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Count- versus MAD-based accelerometry-assessed movement behaviours and associations with child adiposity and fitness

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development of the customized Excel macro.

Conflict of Interest Statement

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Abstract

Estimations of time spent sedentary and in various physical activity intensities may vary according to data reduction methods applied. This study compared associations between children's accelerometer data and adiposity and fitness markers using open source (mean amplitude deviation; MAD) and proprietary (counts) data reduction methods. Complete-case accelerometer, adiposity (Body Mass Index z-score, waist circumference), and fitness (cardiorespiratory, musculoskeletal) data from 118 children (10.4±0.6 years, 49% girls) were analysed. Estimates of sedentary behaviour, light-, moderate-, vigorous- (VPA) and moderate- to vigorous-intensity (MVPA) physical activity were calculated using count- and MAD-based data reduction methods. Linear regression models between intensities and fitness and adiposity markers were conducted. Significant differences in estimates of time spent in all intensities were observed between MAD-based and count-based methods. Both methods produced evidence to suggest that sedentary behaviour was detrimentally, and physical activity (any intensity) was beneficially, associated with waist circumference. MVPA and VPA were beneficially associated with fitness markers using both data reduction measures. Overall, findings suggest that estimates of sedentary time and physical activity were not comparable. However, the strength and direction of the associations obtained between the different data reduction methods and adiposity and fitness outcomes were fairly comparable, with both methods finding stronger associations for VPA compared to MVPA. This suggests that future studies may be able to pool data using different data reduction approaches when examining associations between activity and health risk factors, albeit with caution.

Keywords: Movement; Youth; Objectively-measured; Device-based; Accelerometry; Mean Amplitude Deviation.

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1. Introduction

Regular participation in physical activity has been shown to be beneficial for children's health (Poitras et al., 2016). Benefits include higher cardiorespiratory and muscular fitness, and lower body mass index (BMI) (Poitras et al., 2016). In contrast, excessive sedentary time, and in particular screen time, has been associated with health markers in children, such as unfavourable body composition and lower fitness (Carson et al., 2016). The current Australian 24-hour movement guidelines state that children should accumulate 60 minutes or more of moderate- to vigorous-intensity physical activity (MVPA) per day and spend two hours or less engaged in recreational screen time (Department of Health, 2019). Nevertheless, according to population-based survey data only 7.7% and 8.6% of 9-11 year-old girls and boys in Australia, respectively, are meeting both these physical activity and screen-based activity recommendations (Australian Bureau of Statistics, 2013). It is noted that movement behaviours can be measured using an array of devices (e.g. inclinometers, accelerometers; heart rate monitors) and quantified using different techniques (e.g., intensity cut-points; time sampling intervals), which may lead to different estimates of times spent being active and/or sedentary (Rowlands & Eston, 2007). It is important to accurately assess children's physical activity and sedentary behaviour levels, and their associations with health outcomes, to obtain optimal information that can be used to design intervention programs and health promotion efforts that target the low prevalence of meeting these guidelines.

Accelerometry is the most commonly applied method for the device-based assessment of physical activity and sedentary time (i.e., little to no movement) in children (Ward, Evenson, Vaughn, Rodgers, & Troiano, 2005). In particular, the ActiGraph device (Pensacola, FL, USA) has been extensively used for monitoring as it has been shown to be strongly correlated with energy expenditure derived from doubly-labelled water (Plasqui & Westerterp, 2007). It has also demonstrated good validity and inter-instrument reliability for assessing activity levels in paediatric populations (Trost, McIver, & Pate, 2005). To date, most of the research that has used ActiGraph devices to classify physical activity (ranging from light- [LPA] to moderate- [MPA] to vigorous- [VPA]) and sedentary time (defined as little to no movement) in children have applied the proprietary count-based data reduction method provided by the manufacturer (Poitras et al., 2016).

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Traditionally, this was warranted as older model devices with limited storage capacities stored only the summary measures ("counts") of the raw acceleration signals in pre-specified units of time (epochs) (van Hees, Pias, Taherian, Ekelund, & Brage, 2010). Validated count-based cut-points (e.g., (Evenson, Catellier, Gill, Ondrak, & McMurray, 2008)) were then applied to classify the epochs as a specific intensity of sedentary time or physical activity, such as MVPA. However, other manufacturers have entered the market, and the algorithms behind proprietary counts vary by accelerometer brand and model, which limits the direct comparison of studies using different devices (Aittasalo et al., 2015). In addition, these count-based cut-points have been found to incorrectly classify up to 68% of physical activity intensities among children, as these are affected by a combination of processing error and calibration error (Fridolfsson et al., 2019), which may impact accuracy in determining the relation between movement behaviours and health (Trost, Loprinzi, Moore, & Pfeiffer, 2011). As a result, researchers highlighted the need to be provided with access to raw acceleration data for analysis (Trost et al., 2005), however, it is still uncertain as to whether these methods provide more accurate estimates of movement behaviours.

Newer models of accelerometers with larger storage capacities, offering feasible access to prolonged recordings of raw tri-axial acceleration data have appeared on the market. Raw data refers to data sampled several times per second (e.g., 100 samples per seconds), that was previously summarised in epochs. The samples are expressed in m/s^2 or gravitational acceleration, and are the actual direct measure of physical acceleration and deceleration digitised by the accelerometer (van Hees et al., 2010). As a consequence, raw acceleration-based data reduction techniques have been developed, such as the mean amplitude deviation (MAD; (Aittasalo et al., 2015)), that provide new opportunities to examine physical activity, sedentary time and their associations with health outcomes (John & Freedson, 2012). MAD is calculated from the resultant of the three orthogonal accelerations, per epoch of interest, and it describes the mean variation of the dynamic acceleration component around the static component (Leinonen et al., 2016). Previous research in middle-aged adults has shown that compared to proprietary count-based data reduction, MAD data reduction underestimates free-living light-intensity physical activity (LPA) but overestimates MVPA (Leinonen et al., 2016). However, systematic explorations of the potential impact of the chosen data reduction method on estimated times in different intensities, and particularly associations with health outcomes (e.g.,

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fitness and adiposity) remain scarce.

No previous studies have compared estimates of movement behaviours derived from count- and MAD-based data reduction methods among children. It is possible that differences in estimates using different techniques may impact associations with health risk factors (Leinonen et al., 2016). Exploring movement behaviours derived from different techniques may help to increase understanding of the associations between movement behaviours, assessed using valid and reliable devices, and health risk factors, and provide insights into which techniques may be most sensitive for detecting potential associations. This in turn can inform future studies that compare or combine data obtained using different data reduction methods (Leinonen et al., 2016). Therefore, the aim of this study was to compare estimations of sedentary time and time spent in LPA, moderate- (MPA), MVPA, and vigorous-intensity physical activity (VPA) based on proprietary count- and MAD-based data reduction methods, and to compare associations between these estimates and adiposity and fitness markers, in primary school-aged children.

2. Material and methods

2.1 Study sample

Data for this study were drawn from the Fitness, Activity and Skills Testing (FAST) Study (data collected between July-November 2014; (Ridgers et al., 2018)). Catholic primary schools (n=68) within 30km of the Deakin University Burwood campus in Melbourne, Australia were randomly selected and invited to participate in the FAST Study. Six school principals (9% response rate) provided informed written consent and agreed for their schools to take part. All schools were located in high socioeconomic status (SES) areas based on the Socio-Economic Index for Areas (Australian Bureau of Statistics, 2011). All students in Year 4 and 5 (aged 8-11 years; n=458) at consenting schools were invited to take part in the study. Informed written consent to participate in the primary outcome assessments, which included accelerometry, a survey, and cardiorespiratory and musculoskeletal fitness, was returned by 138 children (51% girls; 30% response rate). The target sample size for the original outcomes paper study was determined as 120 using a sample size

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calculation (Ridgers et al., 2018). Ethical approvals were obtained from Deakin University Human Ethics Advisory Group (HEAG-H 19_2014) and the Catholic Education Office Archdiocese of Melbourne (Project #1998) (Ridgers et al., 2018).

2.2 Procedure

Demographic information, such as age and sex, was reported by the child's main carer in a short survey at the time of consent. Schools were visited by trained research staff on two different occasions. During the first visit, participants were provided with a GT3X+ ActiGraph accelerometer to wear on their right hip for eight consecutive days (except during sleep and contact- or water-based activities) and anthropometry data were collected. During the second visit, children returned the accelerometers, and completed fitness tests in the school gym during class time.

2.3 Health markers

Adiposity markers

Stature and body mass were measured using the SECA portable stadiometer (model 217; SECA, Germany) and Tanita calibrated electronic scale (BC-351; Tanita, Japan), respectively. For both stature and body mass, two measurements were taken and, if there was a difference of ≥0.1cm for stature or ≥0.1kg body mass, a third measurement was taken and the mean of the two nearest measurements was recorded. BMI (kg/m^2) was calculated and converted to BMI z-scores using the age- and sex-standardized World Health Organization growth standards (WHO Multicentre Growth Reference Study Group, 2006). In addition, two measures of waist circumference (cm) were taken, using a flexible steel tape, at the narrowest point between the bottom rib and the iliac crest in the mid-axillary plane. If a discrepancy of ≥1cm was detected, a third measure was taken and the average of the two closest measures was recorded instead. Trained research staff took all measures using standardised practices (Marfell-Jones, Stewart, & De Ridder, 2012).

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Cardiorespiratory and musculoskeletal fitness

Cardiorespiratory fitness was assessed using the multi-stage 20-m shuttle run test using standardised testing protocols (Institute of Medicine, 2012). Participants were required to pace themselves in time to recorded beeps. The time between beeps decreased as the test advanced, meaning that participants were required to increase their speed. The test finished when a child was unable to keep up with the pace of the beeps. The total number of shuttles successfully completed was recorded for use in the analyses. Previous research has shown that this test is strongly associated (R^2 = 0.89) with maximal oxygen uptake in children (Pitetti, Fernhall, & Figoni, 2002) and is the most feasible and appropriate field-based measure of cardiorespiratory fitness (Lang et al., 2018).

Musculoskeletal fitness was assessed using two different sub-tests: 1) handgrip test (upper body) (Fernandez Santos, Ruiz, Gonzalez-Montesinos, & Castro-Pinero, 2016), and; 2) standing long jump (lower body) (Castro-Piñero et al., 2010). The handgrip test involved participants squeezing a dynamometer as hard and as fast as possible, for at least three seconds. Participants were instructed to maintain the elbow in full extension, with the arm straight down one side of the body (Fernandez Santos et al., 2016). Six trials were performed, with children alternating hands after each trial. The observed peak value (kg) with the dominant hand was then divided by their body mass to standardize this value for use in analysis. This test is strongly associated with a 1-repetition maximum bench press (R = 0.79) (Fernandez Santos et al., 2016), an indicator of upper body strength. The standing long jump required children to stand with both feet parallel behind a marked line and jump, with both feet simultaneously, as far as possible (Castro-Piñero et al., 2010). The longest distance from two attempts, measured from the marked line to the landing position (back of the heel), was used in the analyses (Castro-Piñero et al., 2010). This test is reliable (ICC = 0.99) and is strongly associated (R2 = 0.829 - 0.864) with other measures of lower body strength (Castro-Piñero et al., 2010).

2.4 Accelerometer data reduction

For the purpose of this study, GT3X+ ActiGraph accelerometry data were reduced using count- and MAD-based data reduction methods. ActiGraph data were sampled at 30 Hz and the

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normal filter was selected. Cut-offs to determine non-wear time (i.e., 20 minutes of minimal to no movement) were in accordance with their use in published literature specifically for each method and are described below in turn. For both approaches, only the wear time between 6.00am and 10.00pm was analysed. This decision was made to improve consistency across methods. As these vary slightly for each data reduction technique, these are described below in turn. Valid days were defined as those with ≥8 hours of wear time per day (Cain, Sallis, Conway, Van Dyck, & Calhoon, 2013). To be included in the analyses, children were required to have a minimum of four valid days as this has been shown to as this has been shown to indicate habitual physical activity with a minimum between-day intraclass reliability coefficient of r = 0.80 in this age group (Trost, Pate, Freedson, Sallis, & Taylor, 2000).

Proprietary count-based data reduction

Vertical axis data from the accelerometer were downloaded in 5-s epochs using ActiLife software (v.6.11.; ActiGraph, Pensacola, FL) and processed using a customised Excel macro. Non-wear during waking hours was defined as continuous bouts of consecutive 0 counts of at least 20 minutes (Cain et al., 2013). The 5-s epoch was used as longer bouts can underestimate sedentary behaviour and activity at higher intensities, due to the sporadic nature of children's activity (Baquet, Stratton, van Praagh, & Berthoin, 2007). Count-based cut-points of 0-99, 100–2295, 2296–4011, and ≥4012, developed by Evenson and colleagues (Evenson et al., 2008), were modified to 5-sec equivalents and used to calculate the total time spent sedentary and in LPA, MPA, and VPA, respectively, per day. These cut-points were developed in a laboratory study that showed that these can be used to distinguish differing levels of physical activity intensity as well as sedentary time in children (Evenson et al., 2008). Total time in MPA and VPA was summed to obtain MVPA. The proportion of total wear time that children spent sedentary and in LPA, MPA, and VPA per day was also calculated for descriptive purposes.

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Open source MAD-based data reduction

The raw acceleration data (stored in .gt3x format) were downloaded using ActiLife software (v.6.11.; ActiGraph, Pensacola, FL). Custom-made Java and Matlab scripts (R2018a, Mathworks, Inc., Natick, MA, USA) were used to firstly auto-calibrate the acceleration data, following the approach developed by van Hees and colleagues (Van Hees et al., 2014), with the modification of not utilising weights in the optimisation of calibration coefficients (https://github.com/tjrantal/accelerometer-auto-calibration). Our pilot experimentation indicated that marked overfitting may occur if utilising the weights. The calibration was applied on the sampled accelerations and MADs were calculated for non-overlapping 5-s epochs based on the calibrated resultant acceleration signal (Vaha-Ypya, Vasankari, Husu, Suni, & Sievanen, 2015). The auto calibration had minimal, if any, effect on the results. A visualisation of the (very small) calibration coefficients and offsets is provided in the Appendices Figure S1. Consequently, we ran the analyses only on the calibrated values.

Non-wear during waking hours was defined as any continuous bout of 20 minutes or longer with all MAD values less than 0.0042 g. The non-wear threshold was chosen based on pilot experimentation and is close to measurement noise. A value of 0 was then assigned to any epochs falling into non-wear time. MAD intensity cut-points for sedentary (<0. 0167 g), LPA (0. 0167 to <0.091 g), MPA (0.091 to <0.414 g), and VPA (≥0.414 g) were used to divide the data into total time spent in each category (Vaha-Ypya, Vasankari, Husu, Suni, et al., 2015). These intensity cut-offs were based on laboratory-setting research, which identified them as being the optimal classification between sedentary behaviours and slow walking (LPA; (Vaha-Ypya, Vasankari, Husu, Suni, et al., 2015)), and corresponding with 3.0 METs (MPA) and 6.0 METs (VPA; (Vaha-Ypya, Vasankari, Husu, Manttari, et al., 2015)) in adults. Time spent in MVPA and proportions of time spent in each intensity were also calculated.

2.5 Statistical analyses

Stata v16 (StataCorp, College Station, TX, USA) was used to perform statistical analyses. Significance was set at $\alpha = 0.05$ for all analysis. Descriptive analyses (mean and standard deviations)

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were calculated for each variable. Initial multilevel model analyses (using the 'xtmixed' command) were used to make comparisons between absolute and proportional (to the wear time) estimations of sedentary time and time spent in LPA, MPA, VPA and MVPA using proprietary- and MAD-based data reduction methods, whilst accounting for clustering within schools and individuals.

Linear regression models were used to investigate associations between proprietary- and MAD-based accelerometry exposure variables (minutes per day) with health outcomes, including adiposity, musculoskeletal and cardiorespiratory fitness. With the exception of BMI-z score, all health outcomes were standardised to a mean of zero and a standard deviation of one to enable comparisons of the magnitude of the associations. Assumption testing was conducted for linearity, normality of residuals, homogeneity of variance and multi-collinearity; all assumptions were met and variables were normally distributed. Regression models accounted for school-level clustering and were adjusted for decimal age, sex, and monitor wear time. Obtained β-coefficients and 95% confidence intervals (CIs) of the proprietary- and MAD-based data reduction methods were calculated and initially compared in size (as an indicator of strength) and direction. In addition, 84% CIs were calculated and if these did not overlap across data reduction methods, a significant difference (approximating $\alpha = 0.05$) was assumed between findings based on the two different methods (Afshartous & Preston, 2010; Julious, 2004).

3. Results

3.1 Participant characteristics

Complete data, including valid accelerometry, health outcomes and covariate data, were collected from 118 children (58 girls; 86% of sample). No significant differences were observed between children included in analyses versus those excluded. Table 1 shows the descriptive characteristics, including covariates and health outcomes, reported for the overall included sample and by sex. Table 2 presents descriptive statistics for the accelerometry variables derived using each data reduction method for complete cases.

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On average, children were just over 10 years old and just under half of the sample were girls (49%). Boys had 0.4 kg/m^2 lower mean BMI, greater cardiorespiratory fitness (approximately 24 more shuttles), and a greater standing long jump (approximately 13 cm further) than girls.

3.2 Estimations of free-living sedentary and physical activity time

Significant differences were observed between the count-based and MAD-based data reduction approaches for all activity intensity variables when calculated absolutely and proportional to the wear time but not for wear time estimates (Table 2). Overall, participants spent on average 68% of their day sedentary, and 24% and 9% in LPA and MVPA, respectively, when data were reduced using the count-based technique. In comparison, the mean proportions of wear time spent in sedentary, LPA and MVPA were 59%, 25% and 16%, on average, when using the open source MAD-based data reduction approach (Table 2).

3.3 Associations of sedentary time and physical activity with adiposity and fitness markers

Table 3 shows the results from the regression models using the standardized adiposity and fitness markers. The results from regression models using the unstandardized variables can be found in the Appendices Table S1.

Adiposity markers

Table 3 shows the that higher levels of VPA were associated with lower (i.e., a favourable significant [$p<0.05$] negative β-coefficient) BMI z-scores and waist circumference, for the MAD-based data reduction method only. In addition, detrimental associations for sedentary time, and beneficial associations for LPA, MPA and MVPA, with waist circumference were observed for both data reduction methods.

Fitness markers

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Table 3 shows that higher sedentary time was associated with poorer 20m shuttle run and long jump performances, when obtained with the proprietary data reduction method only. Time spent in MPA, MVPA and VPA were beneficially associated with all fitness markers when obtained with the proprietary data reduction method. In contrast, when obtained with the MAD-based data reduction method, beneficial associations were only observed for MVPA and VPA and all fitness markers.

Comparisons between proprietary count- versus MAD-based estimates

Overall, the observed β-coefficients and 95% CIs for the two methods were mostly comparable in the number of significant associations and in terms of their size (as an indicator as the strength of association) and direction. The 84% CIs for the two different methods overlapped for all tested associations, except for MPA, VPA and MVPA and shuttle run scores (e.g., MVPA proprietary count-based β-coefficients [84% CIs]: 0.0216 [0.0192, 0.0239] versus MAD-based: 0.0099 [0.0050, 0.0148]).

4. Discussion

4.1 Estimations of free-living sedentary and physical activity time

This study compared estimations of free-living sedentary time and time spent in LPA, MPA, VPA, and MVPA using proprietary count- and MAD-based data reduction methods. In addition, associations with adiposity and fitness markers in primary school-aged children using the different data reduction methods were examined. Significant differences were observed between the different data reduction methods for time spent sedentary and all physical activity intensities but not for wear time. Using the count-based method, children spent significantly more time SED and in VPA, and less time in LPA, MPA and MVPA than the MAD-based method. Interestingly, while the direction of the associations observed between SED time and physical activity with adiposity and fitness markers were generally consistent between the count-based and MAD-based data reduction methods, the strength of the associations differed depending on the method used. However, based on no

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overlapping CIs, the only observed significant difference was for cardiorespiratory fitness. Specifically, a stronger association was observed with MPA, VPA and MVPA estimated using count-based data reduction methods, compared to the MAD-based data. These findings suggest that different data reduction methods may influence estimations of children's activity levels, though it may be possible to pool studies using different methods when assessing associations with health outcomes.

The results found that using different data reduction methods impacted the estimation of time spent in all activity intensities across the activity spectrum. These differences were particularly evident for MPA, with MAD-based data reduction approaches resulting in almost a threefold estimate of the percentage of time spent in that intensity (~14% of waking hours) compared to count-based data reduction approaches (~5%). Interestingly, differences in time spent in LPA were observed, despite the similarities in the proportion of time spent engaged in LPA (24% and 25%, respectively). The difference between estimates of MVPA between the two data reduction methods appear to largely be driven by differences in estimated MPA, which equated to 69.8 minutes per day. This finding is consistent with previous research by Leinonen and colleagues, albeit in middle-aged adults, who also found higher MVPA levels when using MAD reduced accelerometry data (Leinonen et al., 2016). However, the difference was counteracted by a lower observed free-living LPA in Leinonen and colleagues' study (Leinonen et al., 2016), rather than the observed difference in SED time in the present study. Future research needs to show whether this is caused by actual different behaviours in these age groups (e.g., children versus adults) or may have been caused by different decisions with regards to data processing (e.g, Freedson (Freedson, Pober, & Janz, 2005) versus Evenson (Evenson et al., 2008) cut-points).

Several recent works (Brønd et al., 2019; Brønd, Andersen, & Arvidsson, 2017; Fridolfsson et al., 2019) delineated the impact of processing settings for the propriety ActiGraph count-based method, such as frequency filtering and calibration, which may lead to classification discrepancies that could explain the differences in estimations observed. As the count-based data reduction method is a more processed measure, it is expected that this has a different (i.e., non-linear) relationship with the specific physical activity intensities (Brønd et al., 2019), compared to the raw MAD-based data reduction with a more linear relation (Fridolfsson et al., 2019). For example, Fridolfsson and

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colleagues (Fridolfsson et al., 2019) showed that classification discrepancy caused by frequency filtering was largest at the highest intensities (>MPA), which could explain the large differences observed in the current study for MPA and MVPA. Overall, our findings and that of others (Brønd et al., 2017; Fridolfsson et al., 2019) suggest that the count-based and MAD-based methods may not be comparable when estimating children's daily sedentary time and physical activity. Future studies in children that aim to compare and/or pool data from these different methods should take this into consideration.

4.2 Associations of sedentary time and physical activity with adiposity and fitness markers

The present study investigated associations of free-living SED time and physical activity with adiposity and fitness markers using the two different data reduction methods. Overall, the observed β-coefficients for associations with adiposity and fitness markers were similar in terms of size and direction for the two data reduction methods. The overlapping 95% CIs suggested that there were few differences in findings between the two methods, apart from the association between MVPA and cardiorespiratory fitness, where a significant difference was observed. Both methods produced evidence to suggest that sedentary behaviour was detrimentally and significantly associated with waist circumference, but not with BMI z-score. Although emerging evidence shows similar associations between sedentary time and adiposity outcomes in children, this is not consistent with previous reviews that have summarized the evidence on associations between device-based measures of sedentary time and adiposity and were unable to identify this association in current literature (Carson et al., 2016; Cliff et al., 2016).

Both methods showed that LPA, MPA and MVPA were beneficially associated with waist circumference. Additionally, MAD-based VPA was beneficially associated with BMI z-score and waist circumference. This was not observed while using the count-based approach even though the lower intensities (LPA, MPA and MVPA) were associated with waist circumference in this method also. This is somewhat contrasts previous research that has indicated that favourable associations are typically observed for higher (e.g. VPA) compared to lower intensities (e.g. LPA) (Parikh & Stratton,

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2011; Poitras et al., 2016), though acknowledging that these studies mostly focus on combined MVPA rather than assessing VPA individually.

MVPA and VPA were beneficially and significantly associated with fitness markers using both data reduction measures. Both methods showed larger observed β-coefficients (i.e., stronger associations) for VPA compared to MVPA (e.g., for MAD, $\beta=0.04$ for VPA vs $\beta=0.01$ for MVPA). This was observed across most outcomes, regardless of the data reduction method used. Previous research has shown consistent associations between MVPA and VPA and cardiorespiratory fitness (Parikh & Stratton, 2011; Poitras et al., 2016), though associations with musculoskeletal fitness have been mixed (Owens, Galloway, & Gutin, 2017).

The only notable difference between methods in observed associations with fitness markers was for MPA, which were only significant when using the count-based data reduction approach and not the MAD-based data reduction approach. It is unclear why this was observed given the greater engagement in MPA found when using the count-based as opposed to the MAD-based data reduction approach. The only observed difference between associations between health outcomes and activity intensity was for cardiorespiratory fitness. A stronger association (i.e., larger β-coefficient) was observed with MVPA estimated using count-based data reduction methods, despite the lower engagement in MVPA identified using this method. It is possible that this may be attributable to, in part, the proportion of time that VPA accounted for in the MVPA estimate when derived using the count-based method (~45% compared to ~15%). This requires further research. Overall, while the need to use raw acceleration data instead of proprietary activity counts for measuring the intensity of physical activity has been expressed previously (Aittasalo et al., 2015; Trost et al., 2011), these results suggest that results obtained with both methods are fairly comparable, and the overall conclusion drawn from the study would have remained the same independent of the method used.

4.3 Study limitations

This study has several limitations which should be considered. There are several different acceleration-based techniques and cut-points currently being used by researchers (Aittasalo et al.,

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2015; de Almeida Mendes et al., 2018; Freedson et al., 2005). This study used the Evenson cut-points (Evenson et al., 2008), which have been shown to have acceptable classification accuracy for activity across the activity spectrum. However, it is noted that the cut-points were adapted for 5-sec epochs, and it is unclear whether this is a valid way to analyse data given the non-linear response that counts have to intensities of physical activity (Brønd et al., 2019). In addition, the MAD cut-points were developed in adults and may not be directly applicable in children, which may have led to a measurement error. Comparisons with studies using other MAD cut-points (e.g., (Aittasalo et al., 2015); 0.0269g for LPA) are warranted. Moreover, the comparability of MADs to a range of proprietary count-based techniques and with other methods, such as the Euclidian norm minus one and high pass filter vector magnitude, should be further explored. This will provide valuable insights concerning the impact of choosing these different methods in determining the relation between movement behaviours and outcomes of interest. A second limitation is the potential inability to accurately differentiate between sedentary time and LPA using ActiGraph accelerometers (Cliff et al., 2016), which may have influenced the apparent associations with health outcomes. The present study used the normal ActiGraph filter, however, the low frequency filter could be selected to extend the sensitivity to lower intensity activity. There is a need to replicate this study using data collected using posture-based devices and/or using ActiGraph models with the low frequency extension filter. Thirdly, this study recruited a relatively small sample of primary school-aged children. Whilst the target sample size of 120 participants for the original outcomes paper was met (Ridgers et al., 2018), only 9% of contacted schools participated and the active consent may have reduced the numbers of participants in the study. Due to the small number of participants, sex and age differences in activity levels and associations with health outcomes using the different data reduction methods were not explored. Future studies should examine whether similar observations are found in different population sub-groups. Lastly, this study utilised ActiGraph accelerometers worn on the hip. With the increased use of wrist-worn accelerometers (Rowlands et al., 2014), future studies should examine whether similar findings are observed when using different accelerometer placements.

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4.4 Conclusion

The present study provides a comprehensive comparison between proprietary (count) and open source MAD-based data reduction methods in children. Findings suggest that the estimates of sedentary time and physical activity were significantly different between the two methods used. Future studies that compare estimates of daily sedentary time and physical activity of different intensities should note that these may not be comparable. However, the strength and direction of the associations obtained between the different data reduction methods and adiposity and fitness outcomes were fairly comparable, with both methods finding stronger associations for VPA compared to MVPA. However, as stronger and more significant associations were observed for the count-based versus the MAD-based data reduction approach, comparisons of these techniques with free-living studies in children is needed to inform guidance on whether to pool data from studies using these different techniques.

5. Perspective

Utilizing and comparing movement behaviours derived from different techniques may help to increase the understanding of the associations between movement behaviours and health risk factors, and provide insights into which techniques may be most sensitive for detecting potential associations. No previous studies have compared estimates of movement behaviours derived from count- and MAD-based data reduction methods and associations with health among children. Therefore, the aim of this study was to compare estimations of sedentary time and time spent in a range of physical activity intensities based on proprietary count- and MAD-based data reduction methods, and to compare associations between these estimates and adiposity and fitness markers, in primary school-aged children. Findings suggest that the estimates of sedentary time and physical activity were significantly different between the two methods used. Future studies that compare estimates of daily sedentary time and physical activity of different intensities should note that these may not be comparable. The strength and direction of the associations obtained between the different data reduction methods and adiposity and fitness outcomes were fairly comparable, with both methods

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finding stronger associations for VPA compared to MVPA. However, as stronger and more significant associations were observed for the count-based versus the MAD-based method, merging data obtained with different data reduction methods should be done carefully. This study contributes to the evidence base informing accurate assessment of children's physical activity and sedentary behaviour levels, and their associations with health outcomes. Future studies may progress this exploration by investigating which MAD-values correspond to the count-based cut points – and vice versa – and describing the cut-points variance between the participants. This has the potential to inform future studies that could contribute to movement behaviour guidelines, which in turn may inform the development and evaluation of intervention programs.

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Table 1. Participants characteristics (included sample: n=118)

	Girls (n=58)	Boys (n=60)	Total (n=118)
	Mean **±** ***SD***	***Mean*** **±** ***SD***	***Mean*** **±** ***SD***
Age (y)	10.3 ± 0.6	10.6 ± 0.6	10.4 ± 0.6
Height (cm)	141.0 ± 8.5	143.5 ± 6.0	142.3 ± 7.4
Body mass (kg)	36.3 ± 8.2	36.5 ± 6.6	36.4 ± 7.4
BMI	18.0 ± 2.5	17.6 ± 2.5	17.8 ± 2.5
BMI z-score	0.5 ± 0.9	0.4 ± 1.1	0.5 ± 1.0
BMI (% NW/OW/OB)	66/29/5	70/18/12	68/24/8
Waist circumference (cm)	65.8 ± 8.0	65.8 ± 8.0	65.8 ± 8.0
20m shuttle run (shuttles)	35.4 ± 16.7	59.1 ± 24.2	47.4 ± 23.9
Handgrip (kg)	16.9 ± 4.7	19.2 ± 3.6	18.0 ± 4.3
Handgrip/Weight	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1
Standing long jump (cm)	129.6 ± 20.1	142.1 ± 21.4	135.9 ± 21.6

Abbreviations: BMI Body mass index; NW Normal weight; OW Overweight; OB Obese

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Table 2: Sedentary and physical activity time (mins/day) using different data reduction methods (n=118)

	Count-based data reduction		**MAD-based data reduction**		**Difference in absolute values**	**Difference in proportional values**
	Mean ± SD (mean %)		***Mean ± SD (mean %)***		***p-value***	***p-value***
SED (min/day)	509.3 ± 60.1**	(67.6)	451.5 ± 63.3**	(58.9)	<0.0001	<0.0001
LPA (min/day)	177.8 ± 29.1**	(23.6)	189.0 ± 30.8**	(24.6)	0.0005	0.0053
MPA (min/day)	36.7 ± 9.7**	(4.9)	106.5 ± 22.0**	(13.9)	<0.0001	<0.0001
VPA (min/day)	29.5 ± 11.3**	(3.9)	19.3 ± 8.5**	(2.5)	<0.0001	<0.0001
MVPA (min/day)	66.2 ± 19.5**	(8.8)	125.8 ± 27.6**	(16.4)	<0.0001	<0.0001
Wear time (min/day)	753.3 ± 59.6		766.3 ± 63.6		0.0918	N/A

** Indicates significance at $p \leq 0.01$ for both absolute and proportional (to the weartime) values

Abbreviations: SED Sedentary time; LPA Light-intensity physical activity; MPA Moderate-intensity physical activity; VPA = Vigorous-intensity physical activity; MVPA Moderate- to vigorous-intensity physical activity; N/A: Non Applicable.

Initial multilevel model analyses (using the 'xtmixed' command) were used to make comparisons between absolute and relative (to the wear time) estimations of sedentary time and time spent in LPA, MPA, VPA and MVPA using proprietary- and MAD-based data reduction methods, whilst accounting for clustering within schools and individuals.

Mean %: Proportion of the wear time.

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Table 3: Associations of time (min/day) spent in activity intensity and standardized adiposity and fitness markers with proprietary- and MAD-based data reduction methods (n=118)

	Count-based approach *β-coefficient (95% CI) [84%CI]*	**MAD-based approach** *β-coefficient (95% CI) [84%CI]*
	BMI z-score	
SED	0.0009 (-0.0051, 0.0068) [-0.0030, 0.0047]	0.0031 (-0.0019, 0.0082) [-0.0001, 0.0064]
LPA	0.0023 (-0.0049, 0.0095) [-0.0023, 0.0069]	-0.0042 (-0.0140, 0.0055) [-0.0105, 0.0020]
MPA	-0.0013 (-0.0167, 0.0140) [-0.0112, 0.0085]	-0.0021 (-0.0096, 0.0053) [-0.0069, 0.0026]
MVPA	-0.0086 (-0.0224, 0.0052) [-0.0175, 0.0002]	-0.0051 (-0.0109, 0.0008) [-0.0088-, 0.0013]
VPA	-0.0238 (-0.0585, 0.0110) [-0.0461-, 0.0015]	-0.0365 (-0.0540, -0.0190)** [-0.0477-, 0.0252]
	Waist circumference	
SED	0.0070 (0.0024, 0.0117)* [0.0041, 0.0100]	0.0085 (0.0041, 0.0129)** [0.0057, 0.0113]
LPA	-0.0066 (-0.0124, -0.0008)* [-0.0103-, 0.0028]	-0.0129 (-0.0224, -0.0033)* [-0.0190-, 0.0068]
MPA	-0.0243 (-0.0451, -0.0035)* [-0.0376-, 0.0109]	-0.0122 (-0.0201, -0.0044)* [-0.0173-, 0.0072]
MVPA	-0.0163 (-0.0317, -0.0009)* [-0.0262-, 0.0064]	-0.0121 (-0.0182, -0.0061)** [-0.0160-, 0.0082]
VPA	-0.0292 (-0.0670, 0.0087) [-0.0535-, 0.0049]	-0.0403 (-0.0645, -0.0161)** [-0.0558-, 0.0248]

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	20m shuttle run	
SED	-0.0053 (-0.0067, -0.0039)** [-0.0062-, 0.0044]	-0.0034 (-0.0068, 0.0000) [-0.0055-, 0.0012]
LPA	0.0004 (-0.0033, 0.0042) [-0.0020, 0.0029]	0.0010 (-0.0034, 0.0053) [-0.0018, 0.0038]
MPA	0.0303 (0.0067, 0.0538)* [0.0152, 0.0454]†	0.0057 (-0.0061, 0.0175) [-0.0018, 0.0133]†
MVPA	0.0216 (0.0179, 0.0253)** [0.0192, 0.0239]†	0.0099 (0.0023, 0.0175)* [0.0050, 0.0148]†
VPA	0.0400 (0.0293, 0.0507)** [0.0332, 0.0469]†	0.0607 (0.0401, 0.0813)** [0.0475, 0.0739]†
	Handgrip (divided by weight)	
SED	-0.0039 (-0.0089, 0.0011) [-0.0071-, 0.0007]	-0.0036 (-0.0100, 0.0028) [-0.0077, 0.0005]
LPA	0.0009 (-0.0079, 0.0098) [-0.0047, 0.0066]	0.0024 (-0.0095, 0.0143) [-0.0052, 0.0100]
MPA	0.0240 (0.0075, 0.0405)* [0.0134, 0.0346]	0.0088 (-0.0048, 0.0225) [0.0001, 0.0176]
MVPA	0.0148 (0.0090, 0.0206)** [0.0111, 0.0185]	0.0089 (0.0000, 0.0178) [0.0032, 0.0146]
VPA	0.0250 (0.0113, 0.0388)** [0.0162, 0.0338]	0.0306 (0.0114, 0.0497)** [0.0183, 0.0428]
	Standing long jump	
SED	-0.0064 (-0.0108, -0.0021)* [-0.0092-, 0.0036]	-0.0051 (-0.0107, 0.0005) [-0.0087-, 0.0015]
LPA	0.0034 (-0.0020, 0.0087) [-0.0001, 0.0068]	0.0047 (-0.0052, 0.0147) [-0.0016, 0.0111]
MPA	0.0301 (0.0030, 0.0573)* [0.0127, 0.0475]	0.0102 (-0.0039, 0.0242) [0.0012, 0.0192]
MVPA	0.0205 (0.0114, 0.0296)** [0.0146, 0.0263]	0.0110 (0.0003, 0.0217)* [0.0041, 0.0179]
VPA	0.0369 (0.0277, 0.0461)** [0.0310, 0.0428]	0.0427 (0.0168, 0.0685)** [0.0261, 0.0593]

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* Indicates significance at $p \leq 0.05$. ** Indicates significance at $p \leq 0.01$.

† Indicates that 84% CIs of count- and acceleration-based data reduction methods do not overlap. In that case, a significant difference ($\alpha = 0.05$) was assumed between findings based on the two different methods (Afshartous & Preston, 2010; Julious, 2004).

CI = confidence interval; SED = sedentary time; LPA = Light-intensity physical activity; MPA = Moderate-intensity physical activity; MVPA = Moderate- to vigorous-intensity physical activity; VPA = Vigorous-intensity physical activity.

Regression models accounted for school-level clustering and were adjusted for decimal age, sex, and monitor wear time.
BMI (kg/m^2) was converted to BMI z-scores using the age- and sex-standardized World Health Organization growth standards (WHO Multicentre Growth Reference Study Group, 2006).

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