.

Whilst ‘Prolonged sitters’ spent the most time in MPA bouts, and had comparable total daily volumes of MPA, they were less healthy compared to both other groups. In addition, ‘Breakers’ had the healthiest indicators of adiposity, when compared to both other groups, despite spending less total time being physically active compared to ‘Prolonged movers’. As most children were ‘Breakers’, this is a promising finding for children’s health. It is possible that not only the frequency but also the intensity with which 'Breakers' interrupted their SED time was important. For example, the relatively large amount of time spent in VPA bouts versus MPA bouts in this group compared to other groups, may have contributed to lower zBMI and WC. Perhaps the high levels of time in MPA bouts in 'Prolonged sitters' was not enough to offset the detrimental impact of their prolonged sitting. Whilst future research needs to further investigate the co-occurrence and co-dependence 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 prolonged bouts of SED and PA.

Whilst '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 to 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 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.

As 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 seconds) were shorter and less intense in overweight versus non-overweight 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 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 impact of these patterns on cardiometabolic health requires further investigation. Thus, there is 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 wellbeing.

The possible biological mechanisms by which sporadic, compared to prolonged, behaviors influence adiposity and no other cardiometabolic risk factors are unclear. Based on our findings, patterns appear 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 (24) 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). While no associations were found for ‘Breakers’ 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. Firstly, data were not stratified based on age and sex which may affect activity behaviors and adiposity. Whilst the models were adjusted for age, we were unable to adjust for puberty due to this not being collected in the Transform-Us! study. In addition, the chosen optimal 3-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). Due to the cross-sectional nature of this study, it is not possible to assess the temporal relationships. Whilst BMI is often used as a proxy for adiposity, and results were 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. Whilst 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 from 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 to examine if these patterns can be changed to improve health in youth. The latter is particularly important to inform public health interventions and policies.

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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.

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FIGURE TITLE AND LEGEND

Figure 1. Z-scores with 95% Confidence Intervals of the seven accumulation pattern variables among the three distinct groups of youth

Figure 1 Legend:

Z-score = (value-mean)/SD

95% CI: 95% Confidence Intervals

SUPPLEMENTAL DIGITAL CONTENT LIST

Supplemental Digital Table 1. Key methodological characteristics of the LOOK and Transform-Us! studies

Supplemental Digital Table 2. Comparison of best fit indicators for benchmark model all variance-covariance structures latent profile models of 1 to 6 classes

Supplemental Digital Table 3. Regression coefficients (β) and 95% confidence intervals (CI) for associations between distinct groups and cardiometabolic risk factors

Supplemental Digital Table 4. Odds ratios (OR) and 95% confidence intervals (CI) for overweight or obesity for the three identified distinct groups (n=782)

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 (years; mean±SD)	806	10.5 ± 1.7
Sex (% female)	823	54.7
SES (% low/mid/high SES)	824	3/36/61
Cardiometabolic risk factors[C]		
BMI (kg/m^2, mean±SD)	807	18.6 ± 3.3
BMI status (% overweight/obese)[D]	804	25.0
Waist circumference (cm, mean±SD)	801	64.1 ± 8.9
Waist circumference status (% overweight/obese)[D]	799	41.55
Systolic blood pressure (mmHg, mean±SD)	660	106.7 ± 10.3
Diastolic blood pressure (mmHg, mean±SD)	660	61.0 ± 7.5
HDL-C (mmol/L, mean±SD)	559	1.5 ± 0.3
LDL-C (mmol/L, mean±SD)	559	2.5 ± 0.7
Triglycerides (mmol/L, mean±SD)	559	0.9 ± 0.4
CMR-score (mean±SD)[E]	416	0.2 ± 3.5
Total daily volumes[C]		
SED (min/day, mean±SD)	843	439.4 ± 78.5
LPA (min/day, mean±SD)	843	229.9 ± 35.5
MPA (min/day, mean±SD)	843	45.5 ± 15.4
VPA (min/day, mean±SD)	843	20.3 ± 12.4
Accumulation patterns (included in latent profile analysis)[C]		

Breaks in SED time (number/day, mean±SD)	843	310.7 ± 42.1
≥5-min SED bouts (min/day, mean±SD)	843	171.1 ± 66.7
≥10-min SED bouts (min/day, mean±SD)	843	81.9 ± 46.6
≥1-min LPA bouts (min/day, mean±SD)	843	104.3 ± 25.0
≥5-min LPA bouts (min/day, mean±SD)	843	2.5 ± 3.0
≥1-min MPA bouts (min/day, mean±SD)	843	8.7 ± 4.8
≥1-min VPA bouts (min/day, mean±SD)	843	5.7 ± 5.9

Data are presented as Mean ± SD unless otherwise indicated.

SD: Standard deviation; BMI: Body Mass Index; CMR-score: HDL-C: High-density lipoprotein cholesterol; LDL-C: Low-density lipoprotein cholesterol; Cardiometabolic risk score; SES: Socioeconomic status; SED: Sedentary behavior; LPA: Light Physical Activity; MPA: Moderate Physical Activity; VPA: Vigorous Physical Activity.

[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 waist circumference 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 waist circumference, 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.

Table 2. Comparison of best fit indicators for benchmark model with class-varying, unrestricted latent profile models of 1 to 6 classes

	Benchmark	**1 class**	**2 classes**	**3 classes**	**4 classes**	**5 classes**	**6 classes**
BIC	44503	44503	43734	**43465**	43475	43562	43767
CAIC	44314	44314	43302	42790	42558	42402	**42365**
AWE	44366	44366	43354	42843	42610	42455	**42417**
LL	-22134	-22134	-21628	-21372	-21256	-21178	**-21159**
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

Note: 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 to other models (i.e., class-invariant, unrestricted; class-invariant, diagonal, and; class-varying, diagonal(10)).

The initial 1-class class-invariant, unrestricted model was the ‘benchmark’ model (10); this model has the same values as the 1-class class-varying, unrestricted model.

BIC: Bayesian Information Criteria; CAIC: Consistent Akaike’s Information Criteria; AWE: Approximate Weight of Evidence Criterion; LL: Log likelihood.

[A] The cut-off for classes with too small proportion was set at 0.05 (34).

Table 3. Participant characteristics for distinct groups

	Prolonged sitters	Breakers	Prolonge
	Mean ± SD	**Mean ± SD**	**Mean**
Class size (n)	268	463	11
Demographic characteristics			
Age (years)	11.2 ± 1.5†	10.0 ± 1.6†§	11.0 ±
Sex (% female)	51.2	60.9¥	37
SES (% low/mid/high SES)	3/36/62	4/35/61	1/34
Cardiometabolic health outcomes			
BMI (kg/m^2)[A]	19.8 ± 3.8	18.0 ± 2.9	18.8
zBMI[A]	0.7 ± 1.2	0.4 ± 1.1	0.5 ±
BMI status (% overweight/obese)[A]	36.6	19.8	19
WC (cm)[A]	67.0 ± 10.0	62.1 ± 7.7	65.8
WC status (% overweight/obese)[A]	48.8	36.7	45
Systolic blood pressure (mmHg)[B]	110.0 ± 10.1	104.8 ± 10.0	108.1
Diastolic blood pressure (mmHg)[B]	61.4 ± 7.3	60.9 ± 7.7	60.7
HDL-C (mmol/L)[C]	1.4 ± 0.3	1.5 ± 0.3	1.4 ±
LDL-C (mmol/L)[C]	2.6 ± 0.7	2.6 ± 0.7	2.5 ±
Triglycerides (mmol/L)[C]	0.9 ± 0.4	0.8 ± 0.3	0.9 ±

CMR-score[D]	1.0 ± 3.6	-0.4 ± 3.3	0.8 ±
Total daily volumes			
SED (min/day)	465.7 ± 92.8	428.8 ± 66.8	420.5
LPA (min/day)	225.2 ± 37.7	227.6 ± 31.1	250.4
MPA (min/day)	41.7 ± 15.4	46.9 ± 14.2	48.6 ±
VPA (min/day)	13.3 ± 6.8	22.2 ± 10.9	29.5 ±
Accumulation patterns (included in latent profile analysis)			
Breaks in SED time (number/day)	302.5 ± 48.2	314.6 ± 37.2	314.7
≥5-min SED bouts (min/day)	199.4 ± 82.1	158.9 ± 52.6	153.8
≥10-min SED bouts (min/day)	104.2 ± 60.8	71.8 ± 32.8	69.9 ±
≥1-min LPA bouts (min/day)	106.2 ± 23.4	98.6 ± 21.0	123.2
≥5-min LPA bouts (min/day)	3.2 ± 2.2	1.1 ± 1.1	6.6 ±
≥1-min MPA bouts (min/day)	10.6 ± 6.1	7.4 ± 3.0	9.4 ±
≥1-min VPA bouts (min/day)	2.6 ± 1.8	5.8 ± 4.0	12.9 ±

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 (†, ¥ and §) denote pairwise significant differences between distinct groups. † Significant difference between 'Prolonged sitters' and 'Breakers'. ¥ Significant difference between ‘Prolonged sitters’ and ‘Prolonged movers’. § Significant difference between ‘Breakers’ and ‘Prolonged movers’.

SD: Standard deviation; BMI: Body Mass Index; WC Waist circumference; HDL-C: High-density lipoprotein cholesterol; LDL-C: Low-density lipoprotein cholesterol; CMR-score: Cardiometabolic risk score; SES: Socioeconomic status; SED: Sedentary behavior; LPA: Light Physical Activity; MPA: Moderate Physical Activity; VPA: Vigorous Physical Activity.

[A] Adiposity subset n=782.

[B] Blood pressure subset n=637.

[C] Lipids subset n=525.

[D] CMR-score subset n=404.

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

	Minimally-adjusted Model 1	**Fully-adjusted Model 3**
	zBMI (n=782)	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.15† (-0.57, -0.12)	-0.14† (-0.55, -0.10)
Prolonged movers	-0.06 (-0.47, 0.06)	-0.07 (-0.49, 0.02)
	P for trend: 0.0107	*P for trend:* 0.0169
	Waist circumference (n=782)	

Accumulation pattern	B (95% CI)	B (95% CI)
Prolonged sitters	Referent	Referent
Breakers	-0.12† (-3.91, -0.49)	-0.11† (-3.74, -0.41)
Prolonged movers	-0.03 (-2.85, 1.15)	-0.04 (-3.01, 1.05)
	P for trend: 0.0188	*P for trend:* 0.0308
	Systolic blood pressure (n=637)	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.07 (-3.52, 0.50)	-0.06 (-3.30, 0.68)
Prolonged movers	-0.04 (-3.56, 0.98)	-0.04 (-3.55, 1.16)
	P for trend: 0.3183	*P for trend:* 0.3940
	Diastolic blood pressure (n=637)	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.01 (-2.08, 1.64)	-0.01 (-2.06, 1.65)
Prolonged movers	-0.03 (-2.54, 1.36)	-0.02 (-2.41, 1.51)
	P for trend: 0.8299	*P for trend:* 0.8996
	High-density lipoprotein (n=525**)**	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	0.02 (-0.04, 0.07)	0.03 (-0.03, 0.07)

Prolonged movers	-0.03 (-0.10, 0.05)	-0.05 (-0.12, 0.03)
	P for trend: 0.5838	*P for trend:* 0.3223
	Low-density lipoprotein (n=525**)**	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.01 (-0.14, 0.10)	-0.01 (-0.14, 0.10)
Prolonged movers	-0.03 (-0.23, 0.11)	-0.03 (-0.23, 0.11)
	P for trend: 0.7750	*P for trend:* 0.7982
	Triglycerides (n=525**)**	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.02 (-0.09, 0.07)	-0.02 (-0.09, 0.06)
Prolonged movers	0.04 (-0.06, 0.16)	0.06 (-0.04, 0.17)
	P for trend: 0.5988	*P for trend:* 0.3530
	Cardiometabolic risk score (n=404)	
Accumulation pattern	**B (95% CI)**	**B (95% CI)**
Prolonged sitters	Referent	Referent
Breakers	-0.03 (-0.97, 0.57)	-0.04 (-1.02, 0.52)
Prolonged movers	0.02 (-0.85, 1.28)	0.03 (-0.74, 1.33)
	P for trend: 0.6247	*P for trend:* 0.4323

Significance was assessed at the level of $p<0.05$.

Symbols † denote pairwise significant differences between ‘Prolonged sitters’ and ‘Breakers’.

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, Additional File 1.

Table 5. Odds ratios (OR) and 95% confidence intervals (CI) for overweight or obesity for the three identified distinct groups (n=782)

	Minimally-adjusted Model 1		**Fully-adjusted Model 3**	
	Body Mass Index			
Accumulation pattern	**OR (95% CI)**	**P-value**	**OR (95% CI)**	**P-value**
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
	Waist circumference			
Accumulation pattern	**OR (95% CI)**	**P-value**	**OR (95% CI)**	**P-value**
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 $p < 0.05$.

Symbols † denote significant results.

Logistic regression models estimated the odds ratio (ORs) and 95% confidence intervals of the distinct groups for being overweight/obese (i.e., using the binary variables for BMI and WC, separately). Here, ORs >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, Additional File 2.