The use of the intensity gradient and average acceleration metrics to explore associations with measures of health and wellbeing in children

Duncan S. Buchan*, Gillian McLellan, Samantha Donnelly and Rosie Arthur.

School of Health and Life Sciences, Institute of Clinical Exercise and Health Science, UWS
Lanarkshire Campus, Stephenson Place, Hamilton International Technology Park, South
Lanarkshire, G72 0LH, Scotland, UK

Corresponding author

Duncan S Buchan: Email: duncan.buchan@uws.ac.uk

Twitter handles: @SDonnelly93; @McLellan1993; @drrosiearthur.

Co-author agreement statement

DSB, GMcL, SD and RA are aware of, and agree to this preprint submission.

- This is a pre-print manuscript that has not undergone peer-review.
- Cite this work as *Buchan, D.S., McLellan., Donnelly, S., & Arthur, R. (2019, April 29). The use of the intensity gradient and average acceleration metrics to explore associations with measures of health and wellbeing in children*
- Preprint DOI: [10.31236/osf.io/3pj2e](https://doi.org/10.31236/osf.io/3pj2e)

Abstract

This study used the intensity gradient (IG) and average acceleration metrics to describe children's activity profiles and explore associations with health and wellbeing. Two hundred and forty-six children ($n = 138$ girls) aged 9.6 ± 1.4 years wore a wrist-mounted ActiGraph wGT3X-BT accelerometer for 7 days. Physical activity (PA) metrics captured included: the IG from the log-log values from time and intensity; average acceleration; total moderate-to-vigorous PA (MVPA) and inactive time. Time spent in intensity categories of 50 mg resolution were also calculated based on a complete day. Finally, BMI z-score was calculated for each participant. Associations between average acceleration and the IG were lower ($r=0.60$) than those seen between average acceleration and total MVPA ($r=0.91$) and inactive time ($r=-0.74$). Associations between the IG and total MVPA ($r=0.60$) and inactive time ($r=-0.17$) were weaker than those observed with average acceleration. Average acceleration was negatively associated with BMI z-score ($p<0.05$) independent of age and gender but not IG. The IG was negatively associated with BMI z-score independent of potential correlates and average acceleration. Total MVPA was not associated with BMI-z score. The IG and average acceleration metrics can explore the importance of intensity and volume for health measures in children.

Keywords: ActiGraph; accelerometer; BMI z-score; activity metrics; wrist-worn; raw acceleration.

Introduction:

The use of accelerometers to objectively quantify activity behaviours is widespread. There are several different types of accelerometers available (Actical, Actiwatch, GENEActiv, Axivity, etc), with the ActiGraph (Pensacola, FL, USA) accelerometers being one of the most commonly used by researchers when measuring physical activity (PA) levels (1). A lack of comparability in accelerometer output variables from the use of different devices, postprocessing decisions, cut-points to classify activity estimates and the proprietary nature of accelerometer output has hindered the ability to compare accelerometer output variables across studies (2,3). For instance, The International Children's Accelerometry Database (ICAD) is one example of how waist-worn ActiGraph data can be harmonized to facilitate the pooling of data to investigate diverse research questions by ensuring outcomes are comparable. Similarly, The International Study of Childhood Obesity (ISCOLE) is a multinational cross-sectional study comprising of over 7000 children from 12 countries that employs a consistent measurement and analysis protocol that allows for ActiGraph data to be harmonized (4). The benefits of being able to harmonize accelerometer data from several studies is clear. Nonetheless, research outputs from ICAD and ISCOLE are based on ActiGraphs proprietary counts which limits their comparability with studies using other accelerometer devices.

In order to facilitate comparisons between studies, a key recommendation from a panel of experts meeting held in 2009 was that accelerometer device data should be collected and saved as raw acceleration signals (5,6). Since this recommendation, GENEActiv, ActiGraph and Axivity raw acceleration research grade accelerometer devices are now commercially available and are currently used in large-scale studies to assess children's activity profiles (4,7–9). The use of GENEActiv and ActiGraph accelerometer devices in these studies however makes between study comparisons difficult given the lack of consensus surrounding the most appropriate raw acceleration thresholds to use when estimating time spent in activity categories. Studies that utilize raw accelerations to assess activity levels (10–12) tend to rely upon the Euclidian norm minus one (ENMO) metric to estimate time spent in activity categories using thresholds derived from the laboratory based validation study by Hildebrand and colleagues (13). Since these authors instructed participants to wear both the ActiGraph and GENEActiv on the hip and the wrist during all activities, the resultant raw acceleration thresholds are commonly used by researchers working with raw accelerations to quantify

time spent in activity categories. Much like the limitations associated with the numerous count based thresholds available for ActiGraph devices (14), their utility is limited because of the laboratory protocol used to generate the raw thresholds, the lack of cross-validation in a free-living setting and the sample characteristics. Furthermore, these proposed raw acceleration thresholds and processing methods are yet to be validated in an independent sample.

In an attempt to overcome the reliance upon population and device specific activity thresholds, Rowlands and colleagues have called for the need for acceleration metrics that are standardised, interpretable, comparable between devices and are meaningful (5,15). To address this need, Rowlands has called for raw acceleration values to be reported in future research manuscripts alongside typically reported activity variables in the form of two metrics; average acceleration and the intensity gradient (IG) (5). Average acceleration provides a measure of the volume of activity whereas the IG describes the intensity distribution of accelerations across the monitoring period. Together these two metrics detail both the volume and intensity of activity undertaken across the monitoring period using all of the acceleration data collected. Rather than the limited data that is often used to quantify time spent in an activity category which is typical when using available thresholds.

In the only study thus far to examine the utility of the recently proposed IG metric in children, Rowlands and colleagues found that the average acceleration and IG metrics were independently associated with measures of adiposity (15). This suggest that both metrics can be used to examine the relative importance of intensity and volume of activity for a particular outcome. Crucially, their combined use overcomes the reliance upon thresholds derived from specific populations and protocols to estimate time spent in specific activity categories. The IG is a new metric and limited evidence is available that has examined the utility of both the average acceleration and IG metrics. Moreover, Rowlands and colleagues only examined data from the GENEActiv accelerometer and whether similar findings are evident using the ActiGraph accelerometer devices is unclear. Using data from the wGT3X-BT ActiGraph (ActiGraph; ActiGraph, LLC, Pensacola, FL, USA) accelerometer device, the purpose of this study therefore were: 1) examine whether the IG and average acceleration metrics were more independent from each other than moderate-vigorous PA (MVPA) and inactive time; 2) whether independent relationships were evident between the IG and average acceleration metrics with that of BMI z-score and 3) provide easily understandable activity

recommendations based upon the findings of multiple regression analyses on which metric was associated with the BMI z-score.

Methods:

A convenience sample of participants were recruited from across 14 geographically representative primary schools from South Lanarkshire, Scotland from October 2017 and December 2018. Children aged 8-12 y were invited to participate but due to curriculum demands and staffing availability, the Head Teacher of each school dictated whether all eligible participants or selected classes were recruited. This resulted in the recruitment of 461 children ranging from 11 to 92 from each school. Upon approval being received from the Ethical Committee of the University of the West of Scotland, participants and parents were provided with information packs detailing the aims of the study and their involvement.

Measures:

Participants' stature was measured barefoot to the nearest 0.1cm using a portable stadiometre (Seca Stadiometre, Seca Ltd, Birmingham, UK). Mass was measured barefoot with light clothing to the nearest 0.1kg on electronic scales (Seca Digital Scales, Seca Ltd., Birmingham, UK). From measured stature and mass, a BMI z-score was calculated relative to the UK 1990 BMI population reference data (16). Thereafter, all participants wore one ActiGraph accelerometer on their non-dominant wrist (defined as the hand they do not normally write with) for 7 days. Verbal confirmation of each participant's non-dominant wrist was noted, and device placement was demonstrated. All participants were fitted with their device prior to leaving the measurement session. Prior to distribution, each accelerometer was synchronised with Greenwich Mean Time and initialized to capture data at 80Hz. Participants were instructed to wear the device at all times (i.e., 24 h per day) for 7 days, except during any water-based activities such as swimming or bathing.

Data processing:

Upon the return of each device, data was downloaded using ActiLife (Version 6.13.3; ActiGraph, Pensacola, FL, USA) and saved in raw format as .gt3x files. The .gt3x files were subsequently converted to time-stamp free .csv files which were exported into R v3.5.2 (R Foundation for Statistical Computing, Vienna, Austria, <https://cran.r-project.org/>) and processed using the GGIR package v1.8.1 (17,18). Processing in GGIR involves the detection

of abnormally high values, detection of non-wear time (18) and auto-calibrates the raw triaxial accelerometer signals using local gravity as a reference (17). Furthermore, GGIR calculates ENMO (1 g) averaged over 1 s epochs and expressed in mill-gravitational units (mg) as previously described (15).

Participants were excluded from subsequent analysis if their accelerometer files demonstrated a post-calibration error greater than 0.01 g, there were less than 3 days of valid wear (defined as ≥ 16 h per day (15)) or wear data was not present for each 15 min period of the 24 h cycle. We used the default non-wear setting whereby invalid data were imputed by the average at similar time-points on different days of the week. Therefore, outcome variables were calculated based on the entire 24 h cycle for all included participants.

In line with Rowlands and colleagues (15), PA was expressed as average acceleration across the day (ENMO, mg), time accumulated in MVPA and time spent inactive. Time spent in MVPA was defined as the time accumulated above an acceleration of 201 mg (13) whereas time spent inactive was defined as time accumulated below 50 mg (15,19). Distribution of time spent in intensity categories of 50 mg resolution (0-50, 50-100, 100-150...4000, >4000) was determined to describe a participant's activity intensity distribution. The negative curvilinear relationship between intensity and time accumulated in that intensity can then be transformed into a straight-line relationship by taking the natural log of the two wide ranging quantities of intensity and time, as previously described (15). In this study, the mid-range of each of the activity categories (e.g. 0-50 mg = 25 mg) and the time accumulated in that intensity category was determined. Finally, the R^2 value (indication of the goodness of fit of the linear model) from the linear regression equation was provided for each participant as was the IG and constant. The gradient was always negative and is reflective of the reduced time accumulated within the increasing intensity categories. A higher constant and lower gradient was reflective of a steeper distribution across the intensity categories with a lower constant and higher gradient reflecting a greater distribution of time spent across the intensity categories.

Statistical analyses

Data are presented as mean $\pm$ SD unless otherwise stated. Average acceleration (ENMO) was used as the metric to describe overall activity and the gradient of the participants log-log

regression line (IG) used as the metric to describe the distribution of activity across the intensity categories. Pearson's correlation coefficients examined the inter-correlations between the activity outputs to determine whether the IG was more independent of average acceleration than MVPA and time spent inactive.

A negligible school-level effect was observed ($ICC = 0.01$ to 0.07) which indicated that no clustering was apparent in the dataset. Therefore, multiple linear regression analyses were used to examine whether the IG and average acceleration metrics were associated with BMI z-score (dependant variable), (Model 1). Model 2 further controlled for potential covariates (age and sex) whereas Model 3 additionally controlled for the alternative activity metric to establish whether associations were independent. Analyses were then repeated using time spent in MVPA to compare the results with that from the IG metric. Finally, variables were centred prior to entry into the regression analyses with a variance inflation factor (VIF) of > 5 used to indicate the presence of multicollinearity.

Based on the findings of the multiple regression analyses, meaningful activity targets could be presented based on whether overall activity, the intensity of activity or both are important for improving BMI z-score. Following the recommendations provided by Rowlands and colleagues (5,15), we calculated the mean $\pm$ SD of the average acceleration metric in order to establish how much additional activity would need to be undertaken to increase overall activity levels by 1 SD. Assuming that the additional activity would replace time spent at the average acceleration, the time required for a particular activity was calculated by: $1440 \times (\text{increase in average acceleration required by activity at that intensity}) / (\text{acceleration associated with that activity} - \text{average acceleration})$. The activities used to inform recommendations were taken from Hildebrand and colleagues (13) and consisted of slow walking at approximately 3 km/h, fast walking at approximately 5 km/h and slow running at approximately 8 km/h. These activities were indicative of acceleration values of 100 mg, 200 mg and 800 mg and were used to calculate the time estimates of the additional activity recommendations. To demonstrate the potential utility of these activity recommendations, we provide examples of meaningful activity targets based on both overall activity and the intensity of activity. Statistical analyses were conducted using IBM SPSS statistical software for Windows version 24 (IBM, Armonk, NY) and a p-value of <0.05 used to indicate statistical significance. The `loneway` command in Stata V.13 (Stata Corp. 2013. Stata

Statistical Software: Release 13. College Station, Texas, USA: StataCorp LP) was used to examine if clustering was evident within the dataset.

Results

Participant characteristics are displayed in Table 1 with time spent in intensity categories of 50 mg resolution displayed in Figure 1. Accelerometer files were available for 436 of the 461 participants. There were 6 device malfunctions, 14 participants were absent from school on the day of accelerometer distribution and 5 reported losing their device. The accelerometer files of 190 participants were excluded from subsequent analysis (109 had three incomplete 24 h cycles, 71 fewer than 3-valid days, 10 failed calibration) which left a final sample size of 246. There were no significant differences in BMI z-score between those included and excluded participants, but girls were significantly more likely to be excluded than boys.

Average acceleration was strongly positively associated with time spent in MVPA ($r = 0.91$, $p < 0.001$) and strongly negatively associated with inactive time ($r = -0.74$, $p < 0.001$).

Associations between average acceleration and the IG were significant but weaker ($r = 0.60$, $p < 0.001$) than the associations between average acceleration and time spent in MVPA and inactive time. Associations between the IG and time spent in MVPA ($r = 0.60$, $p < 0.001$) and inactive time ($r = -0.17$, $p < 0.01$) followed similar directions but were weaker than those observed with average acceleration.

Findings from the regression models can be found in Table 2. Average acceleration was negatively associated with BMI z-score but only after adjusting for age and gender in Model 2. These associations were not evident in Model 3 when the additional activity metric (IG) entered the regression analysis. This suggests that the association between average acceleration and BMI z-score was not independent of the IG. The IG was negatively associated with BMI z-score in the unadjusted model (Model 1) and remained after adjusting for age and gender in Model 2. These associations remained in Model 3 when the additional activity metric (average acceleration) entered the regression analysis. This suggests that the associations between the IG and BMI z-score were independent of average acceleration and that the IG may be more important for improving BMI z-score. In all cases, the VIF did not exceed 1.7. Time spent in MVPA was not associated with BMI z-score in either model 1 or 2 (Data not reported). Due to the presence of multicollinearity ($VIF's > 5$), we were unable to establish the independent effects of MVPA and average acceleration.

An increase in the average acceleration of 1 SD corresponded to an increase of 13.4 mg. Increasing activity by 13.4 mg could be achieved by undertaking the following activities instead of spending that time at the average acceleration level with:

- 1) approximately 3.75 h of slow walking OR
- 2) approximately 1.75 h of fast walking OR
- 3) approximately 25 min of slow running

As long as the sum of the increased activity corresponds to the 13.4 mg increase needed, a combination of activities can also be recommended as follows:

4) 40 mins of slow walking (2.7 mg) AND 30 mins of fast walking (4.1 mg) AND 12 mins of slow running (6.6 mg).

5) 22 mins of slow walking (1.5 mg) AND 15 mins of fast walking (2.1 mg) AND 18 mins of slow running (9.8 mg).

Although these activity recommendations will work to increase the average acceleration by the SD of the sample, their effect upon the IG of an example participant with low average acceleration and a low IG (1 SD below the sample mean for each) can be seen in Figure 2. It was evident that activities of a lower intensity had a negative effect upon the participants IG with more positive effects seen when higher intensity activities are recommended, either in isolation or in combination with other light activities. As our analysis indicated that the IG is more important for improving BMI z-score, activity recommendations of 25 min of slow running per day are likely needed to improve BMI z-score for this example participant.

Discussion

Our findings demonstrated that the IG was more independent of overall activity, assessed using average acceleration, when compared to MVPA and inactive time. Moreover, the IG was negatively associated with BMI z-score independently of overall activity. Given the strong associations between average acceleration and MVPA, it was unsurprising we were unable to examine the independent effects of these two variables upon BMI z-score due to the presence of multicollinearity. Nonetheless, the independent negative associations between the

IG and BMI z-score is an important finding and is consistent with previous investigations (15) and personal communications between researchers (5). This is the first study to demonstrate these findings using the ActiGraph accelerometer worn at the wrist.

An important attribute of both the IG and average acceleration metrics are that they are standardized and can be directly compared between different populations which removes the concerns of using laboratory derived thresholds. As these standardized metrics become more widely used, there is an opportunity to move away from the reliance upon thresholds derived from laboratory validation studies and proprietary accelerometer software to more transparent data processing methods using open-source and freely available software. We found that average acceleration and time spent in MVPA and inactive time were highly correlated which is consistent with the findings of others (15,20). As a consequence of this researchers are often unable to establish the relative importance of both the volume and intensity of activity for a particular outcome or risk factor. One such example of this can be seen from Boyer and colleagues who were interested in examining the associations between total volume and intensity of activity with insulin resistance (21). Using two cut-points for bouts of MVPA, the authors found that one of the cut-points violated the assumptions of the linear regression analysis due to the presence of multicollinearity with the total volume measure. The other cut-point did not violate the variance inflation factor statistic and allowed the authors to establish that the total volume of activity rather than the intensity of activity was more strongly associated with insulin resistance. Similar studies have also noted slightly stronger associations between total volume of activity and cardiometabolic risk factors when compared to measures of the intensity of activity (22). Conversely, others have reported that the intensity of activity appears more important than the volume of activity for many musculoskeletal outcomes in middle-aged women (23) and leukocyte telomere length in a racially and ethnically diverse cohort of 161,808 postmenopausal women aged 50–79 years (24).

Whilst this body of research is reflective of the growing interest in establishing the effects of other activity categories rather than just MVPA upon health outcomes, it is also indicative of the challenge's researchers face when comparing findings between studies. For instance, only two studies used the same ActiGraph model 7164 accelerometer and means of quantifying total volume of activity (21,22). No study used the same method to quantify the intensity of activity. For different populations and health outcomes, the relative importance of total

activity and the intensity of activity will likely vary but without a consistent approach to quantify both measures, these variations may be due to different study methodologies and post-processing decisions. Using the average acceleration and IG metrics therefore, offer the opportunity to investigate the independent, additive and interactive effects of total volume and intensity of activity on a range of health outcomes (5) without the concerns and limitations of comparing findings from studies using incomparable metrics.

The need for comparable outputs between different brands of accelerometers was a key outcome from a panel of experts in 2009 (5,6). Using the open-source and freely available GGIR package for R (<https://cran.r-project.org/web/packages/GGIR/GGIR.pdf>) (17,18), researchers are able to produce the IG and average acceleration metrics when using any of the 3 research-grade accelerometers (Axivity, ActiGraph, and GENEActiv) that provide acceleration data in g. Previous investigations have suggested that average acceleration values generated from the Axivity and the GENEActiv can be considered equivalent but is approximately 11% lower for the ActiGraph when all devices are worn on the non-dominant wrist (20). This is lower than the 15% difference in average acceleration found between the GENEActiv and the ActiGraph when worn on the waist by 10-12 year olds for 7 days in a free living setting (25). In a similar study over 7 days involving 9-10 year olds, Fairclough reported a 40% difference in average acceleration values between GENEActive worn at the wrist and ActiGraph worn on the waist (19.73 ± 0.55 mg vs. 49.33 ± 1.23 mg) (11).

That there is a difference in average acceleration between the GENEActiv and the ActiGraph is unsurprising and is likely attributable to the technical differences between devices (13,25,26). How these differences impact upon the acceleration outputs over a prolonged monitoring period however is unknown. To the best of our knowledge, only one published study has examined the comparability in average acceleration between the Axivity, ActiGraph, and GENEActiv devices when worn on the wrist (20). In this study participants wore all three devices on their non-dominant wrist but for only 2 hours in a stimulated living space. Whether equivalent findings across the 3 research-grade accelerometers would be evident over a longer monitoring period is unclear. It has been suggested that the differences in the magnitude of accelerations between the GENEActiv and the ActiGraph are most evident at low accelerations such as when sitting and standing (26). Since children spend the majority of their time in sedentary pursuits which are indicative of low accelerations (27,28), it's possible that the magnitude of acceleration differences between the ActiGraph and both

the GENEActiv and the Axivity when worn at the wrist over a prolonged period could be greater than the 11% differences previously reported by Rowlands and colleagues (20). Encouraging researchers to present the values of the two standardized activity metrics in future studies could allow data captured from the three accelerometer brands to be immediately comparable. In the meantime, further work over a 7-day free-living monitoring period is recommended to determine the magnitude of acceleration differences across and between the 3 research-grade accelerometers to establish whether correction factors are needed to ensure equivalency in the activity metrics across devices.

Various governments and organizations have proposed PA guidelines which encourage increased time spent in MVPA with significant health benefits (29–32). Unfortunately, generic weekly recommendations of 150 minutes for adults and 300 minutes for children may be unattainable for many individuals and especially those that are very inactive. By presenting individuals with a choice of activities that are perceived as feasible for them may be one strategy that can be used to improve activity levels through the development of individual and meaningful objectives. To demonstrate this, accelerations values of representative activities undertaken in a laboratory validation study (13) were applied post-hoc to data produced from the GGIR package for R (Figure 1). The resulting recommendations are presented in Figure 2 and demonstrate how activity recommendations can be produced to increase either average acceleration, the IG or both depending upon which is most appropriate for a given health outcome.

Providing meaningful activity recommendations that are easily understood is vital to inform public health initiatives as well as future intervention strategies which can also be developed to target a particular health outcome. There is a wealth of accelerometer thresholds currently available for researchers to use with ActiGraph accelerometers and can be applied to either youth or adult populations wearing hip or wrist-worn devices (14). Continued technological advancements will see new accelerometer devices become publicly available which will necessitate the need for further laboratory validation studies and the proposal of yet more thresholds to quantify time spent in MVPA as well as other intensity categories. As long as these new devices provide raw acceleration data and researchers present their findings as we have done (Figure 1), researchers are able to translate any new data in to meaningful recommendations and/or compare findings with those previously reported. In doing so, researchers would overcome the current limitations associated with the reliance upon

thresholds derived from laboratory validation studies and proprietary accelerometer software and capitalize on the wealth of wrist-worn accelerometer data currently being collected.

The cross-sectional nature of this study is a limitation as is the recruitment of participants from one location in Scotland which may limit the generalizability of our findings. Furthermore, we only collected data from accelerometers worn on the non-dominant wrist. Whether similar findings are evident when using the dominant wrist is unclear. The use of only one health outcome measure is acknowledged and further work examining the utility of the IG and average acceleration metrics with additional health outcome measures is encouraged. Strengths of this study include the use of a large sample from several schools and the inclusion of correlates known to influence activity levels in our statistical analysis which examined the influence of clustering within the dataset. A particular strength is the examination of the utility of the IG and average acceleration metrics with BMI z-score for the first-time using data collected from the ActiGraph accelerometer device. In summary, our findings confirm the utility of the IG and average acceleration metrics as meaningful measures of an individual's entire activity profile. Future work examining the independent and additive effects of intensity and volume of activity for a particular health outcome in children and youth should report these activity metrics to facilitate comparisons with previous studies that have used wrist-worn acceleration accelerometers.

Acknowledgements:

The authors would like to thank the children, schools, teachers and parents who agreed to participate in this study. This study was funded by The University of the West of Scotland, VP Research Fund. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Authors' Contributions:

GMcL and SD collected all of the data: DSB performed the statistical analysis and drafted the manuscript; DSB conceived, designed and coordinated the study and wrote the manuscript. RA helped to coordinate the study and reviewed the draft manuscript. All authors have read and approved the final version of the manuscript and agree with the order of authors.

None of the authors declare competing financial interests.

Disclosure of interest: The authors report no conflict of interest.

References

1. Wijndaele K, Westgate KL, Stephens SK, Blair SN, Bull FC, Chastin SF., et al. Utilization and Harmonization of Adult Accelerometry Data: Review and Expert Consensus. *Med Sci Sports Exerc.* 2015 Oct;47(10):2129–39.

2. Banda JA, Haydel KF, Davila T, Desai M, Bryson S, Haskell WL, et al. Effects of Varying Epoch Lengths, Wear Time Algorithms, and Activity Cut-Points on Estimates of Child Sedentary Behavior and Physical Activity from Accelerometer Data. *PLOS ONE*. 2016 Mar 3;11(3):e0150534.
3. Logan GRM, Duncan S, Harris NK, Hinckson EA, Schofield G. Adolescent physical activity levels: discrepancies with accelerometer data analysis. *J Sports Sci*. 2016 Nov;34(21):2047–53.
4. Katzmarzyk PT, Barreira TV, Broyles ST, Champagne CM, Chaput J-P, Fogelholm M, et al. The International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE): design and methods. *BMC Public Health*. 2013 Sep 30;13:900.
5. Rowlands AV. Moving Forward With Accelerometer-Assessed Physical Activity: Two Strategies to Ensure Meaningful, Interpretable, and Comparable Measures. *Pediatr Exerc Sci*. 2018 Nov 1;30(4):450–6.
6. Welk GJ, McClain J, Ainsworth BE. Protocols for evaluating equivalency of accelerometry-based activity monitors. *Med Sci Sports Exerc*. 2012 Jan;44(1 Suppl 1):S39-49.
7. Ipsos MORI; CLS. Millennium Cohort Study Sixth Sweep (MCS6): Physical Activity: Time use diary harmonised dataset. London, UK: Centre for Longitudinal Studies, UCL Institute for Education. 2017;134.
8. Li X, Kearney PM, Keane E, Harrington JM, Fitzgerald AP. levels and sociodemographic correlates of accelerometer-based physical activity in Irish children: a cross-sectional study. *J Epidemiol Community Health*. 2017 Jun 1;71(6):521–7.
9. Wake M, Clifford S, York E, Mensah F, Gold L, Burgner D, et al. Introducing Growing Up in Australia's Child Health CheckPoint. *Fam Matters*. 2014;65:15–23.
10. Buchan DS, McLellan G. Comparing physical activity estimates in children from hip-worn Actigraph GT3X+ accelerometers using raw and counts based processing methods. *J Sports Sci*. 2019 Apr 3;37(7):779–87.
11. Fairclough SJ, Noonan R, Rowlands AV, Van Hees V, Knowles Z, Boddy LM. Wear Compliance and Activity in Children Wearing Wrist- and Hip-Mounted Accelerometers. *Med Sci Sports Exerc*. 2016 Feb;48(2):245–53.
12. McLellan G, Arthur R, Buchan DS. Wear compliance, sedentary behaviour and activity in free-living children from hip-and wrist-mounted ActiGraph GT3X+ accelerometers. *J Sports Sci*. 2018 Apr 5;1–7.
13. Hildebrand M, Van Hees V, Hansen BH, Ekelund U. Age group comparability of raw accelerometer output from wrist- and hip-worn monitors. *Med Sci Sports Exerc*. 2014 Sep;46(9):1816–24.
14. Migueles JH, Cadenas-Sanchez C, Ekelund U, Nyström CD, Mora-Gonzalez J, Löf M, et al. Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Med*. 2017 Sep 1;47(9):1821–45.

15. Rowlands AV, Edwardson CL, Davies MJ, Khunti K, Harrington DM, Yates T. Beyond Cut Points: Accelerometer Metrics that Capture the Physical Activity Profile. *Med Sci Sports Exerc.* 2018 Jun;50(6):1323–32.
16. Cole TJ, Freeman JV, Preece MA. Body mass index reference curves for the UK, 1990. *Arch Dis Child.* 1995 Jul;73(1):25–9.
17. Van Hees VT, Fang Z, Langford J, Assah F, Mohammad A, Silva ICM da, et al. Autocalibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: an evaluation on four continents. *J Appl Physiol.* 2014 Oct 1;117(7):738–44.
18. Van Hees VT, Gorzelniak L, Dean Leon EC, Eder M, Pias M, Taherian S, et al. Separating movement and gravity components in an acceleration signal and implications for the assessment of human daily physical activity. *PLoS One.* 2013;8(4):e61691.
19. Hildebrand M, Hansen BH, van Hees VT, Ekelund U. Evaluation of raw acceleration sedentary thresholds in children and adults. *Scand J Med Sci Sports.* 2017 Dec;27(12):1814–23.
20. Rowlands AV, Mirkes EM, Yates T, Clemes S, Davies M, Khunti K, et al. Accelerometer-assessed Physical Activity in Epidemiology: Are Monitors Equivalent? *Med Sci Sports Exerc.* 2018 Feb;50(2):257–65.
21. Boyer WR, Wolff-Hughes DL, Bassett DR, Churilla JR, Fitzhugh EC. Accelerometer-Derived Total Activity Counts, Bouted Minutes of Moderate to Vigorous Activity, and Insulin Resistance: NHANES 2003–2006. *Prev Chronic Dis [Internet].* 2016 Oct 20 [cited 2019 Feb 18];13. Available from: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5072751/>
22. Hatfield DP, Chomitz VR, Chui K, Sacheck J, Economos CD. Exploring New Relationships Between Physical Activity Volume and Intensity and Cardiometabolic Risk in U.S. Adolescents. *J Phys Act Health.* 2015 Sep;12(9):1312–9.
23. Wu F, Wills K, Laslett LL, Oldenburg B, Jones G, Winzenberg T. Moderate-to-Vigorous Physical Activity But Not Sedentary Time Is Associated With Musculoskeletal Health Outcomes in a Cohort of Australian Middle-Aged Women. *J Bone Miner Res.* 2017;32(4):708–15.
24. Shadyab AH, Macera CA, Shaffer RA, Jain S, Gallo LC, LaMonte MJ, et al. Associations of Accelerometer-Measured and Self-Reported Sedentary Time With Leukocyte Telomere Length in Older Women. *Am J Epidemiol.* 2017 Feb 1;185(3):172–84.
25. Rowlands AV, Fraysse F, Catt M, Stiles VH, Stanley RM, Eston RG, et al. Comparability of measured acceleration from accelerometry-based activity monitors. *Med Sci Sports Exerc.* 2015 Jan;47(1):201–10.
26. Rowlands AV, Yates T, Davies M, Khunti K, Edwardson CL. Raw Accelerometer Data Analysis with GGIR R-package: Does Accelerometer Brand Matter? *Med Sci Sports Exerc.* 2016 May 13;48(10):1935–41.

27. McLellan G, Arthur R, Donnelly S, Buchan DS. Segmented sedentary time and physical activity patterns throughout the week from wrist-worn ActiGraph GT3X+ accelerometers among children 7-12 years old. *J Sport Health Sci* [Internet]. 2019 Feb 19 [cited 2019 Feb 20]; Available from: <http://www.sciencedirect.com/science/article/pii/S2095254619300274>
28. Ridgers ND, Timperio A, Cerin E, Salmon J. Within- and between-day associations between children's sitting and physical activity time. *BMC Public Health*. 2015 Sep 23;15:950.
29. Department of Health. Start Active, Stay Active: a report on physical activity for health from the four home countries' Chief Medical Officers. London; 2011.
30. Tremblay MS, Carson V, Chaput J-P, Connor Gorber S, Dinh T, Duggan M, et al. Canadian 24-Hour Movement Guidelines for Children and Youth: An Integration of Physical Activity, Sedentary Behaviour, and Sleep. *Appl Physiol Nutr Metab Physiol Appl Nutr Metab*. 2016 Jun;41(6 Suppl 3):S311-327.
31. US Department of Health and Human Services. Physical Activity Guidelines for Americans. Advisory Committee report 2018. Available from <https://health.gov/paguidelines/second-edition/report.aspx>. Accessed 7th March 2018. [Internet]. Washington DC; 2018. Available from: <https://health.gov/paguidelines/second-edition/report.aspx>.
32. World Health Organization. Global Recommendations on Physical Activity for Health. Available from http://whqlibdoc.who.int/publications/2010/9789241599979_eng.pdf. Accessed 8th August 2011. Geneva: World Health Organization; 2010.

Table 1. Descriptive characteristics of participants

	N = 246
Boys	108
Girls	138
Age (y)	9.6 $\pm$ 1.4
Height (cm)	139.6 $\pm$ 10.3
Mass (Kg)	35.9 $\pm$ 9.9
BMI z-score	0.5 $\pm$ 1.3
Average acceleration (mg)	44.2 $\pm$ 13.4
MVPA (min)	60.5 $\pm$ 32.1
Inactive time <50 mg (min)	1196. 2 $\pm$ 54.8
Intensity gradient	-2.3 $\pm$ 0.2
Constant	14.6 $\pm$ 0.9
Variance explained (R ² , %)	94.7 $\pm$ 1.6

Table 2. Associations between two activity metrics with BMI z-score.

	Model 1		Model 2		Model 3		Independent effect
	<u>Coefficient</u>	<u>95% CI</u>	<u>Coefficient</u>	<u>95% CI</u>	<u>Coefficient</u>	<u>95% CI</u>	<u>(Model 3)</u>
BMI z-score							
Average acceleration (mg)	-0.010	-0.20, 0.00	-0.014	-0.03, 0.00	-0.002	-0.02, 0.01	X
Intensity gradient	-1.074	-1.96, -1.84	-1.491	-2.44, -0.54	-1.396	-2.26, -0.23	✓

Significant associations are indicated in bold. Model 1 unadjusted. Model 2 adjusted for potential co-variates. Model 3 adjusted for alternative activity metric. 95% CI = 95% confidence interval. Whether associations between an activity metric were independent of the other metric is noted in the final column.

Figure captions:

Figure 1. Time spent in intensity categories of 50 mg resolution

Figure 2. Impact of daily activity recommendations upon the IG.

Note: All activity recommendations will also increase the average acceleration by 1 SD for an example participant (average acceleration and IG are both 1 SD below the sample mean).