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Effect of Sampling Rate on Acceleration and Counts of Hip- and Wrist-Worn ActiGraph Accelerometers in Children

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Abstract

Sampling rate (Hz) of ActiGraph accelerometers may affect processing of acceleration to activity counts when using a hip-worn monitor, but research is needed to quantify if sampling rate affects actual acceleration (mg's), when using wrist-worn accelerometers and during non-locomotive activities. **Objective**: To assess the effect of ActiGraph sampling rate on total counts/15-sec and mean acceleration and to compare differences due to sampling rate between accelerometer wear locations and across different types of activities. **Approach**: Children (n=29) wore a hip- and wrist-worn accelerometer (sampled at 100 Hz, downsampled in MATLAB to 30 Hz) during rest/transition periods, active video games, and a treadmill test to volitional exhaustion. Mean acceleration and counts/15-sec were computed for each axis and as vector magnitude. **Main Results**: There were mostly no significant differences in mean acceleration. However, 100 Hz data resulted in significantly more total counts/15-sec (mean bias 4-43 counts/15-sec across axes) for both the hip- and wrist-worn monitor when compared to 30 Hz data. Absolute differences increased with activity intensity (hip: r=0.46-0.63; wrist: r=0.26-0.55) and were greater for hip- versus wrist-worn monitors. Percent agreement between 100 and 30 Hz data was high (97.4-99.7%) when cut-points or machine learning algorithms were used to classify activity intensity. **Significance**: Our findings support that sampling rate affects the generation of counts but adds that differences increase with intensity and when using hip-worn monitors. We recommend researchers be consistent and vigilantly report the sampling rate used, but note that classifying data into activity intensities resulted in agreement despite differences in sampling rate.

Key words: physical activity, monitor, intensity, measurement

Introduction

Accelerometry is widely used to measure physical activity in both adults and children, with ActiGraph (Pensacola, FL; formerly known as Computer Science and Applications Incorporated) being among the most popular research-grade accelerometers (1, 2). Historically, acceleration data collected by ActiGraph monitors were sampled at a rate of 10 or 30 Hz, then filtered and processed within the device using proprietary methods to save battery and storage capacity, and only the processed 'activity counts' were recorded and provided to researchers. These counts correspond to the degree of acceleration, with higher accelerations eliciting more activity counts (3). However, since the ActiGraph GT3X+ was released, researchers can select a sampling rate of up to 100 Hz and have had access to both the 'raw' acceleration data as well as the activity count data that has frequently been used to characterize activity intensity (4).

Although a recent review highlighted that the majority (64%) of studies using the ActiGraph in children and adolescents still use a sampling rate of 30 Hz, approximately 20% of studies did not report the sampling rate used and 15% used a sampling rate of 60, 80, or 100 Hz (5). Moreover, large-scale, national studies, including the National Health and Nutrition Examination Survey (NHANES) and the Family Life, Activity, Sun, Health, and Eating (FLASHE) study also deviated from the standard 30 Hz by sampling at 80 Hz (6, 7). Inconsistencies in, or lack of reporting of, sampling rates across studies (5) is problematic, given that Brønd and Arvidsson (8) recently reported that the sampling rate used for data collection in adults affected the processing of ActiGraph acceleration data to counts, particularly when signal frequency surpassed ~5 Hz and during higher intensity activities. For example, an additional 47 and 1,238 counts/min were recorded when using a 100 Hz sampling rate, in comparison to 30 Hz, during a slow walk and fast run, respectively.

No research has explored whether sampling rate impacts the acceleration data (in g's) recorded by ActiGraph monitors, but researchers have indicated that the 'raw' acceleration data from ActiGraph monitors may be processed/filtered and is not truly unaltered, raw data (8). It could therefore be postulated that sampling rate may affect the processing of these acceleration data, impacting metrics other than activity counts, such as mean acceleration. This would be particularly problematic for new analysis techniques, such as machine learning algorithms, many of which use features extracted from raw acceleration (as opposed to count) data to classify energy expenditure, activity type, and/or activity intensity (9, 10). Perhaps most importantly, it is not yet known whether differences in acceleration or counts due to sampling rate have a substantial impact on the classification of physical activity intensity, either using count-based cut-points, or machine learning algorithms using count or acceleration data. Determining the effect of sampling rate on count and acceleration data, and the impact on activity intensity classification, would facilitate the assessment of physical activity and comparisons between studies.

Brønd and Arvidsson (8) demonstrated the impact of the chosen sampling rate on activity counts, but the sample was comprised of adults and the protocol only included locomotive activities, thereby limiting generalizability to other types of activities (e.g., non-locomotive) or populations (e.g., youth). The frequency patterns of non-locomotive activities vary from those of locomotive activities and therefore the inclusion of both activity types is essential. Moreover, movement frequency also varies between children and adults, both during locomotion (11) and, potentially, during non-locomotive activities due to the sporadic and intermittent nature of children's behavior (12). Furthermore, it is important to consider that Brønd and Arvidsson (8) used two measurement devices (one next to the other) for the walk/run portion of their study, with one recording at 30 Hz, and the other at either 40 or 100 Hz (8). Whilst ActiGraph accelerometers have demonstrated acceptable inter-monitor reliability (13), monitor outputs are not identical (14, 15). Thus, the effect of sampling rate on acceleration and count data could be replicated using just one monitor, to eliminate small inter-monitor differences that may be present when wearing multiple monitors side-by-side.

Finally, Brønd and Arvidsson (8) used only a hip-worn monitor, therefore the impact of sampling rate when using other monitor placements remains to be elucidated. Wrist-worn accelerometers have risen in popularity due to the potential for increased wear compliance and 24-hour monitoring (5, 6). Moreover, wrist-worn monitors have been associated with higher acceleration and count values during more intense activities or those relying on more arm movement (16-18), so the impact of sampling rate may vary between hip- and wrist-worn monitors. Our overarching aim was to compare acceleration and counts of hip- and wrist-worn ActiGraph GT3X+ monitors using 100 versus 30 Hz sampling rates during multiple types of activities. Our specific purposes were to i) compare counts/15-sec and mean acceleration when using 100 and 30 Hz sampling rates; ii) identify the influence of monitor wear location (hip versus wrist) on differences according to sampling rate; iii) identify how differences by sampling rate change with activity intensity and during different types of activities; and iv) determine how differences in count and acceleration data due to differences in sampling rate affect the classification of activity intensity.

Methods

Ethical approval was granted by the local research ethics committee. Following informed written parent/guardian consent and child assent, 29 children (17 boys) aged 10.7 ± 1.2 years

(7.3 – 12.5 years) participated in this study. All children wore an ActiGraph GT3X+ (ActiGraph, Pensacola, FL) on the dorsal side of the left wrist between the styloid processes of the radius and ulna and at the right hip at the anterior axillary line, each affixed with self-adhering bandages to limit extraneous movement. The left wrist was chosen as this is the non-dominant wrist for the majority of the population (19) and the non-dominant wrist and right hip are commonly-used wear locations for accelerometers (5). The triaxial accelerometers were initialized using ActiLife software (version 6.13.3, firmware version 2.2.1, ActiGraph, Pensacola, FL, USA) to collect acceleration data at 100 Hz. Energy expenditure was measured using a portable metabolic unit (MetaMax 3B, Cortex, Biophysik, Leipzig, Germany), but these data are not used in the present analysis.

Children played two active video games (Kinect Adventures! River Rush and Reflex Ridge) that have been previously studied (20). Both games, which are non-locomotive, but involve full-body movement including jumping, squatting, reaching and lateral movements, were played in a randomized order on the Xbox Kinect system (Microsoft, Redmond, WA, USA) for 15 minutes each, with a break between games. Once rested, participants subsequently completed a graded treadmill exercise test to volitional exhaustion (locomotive activity). More detail about the protocol has been reported elsewhere, as this is a secondary data analysis (21). Data from the active video games, breaks between activities, and treadmill test were used in the present analysis.

Data Processing

Accelerometer data (collected at 100 Hz) were resampled to 30 Hz by converting the original .gt3x files to .wav files using Java software, which allowed for the retention of the original resolution and format of the data (Oracle Corp., Redwood Shores, CA, USA), then using the *resample* function available in MATLAB (MathWorks Inc., Natwick, MA, USA). Once resampled, the 30 Hz files were converted back to .gt3x files using the Java program. This method produces data that are in the same format as data sampled at 30 Hz, thus allowing the impact of sampling rate on monitor output using a single monitor to be assessed.

All subsequent processing steps were conducted separately for 100 and 30 Hz data and for hip- and wrist-worn accelerometers. Accelerometer data were downloaded in both raw form and in 1-sec epochs in ActiLife (version 6.13.3). Total counts in each axis and vector magnitude (VM_{counts}; square root of the sum of the squared counts in each axis) were calculated for 15-sec windows using Excel 2016 (Microsoft, Redmond, WA, USA). Counts represent filtered, rectified, and then summed acceleration data, which are calculated using a proprietary method in ActiLife. A 15-sec epoch was chosen as it was recommended in a recent review and because it is the most commonly-used epoch length in this age group (5). Epoch windows were prospective (e.g., 15:00:00 to 15:00:14 was a 15-sec epoch), as this correlates with 15-sec epoch data as exported directly from ActiLife. Mean and variance in acceleration (mg) in each axis, and vector magnitude for acceleration ($VM_{acceleration}$) was obtained in 15-sec epochs using the Feature Extraction tool in ActiLife. For exploratory purposes only (for comparison to Brønd and Arvidsson (8)), the dominant frequency of the y-axis from the 30 Hz wrist- and hip-worn monitors was also extracted in ActiLife.

For count data, each 15-sec epoch was classified into one of four categories: sedentary behavior, or light, moderate, or vigorous activity using cut-points published by Evenson et al. (hip) (22) and Chandler et al. (wrist) (23). VM_{counts} at the right hip were classified as one of three categories: sedentary, light, or moderate-to-vigorous, using cut-points developed by Hangii et al. (24). $VM_{acceleration}$ at the hip and wrist was not classified using cut-points due to lack of availability. In R (version 1.1.442, R Core Development Team, Vienna, Austria), four artificial neural network (ANN) machine learning algorithms were used to predict youth metabolic equivalents (METs) (21). Two (one hip, one wrist) of the ANNs used mean and variance of acceleration in each axis and two (one hip, one wrist) ANNs used mean and variance of counts in each axis (total of four ANNs; available at https://goo.gl/sm5BA3). These predicted youth METs were classified as sedentary (≤1.5 METs), light (>1.5, but <3 METs), moderate (3 to 6 METs), or vigorous (>6 METs).

Statistical Analysis

Normality was assessed using Histograms and Q-Q plots. To compare 100 and 30 Hz data, bias, mean absolute difference (MAD), mean absolute percent difference (MAPD) and correlation coefficients (Pearson's *r*) were calculated for total counts/15-sec in each axis, VM_{counts}, $VM_{acceleration}$, and mean acceleration in each axis, separately for the hip and wrist data, using individual epochs. Data across all activities were then averaged for each participant (e.g., total y-axis counts from all 15-sec epochs were averaged together) and paired t-tests were used to compare total counts/15-sec in each axis, VM_{counts}, $VM_{acceleration}$, and mean acceleration in each axis between sampling rates (100 vs. 30 Hz), separately for hip and wrist data. To identify the influence of monitor wear location, paired t-tests were used to compare MAD between hip and wrist data for total counts/15-sec in each axis, VM_{counts}, $VM_{acceleration}$, and mean acceleration in each axis.

To evaluate whether error was influenced by activity intensity, the relationship between absolute differences in 100 and 30 Hz data and the average count or acceleration values (e.g., average of 100 and 30 Hz counts/15-sec) was evaluated using correlation coefficients (Pearson's *r*) for individual epochs. Bland-Altman plots were made by plotting bias (100 minus 30 Hz data) by the average of the 100 and 30 Hz data for hip and wrist VM counts/15-sec (25). To identify differences by activity type, absolute differences were averaged within each activity (i.e., differences from all 15-sec epochs occurring during the treadmill test were averaged for each child) and two repeated measures ANOVAs (RMANOVAs; one for hip, one for wrist) were used to compare MAD by activity type (rest/break, active video game 1 and 2, and treadmill test). Paired t-tests and repeated measures ANOVAs were conducted in SPSS (IBM; Armonk, NY; version 24) and significance was defined as $p<0.01$. For all RMANOVAs, observed power was greater than 0.80. When necessary, Greenhouse-Geisser correction was used, as well as Bonferroni *post hoc* analyses to identify pairwise differences between activity types.

To determine the impact of sampling rate on activity intensity classification, percent agreement between epoch-level 100 and 30 Hz data was determined for activity intensity (sedentary, light, moderate, vigorous) as determined by hip (22, 24) and wrist-based cut-points (23), or the predicted youth METs from the four machine learning models (count and acceleration for the hip and wrist).

Results

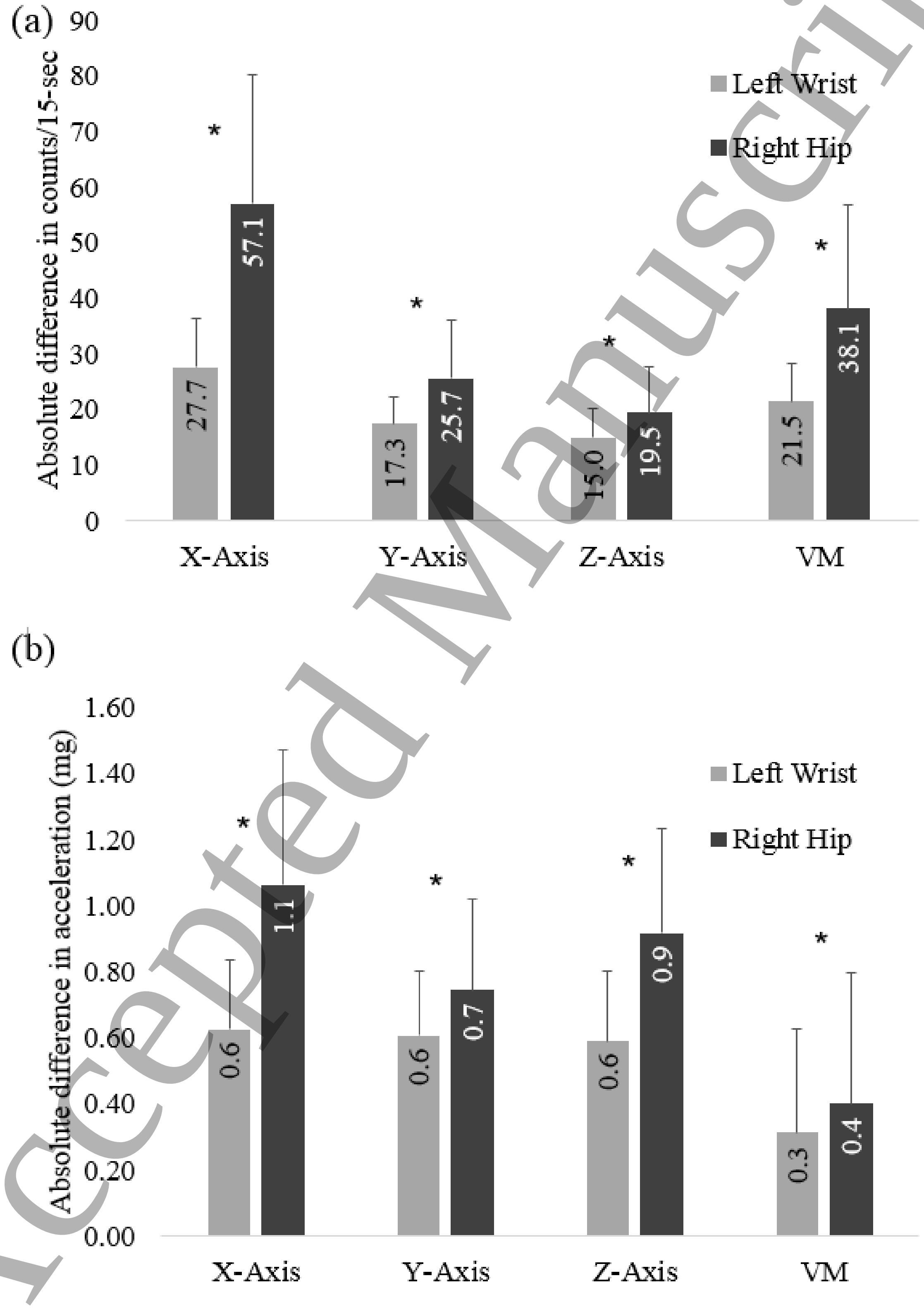
Dominant frequency ranged from 0.117 (hip and wrist) to 10.313 (hip) or 11.484 (wrist) Hz, with 92.9% (hip) to 99.8% (wrist) of epochs below 5 Hz. Total counts/15-sec in each axis and VM_{counts} were significantly higher ($p<0.001$) when sampling at 100 Hz compared to 30 Hz for both hip and wrist data, and $VM_{acceleration}$ was significantly different between sampling rates at the left wrist, with no significant differences in $VM_{acceleration}$ at the hip or mean acceleration in each axis at either the wrist or hip. Bias, MAD, MAPD, and correlation coefficients for hip- and wrist-worn monitors are shown in Table 1 and show positive mean bias for counts and strong correlation coefficients. Paired t-tests revealed that absolute differences were significantly greater ($p \leq 0.002$) for the hip-worn monitor compared to the wrist-worn monitor for total counts/15-sec in each axis and VM_{counts} (Figure 1(a)) and mean acceleration in each axis and $VM_{acceleration}$ (Figure 1(b)).

Table 1. Mean absolute difference, mean absolute percent difference, bias, and correlations between outcomes from hip- and wrist-worn monitors [mean (standard deviation)]

Variable	**MAD**	**MAPD**	**Bias (100-30 Hz)**	***r***
Hip-worn monitor				
Counts				
Y-axis total counts/15-sec	22.0 (39.4)	8.9 (25.7)	16.4 (42.1)	0.998
X-axis total counts/15-sec	46.3 (103.4)	14.2 (24.4)	42.7 (104.9)	0.938
Z-axis total counts/15-sec	16.9 (31.3)	7.5 (18.1)	12.0 (33.5)	0.993
Vector magnitude counts/15-sec	36.9 (75.1)	6.0 (16.3)	33.3 (76.7)	0.995
Acceleration (mg)				
X-axis mean acceleration	0.94 (1.79)	0.10 (0.19)	0.01 (2.02)	0.999
Y-axis mean acceleration	0.67 (1.25)	0.32 (4.56)	0.00 (1.42)	0.999
Z-axis mean acceleration	0.82 (1.52)	0.20 (18.31)	0.00 (1.73)	0.999
Vector magnitude acceleration	0.98 (1.87)	0.09 (0.15)	-0.06 (2.11)	0.999
Wrist-worn monitor				
Counts				
Y-axis total counts/15-sec	16.4 (22.2)	3.5 (13.1)	5.0 (27.1)	0.999
X-axis total counts/15-sec	25.7 (35.5)	4.6 (13.0)	13.5 (41.7)	0.999
Z-axis total counts/15-sec	14.0 (19.1)	2.9 (9.7)	4.2 (23.3)	0.999
Vector magnitude counts/15-sec	21.3 (29.3)	2.5 (10.1)	12.4 (34.0)	0.999
Acceleration (mg)				
X-axis mean acceleration	0.59 (0.89)	0.13 (2.67)	0.01 (1.07)	0.999
Y-axis mean acceleration	0.57 (0.88)	0.22 (7.53)	0.01 (1.04)	0.999
Z-axis mean acceleration	0.57 (0.95)	0.07 (7.80)	-0.00 (1.11)	0.999
Vector magnitude acceleration	0.80 (1.24)	0.00 (0.00)	-0.20 (1.46)	0.999

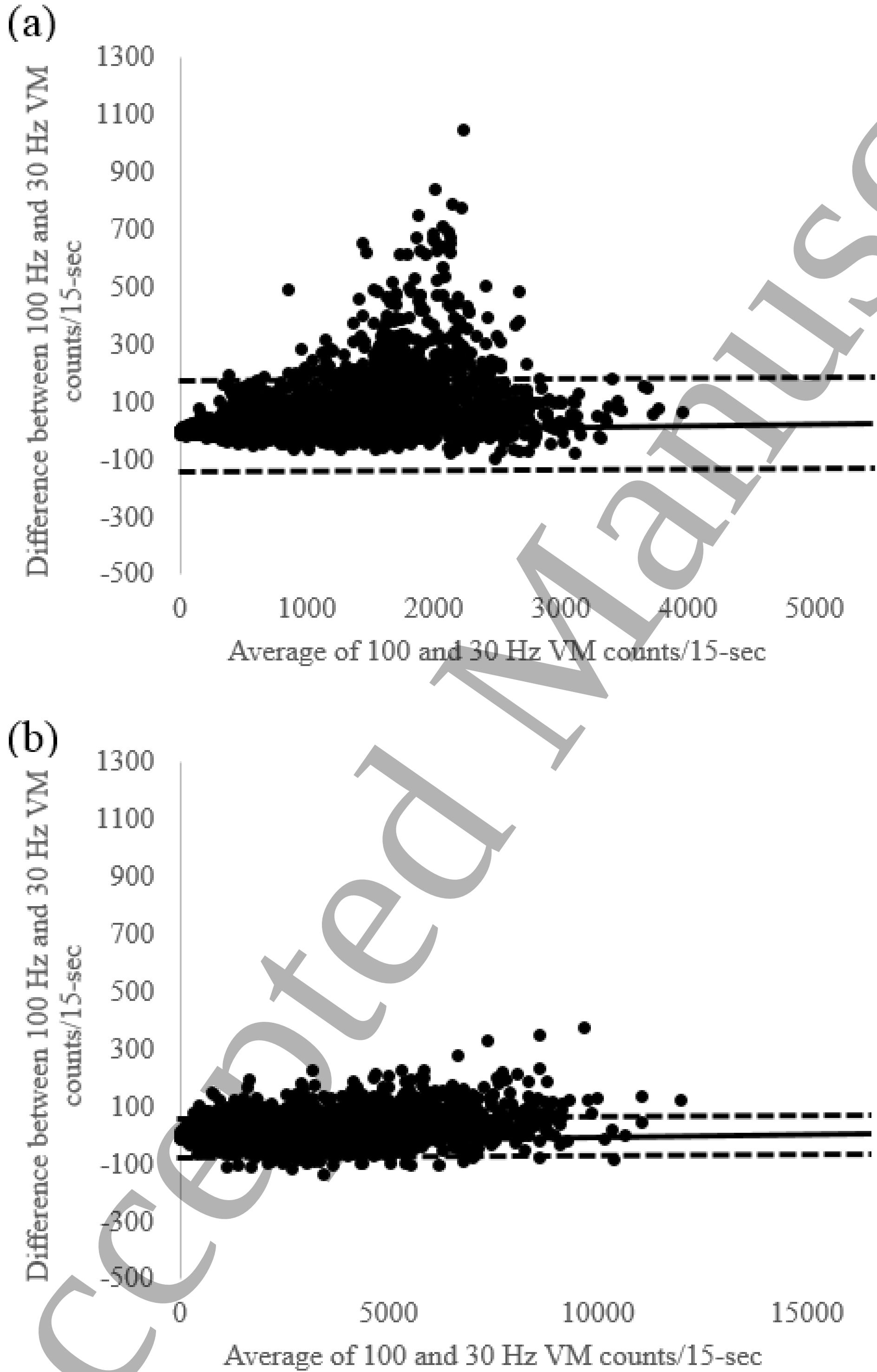
MAD = mean absolute difference; MAPD = mean absolute percent difference; data shown as mean (standard deviation) except for Pearson's *r*

Figure 1. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in total counts/15-sec and vector magnitude (VM) counts (a) and mean acceleration and VM acceleration (b) between hip- and wrist-worn monitors. Data are presented as means, with standard deviation bars and * indicates significant difference between hip and wrist wear locations at $p<0.01$.



As average counts or acceleration increased, the absolute difference (100 minus 30 Hz) in total counts/15-sec and VM_{counts} for each axis (hip: r=0.46-0.56; wrist: r=0.48-0.55) and mean acceleration and $VM_{acceleration}$ for each axis (hip: r=0.48-0.63; wrist: r=0.26-0.45) increased. The Bland-Altman plot for hip VM counts/15-sec shows that differences by sampling rate were uniform until approximately 1,500 counts/15-sec, at which point differences became more variable (Figure 2(a)). Conversely, differences remained uniform as counts/15-sec increased for the wrist-worn monitor (Figure 2(b)).

Figure 2. Bland-Altman plots showing the relationship between mean vector magnitude (VM) counts/15-sec and bias (100 minus 30 Hz data) for the hip-worn (a) and the wrist-worn monitor (b). The solid line represents mean bias and dotted lines represent 95% confidence intervals.



The repeated measures ANOVA indicated that the absolute differences between 100 and 30 Hz data were significantly different (p<0.001) by activity type for hip-based total counts/15-sec [y-axis: $F(1,32)=61.01$; x-axis: $F(1,28)=139.87$; z-axis: $F(1,27)=59.93$; VM: $F(1,30)=117.76$] and mean acceleration [x-axis: $F(1,37)=85.41$; y-axis: $F(1,40)=59.72$; z-axis: $F(2,47)=79.69$; VM: $F(1,38)=78.92$] (*post-hoc* results are shown in Figures 3(a) and 4(a)). Absolute differences in counts/15-sec and acceleration in all axes for the hip-worn monitor were significantly higher (p<0.001) during the treadmill test compared to rest/transition or either active video game.

The RMANOVA indicated significant differences (p<0.001) between activities in wrist-based total counts/15-sec [y-axis: $F(2,55)=30.35$; x-axis: $F(2,42)=34.57$; z-axis: $F(1,45)=22.13$; VM: $F(1,38)=22.87$], and mean acceleration [x-axis: $F(2,54)=13.90$; y-axis: $F(2,66)=25.06$; z-axis: $F(2,56)=13.62$; VM: $F(3,61)=24.03$] (*post-hoc* analysis is shown in Figures 3(b) and 4(b)). Absolute differences in total counts/15-sec for the wrist-worn monitor were significantly lower (p<0.001) during rest/transition compared to either active video game or the treadmill test.

Upon classifying data into activity intensities, agreement between 100 and 30 Hz data was 97.4% when using the hip-based Evenson et al., cut-points (22), 99.2% when using the Hanggi et al. hip-based cut-points (24), and 99.0 to 99.1% agreement when using the wrist-based Chandler et al. cut-points (23). After classifying youth METs predicted by the machine learning models, percent agreement for activity intensity between 100 and 30 Hz data was 98.9%, 99.5%, 99.3%, and 99.7% for the count-based hip, raw acceleration hip, count-based wrist and the raw acceleration wrist models, respectively.

Figure 3. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in total counts/15-sec in each axis and vector magnitude (VM) from a hip-worn (a) and a wrist-worn monitor (b) across four activity types. Data are presented as means, with standard deviation bars. Signficance (p<0.01) is denoted as *a* when there is a significant difference from rest/transition, while *b* indicates a significant difference from active video game (AVG) 1, *c* indicates a significant difference from AVG 2, and *d* indicates a significant difference from the treadmill test.

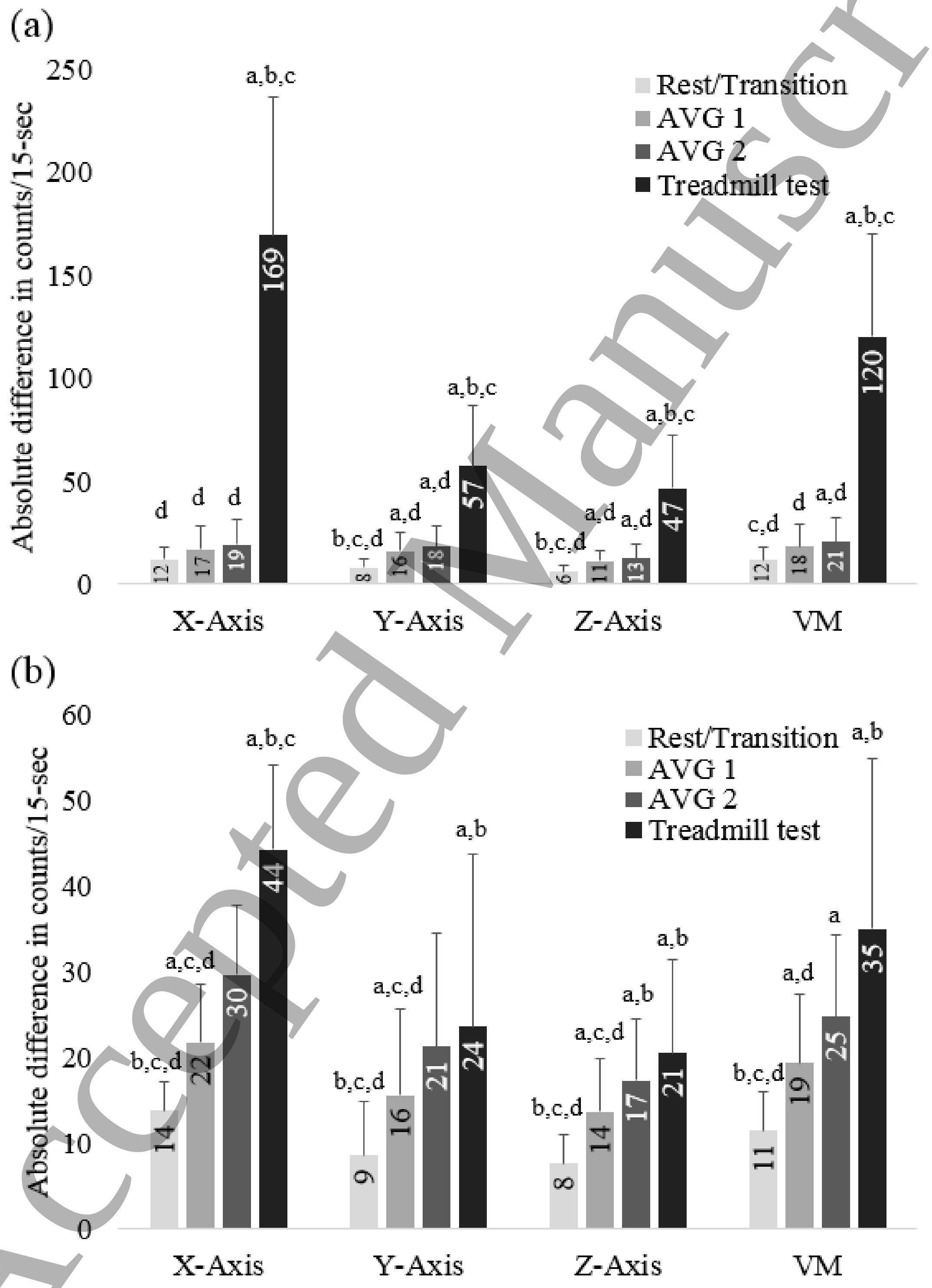
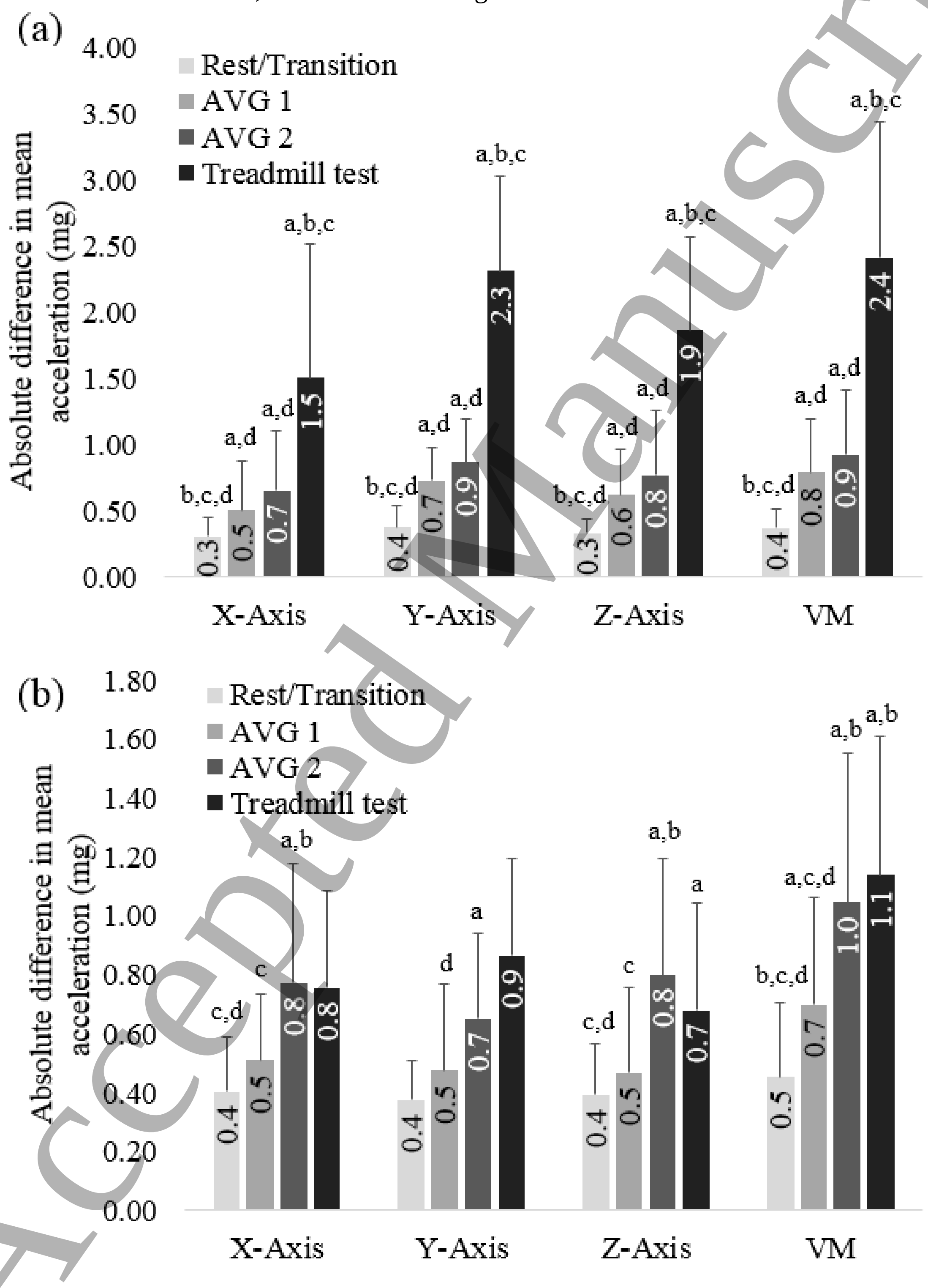


Figure 4. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in mean acceleration in each axis and vector magnitude (VM) from a hip-worn (a) and a wrist-worn monitor (b) across four activity types. Data are presented as means, with standard deviation error bars. Signficance (p<0.01) is denoted as *a* when there is a significant difference from rest/transition, while *b* indicates a significant difference from active video game (AVG) 1, *c* indicates a significant difference from AVG 2, and *d* indicates a significant difference from the treadmill test.



Discussion

Our aim was to compare count and acceleration data from hip- and wrist-worn ActiGraph GT3X+ accelerometers using 100 and 30 Hz sampling rates. Overall, there were differences between 100 and 30 Hz count-based data, but almost no significant differences in acceleration data, and these absolute differences were greater from a hip-worn monitor compared to a wrist-worn monitor. Absolute differences increased with intensity and were therefore lowest during rest/transition and largest during the treadmill test. However, when data were classified as sedentary behavior or light, moderate, or vigorous activity, there was agreement between 100 and 30 Hz data in the vast majority (97.4-99.7%) of epochs.

ActiGraph accelerometers use a proprietary frequency band-pass filter to attenuate signals considered to be outside of the range of normal human movement, although this has also been shown to attenuate signals recorded during vigorous-intensity activity (26, 27). In accord with the present findings, Brønd and Arvidsson (8) reported that additional y-axis counts were generated when using a sampling rate other than 30 Hz (or multiples thereof), particularly as activity intensity increased, and they attributed this to signals 'escaping' the band-pass filter. Moreover, Brønd and Arvidsson (8) showed that difference scores (100 vs. 30 Hz) were fairly consistent until ~6,000 counts/min, then the heterogeneity of differences increased drastically. Indeed, an almost identical pattern (Figure 2(a) for VM_{counts}), in which the range of differences drastically increased around 1,500 counts/15-sec (equivalent to 6,000 counts/min) for the hip-worn monitor was found in the present study (y-axis figure not shown). This corresponds to vigorous-intensity activity (according to the Evenson, Catellier (22) cut-points), indicating the impact of sampling rate on y-axis counts generated by a hip-worn monitor appears greatest for higher intensity activities, when signals may be attenuated by the band pass filter.

Despite similar overall patterns, the magnitude of the differences in recorded y-axis counts due to different sampling rates was generally smaller in the present study compared to previous research (8). In the Brønd and Arvidsson (8) study, differences between 100 and 30 Hz monitors were largest during a fast run (1,238 counts/min), compared to a slow walk (47 counts/min), fast walk (121 counts/min), or slow run (611 counts/min). In the present study, the greatest difference by sampling rate was during the treadmill test, which elicited a MAD of 57.2 counts/15-sec (equates to 229 counts/min). Of note, Brønd and Arvidsson (8) reported bias, not MAD, so direct comparisons between these values cannot be made; but as MAD is never smaller than bias, our conjecture that differences were smaller in the present study holds. The smaller differences by sampling rate in the present study may be attributed to our study design, such as use of only one monitor per wear location, which eliminated inter-monitor differences, and inclusion of primarily non-locomotive (vs. locomotive) activities, which were less impacted by sampling rate. However, there were also differences in the sample and setting that may have impacted our results.

Our study focused on children, so the speed of movement during the locomotive activity was likely lower than in Brønd and Arvidsson (8). Accordingly, we report that peak dominant signal frequencies were mostly low (e.g., > 90% of epochs were <5 Hz and 80% were <2 Hz), so the band-pass filter may have been utilized to a lesser degree, explaining why differences by sampling rate were smaller in the present study. Additionally, in the present study, monitors were affixed to participants and the locomotive activity was completed on a treadmill, both of which may have resulted in less 'noise' compared to wearing monitors on an elastic belt and running on a track (28), as in the Brønd and Arvidsson (8) study. Despite differences in the magnitude of the effect, our findings support the notion that the band pass filter does not work as intended when using a sampling rate other than 30 Hz (or multiples thereof), specifically at high signal frequencies, which can be elicited during high-intensity activities. Future research should directly (e.g., same activity and setting) compare the impact of sampling rate by age as younger children have higher step frequencies (11), but lower amplitudes of acceleration, resulting in a potentially different magnitude of impact of sampling rate compared to adults.

Absolute differences between sampling rates were smaller for the wrist-worn monitor compared to the hip-worn monitor for both counts/15-sec and mean acceleration (Figure 2), and differences between 100 and 30 Hz data were more consistent for the wrist-worn monitor as mean counts/15-sec increased (Figure 2(b)). While counts from a hip-worn monitor have been shown to plateau or decline as running speed increases beyond a certain point (26, 27), it has been reported that the attenuation of signals from a wrist-worn monitor is less apparent (29) as they are less affected by the narrow band-pass filter used by ActiGraph (30). Interestingly, as shown when comparing Figures 3(a) and 3(b), the wrist-worn monitor had larger absolute differences in counts/15-sec during active video games compared to the hip-worn monitor, which could be due to increased reliance on arm movements (31). Our study supports previous research by illustrating that data from wrist-worn devices are less influenced by differences in sampling rate, but more research is warranted that includes a variety of activities, particularly those that rely on upper extremity movement, to confirm.

While many early works focused on using activity counts in the vertical axis (y-axis) for the classification of activity intensity, all recent ActiGraph models provide researchers with acceleration and activity counts in three axes. This has bolstered interest in the use of all three axes to better capture non-locomotive activities and in the potential use of acceleration data (as opposed to proprietary counts) to promote comparability across monitor brands. For example, using count or acceleration data from multiple axes, researchers may calculate vector magnitude (32), Euclidean norm minus one (33), the horizontal vector (34), or extract features from all three axes when using novel analytic techniques, like artificial neural networks (21). For these reasons, we explored the impact of sampling rate on both count and acceleration data from all three axes and corresponding VM_{count} and $VM_{acceleration}$ metrics. While it appears that sampling rate had the largest impact on the x-axis (medial-lateral), particularly during the treadmill test, future work may expand on the frequency patterns of each axis during various activities (both non-locomotive and locomotive) to explain why the x-axis was most affected. Our findings suggest the impact of sampling rate would be minimal when using the vertical axis alone, but greater when using vector magnitude or features from all three axes.

We also report that differences (e.g., MAPD in Table 1) were larger for count data compared to mean acceleration. While ActiGraph's data processing is proprietary, prior research comparing acceleration of ActiGraph to Axivity or GENEA monitors showed that the recorded accelerations were not equivalent across devices, indicating the acceleration data may be processed prior to storage in the ActiGraph monitor (35, 36). This notion is supported in the present study, as mean acceleration was not identical between 100 and 30 Hz data (MAPD 0.07-0.32%) and $VM_{acceleration}$ was significantly different when using 100 versus 30 Hz data at the left wrist. While most differences in acceleration metrics were not significant, and 'raw' acceleration data are still less processed than the filtered count data, the fact that these data may not be truly 'raw' should be considered in future research.

The practical implications of the differences in count and acceleration data due to sampling rate should be explored. For example, Evenson, Catellier (22) categorizes moderate-intensity activity as anything between 574 and 1,002 counts/15-sec, so the mean absolute differences of 14.0 to 46.3 counts/15-sec found in the present study may be negligible. The present study found little difference between the 100 and 30 Hz data (97.4-99.7% agreement) when classified by activity intensity, irrespective of classification technique (i.e., count-based cut-points or METs predicted by machine learning models). However, the implications of these arguably small differences between sampling rates on the measurement of free-living and/or habitual physical activity warrants further investigation. In the present study, 2.6% of epochs were classified differently between 100 and 30 Hz data after using the Evenson, Catellier (22) cut-points to classify the intensity of each epoch based on y-axis counts from the hip-worn monitor. Such a discrepancy would result in approximately 15.4 minutes of activity being differentially classified over a 10-hour wear period. However, it is noteworthy that the present protocol involved more moderate- and vigorous-intensity activity than a typical wear day, so it could be postulated that a difference in sampling rate would not affect the measurement of habitual activity to this degree, though future research in this area is warranted.

Whilst the present data are limited to a protocol with a high proportion of active time accumulated from active video games, a treadmill exercise test, and breaks between activities, there are numerous strengths. Specifically, we add to previous research by assessing the impact of sampling rate on mean acceleration, data from wrist-worn monitors, and data collected in a youth sample. Furthermore, the inclusion of both locomotive and non-locomotive activities, particularly given that non-locomotive activities may be less affected by sampling rate, is a key strength, supporting ecological validity by representing other daily movement patterns. Moreover, the re-sampling of 100 Hz data to obtain 30 Hz data enabled the utilization of data from one monitor, thereby eliminating inter-monitor differences and allowing us to focus on differences due to sampling rate. Indeed, it would have been particularly difficult to place two

ActiGraph GT3X+ monitors on a child's wrist without inadvertently placing them in different locations. Future studies may seek to compare two different monitors, one collecting at 30 Hz and the other at 100 Hz. The 100 Hz data could then be downsampled and the differences could be attributed to inter-monitor differences or differences due to sampling rate.

Overall, the present study supports previous research indicating that sampling rate affects ActiGraph GT3X+ data output and adds that this effect is also found in youth samples, appears to strengthen with increasing intensity, and is greater when using hip-worn monitors and when dealing with count data. However, the effect of sampling rate on the measurement of habitual physical activity or other outcomes, like activity type, remains unknown. Until the implications of sampling rate are better understood, researchers should report the sampling rate used in their studies, and consider the potential impact of sampling rate when making cross-study comparisons.

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Conflict of Interest

Results of the present study do not constitute endorsement by ACSM. We declare that the results of this study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The authors have no conflicts of interest to report.

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Figure Captions

Figure 1. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in total counts/15-sec (a) and mean acceleration (b) in each axis between hip- and wrist-worn monitors. Data are presented as means, with standard deviation bars and * indicates significant difference between hip and wrist wear locations at $p<0.01$.

Figure 2. Bland-Altman plots showing the relationship between mean y-axis counts/15-sec and bias (100 minus 30 Hz data) for the hip-worn (a) and the wrist-worn monitor (b). The solid line represents mean bias and dotted lines represent 95% confidence intervals.

Figure 3. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in total counts/15-sec in each axis and vector magnitude (VM) from a hip-worn (a) and a wrist-worn monitor (b) across four activity types. Data are presented as means, with standard deviation bars. Signficance ($p<0.01$) is denoted as *a* when there is a significant difference from rest/transition, while *b* indicates a significant difference from active video game (AVG) 1, *c* indicates a significant difference from AVG 2, and *d* indicates a significant difference from the treadmill test.

Figure 4. Comparison of absolute differences (100 vs. 30 Hz sampling rate) in mean acceleration in each axis and vector magnitude (VM) from a hip-worn (a) and a wrist-worn monitor (b) across four activity types. Data are presented as means, with standard deviation error bars. Signficance ($p<0.01$) is denoted as *a* when there is a significant difference from rest/transition, while *b*

indicates a significant difference from active video game (AVG) 1, *c* indicates a significant difference from AVG 2, and *d* indicates a significant difference from the treadmill test.