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Average acceleration and intensity gradient of primary school children and associations with indicators of health and wellbeing

Title: Average acceleration and intensity gradient of primary school children and associations with indicators of health and wellbeing

Running title: Standardised physical activity metrics & associations with child health

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Methods

This is a secondary analysis of data collected in the Active Schools: Skelmersdale PA pilot intervention study (ClinicalTrials.gov registration: NCT03283904). The methods have been described previously (8) but are outlined briefly here. Two hundred and thirty two 9-10 year old participants were recruited from 7 primary schools. The schools were situated in a low socioeconomic status (SES) town in West Lancashire, north-west England, where the prevalence of overweight/obesity is above the national average (13). Ethical approval was granted by Edge Hill University's Research Ethics Committee (reference # SPA-REC-2015-330) and informed consent and assent were provided by the participants' parents/carers, and the participants themselves, respectively. Data collection took place between September and December 2017.

Following collection of baseline measurements, schools were randomly assigned to either intervention (4 schools) or control groups (3 schools). The AS:Sk pilot intervention included eight components which were implemented over 8-weeks.

Abstract

Average acceleration (AvAcc) and intensity gradient (IG) have been proposed as standardised metrics describing physical activity (PA) volume and intensity, respectively. *We* examined hypothesised between-group PA differences in AvAcc and IG, and their associations with health and wellbeing indicators in children. ActiGraph GT9X wrist accelerometers were worn for 24-$h \cdot d^{-1}$ over seven days by 145 children aged 9-10. Raw accelerations were averaged per 5-s epoch to represent AvAcc over 24-h. IG represented the relationship between log values for intensity and time. Moderate-to-vigorous PA (MVPA) was estimated using youth cutpoints. BMI z-scores, waist-to-height ratio (WHtR), peak oxygen uptake (VO_2peak), Metabolic Syndrome risk (MetS score), and wellbeing were assessed cross-sectionally, and 8-weeks later. Hypothesised between-group differences were consistently observed for IG only ($p<.001$). AvAcc was strongly correlated with MVPA (r=0.96), while moderate correlations were observed between IG and MVPA (r=0.50) and AvAcc (r=0.54). IG was significantly associated with health indicators, independent of AvAcc (p<.001). AvAcc was associated with wellbeing, independent of IG (p<.05). IG was significantly associated with WHtR (p<.01) and MetS score (p<.05) at 8-weeks follow-up. IG is sensitive as a gauge of PA intensity that is independent of total PA volume, and which relates to important health indicators in children.

Introduction

Until recently, comparability of data collected using different accelerometer brands was not possible because of the reliance on device-specific ‘counts’, which were based on proprietary algorithms (1). In the last decade, the move towards increased accessibility of raw acceleration signals has greatly increased the potential for cross-device comparability. However, studies using raw accelerations still tend to apply population-specific and protocol-specific thresholds or cutpoints to estimate time spent in different movement intensities (2-4). There is though, no consensus as to the most appropriate raw acceleration cutpoints to estimate time spent in different PA intensities. Application of different cutpoints can result in vastly different estimates of PA (5), which is confusing for interpretation and translation of data for surveillance and intervention evaluation. Most of the studies that have used raw accelerations to describe PA outcomes (6-9) have employed the Euclidean norm minus one *g* (ENMO) metric to summarise the raw acceleration signal vector magnitude (10). They have also applied acceleration cutpoints from the laboratory calibration study of Hildebrand et al. (2014) (2), which involved a convenience sample of 30, 7-11 year old children. These cutpoints have been used frequently, but are based on a limited number of activities and have not been cross-validated in free-living settings. As such, they may not be appropriate for all youth populations.

Generating further population-specific accelerometer cut-points limits comparability between studies, but this could be overcome by using standardised PA metrics that could maximise data comparability and the potential for data harmonisation (1). Recently, Rowlands (2018) argued that accelerometer metrics should be standardised so that they are meaningful, interpretable, and comparable (1). In particular, it was suggested that raw acceleration data should be used and reported as (i) the average acceleration (i.e., acceleration due to movement, corrected for gravity) as a measure of activity volume, and (ii) the profile of PA intensity, termed the

Intensity Gradient (IG) (1). The IG describes the straight line negative slope of the natural logs of time and acceleration intensity (11). A better IG is reflected by a shallower (i.e., less negative) slope, whereas a steeper (i.e., more negative) slope would reflect an inferior IG (11). The IG reflects the entire intensity profile, rather than small proportions of cutpoint-derived PA (e.g., moderate-to-vigorous intensity PA; MVPA). Further, it does not depend on the bias introduced by cutpoint calibration protocols, as it uses the full range of recorded data (11). Moreover, the IG is more independent of overall PA level, and therefore can be used in combination with average acceleration to describe intensity and volume of the PA profile. This allows the relative importance of PA intensity and volume to be examined in relation to specific health outcomes (1, 11). This information could subsequently be used to inform content and design of health-related interventions. Using the GENEActiv wrist accelerometer, Rowlands et al. (2018) demonstrated that average acceleration and IG each explained unique variance in PA profiles and were independently associated with body fatness and physical function (11). Average acceleration and IG therefore have potential as standardised measures describing PA volume and intensity, respectively, to explore their relative contributions to health, and to allow comparisons between studies where raw acceleration signals have been used. Importantly, this approach removes the complications of the 'cutpoint conundrum' which often render meaningful between-study comparisons impossible, provide inconsistent estimates of activity levels, and serve to confuse the evidence base and its interpretation (12). Generating and reporting data on PA volume and intensity as standard metrics would increase comparability between studies, with population-specific interpretation of the data (e.g., estimating time in specific intensities) applied post-analysis by the researchers themselves as well as by others (1, 11).

This study further examines the utility of the average acceleration and IG metrics using the ActiGraph accelerometer in a sample of primary school children. The study sought to address the following objectives:

1. Investigate whether hypothesised differences in PA between sex, weight status, obesity risk, metabolic risk, and cardiorespiratory fitness (CRF) status groups are apparent for average acceleration, IG, and MVPA.
2. Explore the magnitude of associations between average acceleration, IG, and cutpoint-based estimates of sedentary time (ST), light PA (LPA), and MVPA to determine whether the IG is more independent of average acceleration than the cut-point based metrics.
3. Investigate cross-sectionally, whether average acceleration and IG are independently associated with obesity indicators, metabolic risk, CRF, and health-related quality of life (HRQoL), when adjusting for covariates.
4. Examine the associations between baseline PA metrics and the health indicators described in #3 above, measured 8-weeks later.

Methods

This is a secondary analysis of data collected in the Active Schools: Skelmersdale PA pilot intervention study (ClinicalTrials.gov registration: NCT03283904). The methods have been described previously (8) but are outlined briefly here. Two hundred and thirty two 9-10 year old participants were recruited from 7 primary schools. The schools were situated in a low socioeconomic status (SES) town in West Lancashire, north-west England, where the prevalence of overweight/obesity is above the national average (13). Ethical approval was granted by Edge Hill University's Research Ethics Committee (reference # SPA-REC-2015-330) and informed consent and assent were provided by the participants' parents/carers, and the participants themselves, respectively. Data collection took place between September and December 2017.

Following collection of baseline measurements, schools were randomly assigned to either intervention (4 schools) or control groups (3 schools). The AS:Sk pilot intervention included eight components which were implemented over 8-weeks. The components were active classroom breaks, high-intensity jumping activities, structured exercise videos, running/walking activities, playground activity challenge cards, physical education teacher training, parental newsletters, and PA homework. Control schools continued with their usual timetabled amount of playground breaks and physical education lessons without any additional time allocated for PA participation. No intervention effects were observed for MVPA but sedentary time (ST) decreased in the intervention schools (8).

Measures

Physical activity

Participants wore an ActiGraph GT9X triaxial accelerometer (ActiGraph, Pensacola, FL, USA) on the non-dominant wrist for 24 $h \cdot d^{-1}$ over seven days. Wrist-worn accelerometers have demonstrated excellent validity against energy expenditure as the criterion measure (14), and in comparison to hip-worn accelerometers (14, 15). ActiGraphs recorded accelerations at 100 Hz, data were downloaded using ActiLife version 6.11.9 (ActiGraph, Pensacola, FL, USA), and saved in raw format as GT3X files, before being converted to raw csv file format for signal processing. These csv files were processed in R (http://cran.r-project.org) using GGIR beta v1.6-1 which carried out autocalibration procedures (16), identified non-wear (10), and converted the raw triaxial accelerometer signals into one omnidirectional measure of acceleration (ENMO) (10). Computed average day (labelled ‘AD’ in GGIR) ENMO values were averaged per 5 s epoch over each of the seven monitored days to represent average acceleration, and were expressed in milligravitational units (m*g*). Accelerometer non-wear was determined based on the SD and value range of the accelerations at each axis, calculated for 60-min windows with a 15-min sliding window (10). If for at least 2 out of the 3 axes the SD was less than 13 m*g* or the value range was less than 50 m*g*, the time window was classified as non-wear (10). By default, GGIR imputed non-wear data by the average at similar time points on other days of the week. Therefore, participants' outcome variables were based on the complete 24-h cycle (i.e., 1440 min). Participants were excluded if the ActiGraph files demonstrated (i) post-calibration error greater than 0.01 *g* (16), (ii) less than 3 valid days of wear (17), which was defined as at least 16 h d^{-1} (11), or (iii) missing wear data for any 15-min window over the 24-h cycle, indicated in GGIR by the '24-h cycle <1' variable.

Total PA was expressed as the average acceleration over 24-h. The IG metric was calculated in GGIR following the method described by Rowlands et al. (2018) (11) and was represented by the 'AD_IG' variable in GGIR. The IG is based on the relationship between log values for intensity (i.e., incremental intensity bins, 0-25 m*g*, 25-50 m*g*, etc) and time (i.e., accumulated time in each intensity bin), and is always negative, reflecting the drop in time accumulated in increasing intensity bins (11). For each participant, their IG over 24-h, the constant of the linear regression equation, and R^2 value (indication of the goodness of fit of the linear model) were produced, as were time spent in LPA, MVPA, and time spent inactive. We used the only available published ENMO prediction equations to identify cut-points for classifying activity as MVPA (3 metabolic equivalents (METs; child-specific); 200 m*g*) (2). Inactive time was defined as time accumulated below 50 m*g*, which is consistent with the previous average acceleration and IG study (11) and recently published sedentary time thresholds (18). LPA was defined as > 50 and < 200 m*g*.

Obesity-related outcomes

Height was measured using a portable stadiometer (Leicester Height Measure, Seca, Birmingham, UK), and body mass was measured using calibrated scales (813 model, Seca). Body mass index (BMI) was calculated for each participant, BMI z-scores were assigned (19) and IOTF BMI cut-points applied to classify the participants as normal weight or overweight/obese (underweight participants were grouped into the normal weight category) (20). Waist circumference was measured using an anthropometric tape measure, and waist-to-height ratio (WHtR) was calculated as a measure of central obesity (21). A WHtR of $\geq$0.5 was used to categorise participants as at risk or not at risk of central obesity (22). Sex-specific equations were used to predict age from peak height velocity (APHV), as a proxy measure of biological maturation (23). For all measurements the participants wore shorts and t-shirt with shoes removed.

Cardiorespiratory fitness

The 20-m multistage shuttle run test was conducted to provide an estimate of cardiorespiratory fitness (CRF). This test has been used extensively with participants of a similar age to those in the current study (24). The running speed at the last completed lap was used to estimate peak oxygen uptake (VO_2 peak; $ml \cdot kg \cdot min^{-1}$) using the Leger et al. prediction equation (25). Participants were classified as having higher or lower CRF levels using the 40th centile for VO_2 peak in European children, which is the normative quintile-based framework cutoff for low to very low fitness (boys: 47.0 $ml \cdot kg \cdot min^{-1}$; girls: 44.4 $ml \cdot kg \cdot min^{-1}$) (24).

Metabolic health

A metabolic syndrome (MetS) score was calculated to describe metabolic risk using non-invasive variables (26). Z-scores were calculated for WHtR and the inverse of CRF (1/ VO_2 peak), summed, then averaged to provide a MetS risk score. This approach has demonstrated sensitivity and specificity of 0.85 in ROC analyses (26) against the International Diabetes Federation definition of MetS encompassing obesity prevalence and elevated levels of triglycerides, HDL-C, blood pressure, and glucose (27). A MetS risk z-score > 0.51 was used to classify participants as low or high risk of MetS (26).

Health-related quality of life

The KIDSCREEN-10 Index questionnaire was used as a measure of global health-related quality of life (HRQoL) (28). KIDSCREEN-10 Index is a 10-item questionnaire which asks participants how they felt in the last week. Items reflect the factors of physical well-being, psychological wellbeing, autonomy and parent relations, peers and social support, and school environment, which are derived from the 27-item version of KIDSCREEN and are presented using a 1-5 Likert scale (29). Raw scores were converted to T-scores using the methodology described in the KIDSCREEN administration manual (28).

Socioeconomic status

Neighbourhood-level SES was calculated for each child using the 2015 Indices of Multiple Deprivation (IMD) (30). The IMD is a UK government-produced deprivation measure for England comprising income, employment, health, education, housing, environment, and crime. IMD rank scores were generated from parent-reported home post codes using the National Statistics Postcode Directory database. Every neighbourhood in England is ranked from one (most deprived area) to 32,844 (least deprived area).

Analyses

Descriptive statistics were calculated for all measures using means (SD) or percentages for continuous and categorical variables, respectively. The main analyses were designed to address each research objective in turn. For objective 1, the dependent variables were average acceleration, IG, and MVPA. Mixed linear models with random intercepts were used to adjust for school-level clustering to compare each dependent variable by sex, weight status, central obesity risk status, MetS risk status, and CRF status. We hypothesised that PA would be greater among boys, participants with normal weight, low central obesity risk, low MetS risk, and higher CRF. Bivariate Pearson correlation coefficients were calculated to address objective 2. For objective 3, separate cross-sectional mixed linear models with random intercepts were constructed accounting for school-level clustering. Model 1 included only the PA metric (i.e., average acceleration or IG). Model 2 was additionally adjusted for sex, maturation, and SES, while Model 3 was further adjusted for the alternate metric (i.e., average acceleration or IG, depending on which was the predictor) to test whether associations were independent of either metric. Multicollinearity was checked using the variance inflation factor (VIF) with a VIF of >5 indicating excessive multicollinearity (31). To allow comparison of the IG results with MVPA, all models were repeated using average acceleration and MVPA as the alternate metrics. For objective 4, the dependent variables for these analyses were average acceleration, IG, and MVPA. Mixed linear models with random intercepts and adjusted for school-level clustering examined the association between the baseline PA metrics and health indicators measured 8-weeks later. Analyses were adjusted for the alternate PA metric, baseline health indicators, group designation (i.e., Control or Intervention group), sex, BMIz, maturation, and SES.

Regression coefficients in the main and interaction models were assessed for significance using the Wald statistic (32). Statistical significance was set at $p<.05$ in all analyses. Analyses for objectives 1, 3, and 4 were performed using MLwiN 2.26 software (Centre for Multilevel Modelling, University of Bristol, UK). IBM SPSS Statistics version 23 (IBM, Armonk, NY) was used to undertake analyses for research objective 2.

Results

Descriptive statistics are presented in Table 1. Baseline accelerometer data were available for 226 of the 232 participants (6 participants were absent on the day the accelerometers were distributed). Forty-one participants wore the accelerometers for $< 16\ h \cdot d^{-1}$ for at least 3 days, 39 participants had incomplete accelerometer data (i.e., missing wear data for any 15-min window over the 24-h cycle), and one participant had spurious accelerometer data. These participants were subsequently removed, which resulted in a final analytical baseline sample of 145 participants (62 boys). Almost 70% of the sample were classified as normal weight, 62.8% of them had higher CRF levels, and just over half engaged in at least 60 min MVPA per day. There were no significant differences between included and excluded participants in obesity-related variables, CRF, and HRQoL. Excluded participants were more likely to be girls ($p<.05$) with more advanced somatic maturity ($p<.05$).

TABLE 1

Objective 1. The hypothesised differences in PA metrics between boys and girls were observed for MVPA ($p<.05$ – $p<.001$), average acceleration ($p<.05$ – $p<.001$), and IG ($p<.001$) (Table 2). Hypothesised differences were observed for IG between normal weight and overweight/obese participants ($p<.001$), between those with low and high risk of central obesity ($p<.001$), those with low and high risk of MetS ($p<.001$), and those with higher and lower CRF ($p<.05$).

TABLE 2

Objective 2. Average acceleration was strongly correlated with MVPA ($r=0.96$) and inactive time ($r=-0.82$) (both $p<.001$), but only moderately with LPA ($r = 0.59$, $p<0.001$) and IG ($r=0.54$, $p<.001$). IG and MVPA were moderately correlated ($r=0.50$, $p<.001$). IG was weakly and non-significantly correlated with inactive time ($r=-0.13$), and LPA ($r=-0.09$).

Objective 3. Results of the models investigating the cross-sectional associations between average acceleration and IG, with health indicators are presented in Table 3. Significant effects for average acceleration or IG, independent of the alternate metric (Model 3), indicated whether volume or intensity were most important for a given health indicator. Average acceleration was significantly associated with BMIz, CRF, and HRQoL in the first (unadjusted) and second (adjusted) models. Average acceleration was not significantly associated with BMIz, WHtR, CRF, and MetS score in the third models when IG was included, indicating that the associations between average acceleration and these health indicators were not independent of IG. Conversely, the association between average acceleration and HRQoL was independent of IG in model 3, indicating that PA volume, rather than intensity was more important for HRQoL. In unadjusted and adjusted models, IG was negatively significantly associated with BMIz, WHtR, and MetS risk score, and positively significantly associated with CRF, HRQoL. These associations were significant independent of average acceleration in the third models, with the exception of HRQoL, indicating that PA intensity rather than volume was most important for the physical health indicators. When average acceleration and MVPA were included as the alternate PA metrics, MVPA was positively associated with CRF and HRQoL in the unadjusted models and the adjusted models 2 (Table S1). This significant association was not observed in model 3 for HRQoL, which demonstrated that the association with MVPA was not independent of average acceleration, while the significant association between CRF and MVPA was maintained in model 3. MVPA was also significantly associated with MetS score in model 3, indicating that this association was independent of average acceleration. Average acceleration was significantly associated with BMIz, WHtR, CRF, and MetS score when adjusted for MVPA in the third models. In all analyses the VIF values ranged from 1.02 (IMD rank) to 4.26 (sex).

TABLE 3

Objective 4. When baseline and follow-up health indicator data were merged, nine participants were lost due to absence on the day of data collection. This resulted in an analytical sample of 136 participants. WHtR and MetS score at follow-up were significantly associated with baseline IG, independent of average acceleration (Table 4). Specifically, significant inverse associations were observed between baseline IG and follow-up WHtR ($p<.01$) and MetS score ($p<.05$), indicating that PA intensity at baseline was more important than volume for follow-up WHtR and MetS score. When the analyses were repeated with baseline average acceleration and MVPA as the alternate metrics, no significant associations were observed with any health indicators at follow-up (Table S2). The Beta values of the health indicators were greatest when baseline IG was the predictor variable compared to average acceleration and MVPA.

TABLE 4

An example of translation and interpretation of the descriptive results is presented in Figure 1, which shows the activity profile for the sample categorised by IG tertile. Acceleration is described according to thresholds of 0-49 m*g* (inactive time), 50-199 m*g* (pottering/slow walking; LPA), 200-699 m*g* (brisk walking/jogging; MPA), and 700 mg+ (slow to fast running; VPA). The time spent inactive is at the base of each column. The time spent inactive and in pottering/slow walking was similar across tertiles. For participants in the High IG tertile, ~12 min and ~20 min more time was spent in activities equivalent to brisk walking/jogging, compared to participants in the Medium and Low IG tertiles, respectively. Moreover, High IG participants accumulated almost twice as much time in the highest intensity acceleration activities (i.e., slow-to-fast running), than those in the medium tertile, and three times as much time as peers in the low IG group.

FIGURE 1

Discussion

This is the first study to use the ActiGraph GT9X wrist accelerometer with primary-school aged children, to investigate the utility of average acceleration and IG relative to hypothesised between-group differences in PA, and in relation to associations with cutpoint-based PA metrics, and health indicators. The higher average acceleration (45.4 m*g*) and lower IG (-1.96) values observed in our primary school sample, compared to previously reported values for adolescent girls (36.3 m*g* and -2.47) and adults (22.1 m*g* and -3.11) (11) are consistent with expected age-related differences in PA (33, 34). When we investigated hypothesised PA differences between dichotomised groups defined by weight status, obesity risk, MetS risk, and CRF status, significant differences were observed for IG in all analyses, whereby the 'healthier' groups had more favourable (i.e., shallower) intensity profiles, which are indicative of engagement in relatively higher PA intensities. When the analyses were repeated with average acceleration and MVPA, no between-group differences were evident. The significant differences in IG in all analyses offers support for the potentially greater sensitivity of this metric to detect between group differences in PA. This is possibly because the IG reflects the full intensity spectrum and uses all of the acceleration information available (35), compared to cutpoint-based methods which are subject to greater sources of error (36) and which only represent a small proportion of the day (e.g., 63.9 min of MVPA or 4% of the day in this sample).

The magnitudes of the correlations between IG and inactivity, LPA, and MVPA (r = -0.09 – 0.50) were smaller than those observed between average acceleration and the cutpoint-based outcomes (r = 0.59 – 0.96). These analyses confirm previous work (11), showing that IG is more independent of average acceleration (i.e., volume of PA) than the cutpoint-based outcomes. Furthermore, the stronger correlations between IG and MVPA compared to those with LPA and inactivity, demonstrate the utility of IG as a PA metric that captures higher intensity PA, which has greatest health benefits (6, 35). The cross-sectional relationships between the PA metrics and indicators of adiposity mirrored those reported in adolescent girls (11) whereby in adjusted analyses, IG was significantly associated with BMIz and WHtR, independent of average acceleration. The same outcome was observed with CRF and MetS score as the dependent variables, indicating that PA intensity is more important that PA volume for these health indicators. In adjusted models, average acceleration was significantly associated with BMIz and CRF but these relationships were no longer significant when IG was added. In contrast, when average acceleration and MVPA (rather than IG) were included in the models, a significant independent association was only observed between MVPA and MetS score. This is consistent with studies using ActiGraph counts which demonstrated time spent in higher intensities of PA were most strongly associated with cardiometablic risk (37, 38). These findings provide further evidence of the sensitivity of IG as an indicator of PA intensity that is relatively independent of total volume of PA (i.e., average acceleration), and which relates to important indicators of physical health in children.

Further interpretation of these findings is possible by considering the unit change in health indicators relative to the change in IG. The SD of the IG in our sample was 0.14 which we employed with the final regression models to demonstrate predicted change in the health indicators (represented by the Beta values in Table 3). For example, a 0.14 increase in IG would be reflected by the following changes: BMIz Δ -0.57, WHtR Δ -0.03, VO_2 peak Δ +1.93 $ml \cdot kg \cdot min^{-1}$, and MetS score Δ -0.23. Such a change in BMIz is greater than reductions reported in intervention studies among obese (39) and non-obese children (40). Moreover, the equivalent change in CRF for a 0.14 increase in IG would be sufficient to shift a 10-year old child up approximately two deciles of recently published normative VO_2 peak values (24). Thus, improved engagement in higher intensity activities (for example through intervention programming, active play, sports participation, etc) would be reflected by shallower intensity profiles represented by the IG, which are associated with meaningful and favourable changes in physical health indicators. In keeping with recent recommendations, there is a need to provide further translation examples so these new PA metrics are interpretable and user-friendly (1). For example, applying the procedure described by Rowlands et al. (11) children in the current sample would need to replace time spent at the average acceleration with brisk walking for 2-h, slow running for 24-min, or medium-paced running for 19-min, accumulated across the day, in order to increase their average acceleration by 1 SD (13.1 m*g*). Such changes could be achieved through increased participation in daily PA opportunities such as active school commuting (41) (i.e., brisk walking), and school-based activities such as active recess play (42) and co-curricular activities like running programmes that are becoming increasingly popular in primary school settings (43) (i.e., slow and medium-paced running). For each child, such changes would have an impact on their IG values, with the greatest impact coming from the more intense activities (i.e. running) (11), as described in Figure 1. Therefore, running (or activities of an equivent intensity) could be recommended for BMIz, WHtR, MetS score, and CRF, which demonstrated an independent effect of IG. Further translation of incremental intensity distributions using health-related acceleration thresholds or indicative activity modes, could also be used to aid public health messaging and intervention programme design.

The analyses of baseline PA metrics relative to the health indicators measured 8-weeks later resulted in significant associations between IG and WHtR and MetS score. When the Beta values were summed by IG SD of 0.14, this resulted in predicted changes of -0.01 WHtR units and -0.07 MetS score. Although such changes are favourable, the short follow-up period limits how meaningful the magnitude of these associations are. Longitudinal studies of at least 2-years have demonstrated prospective associations between MVPA and decreased fat mass (44), and metabolic risk (45), between absence of organised sport participation and increased BMIz (46), and between VPA and decreases in BMIz and waist circumference, and increases in CRF (47). These prospective associations reinforce the importance of higher intensity PA for health in children, and our finidngs show that IG is sensitive to capture such higher intensity PA, independent of PA volume, albeit over a relatively short follow-up period.

The association between HRQoL and IG was not independent of average acceleration, while the the opposite was true when average acceleration was the metric of interest. This suggests that simply moving more (i.e., increasing PA volume), irrespective of intensity was positively associated with increased HRQoL. PA metrics have seldom been studied in relation to wellbeing, and this is the first study to examine the utility of the IG in relation to HRQoL as a wellbeing indicator. A recent systematic review reported that there were inconclusive relationships between PA and wellbeing, mainly due to lack of consistent PA and wellbeing outcome measures between studies, with greatest variability in the latter (48). For example, it was found that children who self-reported meeting the 60 min·d^{-1} MVPA guideline scored higher on the KIDSCREEN-52 dimensions of self-perceptions, social acceptance, and social support (49). A similar finding was observed among youth who self-reported time spent in various sports (deemed equivalent to MVPA) and completed the PedsQL HRQoL questionnaire (50). In contrast, an intervention study where children wore a hip-mounted ActiGraph and completed the KIDSCREEN-27 reported increased MVPA in the control group, yet no corresponding changes in HRQoL (51). Further work is needed to better understand the inter-relationships between objective PA metrics and HRQoL. This would be helped by more consistent choice of measures, which reinforces support to the call for the use of average acceleration and IG as standard PA metrics (1).

This study is limited by the modestly-sized sample that was located in a low SES English town, which may inhibit generalisability of the findings to other populations. Moreover, most of the analyses were cross-sectional, which prohibits conclusions about causality between the PA metrics and health indictors. The cutpoints used to determine MVPA may have been subject to population-specific and protocol-specific biases, which could have influenced the accuracy of the reported MVPA estimates. Further, although accelerometer wear averaged 19.2 hours·valid d^{-1} for 5.2 valid days we cannot be certain that the wear time criteria applied were suitable for use with the average acceleration and IG metrics. Future work may be needed to establish the wear time criteria required to reliably estimate typical 7-day values for these new metrics. The 8-weeks follow-up measures were a strength of the study, but this period may not have been long enough to make meaningful inferences about the associations with the baseline PA metrics. Other strengths included the use of mixed linear models to account for school-level variance and the inclusion of known correlates of PA in the models. Furthermore, the study reported associations between the PA metrics and a range of important physical and mental health indictors.

Conclusions

This is the first study to examine the utility of the recently introduced average acceleration and IG metrics using the wrist-worn ActiGraph monitor with primary-school aged children. Significant differences in IG were observed between sex, weight status, central obesity risk, and CRF status groups. Moreover, IG was significantly associated with BMIz, WHtR, CRF, and MetS score independent of average acceleration. The magnitude of these associations reflected meaningfully beneficial changes in health indicators. Significant associations of a smaller magnitude were apparent between baseline IG and WHtR and MetS score at 8-weeks follow-up. The results provide further evidence of the utility of average acceleration and IG to describe children's PA, and go beyond those reported previously reported, by including health indicators reflecting CRF, metabolic risk, and HRQoL, rather than just obesity-related measures. The IG can be considered a meaningful PA metric that is sensitive as a gauge of PA intensity, that is independent of total volume of PA, and which relates to important indicators of physical health in children.

Discosure of interest

The authors declare no conflicts of interest.

Data access statement

The data that support the findings of this study are available at https://osf.io/tfpk9/.

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Table 1. Descriptive characteristics of the study sample

Table 2. Between-group differences in MVPA, average acceleration, and intensity gradient

Table 3. Cross-sectional associations between the physical activity metrics and health indicators

Table 4. Associations between baseline physical activity metrics and health indicators measured 8-weeks later

Figure 1. Accumulated time spent in acceleration ranges of participants categorised by intensity gradient tertile