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The association between 24-h movement behaviours and adiposity among Australian preschoolers: a compositional data analysis

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Abstract

Introduction The relationship between 24-h movement behaviours (i.e. sleep, sedentary behaviour and physical activity) and adiposity in preschoolers remains unclear. Therefore, this study aims to investigate the associations between 24-h movement behaviours and adiposity in preschoolers making use of compositional data analysis (CoDA).

Methods Australian preschoolers (3–5 years) from the Early Start Baseline Study wore an ActiGraph accelerometer to assess sedentary behaviour (SB), light physical activity (LPA) and moderate-to-vigorous physical activity (MVPA). Their weight and height were measured using standardized protocols and converted to Body Mass Index (BMI) z-scores using the World Health Organisation growth references. Their parents completed a questionnaire to assess their level of education and the child's sleep duration, age and sex. CoDA was employed to investigate the association between 24-h movement behaviours and adiposity in R.

Results This study included 169 preschoolers and their overall 24-h movement behaviour composition was associated with BMI z-scores ($F = 5.02$, $p = 0.002$). When examining the association between each movement behaviour relative to the others and BMI z-scores, we observed a statistically significant favourable association for sleep ($p = 0.025$) and unfavourable association for MVPA ($p = 0.010$), but not for the other behaviours. As such, reallocating 10 min from sleep or from MVPA, proportionally to all other behaviours was associated with a difference of +0.031 (95%CI = 0.004,0.06) and -0.085 (95%CI = -0.15,-0.02) in BMI z-score, respectively.

Conclusion Despite the association between more time spent in MVPA and higher BMI z-scores, promoting a balanced amount of time in each 24-h movement behaviour—more MVPA, less sedentary time, and sufficient sleep—remains important for overall health. Future studies should address methodological challenges (e.g. recruitment bias that may exist in the parents/children willing to participate versus the general population, recall bias in parent reported sleep duration, or other confounding variables such as diet), use larger and more diverse samples, and consider longitudinal designs. Additionally, focusing on other adiposity indicators, such as waist-to-height ratio or fat percentage, could enhance understanding of these relationships.

Keywords 24-hour movement behaviour, Preschooler, Adiposity, Overweight, Compositional data analysis

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Introduction

Childhood overweight is a global burden, with 37 million children under the age of 5 years classified as overweight in 2022 [1]. Preventing and managing childhood overweight and obesity can minimise psychological and physical comorbidities in childhood and in later life, including noncommunicable diseases such as cancer, cardiovascular disease and type 2 diabetes mellitus [2]. Early childhood is a critical period for establishing dietary, physical activity, sedentary and sleep habits that affect adiposity [2–5]. Understanding how these behaviours interact with adiposity from a young age can inform strategies to encourage healthy behaviours.

In this study we focused on sleep, sedentary behaviour (SB) and physical activity (PA). Previous studies showed significant associations between these three behaviours and adiposity indicators (e.g. Body Mass Index (BMI), body fat percentage, waist circumference) in school-aged children (>5 years), with a sufficient amount of sleep, less sedentary time and more PA related to more favourable adiposity outcomes [3, 6, 7]. However, the results in young children (≤5 years) are inconsistent. Specifically for preschool children (3–5 years old), most studies have assessed the association between adiposity and guideline compliance, i.e. achieving 180 min/day of PA of which at least 60 min is moderate- to vigorous-intensity PA (MVPA), no more than 60 min/day of sedentary screen time, and a sleep duration of 10–13 h/day [8–12]. For example, a Canadian study found no statistically significant association between guideline compliance for all three behaviours and weight status or BMI z-scores in 3-to 4-year-olds. However, a Japanese study found an association between complying with all three behaviour guidelines and weight status in 3-to 5 year old preschoolers [8, 11]. Focusing solely on guideline thresholds might result in the loss of important information about time-use over the full 24-h day, and collapsing behaviours into dichotomised categories of complying or not complying, might underestimate the extent of variation [13]. Sleep, SB and PA are time-dependent and together, the time spent in them will always sum to 24 h over a day; hence, they are collectively known as 24-h movement behaviours [14]. Spending more time in one of these behaviours means that less time can be spent in one or more of the other behaviours within those 24 h. This means that the contribution to health of changing one behaviour (e.g. more time spent in PA) will also be the result of compensatory changes among the other behaviours (i.e. less time spent in SB and/or sleep). It is therefore recommended to study these behaviours using an integrated approach instead of in isolation from the other movement behaviours. An analytical approach that accounts for the co-dependency of the 24-h movement behaviours within a finite 24-h day is compositional data analysis (CoDA) [15]. Additionally, prediction models that theoretically reallocate time from one behaviour to others can help illustrate how these behaviours interact in relation to adiposity. These theoretical models can identify which time distribution combinations yield the most favourable adiposity outcomes and whether synergistic effects occur, where the overall impact is greater than the sum of individual changes [15, 16]. To our knowledge, only two studies have used CoDA to study the association between 24-h movement behaviours and adiposity in preschoolers. Both studies showed a significant association between the 24-h movement behaviour composition and BMI z-scores, but not for other adiposity indicators such as body fat percentage and waist circumference [17, 18]. Carson et al. [18] found a cross-sectional association for the overall composition of movement behaviours, but not for any single behaviour relative to the others in a Canadian sample of 2-to 4-year-olds. Conversely, Taylor et al. [17] only found a cross-sectional association for those aged 3.5 years, but not for 1-, 2- or 5-year-olds in New Zealand. Based on these studies, the association between 24-h movement behaviours and adiposity in preschoolers remains unclear. More research is needed to clarify this relationship, particularly considering that preschoolers are at a crucial developmental stage for habit formation and could benefit from early interventions for improved health outcomes, especially when it comes to healthy weight, given the rising global burden of childhood overweight [1]. This study aimed to bridge this gap by investigating the associations between 24-h movement behaviours and BMI z-scores in preschoolers making use of CoDA.

Methods

Study design and participants

The Early Start Baseline Study collected data from preschoolers, parents and educators in Early Childhood Education and Care Centres in New South Wales and the Australian Capital Territory, Australia. Centres were selected based on their location in areas of recognised socio-economic disadvantage from the 2011 postcode based Australian Bureau of Statistics Socio-Economic Indexes For Areas (SEIFA) [19]. All preschoolers (3–5 years) enrolled in these centres were invited to participate through the distribution of a Participant Information Sheet from data collectors and staff. Parents completed a written informed consent for themselves and their preschooler. Preschoolers gave verbal assent to participate. Data were collected between October 2014 and April 2015. Prior to data collection, data collectors were intensively trained in the measurement procedures and were provided with manuals and checklists to use during data collection at the centres. The University of Wollongong Human Research Ethics Committee approved the study procedures (HE14/250).

Measurements

Anthropometry

Height and weight of preschoolers were measured using standardized protocols [20]. To measure height, preschoolers stood upright without shoes against a Seca 217 portable stadiometer (SECA, Hamburg, Germany). To measure weight, a Seca scale 874 (SECA, Hamburg, Germany) was used and preschoolers had to remove heavy clothing (e.g. jacket) and shoes. The measurements were taken twice (to the nearest 0.1 cm and 0.1 kg, respectively). If the difference between the two measurements was more than 0.5 (cm and kg, respectively), a third measurement was undertaken with the average of the two closest measurements used.

BMI (body mass [kg]/height [m^2]) and BMI z-scores, as an indicator of adiposity, were calculated using the Anthro Plus version 1.0.4 and Anthro version 3.2.2 software (World Health Organization, Geneva, Switzerland). Categorization in weight status groups, "non-overweight" and "overweight/obesity", was based on the World Health Organization (WHO) growth references [21]. Children with BMI z-scores of more than 2 (for those aged < 5y), and more than 1 (≥ 5y of age), were considered overweight or obese. Preschoolers with a BMI z-score of < −2, were considered underweight and categorized in the "non-overweight" group.

Accelerometry

PA and SB were measured using ActiGraph (GT3X+, GT3X) accelerometers (ActiGraph, Pensacola, FL). The accelerometers were fitted on the right hip at the right mid-axillary line using an adjustable elastic belt. Participants were instructed to wear the accelerometer continuously (24h) for seven days and remove it for water-based activities. Accelerometer data were recorded in 15-s epochs at 30 Hz and processed in Actilife software version 6.12.1 (ActiGraph, Pensacola, FL).). A predetermined time filter (i.e. 5AM–11PM) was applied to all recording days to exclude sleep periods from the analysis of SB and PA [22]. Sleep was not processed through accelerometery due to a small proportion of preschoolers wearing the device at night. Non-wear time was defined as 20 min of consecutive zero accelerometer output counts. To be included in the study, children had to provide at least three days of valid accelerometry data with a minimum wear time of 8 h/day, which is suggested to provide a reliable estimate for PA in preschoolers [23, 24]. To differentiate SB from light-intensity PA (LPA) and LPA from MVPA cut-points of 25 [25] and 420 [26] vertical axis activity counts/15 s were used respectively [25–27]. Time spent in SB, LPA and MVPA was averaged for all valid days (minutes/day) and used in the analysis.

Questionnaire

Parents completed a questionnaire on demographics and information about the home living environment. The questionnaire took approximately 20 min to complete and consisted of 77 questions (Supplementary file 1). Parents could complete the questionnaire online, on paper, or over the phone administered by a data collector. The questionnaire included questions to assess pre-schoolers' sleep duration and covariates age, sex and parents' highest level of education.

Sleep duration was assessed with the following open-ended questions "How many hours per night does this child usually sleep at the moment?" and "How many hours does this child usually sleep/nap for during the day at the moment?". The sum of both responses was used for analyses. Child's age and sex were obtained from the question "What is this child's date of birth?" and "What is this child's gender?" respectively. The highest level of education was obtained from the parent who completed the questionnaire. This is a commonly used proxy for socio-economic background of the family [28]. For ease of interpretation, responses were dichotomized into low educational level ("No schooling/did not complete Primary school", "Primary school or equivalent", "Year 10 or equivalent (e.g. School certificate)", "Year 12 or equivalent (e.g. Higher School Certificate)", "Trade/apprenticeship/certificate (e.g. hairdresser, plumber)") and high educational level ("Diploma (e.g. Business/Accounting)", "University Degree", "Post-graduate qualification (e.g. Masters, PhD)").

Statistical analysis

All analyses were conducted in R version 4.3.1. [29] and a significance level of alpha = 0.05 was used. The script of the analyses can be found via https://github.com/MDcraen/EarlyStartBaselineCoDA. The analytical sample included participants with complete data without outliers or unrealistic values for weight, height, accelerometer measured SB and PA, questionnaire derived sleep duration, and potential covariates (i.e. parental educational level, age, sex). To assess the potential missing data mechanism, Little's test was used to assess whether missing data deviated from Missing Completely At Random (MCAR) [30]. A p-value below the significance level implies evidence that MCAR cannot be assumed (missing data may be related to some observed or unobserved variables in the dataset). Logistic regression models with the outcome of variable missingness regressed on the remaining variables was performed to further investigate relationships between missing values and the other recorded variables. The included variables were age, sex, BMI z-score, accelerometry data, sleep and parental educational level.

Descriptive statistics were calculated for the overall sample and by weight status (non-overweight and overweight/obesity) [31]. Continuous variables were summarised by means and standard deviations and categorical variables by counts and percentages. Independent two-sample t-tests were used to test the null hypothesis of equal means between weight status groups for continuous variables and chi-squared tests were used to test the null hypothesis of independence in weight status group counts for categorical variables.

CoDA was used to determine associations between the 24-h movement behaviour composition and BMI z-scores [15, 16]. Time spent in the 24-h movement behaviours (Sleep, SB, LPA and MVPA) are considered relative to each other in a CoDA approach instead of using their absolute values. To apply CoDA methods, time-use behaviours were expressed as a set of isometric log-ratios (ILR). The pivot-coordinate approach to creating ILRs was used [32] where four sets of ILRs were established. In this method, the pivot ILR coordinate corresponding to each behaviour is the ILR coordinate that is proportional to the log-ratio of that behaviour relative to the geometric mean of the remaining 24-h movement behaviours.

$$\sqrt{\frac{3}{4}} \quad \ln \quad \frac{\mathrm{MVPA}}{(SB\ .\ LPA\ .\ Sleep)^{1/3}}$$

For example, the pivot ILR co-ordinate corresponding to MVPA (relative to the remaining behaviours) is calculated using the formula:

This transformation effectively allows us to assess the relative contribution of each behaviour to the overall composition of time spent across the 24-h period, thereby addressing the inherent co-dependency among these behaviours [32]. Descriptive statistics of the composition were presented as central tendency. We calculated geometric means of each behaviour, which ensures the proportional relationship among the behaviours is reflected. After calculating these means, a linear adjustment was made so that the behaviours collectively sum to 1440 min (total number of minutes within 24 h), and compositional log-ratio variation was described using a matrix of all possible pair-wise log-ratios variations, [33]. To compare 24-h movement behaviour compositions between weight status groups, a MANOVA was performed and group mean differences with bootstrapped 95% percentile confidence intervals were plotted between the individual behaviour log-ratio differences [34, 35]. The log-ratio differences were calculated using the compositional means of the behaviours of the overweight/obesity group (OWOB) as the numerator and the compositional means of the non-overweight group (NoOW) as the denominator (i.e., ln[OW/NoOW]). A positive value of the log-ratio difference indicates more time spent in the given behaviour in the overweight/obesity group compared to the non-overweight group. Similarly, a negative log-ratio value implies the opposite. The between-group difference in each behaviour was considered significant if the corresponding 95% confidence interval did not include the null difference value of zero.

To explore the association between the 24-h movement behaviour composition and BMI z-scores, multiple linear regression models were applied with the compositional data (i.e. ILR coordinates) as explanatory variables and the BMI z-score as the dependent variable. Before fitting the multiple linear regression models, a Likelihood Ratio Test was used to detect whether clustering by childcare centre (via random intercepts in linear mixed effects modelling) was warranted. Also the presence of zero values in the 24-h movement behaviours was carefully examined, and appropriate adjustments were made where necessary to enable the log-ratio transformations. Parental educational level, sex and age were included as model covariates in the regression models. Model fit was assessed via diagnostic plots of linearity, normality of residuals and homogeneity of variance [36]. When the addition of the 24-h movement behaviour ILRs for each of the pivot coordinates significantly improved the intercept and covariate-only explanatory linear regression model (at the significance level alpha), time reallocation estimates were made using compositional isotemporal substitution (compositional model-based time reallocation) estimates [16, 37]. Time reallocation estimates use the compositional linear regression models to predict estimated mean differences in the outcome (i.e. BMI z-score) if a fixed duration of time were to be reallocated from one behaviour to another behaviour. Models for both proportional reallocation (i.e. time to or from one behaviour proportionally redistributed from or to, respectively, the other behaviours) and one-by-one reallocation (i.e. time to or from one behaviour from or to one other behaviour) were applied in steps of 10 min from −60 to 60 min. No specific guideline exists for selecting volume of reallocation intervals in CoDA. The decision to reallocate time in 10-min increments was made because this amount is considered both practical and realistic for implementation in real-world settings, such as childcare centers or home environments, and aligns with previous research in preschoolers [38–40]. To aid interpretation of the results in context, BMI z-score absolute differences and, effect sizes (ES) (Standarized

Mean Difference = absolute difference/standard deviation) were calculated. To interpret these ES Cohen's interpretation is typically used (small effect ≈ 0.2; medium effect ≈ 0.5; large effect ≈ 0.8) [41]. However, ES should be interpreted in the context of previous studies within the same field and other compositional 24-h movement behaviour studies show rather small ES [42]. Note that in the case of BMI z-values, the estimates by definition are in terms of the assumed population standard deviation for specific age and sex strata.

Interaction terms for weight groups (non-overweight vs. overweight/obesity) and for sex with 24-h movement behaviour compositions on the outcome of BMI z-scores were additionally considered. In the event of a statistically significant interaction, providing evidence that the relationship between the 24-h movement behaviour compositions and BMI z-scores was different between weight status groups or sex groups, the analyses were conducted for each group separately.

Results

In total, 786 preschoolers from 35 Early Childhood Education and Care Centres participated in the Study, of which 169 preschoolers met the data inclusion criteria. Most exclusions were due to invalid accelerometry data ($n = 112$), missing both parental education and sleep data ($n = 144$) or missing data for these three variables together (n = 287), as presented by Supplementary file 2, Figure S1. Little's test showed that there was significant evidence against MCAR (χ^2_{43} = 105, $p < 0.001$). Participants with longer accelerometry wear time were less likely to have missing data for parental education (OR = 0.997; 95%CI = 0.994,0.999). Participants with higher parental education were less likely to have missing accelerometry data (OR = 0.50; 95%CI = 0.30,0.84). There were no significant models for missing data of the other included variables. None of the included participants had zero values for any of the 24-h movement behaviours, meaning no adjustment was needed to enable log-ratio transformations.

Table 1 shows the descriptive characteristics of the included study sample ($n = 169$) stratified by weight status. In total, 14.2% of the study sample was overweight or obese. One child was considered underweight with a BMI z-score of −2.11. The average 24-h composition was (compositional mean, in min/day): sleep = 694; SB = 338; LPA = 309; MVPA = 100. The sample variation matrices for the compositional behaviours for the total sample and each weight status group are presented in Supplementary file 2, Table S1. The two variables with the lowest co-dependence were SB and MVPA (0.144) and the two variables with the highest co-dependence were sleep and LPA (0.036).

There was a difference in the overall 24-h movement behaviour composition between the group with and without overweight or obesity (F = 5.02; $p = 0.002$). Figure 1 shows that preschoolers with overweight/obesity spent on average an estimated 16% more time in MVPA relative to the other behaviours compared to the non-overweight group.

Preschoolers' 24-h movement behaviour composition was significantly associated with BMI z-score ($p < 0.001$) (Table 2). The Likelihood Ratio Test showed clustering for childcare centre was not warranted ($p = 1$). Relative to the other behaviours, more time spent in sleep had an estimated association with lower BMI z-scores (estimated pivot ilr coefficient = −1.27, p = 0.025) and more time spent in MVPA was positively associated with a higher BMI z-score (estimated pivot ilr coefficient = 0.87, p = 0.010). There were no significant associations for the other behaviours with BMI z-scores when considered relative to the remaining behaviours. Predicted mean BMI z-score differences with 95% confidence intervals for time reallocations between the behaviours from the sample compositional mean are shown in Figs. 2 and 3. Figure 2 shows the proportional reallocation of time spent in 24-h movement behaviours from one behaviour to all other behaviours. An additional 10 min of time spent in sleep, proportionally taken from time spent in all other behaviours, was associated with a lower BMI z-score, a difference of −0.031 (ES = −0.03; 95%CI = −0.06,−0.004). Conversely, taking 10 min away from sleep, proportionately redistributed among all other behaviours was associated with an estimated higher BMI z-score, a difference of + 0.031 (ES = 0.03; 95%CI = 0.004,0.06). An additional 10 min of time spent in MVPA, proportionally taken from time spent in all other behaviours, was associated with a higher BMI z-score, a difference of + 0.078 (ES = 0.08; 95%CI = 0.02,0.14). Conversely, taking 10 min away from MVPA, proportionately redistributed among all other behaviours was associated with an estimated lower BMI z-score, a difference of −0.085 (ES = −0.08; 95%CI = −0.15,−0.02). Figure 3 shows the reallocation of time spent from one behaviour to one other behaviour. Significant results were the following. Ten minutes more of sleep at the expense of MVPA was associated with lower BMI z-scores: a difference of −0.10 (ES = −0.10; 95%CI = −0.16,−0.03). Conversely, taking 10 min away from sleep and putting it into MVPA was significantly associated with higher BMI z-scores: a difference of + 0.09 (ES = 0.09; 95%CI = 0.03, 0.15). Ten minutes more of MVPA at the expense of sleep or SB was associated with higher BMI z-scores: a difference of + 0.08 (ES = 0.08; 95%CI = 0.02,0.13) and + 0.07 (ES = 0.07; 95%CI = 0.01,0.12), respectively. Conversely, taking 10 min away from MVPA and putting it into sleep or SB was

Table 1 Descriptive characteristics of the study sample ($n = 169$)

	Total ($n = 169$)	Non-overweight (82.8%, $n = 145$)	Overweight/obese (14.2%, $n = 24$)
Socio-demographics			
Boys (%)	53.8 ($n = 91$)	53.8 ($n = 78$)	54.2 ($n = 13$)
Mean Age in years (SD)	4.64 (0.72)	4.57 (0.71)	5.03 (0.66)*
Parental education (%)			
Low	52.1 ($n = 88$)	50.3 ($n = 73$)	62.5 ($n = 15$)
High	47.9 ($n = 81$)	49.7 ($n = 72$)	37.5 ($n = 9$)
Mean BMI (kg/m^2) (SD)	16.30 (1.72)	15.88 (1.05)	18.84 (2.61)**
Mean BMI z-score (SD)	0.64 (1.04)	0.40 (0.73)	2.12 (1.37)**
24-h movement behaviour composition in minutes/day			
1) Arithmetic mean (SD)			
2) Compositional mean (% of the day)			
Sleep duration			
1)	644 (77)	649 (74)	611 (91)*
2)	694 (48)	698 (48)	669 (46)*
SB			
1)	315 (52)	317 (48)	306 (73)
2)	338 (24)	339 (24)	328 (23)
LPA			
1)	286 (37)	285 (38)	297 (31)
2)	309 (21)	306 (21)	327 (23)
MVPA			
1)	95 (26)	93 (25)	109 (30)*
2)	100 (7)	97 (7)	116 (8)*

Abbreviations: *Body Mass Index (BMI), sedentary behaviour (SB) physical activity (PA), light physical activity (LPA), moderate-to-vigorous physical activity (MVPA).*

*Statistically significant between groups with $0.001 \le p < 0.05$

**Statistically significant between groups with $p < 0.001$

Analyses within this table are not adjusted for covariates.

significantly associated with lower BMI z-scores: a difference of −0.10 (ES = −0.10; 95%CI = −0.16, −0.03) and −0.09 (ES = −0.09; 95%CI = −0.15, −0.02), respectively. There were no significant associations for other combinations of behaviours when reallocating 10 min.

There was no interaction between sex and the 24-h movement behaviour composition on the outcome of BMI z-scores (F = 1.12 (df: 3,158), $p = 0.34$). When weight status group was added to the regression model, there was an interaction between the overall composition and weight status group in relation to BMI z-score (F = 2.83 (df: 3, 158), $p = 0.040$). Stratified analyses by weight status showed an association between the overall composition and BMI z-score in the non-overweight group (F = 3.82 (df: 3, 138), $p = 0.011$) but not in the overweight/obesity group (F = 0.41(df: 3, 17), $p = 0.747$) (Supplementary file 2, Table S2). The model results for the pivot coordinates of the non-overweight group can be found in Supplementary file 2, Table S2. In this group, more time spent in MVPA, relative to the other behaviours, was associated with higher BMI z-scores (pivot ilr coefficient = 0.82, $p = 0.002$). There were no significant associations for the other pivot coordinates.

Discussion

We found that the 24-h movement behaviour composition was associated with BMI z-score among Australian preschoolers. When examining the association between each movement behaviour relative to the others and BMI z-scores, we observed an association for MVPA ($p = 0.010$) and sleep ($p = 0.025$). There was no significant association for the other behaviours. In the overall regression model an interaction effect for weight group was found. In stratified analyses, the association between the overall 24-h movement behaviour composition and BMI z-scores did not apply for the group with overweight and obesity.

Consistent with this finding, two previous studies have also reported statistically significant associations between the 24-h movement behaviour composition and

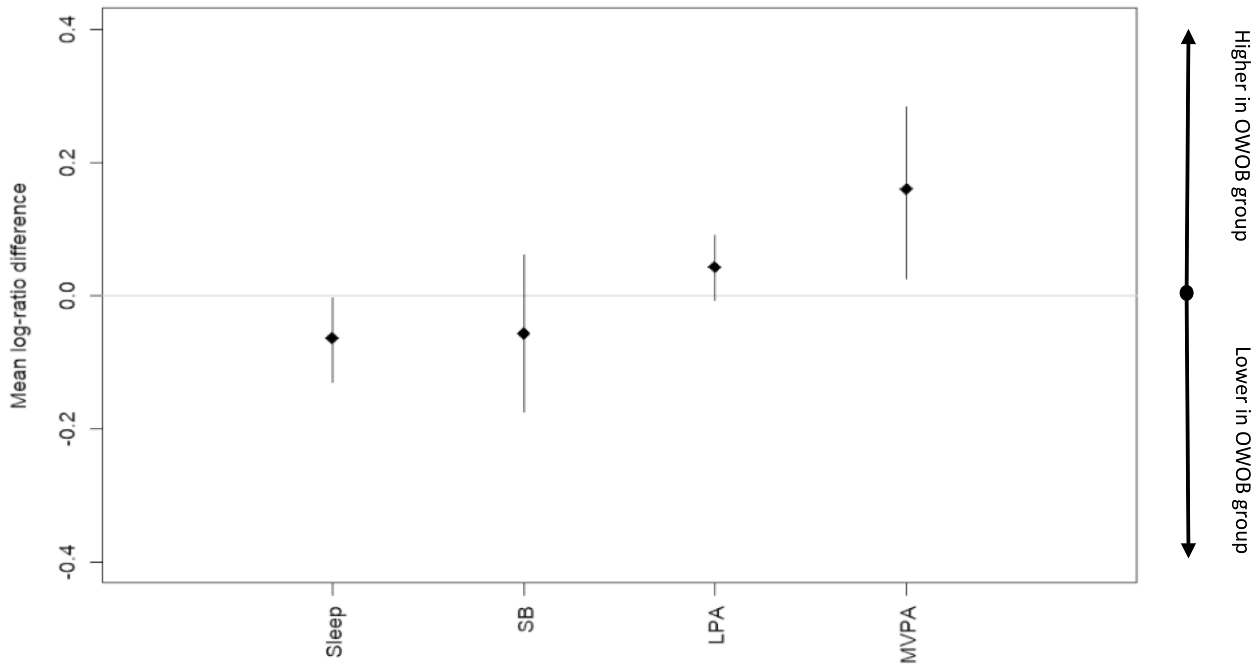

Fig. 1 Bootstrapped log-ratio differences of compositional means of 24-h behaviours between weight groups

Bootstrapped mean and 95% confidence interval for the log-ratio differences of compositional means of the 24-h behaviours between not overweight (NoOW) and overweight/obesity (OWOB) (i.e. ln[OW/NoOWOB]) are represented. A log-ratio difference of 0.16 for MVPA indicates that the time allocated to this domain was 16% higher for the overweight/obese group compared to the non-overweight group (95%CI sleep = −0.13,0.00, sedentary behaviour (SB) = −0.17,0.06, light physical activity (LPA) = −0.01,0.09, moderate-to-vigorous physical activity (MPVA) = 0.02,0.28)

BMI z-scores in pre-schoolers [17, 18]. This suggests that the distribution of time spent on each of the 24-h movement behaviours within a day makes a difference when it comes to healthy weight.

Our finding that more MVPA relative to the other behaviours was related to a higher BMI z-score may appear counterintuitive, considering the more robust evidence among other populations (school-aged children and adults) indicating that more MVPA is associated with lower adiposity [3]. In particular, our prediction of higher BMI z-scores when more time is spent in MVPA relative to the remaining behaviours contradicts previous studies in a school-aged population [3]. The study of Fairclough et al. [43], showed higher BMI z-scores when less time was spent in MVPA, relative to either sleep, SB or LPA (15-min reallocations were associated with + 0.88, + 0.83 and + 0.89 BMI z-score, respectively) [43]. However, the effect sizes observed in our current study are notably small, casting doubt on the clinical significance of our findings (a 10-min reallocation away from MVPA to sleep, SB and LPA collectively was only associated with −0.085 BMI z-score). The direction of our findings align with an 8 year longitudinal study by Moore et al. [44]. In the latter study, children classified as "high active" at 4 years old had higher BMI values compared those classified as "low active". However, the "high active" children had lower BMI gains compared to the "low active" throughout the study. These seemingly contradictory relationships found among preschool populations may be attributed to the onset of adiposity rebound [44, 45]. In the current study we were not able to account for adiposity rebound due to the cross-sectional nature. Additionally, we should be aware that the favourable effect of MVPA on healthy weight might need some time to manifest and may become more evident as the child ages. We should also consider that other confounding factors, including muscle mass, dietary intake and recruitment bias, might have influenced the results. Recruitment bias might be induced as participation in the study was voluntary, meaning that it is possible that parents with a particular interest in movement behaviours were more likely to participate, while those who are less concerned about movement behaviours and health may be opted out of the study [46]. This could have led

Table 2 Associations between compositional 24-h movement behaviours and BMI z-scores

Overall composition			
	F-value (df1,df2)		***P*-value**
Overall composition	5.02 (3,162)		**0.002**
Covariates:			
Parental education	6.92 (1,162)		0.008
Sex	1.79 (1,162)		0.175
Age	0.12 (1,162)		0.728
Pivot coordinates			
	Estimate	**SE**	***P*-value**
Sleep vs. remaining	−1.27	0.56	**0.025**
SB vs. remaining	−0.22	0.47	0.637
LPA vs. remaining	0.62	0.59	0.295
MVPA vs. remaining	0.87	0.34	**0.010**
Covariates:			
Parental education (ref. higher)	−0.41	0.15	0.008
Sex (ref. female)	−0.21	0.16	0.175
Age	−0.03	0.11	0.728

Abbreviations: sedentary behaviour (SB), light physical activity (LPA), moderate-to-vigorous physical activity (MVPA), numerator degrees of freedom (df1), denominator degrees of freedom (df2)

All models were adjusted for parental education, sex and age. The Model R^2 was 0.11.

Significance level of alpha = 0.05

to an overrepresentation of preschoolers with parents who prioritize MVPA [46]. However, we were not able to control for this. To have a better understanding of the relationship between 24-h movement behaviour compositions and preschoolers' adiposity, future studies should consider these possible confounders and include other measures of adiposity (e.g., waist circumference, body fat percentage). In addition, longitudinal studies are recommended and may provide insight in how 24-h movement behaviours affect adiposity levels as children age.

In contrast to our results, Carson et al. [18] did not find significant associations with the individual ILR pivot coordinates representing each behaviour, relative to the remaining behaviours among a group of 3- to 4-year-olds ($n=552$). In line with our results for sleep, Taylor et al. [17] found significant associations for more sleep, relative to the remaining behaviours, and lower BMI z-scores in 3-and-a-half-year-olds ($n=231$). However, they also found an association for SB and LPA, but not for MVPA, each relative to the remaining behaviours. The association between sleep and adiposity is in line with a systematic review of Chaput et al. [8] showing that shorter sleep duration was associated with higher adiposity in 20 out of 30 studies in young children from zero to four years old. However, our one-by-one reallocations showed a significant interaction only with MVPA, meaning that, for instance, more sleep would lead to a lower BMI-z score when time is taken from MVPA. This result seems again counterintuitive, as discussed in the MVPA findings above. Nonetheless, the findings in preschoolers are more mixed compared to studies in school-aged children, showing a more robust relationship between shorter sleep duration and higher adiposity [47]. This is likely because it might be more challenging to identify associations with adverse health indicators in younger children. The effects might become apparent over time if short sleep duration persists. This could be confirmed with longitudinal studies.

We found an interaction effect for weight group in the overall composition regression model. The association between the overall 24-h movement behaviour composition and BMI z-score was statistically significant only for the non-overweight group. It could be that the sample size of preschoolers with overweight and obesity ($n=24$) was too small to provide enough statistical power to observe significant differences. Therefore, this result should be interpreted with caution. To have a better understanding of the association between the 24-h movement behaviour composition and BMI z-scores in weight groups, higher number of participants would be beneficial.

Overall, the association between 24-h movement behaviour composition and adiposity in preschoolers is somewhat equivocal. Nonetheless, promoting a healthy amount of time spent in each of the movement behaviours is recommended due to the strong evidence that exists for school-aged children and the critical period of habit formation in early childhood [3]. Currently, the 24-h movement behaviour guidelines offer the most scientifically supported recommendations for determining how much time a preschooler should spend in each activity [2].

Strengths and limitations

The strengths of this study were the use of a compositional analytical approach and the device-based measurement of SB, LPA and MVPA which are less susceptible to recall bias. The study has several limitations. First, there was a large drop-out of participants. The missingness of data was shown to be not at random, limiting the generalizability of our findings. Participants with higher parental education were less likely to have missing accelerometry data. Parents with a lower educational background might have found it more difficult to understand the study instructions, leading to invalid data and questionable generalizability of the study. However, data of a more disadvantaged population are crucial within public health research as this population is more vulnerable to non-communicable diseases [48]. Therefore,

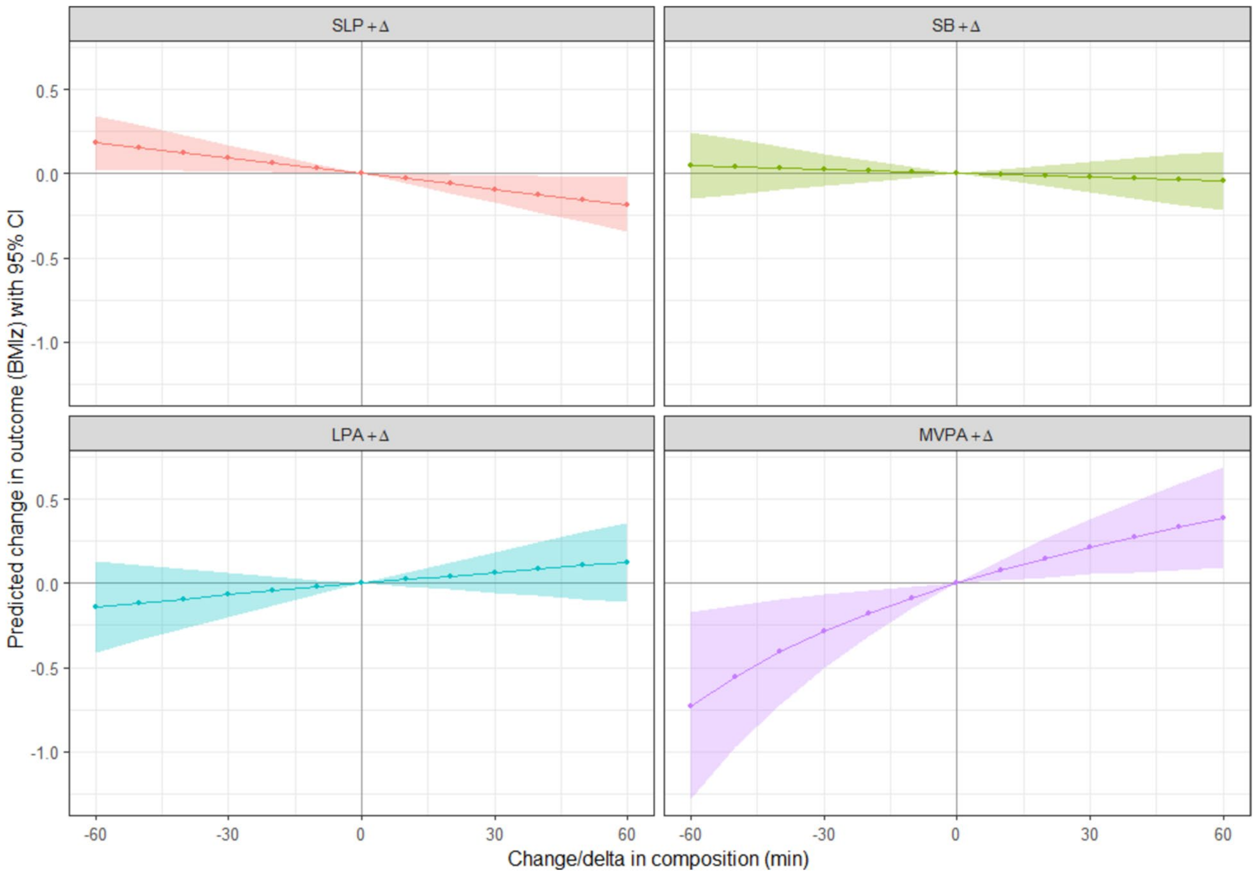

Fig. 2 Prediction of BMI z-score through proportional reallocation of time spent in 24-h movement behaviours

The prediction model shows differences in BMI z-score (vertical axis) when reallocating time (horizontal axis) to one behaviour equally from the other behaviours in steps of 10 min over a time frame of –60 to 60 min. Abbreviations: Body Mass Index (BMI), sleep duration (SLP), sedentary behaviour (SB), physical activity (PA), light intensive physical activity (LPA), moderate-to-vigorous intensive physical activity (MVPA). The shaded zone on each graphs shows the 95% confidence interval

more effort should be made to make these studies more inclusive. Establishing trust and providing participants with personal benefit from participating are success factors for participating, for instance a fun activity as an incentive [49]. Unfortunately, we do not have data on why participants dropped-out. This information would be valuable to avoid drop-out in future studies. Second, sleep was derived from a parent reported questionnaire, which might have caused an over-or underestimation of sleep duration due to social desirability or recall bias [50]. Using device-measured sleep time could overcome these limitations. Third, only BMI-z score was used as adiposity indicator, which does not distinguish between excess body fat and bone/muscle mass [51]. Additional studies using body composition measures are needed to elucidate such associations. Nonetheless, BMI-z scores take into account standards for age and sex, which is important due to natural developmental changes in weight and height with age and sex, as well as their relation to body fatness among children [52]. Previous research using other adiposity indicators, for instance waist-to-height ratio or fat free mass (based on bioelectrical impedance for instance), does not consider what is normal for a specific age and sex among preschoolers or do not have norm data available [3, 53, 54]. For this kind of indicators, this raises the question to what extent we can rely on the results for a sample of children without taking age and sexes into account. Future research should address the need to use sex and age specific adiposity indicators other than BMI z-scores among preschoolers. Fourth, the study has a cross-sectional design, which prevents interpretation of how adiposity in association with 24-h movement behaviour compositions manifests through child development. Fifth, we were not able to control the analyses for potential confounding factors such as adiposity rebound or dietary intake.

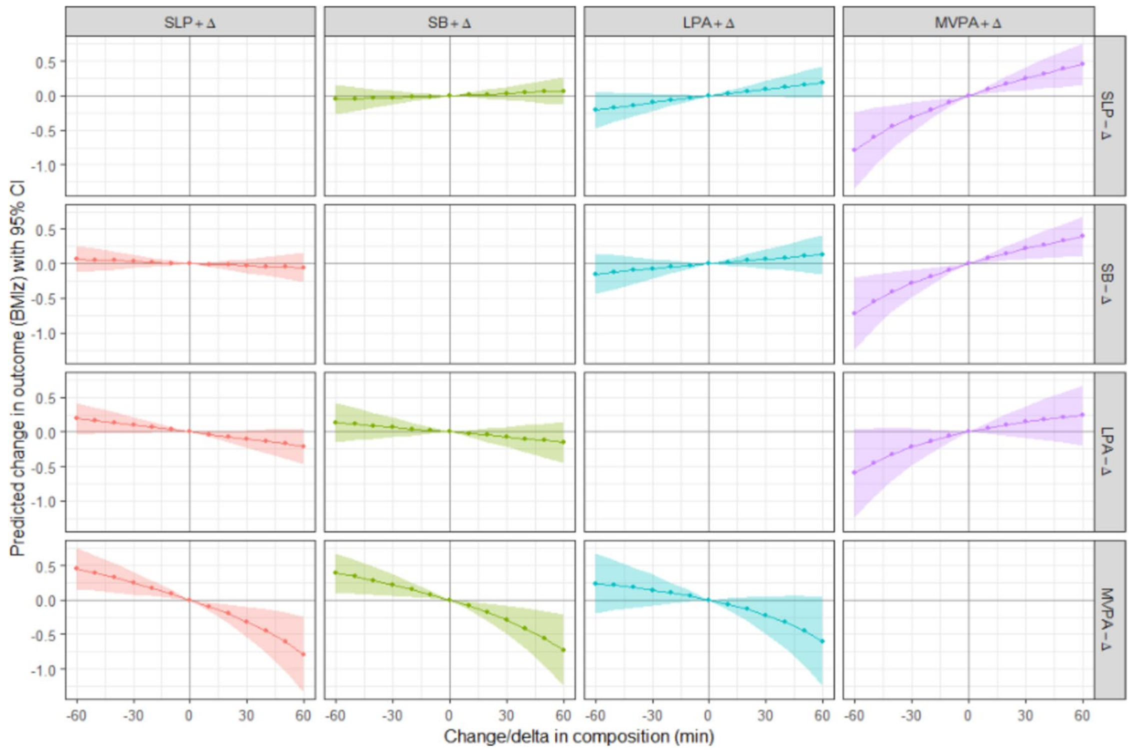

Fig. 3 Prediction of BMI z-score through one-by-one reallocation of time spent in 24-h movement behaviours

The prediction model shows differences in BMI z-score (left vertical axis) when reallocating time (lower horizontal axis) to one behaviour (upper horizontal axis) from one other behaviour (right vertical axis) in steps of 10 min over a time frame of –60 to 60 min. Abbreviations: Body Mass Index (BMI), sleep duration (SLP), sedentary behaviour (SB), physical activity (PA), light intensive physical activity (LPA), moderate-to-vigorous intensive physical activity (MVPA). The shaded zone on each graph shows the 95% confidence interval

Conclusion

Despite the association between more time spent in MVPA and higher BMI z-scores, a healthy amount of time spent in 24-h movement behaviours, including MVPA, among preschoolers needs to be promoted. This is due to the susceptibility of preschoolers to form new habits and the long-term benefits of healthy behaviour for healthy weight and chronic disease prevention in later childhood and adulthood. Future studies should address methodological challenges (e.g. confounders, recruitment bias and recall bias). Larger study samples and longitudinal designs are recommended. It is also advisable to actively engage and support participants from socio-economically disadvantaged backgrounds to ensure representative and actionable research outcomes. Additionally, efforts to use and develop sex- and age-specific references for adiposity indicators among preschoolers, other than BMI z-scores, could enhance the understanding of the relationship between 24-h movement behaviours and adiposity in this age group.

Abbreviations

SB	Sedentary behaviour
PA	Physical activity
LPA	Light-intensity physical activity
MVPA	Moderate-to-vigorous-intensity physical activity
CoDA	Compositional data analysis
BMI	Body Mass Index
WHO	World Health Organisation
MCAR	Missing Completely At Random
ES	Effect size

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

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Authors' contributions
MD led the design and coordination of the paper with the help of AO and KHC. PC was responsible for data coordination. MD, KHC, DD and TS conducted the analyses and interpreted the results. MD led the writing of the paper. All authors (MD, KHC, DD, TS, PC, GC, VV, MDC, AO) were responsible for revising the manuscript critically for important intellectual content. All authors read and approved the final manuscript.

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Data availability
The data analysis script is available via GitHub https://github.com/MDcraen/EarlyStartBaselineCoDA.

Declarations

Ethics approval and consent to participate
The University of Wollongong Human Research Ethics Committee approved the study procedures (HE14/250). Parents completed written informed consent for themselves and their preschooler.

Consent for publication
Not Applicable.

Competing interests
The authors declare no competing interests.

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