Using Compositional Data Analysis to Explore Associations Between Accumulation of Sedentary Behaviour and Physical Activity and Biomarkers of Cardiometabolic Health in Children and Adolescents: A Cross-Sectional Study

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Abstract

Background The consequences for youth cardiometabolic risk might depend on whether sedentary time and physical activity are accumulated sporadically (in shorter bouts) or in a sustained pattern (in longer bouts). This study aimed to: 1) describe daily time-use compositions of youth, including time spent in shorter and longer bouts of sedentary behaviour and physical activity; and 2) examine associations between time-use compositions with cardiometabolic biomarkers.

Methods Accelerometer and cardiometabolic biomarker data (adiposity, blood pressure, lipids) from 7–13 year olds (mean ± SD: 10.4 ± 1.7) from two Australian studies were pooled (complete cases adiposity n = 772). A time-use composition of nine components was formed using compositional data analysis: time in shorter and longer bouts of sedentary behaviour, light-, moderate- and vigorous-intensity physical activity, and "other time" (i.e., non-wear/sleep). Shorter and longer bouts of sedentary time were defined as < 5 and ≥ 5 min, respectively. Longer light-, moderate- and vigorous-intensity physical activity bouts were defined as ≥ 1 min. Linear regression models examined associations between overall time-use composition and cardiometabolic biomarkers. Then, associations between ratios of longer relative to shorter activity patterns, and each intensity relative to more intense activities and/or "other time", with cardiometabolic biomarkers were derived.

Results Confounder-adjusted models showed that the overall time-use composition was associated with zBMI, waist circumference, systolic blood pressure, high-density lipoprotein cholesterol, triglycerides, and a combined cardiometabolic risk score. Specifically, more time in longer relative to shorter bouts of light-intensity physical activity was associated with greater zBMI (β = 1.79, SE = 0.70, p = 0.010) and waist circumference (β = 17.28, SE = 4.87, p < 0.001). More time in longer relative to shorter bouts of vigorous-intensity physical activity was also associated with higher waist circumference (β = 2.54, SE = 1.14, p = 0.026). More relative time in total light- and vigorous-intensity physical activity (including longer and shorter bouts) was associated with lower waist circumference. In contrast, more relative time in sedentary behaviour and moderate-intensity physical activity was detrimental for waist circumference.

Conclusions Accumulating physical activity in frequent short bursts may be beneficial for adiposity compared to engaging in the same amount of these intensities in longer bouts.

Trial registration: 'Lifestyle Of Our Kids' (ACTRN12615000066583 [23/01/2015]) and 'Transform-Us!' (ACTRN12609000715279 [19/08/2009], ISRCTN83725066 [30/06/2010]).

Background

There is increasing interest in understanding the way in which daily activity is accumulated, including the timing, duration, and frequency of bouts [1] of physical activity (PA) and sedentary behaviour (SED), and how such patterns may be associated with cardiometabolic health in youth [2]. There is a need to establish how activity patterns may be associated with cardiometabolic biomarkers, such as obesity and blood lipids from an early age given that they can track into later life [3].

Evidence from large cohort studies and a meta-analysis suggest that, for adults, time spent in ≥ 10-min bouts of high intensity PA is associated with lower mortality risk [4], and that both total SED and longer average SED bout durations are associated with higher mortality risk [5], but breaking up SED with light-intensity PA (LPA) helps improve adiposity and postprandial glycaemia [6]. Whilst evidence in adults suggests that different PA and SED accumulation patterns play an important role in cardiometabolic health, data in youth, for the most part, is limited to measures of adiposity and has been inconsistent [2]. Much remains unknown about whether there may be consequences for cardiometabolic risk, especially in younger populations, depending on whether SED and PA are accumulated sporadically (in shorter bouts)

versus a more sustained pattern (in longer bouts). Such information is key for the development of targeted interventions to benefit health outcomes, and to inform the evolution of 24-h movement guidelines.

From a 24-h behaviour perspective, sleep and waking movement behaviours occur on an activity continuum that range from low- to high-intensity activity. A change in time spent in one activity intensity (e.g., moderate-to-vigorous intensity PA; MVPA) will consequently result in a change in at least one other intensity (e.g., LPA; sleep) in this finite 24-h period [7, 8]. As such, considering the overall daily time-use composition of total time spent in various activity intensities (i.e., volumes) can yield a different perspective to considering each intensity in isolation [7]. This same principle can be applied to considering patterns of accumulation, such as time spent in bouts of varying durations for the different intensities.

Using compositional data analysis, the relative distribution of time use between different activities can be examined, classifying activities by their total volume of intensities (e.g., total SED), activity accumulation patterns (e.g., time in longer versus shorter bouts), other attributes such as behavioural context, or by multiple attributes, simultaneously [7, 8]. Then, these respective elements of time use can be modelled simultaneously and tested for their combined associations with biomarkers of cardiometabolic health [7–9]. This compositional data analysis approach is advanced in that it allows the simultaneous consideration of components that sum to a whole, without statistical problems such as collinearity, commonly encountered in some traditional approaches [7, 8]. To date, the application of compositional data analysis to studying time use and health has mostly been applied to adults [7, 9] rather than in youth [10]. Further, to our knowledge, there have been no studies, in either adults or youth, considering activity intensity and bout duration components across the activity spectrum simultaneously. Although a previous study investigated bout durations alongside total volumes using a compositional approach [11], and found some benefits to adiposity from engaging in shorter versus longer SED bouts, it did not investigate other intensity patterns and health outcomes beyond adiposity. Consequently, this study aims to: 1) describe daily time-use compositions of 7–13 year-old youth, including time spent in longer and shorter SED and PA bouts; and 2) examine associations between time-use compositions with cardiometabolic risk biomarkers.

Methods

Setting and participants

Data from two cluster-randomized school-based trials were pooled for the purpose of this study: ‘Transform-Us!’ (ACTRN12609000715279 [19/08/2009], ISRCTN83725066 [30/06/2010]) and LOOK (ACTRN12615000066583 [23/01/2015]) [12, 13]. Baseline data from Transform-Us! (2010) and data from time point five (i.e., four years post-randomisation) (2009) of LOOK were used [14]. Ethical approval was provided by the Deakin University Human Research Ethics Committee (Transform-Us!: EC 2009 – 141) and the Australian Capital Territory Health Human Research Ethics Committee (LOOK: ETH.9/05.687). Parents provided written informed consent for their children to participate in each assessment (e.g., accelerometry, anthropometry, lipids). Data were obtained for 1219 participants, yet the initial analytic sample included those participants who had valid accelerometry data (n = 843; 69% of the original sample). Details of each study [12, 13] and comparisons between studies [14] are reported elsewhere.

Data collection and measures

Cardiometabolic biomarkers

Seven cardiometabolic measures and related blood biomarkers were collected. Height (cm), weight (kg) and waist circumference (WC; cm) were collected using standardized procedures [15]. Body mass index (BMI; kg/m^2) was calculated and converted to age and sex standardized z-values using the World Health Organization Child Growth

Standards (zBMI) [16]. Both systolic (SBP) and diastolic blood pressure (DBP) measurements were taken in a rested, seated or supine position. Overnight fasted blood samples were collected for the assessment of high-density (HDL-C) and low-density lipoprotein cholesterol (LDL-C), and triglycerides (TG; lipids) [12, 13]. A continuous combined cardiometabolic risk score (CMR-score) was derived using the z-values of WC, SBP, DBP, LDL-C, HDL-C, and TG [17], as previously described [14]. Since the spread of observed values, and prevalence of deviating values, for individual risk factors in a sample of reasonably healthy children is likely to be low compared to adults, the use of this CMR-score is appropriate [18]. The calculation of the CMR-score is in line with previous research in this age group [3, 19].

Accelerometry

Participants wore the ActiGraph™ accelerometer on the right hip during waking hours for eight consecutive days. The output of the different ActiGraph models (GT1M in LOOK [13]; GT3X in Transform-Us! [12]) have been shown to be comparable and can be pooled [20]. ActiGraph data were downloaded and converted to 15-s epochs using ActiLife software (ActiGraph, Pensacola, FL) and then processed using a customized Excel macro. Sustained periods of 20 minutes of consecutive zeros were used to define non-wear time [21, 22]. Total time was sub-divided using validated age-specific cut-points [21, 23] into SED, LPA, moderate-intensity PA (MPA), vigorous-intensity PA (VPA), and “other time” (i.e., including both non-wear time, such as from monitor removals, and time in bed). The “other time” category could not be separated out into sleep and non-wear time because sleep data were not collected in either study. Total volumes of SED, LPA, MPA and VPA were then separated into time in longer and shorter bouts, using thresholds derived from previous literature [2] and the distribution of the data [14]. SED was split into time in longer (≥ 5 min) and shorter (< 5 min) bouts, and LPA, MPA, and VPA into time in longer (≥ 1 min) and shorter (< 1 min) bouts. A valid day was defined as ≥ 8 hours of accelerometry wear time on weekdays and ≥ 7 hours on weekend days [21]. Participants with ≥ 4 complete days were included for analysis and data was averaged across all valid days [22].

Covariates

Participant age and sex were included as continuous and binary variables, respectively. Socioeconomic status (SES) of school location was transformed into deciles, based on the national Index of Relative Socio-economic Disadvantage of the Socio-Economic Indexes for Areas [24] and categorized as low (1–2), mid (3–8) or high (9 – 10) SES [12]. Data source (LOOK or Transform-Us!) was coded as a categorical covariate.

Statistical analyses

Analyses were performed in STATA version 15 (STATACorp, College Station, TX) and RStudio version 3.5.1, using the packages ‘compositions’ (‘acomp’ framework) and ‘lmtest’ (‘lm’ function) [25, 26]. For the purpose of this analysis, the proportion of the 24-h day spent in different intensities were normalized for each participant so that their sum equalled one. A time-use composition of nine distinct components (time in longer and shorter bouts of SED, LPA MPA and VPA, and “other time”) was formed using compositional data analysis. Most activities were ubiquitous, except for the VPA longer bouts component, which was monitored as zero for ten participants. A limitation of compositional data analysis is that zero values cannot be included in log ratios, as dividing by zero or taking the logarithm of zero are undefined mathematical operations [8]. As it can be assumed that the ten participants (1%) with zeros may accumulate some amount of time in longer VPA bouts, just not during the measurement period, these participants were removed from the sample before further statistical analyses were undertaken.

The proportion of time spent in different bouts (longer versus shorter) of SED, LPA, MPA, and VPA, and “other time” were reported using standard descriptive statistics (i.e., median, interquartile range, range) as well as the compositional mean. The compositional mean, or centre, is the vector of geometric means of its parts, rescaled to sum up to 24 hours, and is coherent with the inter-dependent nature of compositional data [7, 8, 27].

Linear regression models were used to test associations between the time-use composition and the cardiometabolic health biomarkers. All models used robust standard errors to account for clustering by school. Adjusted models controlled for age, sex, SES, and data source (i.e., LOOK or Transform-Us!). The nine-part time-use composition was modelled as a set of eight isometric log-ratio (*ilr)* coordinates [28–30]. Values estimated by such models are invariant with regards to the orthonormal basis selected [31]. Accordingly, a basis (i.e., sequential binary partition) consisting of 8 *ilr* coordinates reflecting comparisons of time spent in longer versus shorter bouts (*ilr* coordinates 2 [SED], 4 [LPA], 6 [MPA], and 8 [VPA]), as well as comparisons of volumes of each intensity (SED, LPA, MPA and VPA) versus more intense activities and/or "other time" (*ilr* coordinates 1, 3, 5, and 7), was created [32]. A detailed overview of this basis is displayed in the sequential binary partition and sign matrix Additional File 1 (Supplementary Table S1).

The eight *ilr* coordinates were modelled simultaneously. Thus, estimates of effects of each bout duration are controlled for other bout durations, and relative volumes of each intensity and "other time". Vice versa, effects of relative volumes of each intensity are controlled for "other time", the other activity intensities, and their accumulation pattern in longer versus shorter bouts. This sequential binary partition was chosen to allow direct comparisons between time in longer and shorter bouts within each intensity, and is novel as typically ratios between one-versus-remaining behaviours rather than one-versus-one behaviour, are investigated in compositional data analysis studies to date (e.g., [7, 9]).

Global F-tests of these eight *ilr* coordinates, which reflect the overall effect of the time-use composition, were reported. In addition, individual regression coefficients for each of the eight *ilr* coordinates were reported. As the change in outcome will depend on which other compositional parts change to compensate [28], the estimated regression parameters for individual *ilr* coordinates may produce misleading interpretations when considered in isolation. Therefore, to provide a more interpretable indication of relationships between activity accumulation pattern (more time in longer versus shorter bouts) and cardiometabolic biomarkers, plots were created. These plots included the estimated mean cardiometabolic health biomarker, with 95% confidence intervals [95% CIs]. In these estimations, the overall time within the intensity of interest was kept constant, while the ratio between longer and shorter behaviours was alternated. Times in all other components were set at the mean observed values. Means were estimated for girls and boys separately, keeping age (10.46 years; mean age), SES ('mid') and data source ('LOOK') constant (see Table 1). Estimations were only conducted for the range of activity levels occurring in the observed data, rounded to the nearest 5 min for plotting purposes. That is, data were not extrapolated beyond the observed range for the exposure variables (see Table 2).

Table 1
Participant characteristics (Subset adiposity, n = 772)

Demographic characteristics	Whole sample	Girls (n = 423)	Boys (n = 349)
	Mean ± SD or %	Mean ± SD or %	Mean ± SD or %
Age (years)	10.44 ± 1.69	10.30 ± 1.69	10.61 ± 1.67
Gender (% female)	55%	100%	0%
Socioeconomic status [A]	3%	3%	3%
High	36%	37%	35%
Mid	61%	61%	61%
Low			
Data source (% in LOOK)	52%	49%	56%
Cardiometabolic biomarkers			
zBMI	0.5 ± 1.1	0.5 ± 1.1	0.6 ± 1.2
WC (cm)	64.0 ± 8.9	63.2 ± 8.9	65.0 ± 8.9
Systolic blood pressure (mmHg) [B]	106.4 ± 10.3	105.5 ± 10.5	107.5 ± 10.0
Diastolic blood pressure (mmHg) [B]	61.0 ± 7.5	60.9 ± 7.5	61.0 ± 7.6
HDL-C (mmol/L) [C]	1.5 ± 0.3	1.4 ± 0.3	1.5 ± 0.4

SD: Standard deviation; zBMI: Body Mass Index converted to the World Health Organization Child Growth Standards age and sex standardized z-values [16]; WC Waist circumference; HDL-C: High-density lipoprotein cholesterol; LDL-C: Low-density lipoprotein cholesterol; CMR-score: Cardiometabolic risk score.

[A] Socioeconomic status (SES) of school location was transformed into deciles, based on the national Socio-Economic Indexes for Areas [24] and categorized as low (1–2), mid (3–8) or high (9–10) SES [12].

[B] n = 630 (55% girls)

[C] n = 520 (55% girls)

[D] n = 402 (54% girls)

Demographic characteristics	Whole sample	Girls (n = 423)	Boys (n = 349)
LDL-C (mmol/L) [C]	2.5 ± 0.7	2.6 ± 0.7	2.5 ± 0.7
Triglycerides (mmol/L) [D]	0.8 ± 0.4	0.9 ± 0.4	0.8 ± 0.3
CMR-score [D]	0.0 ± 3.4	0.1 ± 3.2	-0.1 ± 3.7
SD: Standard deviation; zBMI: Body Mass Index converted to the World Health Organization Child Growth Standards age and sex standardized z-values [16]; WC Waist circumference; HDL-C: High-density lipoprotein cholesterol; LDL-C: Low-density lipoprotein cholesterol; CMR-score: Cardiometabolic risk score.			
[A] Socioeconomic status (SES) of school location was transformed into deciles, based on the national Socio-Economic Indexes for Areas [24] and categorized as low (1–2), mid (3–8) or high (9–10) SES [12].			
[B] n = 630 (55% girls)			
[C] n = 520 (55% girls)			
[D] n = 402 (54% girls)			

Table 2
Standard and compositional descriptive statistics of the proportion of time spent in longer and shorter bouts of SED, LPA, MPA, and VPA, and "other time" (Subset adiposity, n = 772)

	Standard descriptive statistics, *min/day*				**Compositional descriptive statistics, *% (min) per 24-h***
	Q1	Median	Q3	Range	Mean
SED					
Longer bouts	122.6	159.6	207.7	28.0-512.2	12% (173.9)
Shorter bouts	242.9	265.3	293.2	162.7-465.7	19% (276.0)
LPA					
Longer bouts	87.9	101.4	119.5	44.0-197.3	7% (107.1)
Shorter bouts	115.1	126.6	137.2	79.6-189.7	9% (130.1)
MPA					
Longer bouts	5.6	7.8	10.6	1.0-40.2	< 1% (9.0)
Shorter bouts	27.3	36.8	47.2	10.2–82.5	3% (38.8)
VPA					
Longer bouts	2.0	4.1	7.6	0.1–49.1	< 1% (6.1)
Shorter bouts	8.8	13.7	19.7	1.5–43.6	1% (15.5)
614.2	668.2	718.7	301.8-889.2	47% (683.7)	

Longer bouts of SED were defined as ≥ 5-min bouts. Shorter SED was defined as bouts of < 5 min. Similarly, longer PA bouts (i.e., LPA, MPA and VPA) were defined as ≥ 1-min bouts and shorter PA bouts as the time accumulated in < 1-min bouts. "Other time" consisted of sleep and non-wear time.

Q1: First interquartile; Q3: Third interquartile; SED: Sedentary time; LPA: Light-intensity physical activity; MPA: Moderate-intensity physical activity; VPA: Vigorous-intensity physical activity.

Results

Participant characteristics

Of the 843 participants with valid accelerometry data, 61 (7%) had missing data for BMI, WC and/or covariates, and were therefore excluded from data analysis. After removal of the ten participants with recorded zeros on the longer VPA component, 772 participants were included in the analysis ("Subset adiposity"). Next, subsets with complete data were created for blood pressure (n = 630 [75% of sample with valid accelerometry]), lipids (n = 520 [62%]) and CMR-score analysis (n = 402 [48%]). These smaller analytic samples were attributable to fewer children participating in blood pressure and blood assessments. The included sample for each subset was compared with the excluded participants and no major differences were observed (data not shown). Demographic characteristics and cardiometabolic biomarker values for girls and boys were comparable and thus data were pooled for analysis (see Table 1).

Participants were on average 10 years old (55% girls) and most (61%) attended schools located in low SES areas relative to the Australian average (Table 1). Standard and compositional descriptive statistics of the proportion of time

spent in longer and shorter bouts of SED, LPA, MPA and VPA are presented in Table 2. Approximately 12% and 19% of the total time per 24-h day was spent in longer and shorter SED bouts, respectively. The proportions of time spent in longer and shorter bouts of LPA, MPA and VPA ranged from < 1–9%.

Associations between time-use composition and cardiometabolic biomarkers

Results from the linear regression analysis modelling the relationship between the time-use compositions, including the eight *ilr* coordinates, and cardiometabolic biomarkers are provided in Table 3 and Additional File 2 (Supplementary Table S2). Table 3 presents the global F-test and the parameters corresponding to time in longer versus shorter of SED, LPA, MPA and VPA (*ilr* coordinates 2, 4, 6, and 8). Supplementary Table S2 in Additional File 2 presents the parameters corresponding to relative volumes of SED, LPA, MPA and VPA (*ilr* coordinates 1, 3, 5, and 7). These were obtained within the same time-use composition models as the parameters presented in Table 3. While all results are presented in Table 3 and Additional File 2 (Supplementary Table S2), the following text only focuses on the overall time-use composition models, and the individual *ilr* regression coefficients within the confounder-adjusted models, which showed evidence of an association between the time-use composition and the cardiometabolic biomarkers (global F-test $p < 0.05$; specific values reported in Table 3).

Table 3
Associations of the ratio of time in longer versus shorter bouts, controlled for all other intensities, with cardiometabolic biomarkers in children aged 7–13 years

Outcome	Model	SED [*ilr2*]		LPA [*ilr4*]		MPA [*ilr6*]		VPA [*ilr8*]		Overall	
		β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	$F_{(df)}$; p	Adj. R^2
zBMI	**Unadj.**	-0.31 (0.48)	0.517	**1.43 (0.66)**	**0.031**	**-0.58 (0.27)**	**0.033**	0.29 (0.16)	0.071	**$6.64_{(8,763)}$; <0.001**	**0.06**
(n = 772)	**Adj.**	-0.36 (0.49)	0.454	**1.79 (0.70)**	**0.010**	-0.05 (0.30)	0.880	0.19 (0.16)	0.246	**$13.45_{(13,758)}$; <0.001**	**0.07**
WC (cm)	**Unadj.**	**-8.48 (3.44)**	**0.014**	**26.45 (4.71)**	**< 0.001**	1.00 (1.93)	0.604	1.34 (1.14)	0.241	**$29.73_{(8,763)}$; <0.001**	**0.23**
(n = 772)	**Adj.**	-5.52 (3.41)	0.106	**17.28 (4.87)**	**< 0.001**	-2.80 (2.12)	0.186	**2.55 (1.14)**	**0.026**	**$22.16_{(13,758)}$; <0.001**	**0.26**
SBP	**Unadj.**	-3.69 (4.39)	0.401	**18.59 (6.05)**	**0.002**	**12.33 (2.55)**	**< 0.001**	**-3.77 (1.58)**	**0.018**	**$21.97_{(8,621)}$; <0.001**	**0.21**
(n = 630)	**Adj.**	-0.85 (4.30)	0.843	7.85 (6.10)	0.199	4.54 (2.78)	0.103	-1.45 (1.57)	0.356	**$18.68_{(13,616)}$; <0.001**	**0.27**
DBP	**Unadj.**	0.06 (3.61)	0.987	-0.51 (4.97)	0.919	1.35 (2.10)	0.520	0.28 (1.30)	0.827	$0.81_{(8,621)}$; 0.598	0.00
(n = 630)	**Adj.**	0.06 (3.67)	0.987	-0.10 (5.21)	0.984	1.80 (2.38)	0.450	0.44 (1.34)	0.743	$0.82_{(13,616)}$; 0.637	0.00
HDL-C	**Unadj.**	-0.06 (0.16)	0.679	-0.31 (0.21)	0.150	**-0.28 (0.09)**	**0.001**	0.00 (0.05)	0.947	**$13.94_{(8,511)}$; <0.001**	**0.16**
(n = 520)	**Adj.**	-0.08 (0.16)	0.604	-0.14 (0.23)	0.533	-0.09 (0.09)	0.329	-0.04 (0.05)	0.431	**$10.45_{(13,506)}$; <0.001**	**0.19**
LDL-C	**Unadj.**	-0.02 (0.35)	0.944	0.24 (0.48)	0.627	**-0.51 (0.20)**	**0.010**	0.20 (0.11)	0.078	**$2.01_{(8,511)}$; 0.044**	**0.02**
(n = 520)	**Adj.**	-0.07 (0.36)	0.856	0.36 (0.52)	0.489	**-0.50 (0.22)**	**0.023**	0.20 (0.12)	0.090	$1.38_{(13,506)}$; 0.0167	0.01
TG	**Unadj.**	0.25 (0.19)	0.194	0.06 (0.26)	0.808	0.19 (0.11)	0.073	0.09 (0.06)	0.144	**$8.37_{(8,511)}$; <0.001**	**0.10**
(n = 520)	**Adj.**	0.17 (0.20)	0.394	0.15 (0.28)	0.589	0.10 (0.12)	0.405	0.08 (0.06)	0.180	**$6.77_{(13,506)}$; <0.001**	**0.13**
CMR	**Unadj.**	-0.05 (1.77)	0.779	**5.67 (2.41)**	**0.019**	1.83 (1.02)	0.074	0.64 (0.63)	0.312	**$18.35_{(8,393)}$; <0.001**	**0.26**
(n = 402)	**Adj.**	0.18 (1.78)	0.919	2.76 (2.53)	0.278	-0.32 (1.13)	0.779	1.20 (0.64)	0.062	**$13.45_{(13,388)}$; <0.001**	**0.29**

Bold values denote statistical significance at the $p < 0.05$ level.

Outcome	Model	SED [*ilr2*]	LPA [*ilr4*]	MPA [*ilr6*]	VPA [*ilr8*]	Overall
Unadjusted and adjusted models accounted for school clustering using robust standard error and included effects of the time-use composition tested as a series of *ilr* coordinates. Adjusted models additionally adjusted for data source (LOOK/Transform-Us!), age, sex and SES.						
All [*ilr*] coordinates represent isometric log ratio of simplex coefficients of time in longer versus shorter bouts of one intensity, keeping the total time within that intensity constant. The β-estimates evaluate associations between an outcome and an increase in time accumulated in longer versus shorter bouts.						
Longer bouts of SED were defined as ≥ 5-min bouts. Shorter SED was defined as bouts of < 5 min. Similarly, longer PA bouts (i.e., LPA, MPA and VPA) were defined as ≥ 1-min bouts and shorter PA bouts as the time accumulated in < 1-min bouts. "Other time" consisted of sleep and non-wear time.						
SED: Sedentary behaviour; LPA: Light-intensity physical activity; MPA: Moderate-intensity physical activity; VPA: Vigorous-intensity physical activity; Adj: Adjusted; Unadj: Unadjusted; SE: Standard error; zBMI: Body Mass Index converted to the World Health Organization Child Growth Standards age and sex standardized z-values [16]; WC: Waist circumference; SBP: Systolic blood pressure; DBP: Diastolic blood pressure; HDL-C: High-density lipoprotein cholesterol; LDL-C: Low-density lipoprotein cholesterol; CMR: Cardiometabolic risk score.						

The unadjusted and adjusted models showed evidence of an association of the overall time-use composition with six of eight cardiometabolic health biomarkers: zBMI, WC, SBP, HDL-C, triglycerides, and the CMR score (global F-test $p < 0.05$; specific values reported in Table 3). The overall time-use composition was associated with LDL-C in the unadjusted model only. Closer inspection of the individual *ilr* coordinates within the six significant adjusted models (Table 3) showed that a higher ratio of time in longer relative to shorter bouts of LPA (Long LPA : Short LPA) was associated with higher zBMI (β = 1.79, SE = 0.70, p = 0.010) and WC (β = 17.28, SE = 4.87, p < 0.001). Thus, higher levels of continuous LPA relative to sporadic LPA was associated with higher estimated zBMI and WC. In addition, a higher ratio of time in longer relative to shorter bouts of VPA was significantly associated with higher estimated WC (β = 2.55, SE = 1.14, p = 0.026). The associations for other individual *ilr* coordinates, across the other significant, adjusted time-use models (global F-test $p < 0.05$), were smaller and not statistically significant (all $p \geq 0.05$; specific values reported in Table 3). The unadjusted models revealed some further associations that were attenuated in size and no longer statistically significant after adjustment for confounders.

More time in LPA relative to MPA, VPA and "other time" was associated with lower WC (β=-8.62, SE = 3.80, p = 0.023). More time in VPA relative to "other time" was also associated with lower WC (β=-3.26, SE = 1.18, p = 0.006). In addition, more time in SED versus all other behaviours, and more time in MPA relative to VPA and "other time" was detrimental for WC (β = 7.06, SE = 3.37, p = 0.037 and β = 4.35, SE = 1.85, p = 0.019, respectively). No evidence of an association between any of the other individual *ilr* coordinates with zBMI, WC, SBP, HDL-C, triglycerides, or CMR, after accounting for confounders, was observed.

Estimated cardiometabolic biomarkers based on different ratios of time spent in longer versus shorter bouts

Estimated mean zBMI and WC for different ratios of longer and shorter LPA and VPA, are visually presented in Fig. 1, as these individual *ilr* coordinates indicated significance ($p < 0.05$) within the adjusted models with an observed overall significance between the time-use composition and a cardiometabolic health marker (global F-test $p < 0.05$). All other estimations are visualized in Figures S1-S8 in Additional File 3. Coloured images depict significant *ilr* coordinates within the adjusted models with an observed overall significance between the time-use composition and a cardiometabolic health marker (global F-test $p < 0.05$); all other *ilr* coordinates are in grey-scale.

Figures 1a and 1b show that accumulating 10 minutes of LPA in longer bouts rather than shorter bouts (relative to the existing compositional mean) was consistent with approximately 0.2 higher mean zBMI (0.9 versus 0.7) and 2.1 cm

higher mean WC (67.5 versus 65.4 cm) in girls. Similarly, girls' average WC was estimated to be higher (66.8 cm) if five minutes more time was accumulated in longer VPA bouts compared to the existing compositional mean (65.4 cm; see Fig. 1c). Similar estimations were predicted for boys (see Fig. 1).

Discussion

This study examined daily time-use compositions of 7–13 year-old youth and associations with cardiometabolic biomarkers. It was novel in that it not only factored in activity intensity (SED, LPA, MPA, VPA), but also whether these activity intensities were accumulated in longer bouts (≥ 5 min SED, and ≥ 1 min PA) or shorter bouts (< 5 min and < 1 min, respectively) within a 24-hour composition. In particular, the novel sequential binary partition chosen was advantageous for the comparison of relative time spent in longer versus shorter bouts. Although this provided a slightly complicated view of relative volume of time spent in each activity intensity versus others, this makes the current research an original contribution to activity pattern research in youth.

The results demonstrated that the overall time-use composition was associated with most cardiometabolic biomarkers. Specifically, they suggest that bout duration (i.e., ratio of time in longer relative to shorter bouts of LPA and VPA) contributed to these associations, particularly for adiposity. This indicates that a more continuous accumulation pattern (i.e., more time in longer rather than shorter bouts) was linked with a poorer biomarker profile (LPA with WC and zBMI; VPA with WC). It should be noted that this was modelled with a constant total time in those intensities and the results thus suggest that a specific amount of LPA and VPA performed more frequently in short bursts may be beneficial for adiposity than the same activity performed less frequently for longer periods. Results also suggested that more relative time in total LPA and VPA (including longer and shorter bouts) was associated with lower waist circumference. In contrast, more relative time in SED and MPA was detrimental for waist circumference. Effect sizes were in similar direction for other health markers, but these were not statistically significant.

To the best of the authors' knowledge, no research has used compositional data analyses to examine bout durations across the activity spectrum, including both SED and PA bouts, to assess associations with a range of cardiometabolic outcomes. One study by Gába and colleagues [11] used a similar approach, yet only investigated SED bout durations alongside total volumes of other intensities, and associations with adiposity. Their results suggested benefits to adiposity from replacing middle bouts (defined as 10–29 min) with shorter SED bouts (1–9 min), yet found no associations for replacements with long bouts (≥ 30 min duration) [11]. This contrasts with the present study that did not find benefits of engaging in a particular (shorter or longer) type of SED bouts. These contrasting results may be explained by methodological differences, such as the sequential binary partition chosen and the different thresholds for longer versus shorter bouts. As no other studies were found that have used compositional analysis to assess bout durations in youth, it is difficult to further compare our, and Gába and colleagues', findings with additional research.

Nevertheless, a few studies have investigated youth activity patterns and associations with cardiometabolic biomarkers [33, 34] using different analytical methods. For example, Holman and colleagues [33] used logistic regression models to evaluate all MVPA (i.e. total volume), and MVPA accumulated in short bouts (i.e., < 5 min, < 10 min) or long bouts (i.e., ≥ 5 min, ≥ 10 min) in 6–19 year old participants and did not observe differences with high versus normal cardiometabolic risk. This contrasts with our study, which may be explained by a number of methodological differences, in addition to the analytic approach. The studies used different device-based measures (60-s epoch versus 15-s epoch) with correspondingly different thresholds for longer versus shorter bouts, as well as different classifications of behaviour. Notably, Holman and colleagues [33] evaluated MVPA bouts, not MPA and VPA separately. Since MVPA bouts only cease

when activity becomes less intense (SED or LPA), whereas MPA bouts can be curtailed by either less intense activity or by VPA, it is unsurprising to see different results for MPA versus MVPA patterns.

Recently, Aadland and colleagues compared shorter and longer bouts of PA in youth using a multivariate pattern analysis approach, which included different bout lengths and total volumes within the same analysis [34]. Similar to the present study, they found that shorter bursts (including ≤ 30 s and ≤ 60 s) of PA were more favourable for children's metabolic composite score than longer bouts – but not for SED [34]. In addition, that study noted that the epoch setting used for accelerometer data processing (1 s, 10 s, and 60 s) affected the results. Specifically, the use of shorter epochs to capture VPA was recommended, yet stronger evidence of associations with MPA were found when analysed using longer epochs. This reinforces the supposition that shorter epoch lengths in our study versus the longer epochs in the study by Holman and colleagues [33] may have contributed to differing findings.

The present findings suggest that activity patterns may play a role in children's cardiometabolic health, particularly adiposity. The results were more supportive of encouraging children to accumulate PA through facilitating their natural sporadic accumulation patterns [35] rather than trying to alter these patterns to accrue PA in longer bouts. One important caveat in the practical application of this type of evidence is that statistical models of effects of patterns at a fixed volume are hypothetical scenarios of what might be expected. In real-life practical terms, changes in volume may well occur alongside any intervention which targets accumulation patterns because these two characteristics of physical activity are intrinsically linked. Although the main focus of this study was on PA and SED bouts, and not necessarily total volumes, the results do suggest that it is not just bouts that are important for health. Specifically, more relative time in total LPA and VPA (including longer and shorter bouts) was beneficial for waist circumference, and more relative time in SED and MPA was detrimental for waist circumference. While further evidence is required to determine the impact of longer activity bouts on children's health, the present findings support the recent removal of a minimum threshold of 10 minutes, and instead focus on total volumes within intensities, in the US guidelines [36].

The main strengths of the present study are the large sample size with objective measurement of activity patterns and cardiometabolic biomarkers. A main limitation in most previous PA and SED accelerometer and health studies is the combined assessment of intensities, adjustment for other intensities, and the consequent potential collinearity issues arising from that (particularly when investigating SED with inclusion of PA adjustment). This issue was overcome within the current study by use of compositional data analysis, which allows for handling of multiple PA and SED patterns within a joint statistical model. This study also had some limitations. Firstly, cross-sectional data were pooled. Thus, the estimated differences in cardiometabolic biomarkers cannot be directly interpreted as an effect of time reallocation from one component to another. The current study does not explain the possible biological mechanisms by which shorter, compared to longer, accumulation patterns may impact adiposity differently to other outcomes. The findings may perhaps be explained by the participant age range and their limited cumulative exposure to unhealthy lifestyle behaviours, such as extensive sitting. The measurement protocol used assumes that habitual patterns were captured, yet only truly reflects the past 4–7 days. As the present study was potentially underpowered to detect associations with other cardiometabolic biomarkers than adiposity, longitudinal studies with larger samples with data on risk factors other than adiposity are needed to investigate the long-term health effects of continuous and sporadic activity patterns. In addition, the data came from behaviours classified by waist-worn accelerometers processed by applying thresholds to epoch data. This measurement approach has acceptable validity for capturing total volumes of PA but has limited validity for measuring accumulation patterns, such as SED bout durations [37]. Also, the wear protocol provided to participants did not allow distinguishing between sleep and non-wear time. As sleep is an important factor in youth health [38, 39], future studies should consider 24-h wear protocols using posture-based devices. Data collected from posture-based devices (such as the activPAL http://www.palt.com/) worn 24 h/day that can measure SED posture and accumulation accurately would add value to the existing literature, and help to confirm or refute the current findings. Finally, as this exploratory study included a high number of findings, there may be an increased likelihood of false

discovery due to multiple testing. Nevertheless, as this is an understudied area of behavioural research in youth, a deliberate decision was made not to adjust for multiple comparisons [40, 41]. While for brevity the main results in the text have focused on the statistically significant findings (using p-values) – which can be problematic [42] – the full results are available in the tables and the supplementary material to allow interpretation with and without p-values.

Conclusions

This study is the first, to our knowledge, to investigate associations between patterns of PA and SED with a range of cardiometabolic health markers using compositional data analysis in youth. The main findings were that the time-use composition, which specifically included time in longer and shorter bouts of SED and PA, was significantly associated with most cardiometabolic biomarkers. Specifically, the accumulation of LPA in a more sporadic rather than sustained manner (i.e., shorter versus longer bouts) was associated with lower zBMI and WC. This association was also observed for the accumulation of VPA and lower WC. This suggests that accumulating PA (particularly LPA and VPA) frequently in short bursts may result in healthier adiposity values than engaging in the same amount of PA in longer bouts less regularly. However, the preliminary findings of this study and the extant literature should be corroborated (or refuted) with evidence from other samples, collected using alternative device-based measurement (especially with high validity for accumulation patterns, and assessment of SED), with measurement of sleep and using longitudinal designs. This is warranted for the development of targeted interventions to benefit health outcomes and establishment of whether existing movement guidelines need to be refined to include recommendations relating to specific activity patterns and intensities.

Abbreviations

BMI
Body mass index
CMR-score
Cardiometabolic risk score
DBP
Diastolic blood pressure
HDL-C
High-density lipoprotein cholesterol
LDL-C
Low-density lipoprotein cholesterol
LPA
Light-intensity physical activity
LOOK
Lifestyle Of Our Kids
MPA
Moderate-intensity physical activity
MVPA
Moderate- to vigorous-intensity physical activity
PA
Physical activity
SBP
Systolic blood pressure
SED

Sedentary behaviour
SES
Socioeconomic status
SD
Standard deviation
SE
Standard error
US
United States
VPA
Vigorous-intensity physical activity
WC
Waist circumference
zBMI
Body mass index converted to the World Health Organization Child Growth

Declarations

Ethics approval and consent to participate

This study is a secondary data analysis of data from two cluster-randomized school-based trials: "Lifestyle Of Our Kids' (ACTRN12615000066583 [23/01/2015]) and 'Transform-Us!' (ACTRN12609000715279 [19/08/2009], ISRCTN83725066 [30/06/2010]) [12, 43]. Ethical approval was provided 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). Parents provided written informed consent for their children to participate in each assessment (e.g., accelerometry, anthropometry, lipids).

Consent for publication

Not applicable

Availability of data and materials

The data that support the findings of this study were originally collected for the 'Lifestyle Of Our Kids' and 'Transform-Us!' trials. Data sharing is thus not applicable to this article as no new data were created or analysed in this study.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

SJJMV led the project, including running the data analyses and drafting the manuscript. KEL, JAMF, and EW provided statistical advice. NR, KEL, AT, JS and RML contributed equally in designing the study and writing the manuscript. JS was additionally chief investigator on the original Transform-Us! trial. RMD, EC, DWD, RMT, RT, and LSO have been closely involved in the design and/or data collection for the original trials and contributed equally in the writing of the manuscript.

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Figures

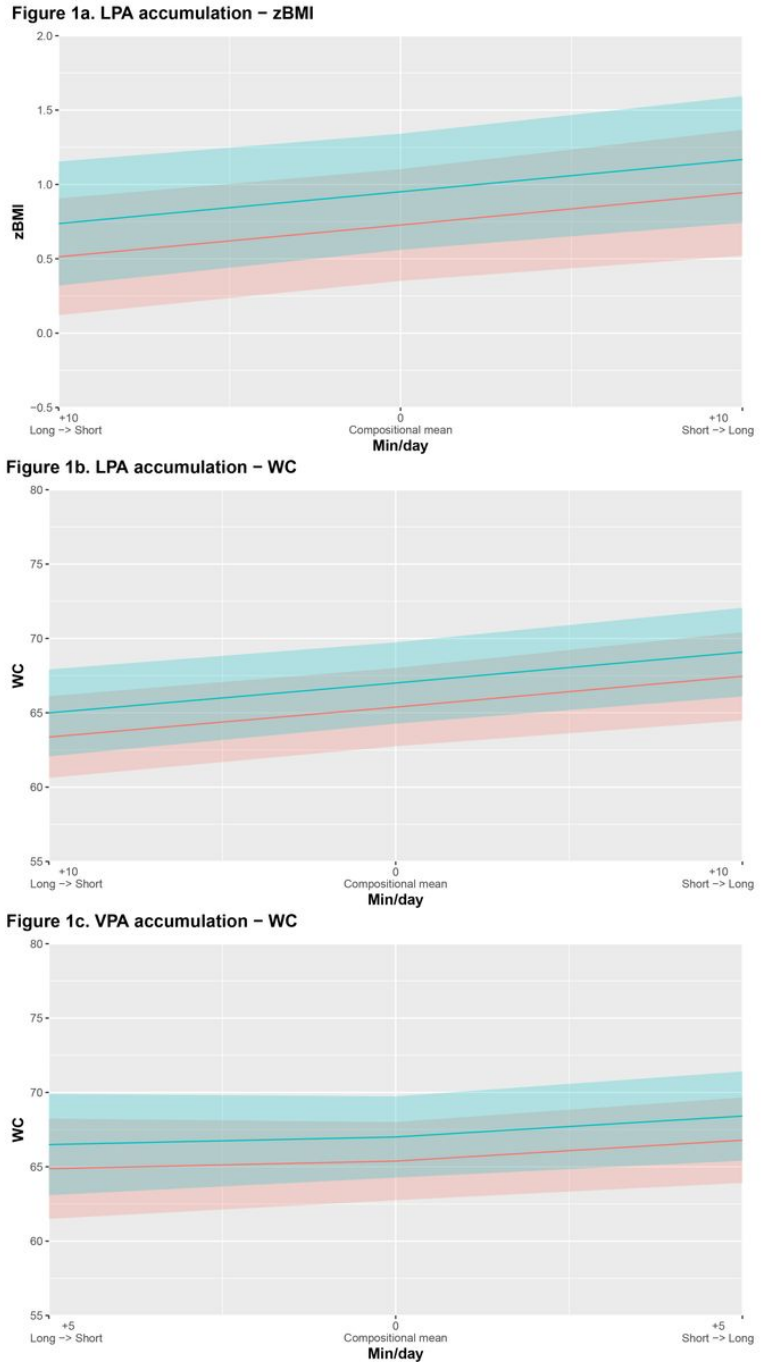

Figure 1

Estimated zBMI and WC for different ratios of longer and shorter LPA and VPA bouts Boys Girls Overlapping 95% confidence intervals Plots include estimated mean zBMI and WC with 95% confidence intervals. The overall time within the intensity of interest was kept constant, while the ratio between longer and shorter behaviours was alternated. Times in all other components were set at the mean observed values. LPA: Light-intensity physical activity; zBMI: Body Mass Index converted to the World Health Organization Child Growth Standards age and sex standardized z-values [16]; WC: Waist circumference; VPA: Vigorous-intensity physical activity.

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