

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

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30 **ABSTRACT**

31 **Introduction:** This cross-sectional study aimed to: i) identify and characterize youth according
32 to distinct physical activity (PA) and sedentary (SED) accumulation patterns; and ii) investigate
33 associations of these derived patterns with cardiometabolic risk factors.

34 **Methods:** ActiGraph accelerometer data from 7-13 year olds from two studies were pooled
35 (n=1,219; 843 [69%] with valid accelerometry included in analysis). Time accumulated in ≥ 5 -
36 min and ≥ 10 -min SED bouts, ≥ 1 -min and ≥ 5 -min bouts of light (LPA), and ≥ 1 -min bouts of
37 moderate (MPA) and vigorous (VPA) PA were calculated. Frequency of breaks in SED were
38 also obtained. Latent profile analysis was used to identify groups of participants based on their
39 distinct accumulation patterns. Linear and logistic regression models were used to test
40 associations of group accumulation patterns with cardiometabolic risk factors, including
41 adiposity indicators, blood pressure and lipids. Total PA and SED time were also compared
42 between groups.

43 **Results:** Three distinct groups were identified: ‘Prolonged sitters’ had the most time in
44 prolonged SED bouts and the least time in VPA bouts; ‘Breakers’ had the highest frequency of
45 SED breaks and lowest engagement in sustained bouts across most PA intensities; ‘Prolonged
46 movers’ had the least time accumulated in SED bouts and the most in PA bouts across most
47 intensities. ‘Prolonged movers’ and ‘Breakers’ had lower odds of being classified as
48 overweight/obese based on body mass index compared to ‘Prolonged sitters’. Whilst
49 ‘Breakers’ engaged in less time in PA bouts compared to other groups, they had the healthiest
50 adiposity indicators. No associations with the remaining cardiometabolic risk factors were
51 found.

52 **Conclusion:** The current results suggest that youth accumulate their daily activity in three
53 distinct patterns (‘Prolonged sitters’, ‘Breakers’ and ‘Prolonger movers’), with those breaking

54 up sitting and most time in sporadic PA across the day having a lower adiposity risk. No
55 relationships with other cardiometabolic risk factors were identified.

56 **Key words**

57 Physical activity; Sedentary behavior; Accumulation patterns; Accelerometry; Latent profile
58 analysis; cardiometabolic health.

59

60 INTRODUCTION

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

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

81 Previous research has focused solely on daily accumulation of PA intensities (i.e., moderate
82 [MPA], VPA, or MVPA) or total SED in isolation, and how this is associated with children’s
83 cardiometabolic risk factors. This approach has limitations as it fails to consider the fact that
84 activity occurs across a spectrum and that all PA intensities and SED intermittently occur

85 within a child's day (2). For example, youth with low levels of MVPA may also engage in high
86 levels of prolonged sitting, and thus have a distinct 'accumulation pattern' which may have
87 specific associations with certain health outcomes. If recommendations are to be developed
88 regarding how accumulation of PA and SED should occur, consideration of distinct
89 accumulation patterns among groups in the population needs to be explored.

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

106 Another key limitation in studies to date is the almost exclusive focus on indicators of adiposity
107 as the main cardiometabolic risk factor (4). Indeed, elevated blood pressure and dyslipidemia
108 are established factors for cardiometabolic diseases which can initially manifest during the
109 early years of life and are subsequently maintained throughout the life course (14-16).

110 Therefore, it is important to consider a range of biomarkers among youth, yet associations
111 between accumulation patterns and other cardiometabolic risk indicators, such as lipoprotein-
112 related biomarkers and blood pressure have not been studied (4). Consequently, the aims of
113 this study were to: i) identify and characterize youth according to distinct PA and SED
114 accumulation patterns; and ii) investigate associations of these derived patterns with
115 cardiometabolic risk factors.

116

117 **METHODS**

118 **Participant information**

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

134 **Accelerometry**

135 Participants wore an ActiGraph accelerometer (GT1M in LOOK (18); GT3X in Transform-
136 Us! (17)) on their right hip during waking hours for at least seven consecutive days. These
137 monitors have acceptable comparability (19). As LOOK collected data using 5 second epochs,
138 ActiLife software (v5.1.5) was used to reintegrate these into 15-second epochs to be consistent
139 with Transform-Us! a customized Excel Macro was then used to further process the files. Non-
140 wear time (≥ 20 minutes of consecutive zeroes) was subtracted from each day to determine wear
141 time (20). Participants with ≥ 4 valid days (defined as 8 hours of wear time on weekdays and
142 7 hours on weekend days (20)) were included for further analysis (21). The different intensities
143 across the activity spectrum were defined as per previously validated age-specific cut-points;
144 SED < 100 counts/min (20); and, light PA (LPA), MPA (≥ 4 and < 6 METs; (22)) and VPA (≥ 6
145 METs) (23). Total time spent in each of these intensities averaged over all valid days.

146

147 *Accumulation patterns across the activity spectrum*

148 Based on existing literature (4) and preliminary exploration of this sample's accumulation
149 patterns, seven accumulation pattern variables of interest were identified; number of breaks in
150 SED time (i.e., an interruption [≥ 25 cpm for ≥ 1 epoch] between sedentary epochs (21, 24)),
151 and time accumulated in ≥ 5 -min SED; ≥ 10 -min SED; ≥ 1 -min LPA; ≥ 5 -min LPA; ≥ 1 -min
152 MPA, and ≥ 1 -min VPA bouts. Longer bout durations (e.g. ≥ 5 -min and ≥ 10 -min MPA/VPA
153 bouts), were not included as a low proportion of the participants engaged in these patterns (i.e.,
154 a quarter of the sample or less). Based on previous recommendations for SED bouts (25), bouts
155 did not include interruptions of any duration (i.e., no tolerance). Any interruption in intensity
156 marked the end of a bout. Total time (min/day) spent in bouts at each intensity and frequency
157 of breaks in SED per day were averaged across all valid days. Variables that were highly

158 correlated with wear time were adjusted using the residuals method (26). This method is
159 commonly used within PA and SED research (26).

160

161 **Cardiometabolic risk factors**

162 Objective data on seven continuous cardiometabolic risk factors were collected using
163 standardized procedures: BMI, WC, systolic (SBP) and diastolic blood pressure (DBP), high-
164 density lipoprotein (HDL-C) and low-density lipoprotein (LDL-C) cholesterol, and
165 triglycerides (TG; lipids). Standardized procedures were used to objectively measure stature,
166 body mass and WC in both studies (27). Continuous World Health Organization Child Growth
167 Standards age- and sex-standardized z-values (zBMI) were computed based on BMI (kg/m^2)
168 (28). Then, a binary variable was created to classify participants as overweight/obese or healthy
169 BMI (including those classified as underweight, $n=1$) as per the international age-specific cut-
170 points for boys and girls (29). Australian percentile curves for WC were utilized to determine
171 age- and sex-specific WC percentiles (30). WC was dichotomized as: $\geq 75^{\text{th}}$ percentile (31) as
172 being overweight (including obese participants $\geq 90^{\text{th}}$ percentile (32)) or $< 75^{\text{th}}$ percentile as
173 being healthy weight (including those classified as underweight [i.e., $\leq 5^{\text{th}}$ percentile]; 3% of
174 the sample). For both BMI and WC, a low proportion of participants were underweight, and
175 these were therefore included in the healthy weight category. Blood pressure and blood samples
176 taken from a forearm vein were measured in a seated posture following overnight fasting (17,
177 18). A continuous cardiometabolic risk score (CMR-score) was calculated using the z-values
178 of WC, SBP, DBP, LDL-C, HDL-C, and TG (25). Higher CMR-scores indicate a higher risk.
179 HDL-C was multiplied by -1 before inclusion in the score as it is inversely related to
180 cardiometabolic risk.

181

182 **Participant characteristics**

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

189

190 **Statistical analyses**

191 *Latent profiles of accumulation patterns*

192 Statistical analyses were performed using Stata Version 15.0 (StataCorp, College Station, TX,
193 USA). All participants with valid accelerometry data (n=843; 69%), regardless of health data
194 availability, were included in the latent profile analysis to identify distinct classes of youth who
195 share similar accumulation patterns. Latent profile analysis is a statistical technique that
196 describes similarities and differences among individuals regarding how observed continuous
197 variables relate to each other and assumes that the population is heterogeneous with respect to
198 the relationships between variables (10). The seven accumulation pattern variables of interest
199 (i.e., breaks in SED time; and ≥ 5 -min SED, ≥ 10 -min SED, ≥ 1 -min LPA, ≥ 5 -min LPA, ≥ 1 -min
200 MPA, and ≥ 1 -min VPA bouts) were used as observed variables in the latent profile models
201 (10). Whilst these variables are not mutually exclusive, consistent with previous research (11,
202 12), the decision was made to include all of them in the latent profile analysis as they showed
203 unique associations with cardiometabolic health (4). The variables were not treated as a sub-
204 composition of waking hours, as the elements together are not ‘closed’ so that they sum to one
205 (33). This is partially due to the inclusion of frequency of SED breaks as a variable of interest,

206 as well as different minimum bout lengths for SED and LPA and multiple variables within the
207 same intensity.

208 Four different variance-covariance structures were compared in order to identify the best fit
209 model: 1) class-invariant, diagonal (most constrained; conditional independence is imposed
210 and covariances between the indicators are fixed at zero within class, while the variances are
211 constrained to be equal across classes); 2) class-varying, diagonal (conditional independence
212 is imposed and covariances between the indicators are fixed at zero within class, while the
213 variances are freely estimated and allowed to be different across classes); 3) class-invariant,
214 unrestricted (all indicator variables are allowed to covary within class, and variances and
215 covariances are constrained to be equal across classes); and, 4) class-varying, unrestricted (least
216 restrictive; all indicator variables are allowed to covary within class, and the variances and
217 covariances are allowed to be different across classes) (10). The optimal number of classes
218 were identified by analyzing 1-class through to 6-class models within each of the above
219 variance-covariance structures using the Bayesian Information Criteria (BIC), Consistent
220 Akaike's Information Criteria (CAIC), Approximate Weight of Evidence Criterion (AWE),
221 Log Likelihood, class size (i.e., lowest proportion cut-off was set at 0.05 (34)) and the
222 interpretation of classes (10). The 'best' model was identified as the model with the fewest
223 number of classes with a better relative fit than the initial 'benchmark' 1-class class-invariant,
224 unrestricted model (10); the identified classes in that model were the groups (i.e., with distinct
225 accumulation patterns) used to represent accumulation patterns in further analyses.

226

227 *Group characteristics and associations with cardiometabolic risk factors*

228 Subsets of participants provided BMI and WC (n=782 [93% of sample with valid
229 accelerometry]), blood pressure (n=637 [76%]), and/or lipids (n=525 [62%]) data. Only

230 participants with complete data on all variables were included in the CMR-score analysis
231 (n=404 [48%]). These smaller analytic samples were mostly due to participants opting out for
232 consent for those assessments.

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

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

253

254 **RESULTS**

255 **Participant characteristics**

256 The characteristics of the sample are presented in Table 1. Participants were aged between 7
257 and 13 years. Three-quarters of the participants were not overweight or obese based on BMI
258 and more than half based on WC classifications. The mean characteristics were similar across
259 the different analytic samples (i.e., adiposity, blood pressure, lipids, and CMR-score). There
260 was moderate agreement between the BMI and WC weight status categories (kappa = 0.60,
261 82% percent agreement). The average time spent SED and in LPA, MPA and VPA was 7 hours
262 and 20 minutes, 3 hours and 50 minutes, 45 minutes, and 20 minutes, respectively.

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

264 **Latent profiles of accumulation patterns**

265 A comparison of fit indicators for the benchmark model and class-varying, unrestricted latent
266 profile models are presented in Table 2. These models had the best fit compared to other models
267 (i.e., class-invariant, unrestricted; class-invariant, diagonal, and; class-varying, diagonal(10)).
268 Of the 1-6 class models examined, the class-varying unrestricted 3-class model demonstrated
269 the biggest drop in CAIC, BIC and AWE values, when each solution was compared to the
270 previous solution. The 3-class model also had the lowest BIC overall. Whilst CAIC and AWE
271 values were slightly better for the class-varying unrestricted, 5- and 6-class models, compared
272 to the class-varying unrestricted 3-class model, some classes identified in these two models
273 were very small (i.e., n=40 [5%] and n=31 [4%], respectively), and below the recommended
274 cut-off (<5%, (34)) for inclusion. Based on the model fit indices, interpretability of the models
275 (i.e., particularly for the 4-class model), and size of the extracted classes (i.e., particularly for
276 the 5- and 6-class models), the class-varying unrestricted 3-class model was adopted for further

277 analyses. An overview of ‘best fit’ indicators of all other variance-covariance latent profile
278 models can be found in Supplemental Digital Table 2.

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

280 Groups of participants with similar accumulation patterns were labelled according to their
281 distinguishing features, as shown by high and low Z-values (Figure 1) and means (SD) for the
282 seven accumulation pattern variables relative to other patterns (Table 3). Group 1 (‘Prolonged
283 sitters’) was characterized by the most time in prolonged SED bouts and the least time in VPA
284 bouts (n=268; 32%). Youth in Group 2 (‘Breakers’) had the highest frequency of SED breaks
285 and lowest engagement in sustained bouts across most PA intensities (n=463; 55%). The
286 smallest group (Group 3; n=112; 13%) had the least time accumulated in SED bouts and the
287 most time accumulated in PA bouts across almost all intensities (‘Prolonged movers’).
288 ‘Prolonged sitters’ were selected as the referent group for the linear and logistic regression
289 models as ‘Breakers’ and ‘Prolonged movers’ were considered to be groups with healthier
290 accumulation patterns.

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

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

293 **Differences between groups**

294 ‘Breakers’ (~10 years old) were, on average, approximately one year younger compared to
295 both ‘Prolonged sitters’ and ‘Prolonged movers’ (~11 years old). ‘Prolonged movers’ included
296 the lowest proportion of girls (38%), followed by ‘Prolonged sitters’ (51%) and ‘Breakers’
297 (61%). No differences in SES across groups were observed.

298 Descriptive statistics showed that the total daily volumes of intensities were mostly in line with
299 the accumulation pattern variables that were used in the latent profile analysis. ‘Prolonged

300 sitters' engaged in the most SED time and the least VPA compared to both other groups. Whilst
301 'Prolonged sitters' spent a similar amount of time in prolonged MPA bouts as 'Prolonged
302 movers', their total daily volume of MPA was lower. 'Prolonged movers' spent the most
303 amount of time in PA across intensities and the least amount in SED time. Whilst 'Breakers'
304 spent the least amount of time in sustained bouts across PA intensities compared to both other
305 groups, their total daily volume in all PA intensities was higher than 'Prolonged sitters'.

306

307 **Associations between groups with distinct accumulation patterns and cardiometabolic** 308 **risk factors**

309 Table 4 shows the associations between the distinct groups and cardiometabolic risk factors for
310 the minimally- (Model 1) and fully-adjusted models (Model 3). The overall p-value for group
311 trend was significant for BMI and WC only. Pairwise comparisons showed that 'Breakers' had
312 the healthiest zBMI and WC values; this remained after adjusting for confounders. After
313 adjustment for confounders, 'Breakers' had a significantly lower zBMI (mean difference = -
314 0.30, see Table 3) compared to 'Prolonged sitters'. Similarly, 'Breakers' had an approximately
315 five cm smaller WC compared to 'Prolonged sitters' (mean differences reported in Table 3).
316 No associations between the distinct groups and the remaining cardiometabolic risk factors
317 were found. The increment in the partially-adjusted linear Model 2 did not specifically
318 influence results and are therefore only reported in Supplemental Digital Table 3.

319

320

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

321 'Breakers' and 'Prolonged movers' had both significantly lower odds (59%) of being classified
322 as overweight/obese based on their BMI compared to 'Prolonged sitters', which remained after
323 adjusting for confounders (Table 5). Whilst the odds for being overweight based on WC

324 seemed lower for ‘Prolonged movers’ versus ‘Prolonged sitters’, no consistent significant
325 results were found for WC across the logistic models. ‘Breakers’ did have significantly lower
326 odds of being classified as overweight/obese compared to the ‘Prolonged sitters’. The
327 increment in the partially-adjusted logistic Model 2 did not specifically influence results and
328 are therefore only reported in Supplemental Digital Table 4.

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

330

331 **DISCUSSION**

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

345 For most intensities, the total accumulated daily volumes across groups reflected the specific
346 accumulation patterns. For example, ‘Prolonged sitters’ spent the most time in SED and least
347 time in different PA intensities, and ‘Prolonged movers’ engaged in the highest daily volume

348 of activity across intensities. Whilst 'Breakers' spent the least time in prolonged PA bouts
349 compared to the other groups, they engaged in more total daily PA across all intensities
350 compared to 'Prolonged sitters'. This suggests that sporadic activity accumulation (i.e., <5-min
351 bouts of LPA and <1-min bouts of MPA and VPA) and breaking up sitting throughout the day
352 may be typical in active lifestyles. Previous evidence in this age group has shown that higher
353 levels of physical activity, and in particular VPA, are important for the cardiometabolic health
354 in children (35). Consequently, the observed beneficial health outcomes in 'Breakers' and
355 'Prolonged movers' versus 'Prolonged' sitters may be explained by higher VPA levels in these
356 groups. Evidence regarding potential effects of sporadic versus prolonged behaviors on total
357 daily volumes of activities is scarce, particularly in youth. Willis and colleagues (13) found
358 that children aged 6-9 years who accumulated a greater percentage of their MVPA in prolonged
359 MVPA bouts (defined as 5–10 min and ≥ 10 min) and a lower percentage in sporadic MVPA
360 (<5 min) had a higher total daily volume compared to children with a lower percentage of
361 prolonged MVPA bouts and a higher percentage of sporadic MVPA. Whilst this contrasts with
362 findings from the present study, bouts were defined differently in that study which makes it
363 difficult to compare with the current study. This highlights the lack of consistency in the
364 definition of bouts, and suggests that the field would benefit from a consensus on bout
365 definitions. This would then enable researchers to compare findings across studies, and
366 examine the contribution of these patterns to time-use compositions including total daily PA
367 and SED.

368 Whilst 'Prolonged sitters' spent the most time in MPA bouts, and had comparable total daily
369 volumes of MPA, they were less healthy compared to both other groups. In addition, 'Breakers'
370 had the healthiest indicators of adiposity, when compared to both other groups, despite
371 spending less total time being physically active compared to 'Prolonged movers'. As most
372 children were 'Breakers', this is a promising finding for children's health. It is possible that not

373 only the frequency but also the intensity with which ‘Breakers’ interrupted their SED time was
374 important. For example, the relatively large amount of time spent in VPA bouts versus MPA
375 bouts in this group compared to other groups, may have contributed to lower zBMI and WC.
376 Perhaps the high levels of time in MPA bouts in ‘Prolonged sitters’ was not enough to offset
377 the detrimental impact of their prolonged sitting. Whilst future research needs to further
378 investigate the co-occurrence and co-dependence of these accumulation patterns (i.e., whether
379 and why do these patterns occur alongside each other), our data suggest that breaking up SED
380 time and sporadic engagement in PA is inversely related to overweight/obesity relative to
381 engaging in prolonged bouts of SED and PA.

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

392 As this is the first study in youth to examine accumulation patterns across the activity spectrum
393 in this way, comparisons with prior research is difficult. Nonetheless, previous cross-sectional
394 research in this age group found that sporadic MVPA (i.e., <5 min) and bouts of MVPA (i.e.,
395 ≥ 5 min) had similar relationships for both of these patterns with cardiometabolic risk factors
396 (including WC and SBP) (38), and that bouts (defined as ≥ 4 seconds) were shorter and less
397 intense in overweight versus non-overweight boys (39). However, these studies investigated

398 patterns of PA intensities separately (38, 39) and not in combination with other intensities,
399 which may explain the differences between those and our findings. There is also the potential
400 of reverse causality where children who are overweight or obese may be less likely to engage
401 in prolonged MPA or VPA. The explanations as to why accumulation patterns across the
402 activity spectrum cluster in an unhealthy way in some groups, but not others, are underexplored
403 and the impact of these patterns on cardiometabolic health requires further investigation. Thus,
404 there is need for longitudinal research that will help with understanding the causal pathway of
405 patterns of accumulation across the activity spectrum in relation to cardiometabolic health. This
406 could inform recommendations around PA and SED-specific accumulation patterns that
407 promote health and wellbeing.

408 The possible biological mechanisms by which sporadic, compared to prolonged, behaviors
409 influence adiposity and no other cardiometabolic risk factors are unclear. Based on our
410 findings, patterns appear to be important for adiposity, which may be the first indicator of an
411 unhealthy profile in this age group (14-16). Some cross-sectional evidence in adults (24) and
412 experimental studies in youth (40) have provided preliminary evidence that breaking up SED
413 may provide beneficial metabolic effects on measures such as postprandial glucose and insulin
414 levels. These indicators are closely linked to cardiometabolic pathways, such as adipocyte
415 dysfunction, and risk of obesity (14-16). While no associations were found for 'Breakers' with
416 blood pressure and lipids in the present study, this may be explained by the participant age-
417 range and their limited cumulative exposure to unhealthy lifestyle behaviors. In addition,
418 evidence suggests that activity behaviors (i.e., total volumes) and cardiometabolic health
419 parameters track across time (7). However, it is unclear if accumulation patterns also track over
420 time. Longitudinal studies are therefore needed to assess whether long-term exposure to
421 different accumulation patterns, independent of total volumes, predict cardiometabolic health
422 later in life.

423 Strengths of this study included the use of a data-driven method to derive accumulation patterns
424 and the novel application of these distinct patterns to identifying associations with a range of
425 cardiometabolic risk factors in a large sample of youth. These patterns were derived from
426 objective measures of PA and SED. Nevertheless, there were some limitations. Firstly, data
427 were not stratified based on age and sex which may affect activity behaviors and adiposity.
428 Whilst the models were adjusted for age, we were unable to adjust for puberty due to this not
429 being collected in the Transform-Us! study. In addition, the chosen optimal 3-class solution
430 may have oversimplified activity patterns. This work needs to be replicated to understand if
431 these accumulation patterns are consistent across youth (i.e., including other populations) and
432 if this is influenced by maturity status. The use of accelerometers and the cut-points made it
433 impossible to collect postural information and isolated upper body activities (41). Due to the
434 cross-sectional nature of this study, it is not possible to assess the temporal relationships. Whilst
435 BMI is often used as a proxy for adiposity, and results were in line with the findings for WC,
436 this is not a direct measure of fat mass and thus results should be interpreted cautiously (42). It
437 is important to note that we classified participants categorized as underweight as being of
438 healthy weight. Whilst the exclusion of these participants from the analyses did not change the
439 findings, this should be acknowledged. In addition, despite not targeting activity patterns (i.e.,
440 breaking up sitting) and finding no intervention effect on PA during the school week, it is
441 possible that the intervention delivered within the LOOK study may have influenced our
442 findings. Finally, some of the cardiometabolic risk factors (e.g., lipids) were only collected
443 from between 43% and 52% of the original sample.

444 In summary, this study identified three distinct groups with unique activity patterns using latent
445 profile analysis: ‘Prolonged sitters’, ‘Breakers’ and ‘Prolonged movers’. In addition, sporadic
446 PA and breaking up SED time were positively related to total daily PA and inversely associated
447 with adiposity, but not other cardiometabolic risk factors including blood pressure or blood

448 lipids. However, future research is needed to determine whether the identified accumulation
449 patterns are replicable in other populations, discover why these patterns occur in some groups
450 but not others, investigate biological processes and longitudinal effects in sporadic versus
451 prolonged physical activities, and to examine if these patterns can be changed to improve health
452 in youth. The latter is particularly important to inform public health interventions and policies.

453

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482

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632 **FIGURE TITLE AND LEGEND**

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

635

636 **Figure 1 Legend:**

637 $Z\text{-score} = (\text{value} - \text{mean}) / \text{SD}$

638 95% CI: 95% Confidence Intervals

639

640 **SUPPLEMENTAL DIGITAL CONTENT LIST**

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

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

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

647 Supplemental Digital Table 4. Odds ratios (OR) and 95% confidence intervals (CI) for
648 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

649 Data are presented as Mean ± SD unless otherwise indicated.

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

654 ^A The LOOK participants who were lost between time-point 1 and time-point 5 were mostly
655 lost due to school relocation. In Transform-Us!, some participants from the original consented
656 sample were lost before being allocated to the control group or intervention group.

657 ^B Participants who had raw data for one or more assessed variables relevant to this study.

658 ^C Participants included in the latent profile analysis (i.e., those who had valid accelerometry
659 data).

660 ^D Overweight and obese BMI and waist circumference categories were classified by
661 international age specific cut-points for boys and girls (28-30).

662 ^E A continuous combined CMR-score was derived using the z-values of waist circumference,
663 SBP, DBP, LDL-C, HDL-C, and TG (25). Higher CMR-scores indicate a higher risk. HDL-C
664 was multiplied by -1 before inclusion in the score as it is inversely related to cardiometabolic
665 risk.

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

		1	2				
	Benchmark	classes	classes	3 classes	4 classes	5 classes	6 classes
BIC	44503	44503	43734	43465	43475	43562	43767
CAI	44314	44314	43302	42790	42558	42402	42365
AW	44366	44366	43354	42843	42610	42455	42417
LL	-22134	-22134	-21628	-21372	-21256	-21178	-21159
Cases							
per			673/1	268/463/	222/208/30	232/40/158/3	154/31/124/303/
class	843	843	70	112	8/105	15/98	141/90
s							
(n) ^A							

667 Note: Bolded values indicate the value corresponding to the 'best' model according to each fit
668 indicator.

669 Only class-varying, unrestricted latent profile models are presented in this table; these models
670 had the best fit compared to other models (i.e., class-invariant, unrestricted; class-invariant,
671 diagonal, and; class-varying, diagonal(10)).

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

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

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

677

Table 3. Participant characteristics for distinct groups

	Prolonged sitters	Breakers	Prolonged
	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 ± 1.5
Sex (% female)	51.2	60.9 [¥]	37.5
SES (% low/mid/high SES)	3/36/62	4/35/61	1/34/65
Cardiometabolic health outcomes			
BMI (kg/m ²) ^A	19.8 ± 3.8	18.0 ± 2.9	18.8 ± 3.0
zBMI^A	0.7 ± 1.2	0.4 ± 1.1	0.5 ± 1.0
BMI status (% overweight/obese) ^A	36.6	19.8	19.5
WC (cm) ^A	67.0 ± 10.0	62.1 ± 7.7	65.8 ± 9.0
WC status (% overweight/obese) ^A	48.8	36.7	45.5
Systolic blood pressure (mmHg) ^B	110.0 ± 10.1	104.8 ± 10.0	108.1 ± 10.0
Diastolic blood pressure (mmHg) ^B	61.4 ± 7.3	60.9 ± 7.7	60.7 ± 7.0
HDL-C (mmol/L) ^C	1.4 ± 0.3	1.5 ± 0.3	1.4 ± 0.3
LDL-C (mmol/L) ^C	2.6 ± 0.7	2.6 ± 0.7	2.5 ± 0.7
Triglycerides (mmol/L) ^C	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 ± 3.3
Total daily volumes			
SED (min/day)	465.7 ± 92.8	428.8 ± 66.8	420.5 ± 66.8
LPA (min/day)	225.2 ± 37.7	227.6 ± 31.1	250.4 ± 31.1
MPA (min/day)	41.7 ± 15.4	46.9 ± 14.2	48.6 ± 14.2
VPA (min/day)	13.3 ± 6.8	22.2 ± 10.9	29.5 ± 10.9
Accumulation patterns (included in latent profile analysis)			
Breaks in SED time (number/day)	302.5 ± 48.2	314.6 ± 37.2	314.7 ± 37.2
≥5-min SED bouts (min/day)	199.4 ± 82.1	158.9 ± 52.6	153.8 ± 52.6
≥10-min SED bouts (min/day)	104.2 ± 60.8	71.8 ± 32.8	69.9 ± 32.8
≥1-min LPA bouts (min/day)	106.2 ± 23.4	98.6 ± 21.0	123.2 ± 21.0
≥5-min LPA bouts (min/day)	3.2 ± 2.2	1.1 ± 1.1	6.6 ± 1.1
≥1-min MPA bouts (min/day)	10.6 ± 6.1	7.4 ± 3.0	9.4 ± 3.0
≥1-min VPA bouts (min/day)	2.6 ± 1.8	5.8 ± 4.0	12.9 ± 4.0

678 Data are presented as Mean ± SD unless otherwise indicated.

679 Linear regression models accounted for school clustering were conducted to determine whether
680 there were any differences in continuous demographic characteristics across the distinct
681 groups. Differences according to demographic characteristics were assessed using logistic
682 regression models accounted for school clustering. Post hoc Bonferroni tests were used to
683 identify where the specific differences occurred between the groups.

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

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

687 between ‘Prolonged sitters’ and ‘Prolonged movers’. § Significant difference between
 688 ‘Breakers’ and ‘Prolonged movers’.

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

693 ^A Adiposity subset n=782.

694 ^B Blood pressure subset n=637.

695 ^C Lipids subset n=525.

696 ^D CMR-score subset n=404.

697

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)
	<i>P for trend: 0.0107</i>	<i>P for trend: 0.0169</i>
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)
	<i>P for trend: 0.0188</i>	<i>P for trend: 0.0308</i>

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)
	<i>P for trend: 0.3183</i>	<i>P for trend: 0.3940</i>

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)
	<i>P for trend: 0.8299</i>	<i>P for trend: 0.8996</i>

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)
	<i>P for trend: 0.5838</i>	<i>P for trend: 0.3223</i>

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)
	<i>P for trend: 0.7750</i>	<i>P for trend: 0.7982</i>

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)
	<i>P for trend: 0.5988</i>	<i>P for trend: 0.3530</i>

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)
	<i>P for trend: 0.6247</i>	<i>P for trend: 0.4323</i>

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

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

700 Linear regression models were conducted to analyze associations between the groups and each
 701 of the continuous cardiometabolic risk factors. The trend p-values for overall group effect are
 702 presented. Post hoc Bonferroni tests were used to identify where specific differences occurred
 703 between the groups.

704 Three incremental models were used: Model 1 (minimally-adjusted model) adjusted for study
 705 involvement, accounted for clustering within schools; Model 2 additionally adjusted for
 706 participants' age and sex; and, Model 3 (fully-adjusted model) further adjusted for SES.
 707 Results for Model 2 can be found in Supplementary Table 3, Additional File 1.

708

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

710 Symbols † denote significant results.

711 Logistic regression models estimated the odds ratio (ORs) and 95% confidence intervals of the
712 distinct groups for being overweight/obese (i.e., using the binary variables for BMI and WC,
713 separately). Here, ORs >1 imply a higher chance for being overweight/obese relative to the
714 accumulation pattern reference group.

715 Three incremental models were used: Model 1 (minimally-adjusted model) adjusted for study
716 involvement, accounted for clustering within schools; Model 2 additionally adjusted for
717 participants' age and sex; and, Model 3 (fully-adjusted model) further adjusted for SES.
718 Results for Model 2 can be found in Supplementary Table 4, Additional File 2.

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