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Trajectories of children's physical activity volume and intensity across the school year: the Ready, Set, Move project

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Abstract

Background Average acceleration (AvAcc) and intensity gradient (IG) are accelerometer metrics which when combined describe the volume and intensity distribution of physical activity, sedentary behaviour, and sleep across the 24-h cycle. Little is known about trajectories of children's AvAcc and IG over time on weekdays and weekends. This study describes school year trajectories of children's weekday and weekend AvAcc and IG.

Methods During 2023–24 249 children (8–9 years old; 51.4% girls) wore accelerometers for 24 h·day^{-1} over 7-days at three time points (Autumn, Winter/Spring, Summer). AvAcc and IG were calculated for weekdays and weekends. K-means cluster analyses were performed on Autumn data to group participants according to their combined AvAcc and IG profiles. Linear mixed models examined school year weekday and weekend AvAcc and IG trajectories for the whole sample (Aim 1) and for the clusters (Aim 2).

Results Aim 1: There were significant increases in weekday AvAcc in Summer compared to Winter/Spring (β = 3.94, 95% CI = 1.20, 6.68) and Autumn (β = 4.43, 95% CI = 2.47, 6.40), but not IG. Weekend AvAcc and IG were relatively stable. Aim 2: Three cluster groupings of children were identified (Most Active, Somewhat Active (weekdays) / Active (weekends), and Least Active). Weekday AvAcc increased significantly from Winter/Spring to Summer in all groups (+ 3.6–4.6 mg, 95% CIs > 0) and from Autumn to Summer in the less active groups only (+ 5.2–5.8 mg, 95% CIs > 0). IG remained stable for the Most and Somewhat Active groups, with a significant increase from Autumn to Summer observed in the Least Active group (+ 0.05, 95% CI = 0.01–0.09). There were no significant within-cluster group changes in weekend AvAcc or IG, although the Least Active children had the most positive AvAcc and IG trajectories.

Conclusions Weekday physical activity volume but not intensity increased over the school year, while both dimensions of weekend activity had stable trajectories. Weekday and weekend cluster groups had distinct physical activity profiles which followed subtly different AvAcc and IG trajectories. The results reinforce the complementary insights provided by studying AvAcc and IG together and have implications for children's physical activity intervention programming.

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Keywords Average acceleration, Intensity gradient, Longitudinal, Accelerometer, 24-h movement behaviours, Seasonal, Weekday, Weekend

Background

Assessing 24-h movement behaviours with accelerometry captures duration, volume, and intensity characteristics relevant to physical activity, sedentary behaviour, and sleep [1]. Average acceleration (AvAcc) and intensity gradient (IG) are directly measured accelerometer metrics which when applied over the 24-h cycle describe the volume (AvAcc) and intensity distribution (IG) of all daily movement [2]. AvAcc but not IG is strongly correlated with cut-point derived moderate-to-vigorous physical activity (MVPA) [2, 3], which is traditionally reported in accelerometer studies. Moreover, AvAcc and IG are independently associated with health and wellbeing outcomes in children [3] and adults [2, 4] and thus, provide more nuanced information on how physical activity volume and intensity relate to such outcomes than cut-point-based metrics.

Previous studies of children's AvAcc and IG have been limited by reliance on cross-sectional data, which are typically averaged across all days of the week [3, 5, 6]. Consequently, no empirical evidence exists reporting longitudinal trajectories of these metrics, and little is known about how they differ between weekdays and weekends [7]. Weekdays and weekends provide very different stimuli for children to engage in physical activity, including structure of the days, physical activity opportunities, home routines, and social environments [7–9]. Most cross-sectional studies observe higher levels of physical activity and less time spent sedentary on weekdays compared to weekends [7, 8, 10], while longitudinal studies suggest that trajectories of cut-point derived MVPA are generally stable [11]. However, little is known about weekday and weekend AvAcc and IG, particularly when assessed longitudinally. This study aims to add to the current knowledge base by addressing this gap.

Children's physical activity is characterised by substantial inter-individual variability which may predict distinct patterns of change [12], whereby children with different activity profiles may respond differently over time to seasonal influences, environmental changes, or maturational processes [13]. Further, from a public health perspective, understanding whether physical activity inequalities widen or narrow over time is important for targeting interventions and services effectively [14]. Cluster-based analysis can allocate participants into groups based on common characteristics, such as physical activity profiles. The longitudinal stability of physical activity for each cluster can subsequently be examined to provide deeper insights into children's physical activity trajectories (e.g., whether less active children show increases over time relative to more active peers [15, 16]. Such approaches have potential to reveal heterogeneity in children's physical activity trajectories [17], but to date these analyses have not been used with AvAcc and IG.

For 9–10 months of the year children's lives in and out of school are largely structured around the school calendar and its associated social and environmental contexts [9]. Thus, the school year is a critical annual period in children's development, which has strong ecological validity as a longitudinal window for examining their physical activity. Furthermore, the school year in the UK typically spans autumn, winter, spring, and summer, encompassing the full range of climatic- and environmental-related influences on physical activity, particularly outdoor activity [18]. Based on these combined factors, the school year arguably provides a more representative picture of longitudinal variation in children's 'typical' activity behaviours than a calendar year, which includes extended school summer breaks that dramatically alter children's movement behaviour routines [9, 18].

Understanding children's physical activity volume and intensity distribution trajectories across the school year can inform critical periods for the implementation of targeted interventions. Moreover, directly measured physical activity volume and intensity profiles may better reflect nuanced changes in activity behaviours than traditional accelerometer cut-point approaches, and thus be more informative for children's health promotion efforts. To address these evidence gaps, this longitudinal study aimed to [1] describe the school year trajectories of children's weekday and weekend AvAcc and IG, and [2] examine whether these trajectories varied between children with different AvAcc and IG profiles.

Methods

Participants and settings

Participants were 249 children aged 8–9 years (51.4% girls) who attended seven primary schools in Pennine Lancashire, northwest England. The schools were located in areas of varying deprivation (median English Indices of Multiple Deprivation (EIMD) decile = 5 [19]) and ranged in size from 206 to 446 enrolled children (mean school enrolment = 296 children). Of these, 22.2% were eligible for free-school meals (FSM) which is similar to the 24.2% average for the region within which the schools were situated [20]. Schools were recruited through the Together an Active Future (taaf.co.uk) 'Ready, Set, Move' active schools network in Pennine Lancashire. In accordance with the project ethical approvals granted by Edge

Hill University's Science Research Ethics Committee (#ETH2324-011), consent materials were distributed to schools with signed informed parent/carer consent and child assent required for each child to participate in the project. Consent materials were distributed to all Year 4 children (aged 7–8 years) in the seven schools (N = 305) with informed consent provided for N = 249 children (81.6% participation rate). Data collection occurred at three time points during the 2023–24 school year over four-week periods in November–December 2023 (Autumn), February–March 2024 (Winter/Spring), and June-July 2024 (Summer).

Measures

Demographic characteristics

Schools provided child participant-level data related to sex, birth date, ethnicity, FSM eligibility, home postcode, and academic attainment. FSM eligibility (coded as yes/no) was used as a child-level indicator of socioeconomic status (SES). Five ethnicity categories were adapted from the UK Census ethnicity classifications (White/White British, Mixed ethnicity, Asian/Asian British, Black/Black British/Caribbean/African, Other ethnicity) [21]. For additional contextual data, EIMD rank scores were calculated from home postcodes to provide a neighbourhood-level ranked measure of deprivation ranging from 1 (most deprived) to 32,844 (least deprived) [19].

Anthropometric measures

Height and body mass were measured using a portable stadiometer (Leicester Height Measure, Seca, Birmingham, UK) and calibrated scales (813 model, Seca), respectively, with participants in light clothing with shoes removed. Body mass index (BMI) was calculated for each participant and BMI z-scores (BMIz) were assigned [22]. International Obesity Task Force BMI cut-points were then applied to classify participants as normal weight or overweight/obese [23].

Physical activity outcomes

Participants wore ActiGraph GT9X (ActiGraph, Pensacola, FL, USA) or Axivity AX3 (Axivity Ltd, Newcastle-Upon-Tyne, UK) triaxial accelerometers on the non-dominant wrist for 24 h·day^{-1} over 7 days with recording frequency set to 100 Hz. Choice of device deployment depended on availability during each data collection time point, with ActiGraph devices being most commonly used (68.3% vs. 31.1%; Additional file 1, Table S7). ActiGraph data were downloaded using ActiLife version 6.11.9 (ActiGraph, Pensacola, FL, USA) and saved in raw format as GT3X files. Axivity AX3 data were downloaded using OMGUI software version 1.0.0.43 (Axivity Ltd, Newcastle-Upon-Tyne, UK) and saved as cwa format raw files. Raw accelerometer data files were processed and all accelerometer outcomes were generated using the GGIR R package [24] v3.0–0, which included autocalibration using local gravity as a reference [25] and detection of implausible values and of non-wear. Non-wear was imputed by default in GGIR whereby invalid data were imputed by the average at similar times on other days of the week [26]. Wear time criteria were at least three valid days with ≥ 960 min·day^{-1} defined as a valid wear day, with accelerometer data excluded from analyses if post-calibration error was > 10 mg (milli-gravitational units) and/or the wear time criteria were not achieved. The triaxial accelerometer signals were converted into one omnidirectional summary measure of acceleration (ENMO; i.e., the Euclidean norm of the three accelerometer axes with 1 g subtracted and negative values truncated to zero [26]). Computed valid day ENMO values expressed in m*g* were averaged over 1-s epochs to reflect the intermittent nature of children's physical activity behaviour and to ensure higher intensity physical activity was captured [27]. ENMO values were then used to generate all subsequent physical activity outcomes, as follows:

Average acceleration (AvAcc) is the average magnitude of dynamic acceleration (i.e., ENMO). It represents the average intensity across the day and is a proxy for physical activity volume [2]. *Intensity gradient (IG)* reflects the negative curvilinear relationship between intensity and time accumulated at any given intensity, and describes the physical activity intensity distribution across the day [2]. IG values are always negative, with higher (i.e., less negative) values indicating proportionately more time being spread across the full intensity profile, whereas a lower or more negative IG reflects proportionately less time spent in mid-range and higher intensities. AvAcc and IG are independently associated with a range of health and wellbeing outcomes in children [3]. Both metrics measured by ActiGraph and Axivity devices worn on the non-dominant wrist have demonstrated equivalence in adults without adjustment for any correction factors [28]. *MX* metrics (where X refers to an accumulated duration of time in minutes) represent the acceleration in m*g* above which the most active X minutes are accumulated. MX metrics are a population-independent continuous variable, derived from directly measured accelerations, and capture intensity irrespective of level of activity, or fitness status [29]. Fourteen MX metrics were computed to cover different durations of interest and thus give a comprehensive picture of participants' physical activity profiles. These were M1, M2, M5, M10, M15, M30, M60, M120, M240, M360, M480, M600, M720, and M960.

Data analysis

Data preparation and analyses were performed in R (version 4.3.3) and R Studio (v2021.09.0). Following data cleaning and error checking, preliminary analysis of valid accelerometer wear at each data collection time point was conducted as device non-wear was anticipated to be the most likely cause of data attrition. Accelerometer wear time criteria were achieved by 185 (Autumn), 138 (Winter/Spring), and 151 (Summer) participants, which reflected 25.7%, 44.6%, and 39.4% attrition, respectively (36.5% overall). Visual inspection of the distribution and patterns of missing data and analysis of participant characteristics between those with and without accelerometer outcomes indicated non-systematic differences in age, sex, ethnicity, FSM eligibility, BMIz, or school attended (Additional file 1, Table S8). We therefore proceeded with the assumption that the data were missing at random and used the *mice* package v. 3.17.0 [30] to perform multiple imputation by chained equations to replace missing values.

Multiple imputation

Multiple imputation aims to minimise the impact of data attrition or non-response bias on data analysis by using available information about study participants to adjust parameter estimates, which can be subject to biases when data are missing [31]. Multiple imputation can therefore approximate what results would look like with complete observations while allowing for representation of uncertainty in the results and maximising a dataset's statistical power [32]. Our dataset contained a large number of accelerometer variables representing identical outcomes for different parts of the week (e.g., AvAcc averaged across the week, on weekdays, and on weekends). Including all of these variables in the same multiple imputation analysis presented a high risk of multicollinearity and poor model convergence with unreliable imputation estimates. To address this, two separate longitudinal datasets were created which included accelerometer data that were averaged across weekday or weekend days only. To prepare each dataset for multiple imputation, the fraction of missing information (FMI) was calculated for AvAcc, IG, and other movement behaviour outcomes. The highest FMI values for the outcomes of interest were 28% for weekday IG, and 40% for weekend AvAcc. Guided by recommendations to set m (i.e., the number of imputations) to ≥ 100 times the highest FMI [33], the total imputations in each model were set at 30 (weekday) and 40 (weekend). The number of weekday imputations reflected the 30% FMI for weekday sleep, which was a measured movement behaviour outcome in the wider project dataset, but not one that was a focus of the current study. The models used predictive mean matching and proportional odds logistic regression imputation methods and accounted for school-level clustering. The number of iterations per imputation was adjusted and checked by inspections of trace plots, density plots, box plots, and descriptive statistics to determine when satisfactory convergence had been achieved. Two fully converged imputed datasets were generated representing the weekday and weekend datasets.

All subsequent weekday and weekend analyses were conducted separately on the multiply imputed datasets, but to help with comparative interpretations weekday and weekend model results are presented together. For Aim 1, linear mixed models were generated using the *lme4* v. 1.1–36 [34] and *car* v. 3.1–3 [35] R packages to examine AvAcc and IG trajectories. Covariates were sex, SES, ethnicity, and BMIz, with school included as a random effect. Physical activity profiles were examined through radar plot visualisation of MX metrics for durations where differences between time points were evident (i.e., M60 to M1).

For Aim 2, the *mclust* package v. 6.1.1 [36] was used to perform k-means cluster analyses on Autumn AvAcc and IG to group participants according to their combined physical activity volume and intensity distribution profiles. This cluster analysis method was selected as it is computationally more straightforward to achieve successful model convergence with longitudinal multiply imputed data. To account for the different units of measurement used for AvAcc and IG, and to avoid one outcome artificially dominating the clustering process, AvAcc and IG were firstly converted to z-scores to allow the analyses to be conducted using standardised values. This ensured that true multivariate patterns in the data were identified rather than the clustering being biased by the different measurement scales. K-means clustering solutions from 1 to 6 clusters were evaluated using the elbow plot method (Additional file, Figures S1 and S2) and silhouette analysis. Cluster separation was visualised with t-distributed Stochastic Neighbour Embedding (t-SNE) plots generated using the *RTsne* package v. 0.15 [37]. Once the number of clusters were decided, cluster trajectories for AvAcc and IG were analysed using separate linear mixed models (*lme4* [34] and *mitml* v. 0.4–5 [38] packages). For each cluster, pairwise comparisons of time point predicted means were undertaken with the Holm–Bonferroni adjustment applied to control for familywise error. All models were adjusted for cluster*time-point interactions, sex, SES, ethnicity, and BMIz. School-level random effects were not included as preliminary models indicated negligible between-school variance. Weekday and weekend physical activity profiles of each cluster over the school year were visualised with radar plots [39] of M60, M30, M15, M10, M5, M2, and M1 values. For all Aim 1 and 2 analyses, the *mice* [30] and *mitml* [38] packages were used to pool estimates from each imputed dataset using Rubin's Rules [40]. Statistical significance was determined by 95% confidence intervals. The Anthropic Claude Sonnet 4.5 Large Language Model was used within Microsoft Visual Studio Code v. 1.100.3 for data analysis code troubleshooting and refinement.

Results

The weekday and weekend imputed datasets included data from 249 children. Intra-class correlations for school-level variance across time points were low (weekday ICC range = 0.003–0.03; weekend = 0.01–0.02), indicating that schools were too similar for a school-level effect on the children's physical activity volume and intensity distributions to be detected. Descriptive characteristics of the children and their Autumn unadjusted physical activity outcomes are presented in Table 1.

Aim 1

Aim 1 examined adjusted trajectories of AvAcc and IG across the school year separately for weekday and weekends (Additional file 1, Tables S1 and S2). Weekday AvAcc was stable between Autumn and Winter/Spring then significantly increased from Winter/Spring to Summer (β = 3.94, 95% CI = 1.20, 6.68; Fig. 1). Summer AvAcc was also significantly higher than at Autumn (β = 4.43, 95% CI = 2.47, 6.40). Weekday AvAcc was significantly associated with sex (boys > girls; β = 7.04, 95% CI = 5.48, 8.61), and there was an inverse association between BMIz and AvAcc (β = -0.72, 95% CI = −1.38, −0.07). Follow-up analyses indicated no significant sex*time point or BMIz*time point interactions. Weekday IG was stable across the three time points with only small non-significant increases evident between Autumn, Winter/Spring, and Summer (Fig. 1). Risk of multicollinearity in all models was low (VIF range = −1.0 to 3.0).

Adjusted weekend AvAcc values were lower than weekday values at Autumn and Summer, whereas weekend IG values (Fig. 1) were lower at all time-points. Both weekend metrics were relatively stable with no significant changes evident between time points (Additional file 1, Table S2).

Figures 2a and b present the children's respective weekday and weekend MX values describing the physical activity profiles underlying the trajectories of AvAcc and IG over the school year. On weekdays, physical activity profiles overlapped at Autumn and Winter/Spring and increased in intensity linearly at Summer for all MX durations. These increases were particularly evident from M30 and were most pronounced during the most active 5, 2, and 1 min of the day (Fig. 2a). Weekend physical activity profiles showed that activity intensity from M60 to M1 increased between Autumn to Winter/Spring and Summer when similar levels of acceleration were apparent at all MX durations (Fig. 2b). Further, at all time points, weekend M10 (range = 756 to 826 mg) to M1 (range = 1879 to 2004 mg) were lower than for weekday (M10 range = 797 to 875 mg; M1 range = 2203 to 2434 mg), which reflects the higher observed weekday AvAcc and IG. Irrespective of weekday or weekend, at all time points the most active accumulated 60 min were at intensities greater than brisk walking/3 Metabolic Equivalents of Task (METS) (i.e., > 200 mg [41]). The children also accrued between 10 and 15 min of accelerations at or above 6 METS (i.e., 707 mg [41]; i.e., at an equivalent intensity to running), highlighting that this was a highly active sample of children.

Table 1 Participants' descriptive characteristics and unadjusted Autumn physical activity outcomes (Mean (SD) unless otherwise stated)

Variable	All (N = 249)	Boys (n = 121)	Girls (n = 128)
Age (y)	8.70 (0.42)	8.71 (0.43)	8.69 (0.42)
Height (cm)	132.43 (5.91)	133.09 (5.77)	131.81 (5.99)
Weight (kg)	31.29 (6.86)	31.28 (6.47)	31.29 (7.24)
BMI (kg·m^2)	17.72 (3.01)	17.55 (2.84)	17.88 (3.16)
BMIz	0.35 (1.09)	0.60 (1.14)	0.12 (0.99)
Weight status			
Normal weight (%)	72.17	75.92	68.62
Overweight/obese (%)	27.83	24.08	31.38
FSM eligibility (%)	16.87	14.88	18.75
EIMD rank	14,865.39 (1015.62)	14,346.12 (1018.51)	15,356.27 (1015.38)
Ethnicity			
White/White British (%)	78.31	79.34	77.34
Mixed ethnicity (%)	3.61	2.48	4.69
Asian/Asian British (%)	17.67	18.18	17.19
Other ethnicity (%)	0.40	0.00	0.78
Physical activity outcomes			
Number of valid weekdays	4.41 (0.94)	4.29 (1.0)	4.52 (0.88)
Weekday wear time (min·day^{-1})	1363.81 (108.97)	1355.82 (105.91)	1371.36 (111.29)
Weekday AvAcc (mg)	46.89 (10.86)	51.12 (10.78)	42.89 (9.36)
Weekday IG	−2.08 (0.14)	−2.03 (0.12)	−2.14 (0.13)
Number of valid weekend days	1.57 (0.77)	1.48 (0.80)	1.65 (0.73)
Weekend wear time (min·day^{-1})	1351.40 (140.48)	1335.79 (149.73)	1366.15 (129.61)
Weekend AvAcc (mg)	43.60 (19.49)	45.60 (20.34)	41.70 (18.49)
Weekend IG	−2.18 (0.18)	−2.15 (0.18)	−2.20 (0.17)

Legend. *BMI* body mass index, *FSM* free-school meals, *EIMD* English Indices of Multiple Deprivation, *min* minutes, *AvAcc* average acceleration, *mg* milligravitational unit, *IG* intensity gradient

Aim 2

Aim 2 identified clusters of children with distinct physical activity volume and intensity profiles and examined cluster-specific trajectories of AvAcc and IG over the school year. Clusters were developed separately for weekday and weekend. Descriptive characteristics of the children in each cluster are presented in Additional file 1 (Tables S3 (weekday) and S4 (weekend)). For weekday

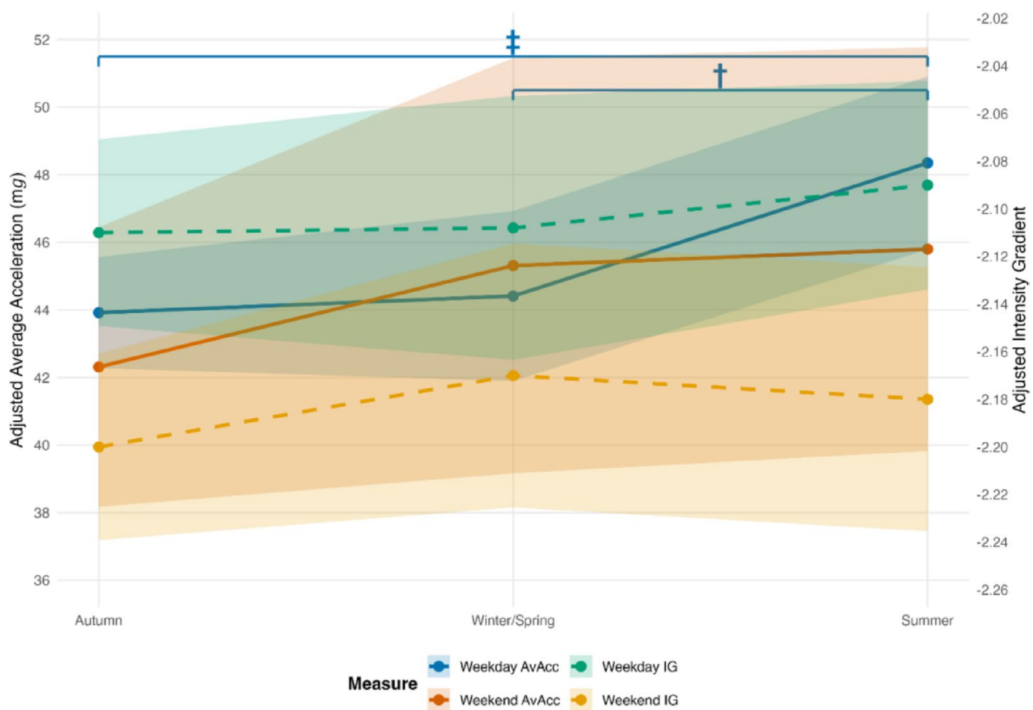

Fig. 1 Adjusted weekday and weekend average acceleration and intensity gradient trajectories over the school year. *Note* Estimates are adjusted for sex, SES, ethnicity, and BMIz. Ribbons indicate 95% confidence intervals with the Y-axis scales reflecting the full range of 95% confidence intervals. ‡ = Summer > Winter/Spring ($p = .005$); † = Summer > Autumn ($p < .001$). *AvAcc* average acceleration, *IG* intensity gradient, *mg* milligravitational units

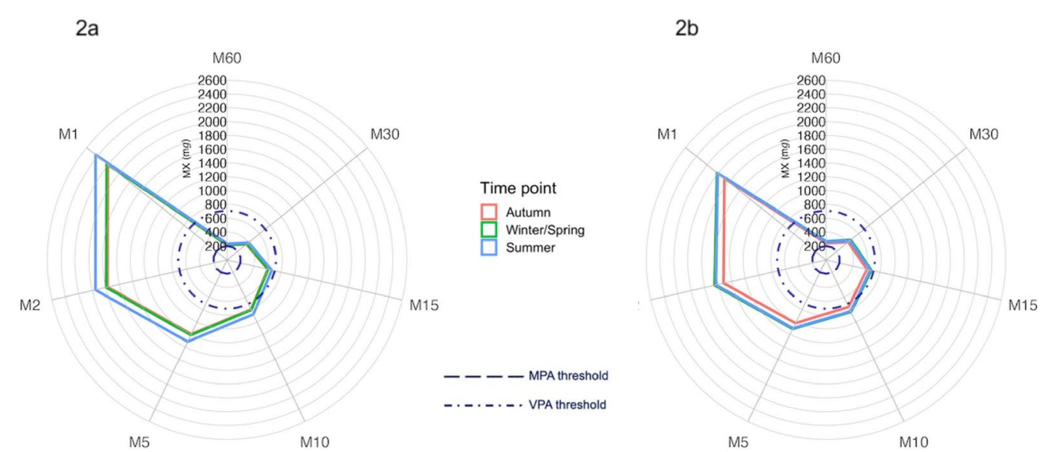

Fig. 2 MX metrics school year **a** weekday and **b** weekend physical activity profiles. Each plot shows M60, M30, M15, M10, M5, M2, and M1

physical activity, elbow plot inspection demonstrated the presence of 3-cluster groupings (Additional file 1, Figure S1) and the pooled silhouette score of 0.33 supported a moderate and acceptable cluster structure that reflected the typical variation in children's physical activity levels. The weekday t-SNE plot showed clear cluster separation confirming the presence of three distinct groups (Fig. 3a). The clusters were balanced, representing 30.7% (n = 76), 34.5% (n = 86), and 34.8% (n = 87) of the sample and were characterised as follows: Cluster 1 (*Most Active*) was above the sample average physical activity volume and intensity (mean combined standardised AvAcc and IG = 0.54), was made up of 61.60% boys with 73.40% classified as normal weight; Cluster 2 (*Somewhat Active*) was marginally below average (mean combined standardised AvAcc and IG = – 0.10), had 39.70% boys, and 73.10% classed as normal weight; Cluster 3 (*Least Active*) was more substantially below average (mean combined standardised AvAcc and IG = – 0.32), consisted of 39.50% boys and 70.20% of participants with normal weight. The cluster centroids for AvAcc were 53.0 mg (Most Active), 45.3 mg (Somewhat Active), and 43.9 mg (Least Active). The corresponding values for IG were – 2.01, – 2.09, and – 2.14, respectively.

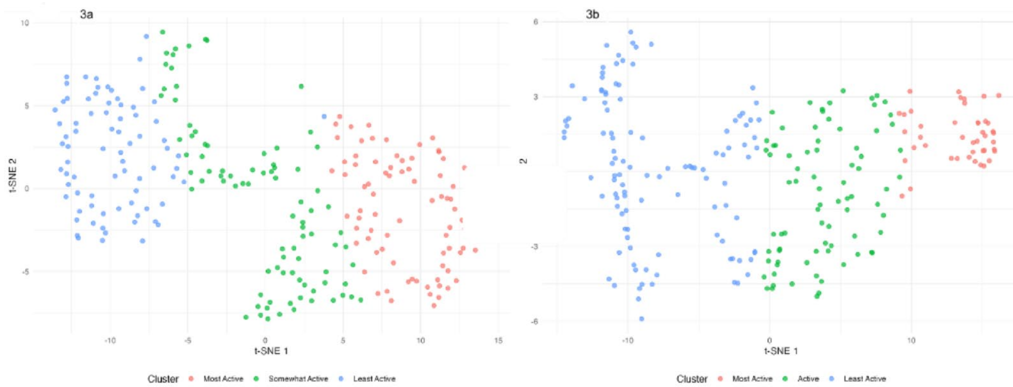

Fig. 3 t-distributed Stochastic Neighbour Embedding plots demonstrating cluster separation for pooled **a** weekday and **b** weekend data

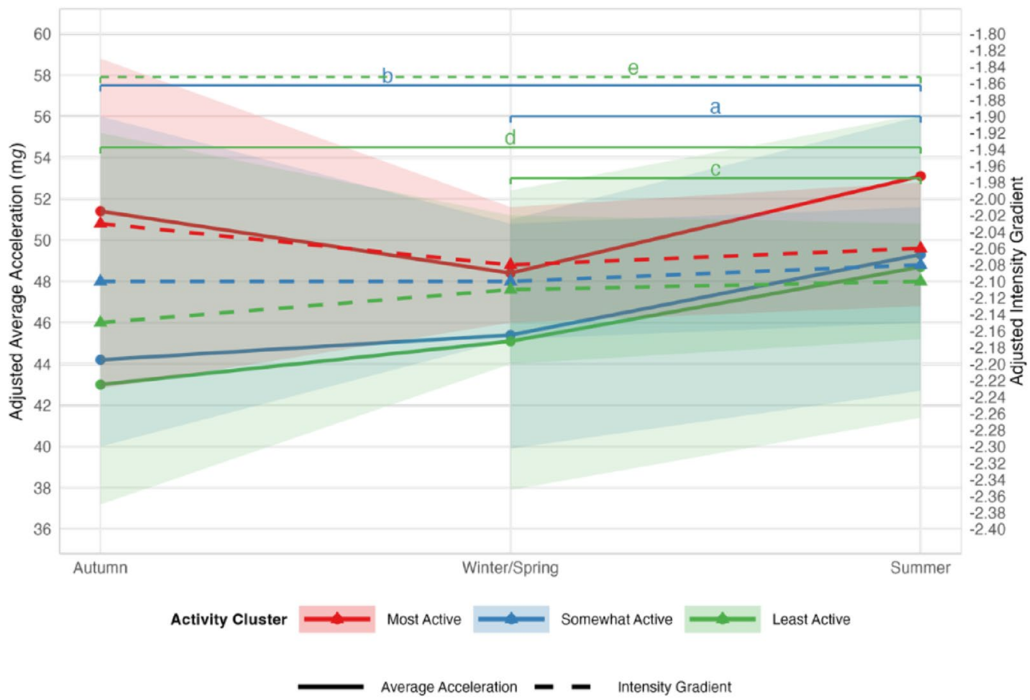

Fig. 4 Adjusted weekday average acceleration and intensity gradient trajectories of the three clusters over the school year. *Note* Estimates are adjusted for sex, SES, ethnicity, and BMIz. Ribbons indicate 95% confidence intervals with the Y-axis scales reflecting the full range of 95% confidence intervals. **a** Somewhat Active AvAcc Summer > Winter/Spring; **b** Somewhat Active AvAcc Summer > Autumn ($p = .009$); c = Least Active AvAcc Summer > Winter/Spring ($p = .03$); d = Least Active AvAcc Summer > Autumn ($p = .009$); e = Least Active IG Summer > Autumn ($p = .007$). *AvAcc* average acceleration, *IG* intensity gradient, *mg* milligravitational units

A 3-cluster solution was also evident for weekend physical activity based on the inflection point in the elbow plot (Additional file 1, Figure S2) and pooled silhouette score of 0.48. Figure 3b demonstrates the distinct cluster separation between the three groups. The sample was relatively equally distributed between the clusters (Cluster 1 = 31.2%/n = 78, Cluster 2 = 33.6%/n = 84, and Cluster 3 = 35.1%/n = 87). These were labelled as *Most Active* (Cluster 1; mean combined standardised AvAcc and IG = 0.38, 49.40% boys, 72.20% normal weight), *Active* (Cluster 2; mean combined standardised AvAcc and IG = 0.32, 48.70% boys, 71.70% normal weight), and *Least Active* (Cluster 3; mean combined standardised AvAcc and IG = -0.09, 47.80% boys, 72.50% normal weight). The cluster centroids for weekend AvAcc were 51.1 mg (most Active), 49.7 mg (Active), and 41.0 mg (Least Active), and − 2.11, − 2.12, and − 2.18, respectively for IG.

Cluster-specific trajectories of physical activity volume and intensity

Weekday physical activity volume and intensity distribution trajectories differed substantially (Fig. 4; Additional File, Table S5). In all three cluster groups AvAcc significantly increased between Winter/Spring and

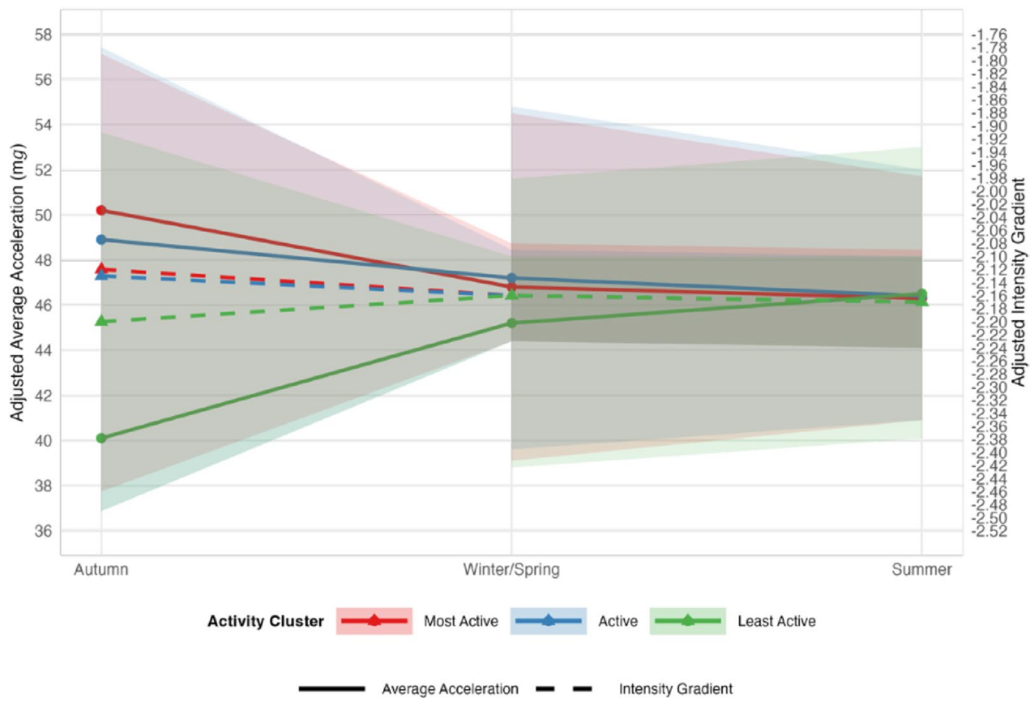

Fig. 5 Adjusted weekend average acceleration and intensity gradient trajectories of the three clusters over the school year. Note. Estimates are adjusted for sex, SES, ethnicity, and BMIz. Ribbons indicate 95% confidence intervals with the Y-axis scales reflecting the full range of 95% confidence intervals. *mg* milligravitational units

Summer (Most Active: predicted change = 4.63 mg, 95% CI = 1.96, 7.29; Somewhat Active: predicted change = 3.87 mg, 95% CI = 1.36, 6.38; Least Active: predicted change = 3.60 mg, 95% CI = 1.12, 6.08). Increases in AvAcc were also evident between Autumn and Summer in the two lesser active groups (Somewhat Active: predicted change = 5.17 mg, 95% CI = 2.66, 7.68; Least Active: predicted change = 5.78 mg, 95% CI = 3.29, 8.26). IG trajectories were stable for the Most and Somewhat Active groups, although there was a significant increase between Autumn and Summer for the Least Active group (predicted change = 0.05, 95% CI = 0.01, 0.09). Sex was associated with weekday AvAcc and IG, indicating that boys were more active than girls (AvAcc: β = 2.97, 95%CI = 0.76, 5.18; IG: β = 0.04, 95%CI = 0.01, 0.06). Further, there was a significant inverse association between BMIz and weekday IG (β = − 0.01, 95%CI = − 0.02, − 0.004), but not any significant sex or BMIz interaction effects with time-point or cluster.

There were no significant within-cluster group changes in weekend AvAcc or IG, although the temporal patterns were inconsistent between groups (Fig. 5; Additional file 1, Table S6). Specifically, while the Most Active and Active groups showed modest reductions in weekend AvAcc and IG, both metrics had small upwards trajectories in the Least Active group (all adjusted $p > 0.05$). Boys recorded significantly higher weekend IG than girls (β = 0.04, 95% CI = 0.01, 0.07), but there were no significant sex* time point or sex*cluster interactions.

The weekday and weekend physical activity profiles of participants in the Least Active and Somewhat Active (weekday)/Active (weekend) clusters were characterised by increased MX intensities for durations between 10 and 1 min at Summer compared to Autumn (Additional file 1; Figures S3 and S4). For the Most Active clusters, changes in weekday MX metrics between Autumn and Summer were negligible but decreased between M15 and M1 in Winter/Spring. Weekend MX outcomes for the Most Active cluster overlapped all three time points from M5 to M1. As was observed for the whole sample, irrespective of weekday or weekend at all time points M60 values for each cluster were at an intensity greater than brisk walking/3 METS (i.e., > 200 mg [41]).

Discussion

This study analysed school year trajectories of weekday and weekend physical activity volume and intensity distribution in a sample of 8–9-year-old children and in groups clustered by AvAcc and IG profiles. The findings demonstrate distinct trajectory patterns for physical activity volume versus intensity distribution, particularly on weekdays where significant changes in AvAcc were observed for the whole sample and cluster groups.

Aim 1

Summer weekday AvAcc was significantly higher than Winter/Spring and Autumn, which contrasted with the more stable trajectory of weekday IG. Although our study is the first to report longitudinal changes in children's AvAcc and IG the results are consistent with previous seasonal variation research using MVPA, which is strongly correlated with AvAcc in children (e.g., r = 0.96 [3]). For example, a 2022 meta-analysis showed that MVPA was significantly higher in summer relative to fall (autumn) [18], while an earlier study of a population-representative sample of UK 7–8 year olds reported most MVPA during the summer months [13]. The finding that weekday IG was relatively stable with only small increases evident between time points suggests that increases in physical activity volume were quite evenly spread across the intensity distribution, rather than being due to increases in higher intensity activities. The stable weekday IG values could also reflect increases in AvAcc through lower intensity activities which would have blunted any gains in IG. Moreover, it is plausible that IG was less variable among children who participated in organised sports and therefore accumulated comparatively more time in higher intensity activities across the school year, irrespective of season (e.g., netball in autumn and winter and track and field in summer, or football throughout the year [42]). The weekday IG trajectory also shows that intensity distributions across the physical activity intensity spectrum were consistent over the school year, indicating that the volume of weekday physical activity rather than the intensity distribution may have been be more influenced by multidimensional seasonal factors (e.g., weather and daylight hours [18], access to outdoor open/play spaces [43], parental restrictions [44], school policies [45], and physical activity opportunities offered by schools [46]). These results highlight how AvAcc and IG together provide a more nuanced picture of physical activity engagement, than reporting either in isolation, or than MVPA which shares a high proportion of variance with AvAcc [2, 3].

Weekend AvAcc and IG trajectories were relatively stable, with only small increases observed between time points. This concurs with longitudinal studies of cut-point derived MVPA on weekday and weekend days [11]. As anticipated, AvAcc and IG were lower on weekend days which corresponds with a previous weekday vs weekend comparison of children's AvAcc and IG [7] and other studies reporting alternative weekday and weekend physical activity outcomes [18]. It is possible that different mechanisms were driving weekend physical activity volume and intensity, which were characterised by greater variability than the weekday data. Weekdays follow a highly consistent structure with repeated opportunities for physical activity engagement over the week [9]. During weekends there is far less structure and greater within- and between-child discretionary time which gives children more autonomy to participate in a range of activities across the intensity spectrum [8]. When children have increased choice and agency over their recreational activities, they may be more likely to choose sedentary and low intensity activities [47]. This would be reflected in low IG values with a greater proportion of time spent at the lower end of the intensity distribution. This supposition aligns with our weekend vs. weekday findings and those of others [8, 11, 48], although we acknowledge the absence of supporting contextual data.

It is not possible to discern precisely what drove the differences in the trajectory patterns of AvAcc and IG over the school year from accelerometer data alone, but it is likely that weather and climatic conditions played a role. In Autumn and Winter/Spring the average temperature and daylight hours were relatively similar (4.0 and 6.7 °C, and 8.5 and 10.6 hday^{-1}, respectively [49]), but in Summer increased substantially to 18.3 °C and 16.7 hday^{-1} [49], respectively. On weekdays the consistent structure of school and daily routines may have contributed to the children's physical activity behaviours being largely unaffected by the cooler and shorter days in Autumn and Winter/Spring. Conversely, the longer daylight hours and higher temperatures in Summer likely afforded increased opportunities for physical activity-promoting adaptations to the weekday structure (e.g., fewer break times spent indoors due to poor weather, more outdoor physical education and school sports, increased active commuting, more outdoor activities in the home and neighbourhood). It is also possible that improved weather and climatic conditions in Summer predisposed some children to be more active at weekends. This though was not supported by our results, potentially due to the mitigating influences of low structure, increased discretionary time, and greater autonomy [8] at weekends for children to choose low active and sedentary pursuits [47].

Aim 2

Cluster analysis of combined AvAcc and IG profiles resulted in three groups each from the weekday and weekend datasets. For weekday clusters there was a disproportionate number of girls in the Most Active (38.40%) and Least Active groups (60.50%) (Additional file 1, Table S5). This was consistent with the significant associations between sex and both physical activity metrics and sex differences typically reported in children's physical activity studies [3, 7, 16, 50]. In contrast, weekend cluster memberships were more balanced (Most Active = 50.60% girls, Active = 51.30% girls, Least Active = 52.20% girls). This could reflect that for some children, and girls in particular, the more flexible structure of weekend days facilitated different opportunities for physical activity that were not available or as appealing on weekdays [51] (e.g., structured community sports activities not offered at school or family-oriented walking and play in natural spaces [52]).

For weekdays, consistent within-cluster changes in AvAcc but not IG were observed, which aligned with our Aim 1 results. Nevertheless, there were some differences between clusters which may provide valuable insights to inform targeted physical activity promotion strategies. For example, the largest increases in weekday AvAcc and IG between Autumn and Summer were in the Least Active children, with the smallest increases in the Most Active. These weekday differences were reflected in the school-year changes in MX metrics for the most active 10 min to 1 min of the day. In contrast, the weekend results were more inconsistent. There are some similarities between these results and those from an earlier group-based trajectory modelling of UK Millennium Cohort Study physical activity data [16]. In boys and girls the steepest declines in MVPA over 8-years were in the most active groups, while the least active groups had the smallest reductions [16]. Although the trajectory duration of this study is much longer than in ours, it still highlights how changes in physical activity over time are not uniform for all children but vary between groups with different baseline physical activity levels. This has implications for targeted physical activity programming and interventions, which are often overlooked in favour of a universal 'one-size-fits-all' approach [53]. The AvAcc and IG cluster trajectories and MX metrics also show that the Least Active children's gains in physical activity were more consistent than the other groups, suggesting that the influence of seasonal variation and associated enhanced opportunities for activity [43, 45] may have been strongest for these children.

The practical meaningfulness of these seemingly small within-cluster changes merits further exploration. Preliminary evidence exists proposing AvAcc of ~ 1 mg as the minimum clinically important difference (MCID) for physical activity health benefits in inactive adults [54]. This MCID is derived from converging empirical evidence demonstrating alignment between a daily AvAcc increase of 0.8 to 1.0 mg and robust health-related criteria [54–56]. Whilst this proposed MCID is caveated with some limitations [54] it does illustrate that small volumes of additional physical activity may be beneficial for health, particularly among inactive and less active populations. Similar robust evidence would be needed for an equivalent MCID in children. Notwithstanding this, our recent work illustrates that modest increases in children's physical activity would confer significant health benefits. For example, increases in daily AvAcc of 16 mg (girls) and 23 mg (boys) would be sufficient volumes of physical activity for overweight children to move into the healthy weight classification based on UK BMI reference data [57]. We have also shown that adding as little as 3 min of vigorous intensity physical activity (i.e., intensity ≥ 700 mg) into the day is associated with meaningful decreases in children's BMIz [58]. Such findings are consistent with those from adult epidemiology studies demonstrating how short bouts of moderate and vigorous intensity intermittent non-exercise physical activity are associated with reduced cardiovascular event incidence and mortality [59, 60]. Collectively, these findings align with an approach to increasing children's physical activity opportunities throughout the day focused on incremental and incidental accumulation of short intermittent activity bouts.

Strengths and limitations

This study is the first to report children's weekday and weekend AvAcc and IG trajectories over the school year. A robust analytical approach was employed using multiple imputation to ensure the full sample size was maintained and statistical power optimised for the subsequent trajectory analyses. A further strength was the novel application of data-driven clustering to examine changes in school year physical activity across distinct groups of children. Moreover, the study had strong ecological validity by focusing on the school year which is a critical annual period for children's development and physical activity behaviours. There were also a number of limitations which warrant discussion. The sample was recruited from one geographical region, and even though the school day structures and practices were typical of primary schools elsewhere, other un-measured factors may have influenced the results which limits their generalisability to other locations and particularly those with different climates. Moreover, the possibility of sampling bias cannot be overlooked as the schools were all involved in a wider active schools initiative, which may have contributed to the children's relatively high physical activity levels. This may have created a ceiling effect which limited the potential for increases in AvAcc and IG across the time points. A further limitation was that the stability of the activity profile groups may have changed over time but using k-means clustering on the Autumn data precluded analysis of this. Further, although rigorous analytical processes were followed, the proportion of missing data and resultant between-imputation variance were higher than desired, particularly for weekend data. This was reflected in the wide cluster trajectory confidence intervals, which indicated a degree of uncertainty in some of the model estimates. However, had complete case analyses been performed 26% of the weekday sample and 43% of the weekend sample would have been lost (N = 184 and N = 142, respectively). Moreover, this approach would have reduced statistical power and increased the likelihood of bias in the analyses leading to inefficient estimations of model parameters and confidence intervals [61], thus reducing the validity and reliability of the conclusions [31]. Multiple imputation also necessitated having separate datasets for weekday and weekend data, which restricted our ability to make true comparisons between day-type estimates of AvAcc and IG. Lastly, accelerometer data alone cannot discern the mechanisms responsible for the observed physical activity trajectories. Aside from school and participant characteristics, we did not collect any contextual data on specific environmental or physical activity programming factors which could have influenced potential changes over the school year.

Conclusions

This study is the first to report weekday and weekend AvAcc and IG trajectories across the school year. Weekday but not weekend AvAcc significantly increased across the school year while IG had relatively stable trajectories irrespective of weekday or weekend. The results reinforce the complementary insights provided by studying AvAcc and IG together. The findings also have implications for children's physical activity intervention programming, which should leverage seasonal influences on physical activity volume (e.g., longer, dryer, warmer days) and consider different strategies for weekday and weekend days. The weekday and weekend clusters highlighted the presence of sub-groups characterised by different physical activity volume and intensity patterns, which may warrant differentiated intervention approaches, particularly at weekends. Future research should build on these findings by employing longer-term follow-ups and investigating contextual factors influencing AvAcc and IG so the mechanisms of trajectory changes and between-group differences are better understood. Further, analysis of the longitudinal associations between AvAcc and IG with health and development outcomes would provide important insights to guide intervention development.

Abbreviations

AvAcc	Average acceleration
BMI	Body mass index
EIMD	English indices of multiple deprivation
ENMO	Euclidean norm minus one
FMI	Fraction of missing information
FSM	Free school meals
IG	Intensity gradient
MCID	Minimum clinically important difference
MET	Metabolic equivalent of task
MVPA	Moderate-to-vigorous physical activity
SES	Socioeconomic status
UK	United Kingdom
VIF	Variance inflation factor

Supplementary Information

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Supplementary file1

Supplementary file2

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Author contributions

Conception or design of the work: SJF, RT, MM, LC; Data acquisition: LC, SJF, RT, MM, AMG, JB, PE; Data analysis and interpretation: SJF, AVR; Manuscript drafting, revision, and final approval: SJF, LC RT, MM, AMG, JB, PE, DMYB, AVR.

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Data availability

The dataset(s) supporting the conclusions of this article are available in the Open Science Framework repository [https://osf.io/gkxzs/files/osfstorage#].

Declarations

Ethics approval and consent to participate

Ethical approval was granted by Edge Hill University's Science Research Ethics Committee (#ETH2324-011). Signed informed parent/carer consent and child assent were obtained for each child to participate in the project.

Consent for publication

Not applicable.

Competing interests

SJF is temporarily seconded to Together an Active Future from Edge Hill University on a part-time basis. SJF and DMYB are members of the Editorial Board of Journal of Activity, Sedentary and Sleep Behaviors. SJF and DMYB were not involved in the Journal's peer review process of, or decisions related to, this manuscript. All other authors declare that they have no competing interests.

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