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Comparison of physical activity metrics from two research-grade accelerometers worn on the non-dominant wrist and thigh in children

Duncan S Buchan[a] and Benjamin D Maylor[b]

[a]Division of Sport and Exercise, School of Health and Life Sciences, University of the West of Scotland, Blantyre, UK; [b]Leicester Lifestyle and Health Research Group, Diabetes Research Centre, University of Leicester, Leicester, UK

ABSTRACT

This study compared physical activity metrics from the activPAL (AP) worn on the thigh with the ActiGraph worn on the non-dominant wrist using open-source methods. Measures included average acceleration, intensity gradient (IG) and the minimum acceleration value of the most active X mins (MX). Fifty-two children (26 boys; age: 10.4 ± 0.6 years) provided≥1 day (24 h) of concurrent wear time from the activPAL and ActiGraph. Measures tended to be lower from the activPAL versus the ActiGraph. Poor agreement was evident for average acceleration but good for the IG. For the IG, the absolute and relative zones needed to reach equivalence was 4% and 0.4 SDs, respectively and for average acceleration were 10% and 1.2 SDs, respectively. Good agreement was evident for M60, M30, M20, M15 and M10 between devices. Regardless of the reference device used, equivalent estimates for the intensity gradient, M60, M30, M20, M15 and M10 were observed with relative and absolute equivalence zones being≤4% and≤0.5 SDs, respectively. The IG, M60, M30, M20, M15 and M10 appear good candidates for comparing activity data collected from the activPAL and ActiGraph. Future research can use the AP to report on sedentary behaviours as well as PA outcomes.

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GGIR; agreement; equivalence; intensity gradient; average acceleration; MX

Introduction

The first device-assessed measure of moderate-to-vigorous physical activity (MVPA) and sedentary time was provided from hip-worn ActiGraph devices (Matthews et al., 2008; Troiano et al., 2008), and their continued use in research has helped advance our understanding of the relationship between PA and health outcomes. Although accelerometer devices were traditionally worn at the hip, poor wear time compliance was common resulting in significant data loss and selection bias (Cain et al., 2013). For instance, data from NHANES found compliance to wrist-worn protocols in 2011–2012 (70 to 80% compliance) exceeded the hip-worn protocols used in previous cycles (40 to 70% compliance) (Freedson & John, 2013). The use of wrist-worn devices not only encourages greater compliance, they have shown to be acceptable for continuous wear (Buchan et al., 2019; Scott et al., 2017), have been validated for estimating time spent in PA (Chandler et al., 2016; Hildebrand et al., 2014), sedentary time (Hildebrand et al., 2017) and sleep (van Hees Vt et al., 2015) and may provide better estimates of energy expenditure compared to hip-worn accelerometers (Crouter et al., 2015). For these reasons, wrist-worn accelerometer devices are increasingly being used in large cohort studies (Belcher et al., 2021; da Silva et al., 2014; Doherty et al., 2017).

Accelerometer devices such as those offered by ActiGraph continue to be the most widely used in research studies (Neishabouri et al., 2022). ActiGraph devices capture the frequency and amplitude of accelerations generated from ambulatory movements, with the captured data then analysed using proprietary software to provide counts. These counts can be calculated over a specified time interval (epoch length) which users can then apply validated cut-points to estimate time spent in activity intensities (e.g., time spent in MVPA) (Chandler et al., 2016; Migueles et al., 2017). For instance, the vector magnitude MVPA cut-points provided by Chandler et al. (Chandler et al., 2016) demonstrated a receiver operator characteristic – area under the curve value of 0.89 against direct observation in a cross-validation group. Such an approach has also been used to quantify sedentary time with the commonly used cut-point of < 100 counts/minute often applied for children to estimate time spent sedentary (Cooper et al., 2015; Matthews et al., 2008). However, this cut-point results in the misclassification of some standing activities (i.e., Light PA) as sedentary behaviour (SB) and results in overestimating daily sedentary time (Silva et al., 2019).

A more recent addition to SB research is the activPAL device (PAL Technologies Ltd, Glasgow UK). The activPAL is a thigh-worn accelerometer and is considered the gold standard for measuring SB (Kozey-Keadle et al., 2011; Sellers et al., 2016). Whilst the activPAL has demonstrated a sensitivity of 84% for children and adolescents and 98% for adults for correctly identifying SB against direct observation (Sellers et al., 2016), time spent in MVPA is not typically provided by the manufacturers proprietary software. Even though the activPAL proprietary software has a built-in algorithm that provides an activity score that estimates energy expenditure (expressed as METs) (PAL technologies, 2022). Of the limited studies that have

CONTACT Duncan S Buchan duncan.buchan@uws.ac.uk Division of Sport and Exercise, School of Health and Life Sciences, University of the West of Scotland, Lanarkshire Campus, Blantyre G72 0LH, Scotland UK

examined the accuracy of the activPAL device for estimating time spent in different intensities of PA, findings suggest that the METs algorithm does not provide a valid method for determining time spent in activity intensities (Harrington et al., 2011; Lee & Dall, 2019; Lyden et al., 2017; Montoye et al., 2017; Wu et al., 2021). Nor does it seem to provide comparable outcomes to that offered from the ActiGraph.

With time spent in MVPA an important feature of international PA guidelines, alongside the need to reduce SB (UK Government Department of Health and Social Care, 2019; US Department of Health and Human Services, 2018; World Health Organization, 2020), researchers interested in capturing the concurrent measurement of SB and PA may require participants to wear two devices: one that captures MVPA (e.g., ActiGraph) and the other for SB outcomes (e.g., activPAL) (Barboza et al., 2021; Biddle et al., 2019; Lynch et al., 2019). Although time spent in MVPA is often reported by researchers, this measure is not without its limitations (Rowlands, Sherar, et al., 2019; Troiano et al., 2014). For instance, to estimate time spent in activity intensities, cut-points are applied to data which are protocol and population specific. With multiple cut-points available, studies examining the prevalence of individuals meeting MVPA recommendations vary (i.e., from 8 to 96%) depending on which cut-point is applied (Migueles, Cadenas-Sanchez, et al., 2019). Moreover, when studies use different cut-points to estimate time spent in activity intensities, it is impossible to then subsequently compare or pool datasets together (Rowlands, Dawkins, et al., 2019).

To overcome the limitations of reporting time spent in activity intensities, alternative metrics that are derived from the measured raw acceleration values provided by brands of accelerometers, such as ActiGraph, have been proposed (Rowlands, 2018; Rowlands, Sherar, et al., 2019). These include average acceleration which provides a measure of the volume of activity undertaken and the intensity gradient which describes the slope of the intensity distribution of accelerations across the monitoring period (Rowlands, 2018). Together, these metrics detail both the volume and intensity of activity undertaken across the monitoring period using all of the acceleration data collected. These continuous data-driven metrics can also be used to examine the independent, additive, and interactive effects of volume and intensity of PA upon health outcomes (Rowlands, Dawkins, et al., 2019). With respect to time spent in MVPA, an alternative approach is to identify the minimum acceleration value for a certain duration (MX), where X refers to the duration, and for instance an individual's most active 30 min or 60 min (M30, M60) (Rowlands, Sherar, et al., 2019). The minimum acceleration value can then be compared to available cut-points i.e., 200 m*g* to estimate time spent in MVPA from wrist-worn accelerometers (Hildebrand et al., 2014), or compared to the acceleration values associated with typical activities such as walking or running (Rowlands, Dawkins, et al., 2019). An important strength of the MX metric is that the acceleration value can be interpreted post-processing unlike the use of cut-points which need to be applied prior to the processing of the accelerometer data. These metrics therefore can provide additional insights into the relationship between PA and health outcomes and can be used to facilitate comparisons between studies. Moreover, processing accelerometer data using GGIR affords greater transparency and facilitates consistent processing methods. As both the activPAL and ActiGraph devices measure raw acceleration across three axes, there is the possibility for data outcomes to demonstrate similar trends which could be useful for data harmonization.

Although several studies have compared the concurrent validity of activPAL and ActiGraph metrics, different processing methods were used for each device (Dowd et al., 2012; Koster et al., 2016; Ridgers et al., 2012). It is unclear therefore whether activity metrics are comparable between devices, or whether differences are a consequence of the different processing methods used. Moreover, no study has explored whether acceleration magnitude-based activity metrics are comparable between the activPAL and ActiGraph devices when worn on the thigh and non-dominant wrist using identical processing methods. We hypothesize that there will be differences in the activity metrics with lower values evident from the activPAL in comparison to the ActiGraph. For instance, wrist movements can be independent of body posture and the activPAL has a lower dynamic range and sampling frequency than the ActiGraph. Yet, since accelerometer devices are increasingly being worn on the thigh to measure physical behaviours (Stamatakis et al., 2020), understanding which activity metrics are comparable across accelerometer brands and body locations is vital for potential data harmonization across studies. Therefore, the aim of this study is to compare PA metrics from the activPAL worn on the thigh with that from the ActiGraph worn on the non-dominant wrist using the same open-source processing software GGIR (Migueles, Rowlands, et al., 2019).

Materials and methods

The data used for the current study were collected during the baseline assessment of a previous study (McLellan et al., 2021). Ethical approval for the study was received from the University of the West of Scotland with baseline measures undertaken in October 2018. Briefly, 146 child participants aged 8–12 years attending eight primary schools in North Lanarkshire, Scotland, volunteered to participate and provided baseline measures.

Stature and mass were measured using a calibrated scale (Seca Digital Scales, Seca Ltd, Birmingham, UK) and stadiometer (Seca Stadiometer, Seca Ltd, Birmingham, UK), respectively, without shoes and in light clothing. Participants were asked to wear the ActiGraph wGT3×+ (herein ActiGraph) (ActiGraph LLC, Pensacola, FL, USA) on their non-dominant wrist (after verbal confirmation of their handedness) and the activPAL Micro4 (herein activPAL) on the anterior midline of the right thigh. The activPAL (PAL Technologies LTS, Glasgow, UK) was placed in a nitrile sleeve and attached to the skin using medical dressing (Hypafix; BSN Medical) to waterproof (Edwardson et al., 2017). Participants were instructed to wear the devices for 7 days, only removing the ActiGraph whilst swimming. Finally, all participants were fitted with both devices prior to leaving the data collection session.

Accelerometers

The ActiGraph is a triaxial accelerometer with a dynamic range of ± 8 *g*, where *g* is equal to the Earths gravitational pull. ActiGraph devices were initialized to record data at a frequency

of 80 Hz with the "idle sleep mode" disabled in ActiLife v6.13.3 (ActiGraph, Pensacola, FL, USA). Data was downloaded using ActiLife v6.13.3 with data files saved in raw format as.gt3× files. The activPAL is a triaxial accelerometer with a dynamic range of ±4 *g*. ActivPAL devices were initialized using PAL Connect version 8.10.5.55 to record data using the default settings (20 Hz, 10 second minimum sitting and upright period). Data was subsequently downloaded using PAL batch version 8.10.12.57 and saved in raw format as.csv files. All accelerometer devices were initialized using the same computer and programmed to commence data collection the following day.

Data processing

All files were processed using the GGIR package version 2.6–0 in R statistical software (R Foundation for Statistical Computing, Vienna, Austria, https://cran.r-project.org/) (Migueles, Rowlands, et al., 2019) which detected sustained and abnormally high values, non-wear time and auto calibrated the files using local gravity as a reference (van Hees Vt et al., 2014). Abnormally high values are identified by GGIR when the acceleration signal from one of the three axis is near the edge of the dynamic range of the accelerometer device, for more that 80% of the data points within a 15 min window. Non-wear time was estimated based on the SD and value range of each axis, calculated for 60 min windows with 15 min moving increments (van Hees et al., 2013). Non-wear is then recorded if the SD is less than 13 m*g* or the value range is less than 50 m*g* during the time window for at least 2 out of the 3 axes. This processing method also calculated Euclidean Norm Minus One (ENMO) (1 *g*) averaged over 5-second epochs and expressed in milli-gravitational units (m*g*), as previously described (van Hees et al., 2013). To maximize generalizability, non-wear was imputed using the default settings in GGIR whereby invalid data were imputed by the average at similar times of different days of the monitoring period. Participant files were excluded from subsequent analyses if post-calibration error was>0.01 g or participants had less than 1 day of valid wear data (defined as 24 h per day) from each accelerometer device. As different movement patterns are apparent between the thigh and the wrist (Montoye et al., 2016), having a valid day comprising of 24 h per day wear time ensured that movement patterns for an entire day were captured from both devices.

Several metrics were provided from both devices which were averaged across the number of valid days of wear time, and included: ENMO (herein average acceleration (m*g*); intensity gradient; acceleration above which a participant's most active (MX with X indicating the duration) 16 hours (h), 12 h, 10 h, 8 h, 6 h, 4 h, 2 h, 1 h, 60 minutes (m), 30 m, 20 m, 15 m, 10 m, 5 m, 2 m and 1 m (M960, M720, M600, M480, M360, M240, M120, M60, M30, M20, M15, M10, M5, M2 and M1) are accumulated (Rowlands, Sherar, et al., 2019). To aid interpretations of the acceleration values associated with the MX metrics, users can apply (*post hoc*) indicative acceleration values associated with every day activities (Rowlands, Dawkins, et al., 2019). For instance, acceleration values between100–200 m*g* are reflective of a slow walk; >200–350 mg, a brisk walk; >350–500 mg, fast walk or jogging; >500–100 mg is indicative of slow running; >1000–1500 mg, medium running; >1500–2000 mg, fast running and>2000 m, sprinting or jumping (Rowlands, Fairclough, et al., 2019). Average acceleration provided a proxy measure of the volume of activity undertaken during the monitoring period whereas the intensity distribution of accelerations throughout the monitoring period is described by the intensity gradient (Rowlands, 2018). The config.csv files used in GGIR are provided as supplementary files 1 and 2.

Statistical analysis

Participants had to provide at least 1 valid day of wear time (24 h) concurrently from both devices to be included in subsequent analysis. This was confirmed numerically for each device from the outputs provided by GGIR. As the aim of this study was to compare the metrics provided by GGIR from both the ActiGraph and ActivPAL devices, sleep data was not excluded. Descriptive statistics were calculated for all metrics (mean ± SD) or median (25^{th} –75^{th} percentile) following normality testing. Level of agreement between the activity metrics was examined using mean percentage error (MPE), mean absolute percent error (MAPE) and intraclass Correlation Coefficients (ICC, two-way mixed effects, single measures, absolute agreement) with 95% confidence intervals (CI). MPE was provided to indicate the direction and magnitude of error at a group-level whereas the MAPE provided an indicator of individual agreement by accounting for each participant's error. Values<0.5, 0.5–0.75, 0.75–0.9 and>0.90 were indicative of poor, moderate, good, and excellent agreement, respectively, based on the lower bound 95%CI of the ICC estimate (Koo & Li, 2016).

Finally, pairwise 95% equivalence tests were used to establish whether the 95%CI for the mean of one accelerometer fell within the proposed equivalence zone of the alternate accelerometer (Dixon et al., 2018). Log transformation of the original data was performed if not normally distributed and was used in the equivalence analyses. A 10% equivalence zone has been applied in similar studies (Buchan et al., 2020; Buchan, 2021; Edwardson et al., 2021) but such an approach can be lax when values are very high and across a narrow range of values, but strict when values are smaller and highly variable. Therefore, when applying an absolute equivalence zone, the required percentage need to reach equivalence is provided alongside the zone necessary to achieve equivalence as a proportion of the SD (O'brien, 2021). Providing the required percentage needed to reach equivalence provides more detailed information, lessens the reliance upon arbitrary thresholds, and can help facilitate between-study comparisons which is important for future systematic reviews and meta-analyses (O'brien, 2021). Although no device or body location can be considered the gold standard, the ActiGraph was used as the reference device in subsequent analyses to reflect the study aims. Statistical analyses were undertaken using IBM SPSS statistical software for Windows version 25 (IBM, Armonk, NY). Equivalence testing was undertaken in Minitab (v17) with alpha set at 0.05.

Results

Of the 146 participants that provided baseline accelerometer measures, eight participants withdrew consent and four were withdrawn from the study by their teacher. Five participants

failed to return their ActiGraph device, and another five separate participants failed to return their activPAL device. This meant the data provided from their returned device had to be removed from subsequent analysis. One activPAL device suffered a battery malfunction shortly after distribution with the corresponding ActiGraph device removed from subsequent analysis. This left 123 participants data files to be processed in GGIR. Thirty-one participants were removed from subsequent analysis as they failed to provide 24 h of wear time from each device for the same day. Specifically, 11 failed to provide at least 24 h of wear time from the ActiGraph device; 7 failed to provide 24 h of wear time from the activPAL device and 13 participants failed to provide 24 h of wear time from both the ActiGraph and activPAL devices. Finally, 40 participants were removed from subsequent analysis as their activPAL device recorded a post-calibration error that was>0.01 *g*. No post-calibration error>0.01 *g* was evident from the ActiGraph files. This left valid data for 52 participants (26 boys; mean age: 10.4 ± 0.6 years). Devices were worn on average for 3.1 ± 1.5 days. Participants spent 10.6 h ±2.2 h per day sedentary (excluding sleep) and reported 10,254 ± 2576 steps per day (calculated from PAL analysis v8.11.6.70). Descriptive data are provided in Table 1 with findings from the MPE, MAPE and ICCs provided in Table 2. Findings from the equivalency analysis are displayed in Figure 1.

Activity metrics tended to be lower from the activPAL compared to the ActiGraph, apart for M60 and M30. This is further illustrated with radar plots (Figure 2). The MPE for the intensity gradient was<2% whereas the MAPE was less than<6%. Differences increased in magnitude for average acceleration with group level differences of −26% and an MAPE of 27.6%. Agreement from the ICCs was poor for average acceleration but moderate for the intensity gradient. For the MX metrics, MPE was highest for M960 at −64.5% but continually decreased as the MX duration decreased, up until M20 (−1.1%). The group level differences were less than 11% for M60, M30, M20 and M15 (approx. 11%, 8%, −1% and −7%, respectively), but then increased for M10, M5, M2 and M1 (range −14.9% to −36.6%). The MAPE was highest for M960 at 70.6% but in general, the magnitude of individual level differences decreased as the MX duration decreased up until M10 (MAPE = 18%). Individual differences then increased for M5, M2 and M1 (range 22.2% to

Table 1. Descriptive statistics of physical activity metrics from activPAL and ActiGraph devices ($N = 52$).

	activPAL	ActiGraph
Average acceleration (mg/day)	30.61 (24.1–38.8)	42.8 (32.1–48.8)
Intensity Gradient (mg/day)	−2.04 ± 0.16	−2.01 ± 0.22
MX metrics (m*g*)		
M960	2.8 (2.0–3.3)	6.1 (3.9–12.8)
M720	6.5 (5.1–8.3)	16.2 (12.0–21.1)
M600	8.9 (7.4–10.8)	21.0 (17.0–25.7)
M480	12.3 ± 3.3	28.5 ± 7.9
M360	17.7 (13.9–20.1)	36.6 (30.5–43.3)
M240	28.7 (22.6–37.4)	56.1 (46.0–65.9)
M120	83.8 (61.4–107.2)	103.1 (87.6–124.2)
M60	181.8 (142.2–249.0)	165.9 (136.3–341.4)
M30	294.1 (240.8–397.0)	260.1 (201.1–341.4)
M20	381.5 (297.0–447.9)	352.5 (269.8–477.4)
M15	434.5 (333.8–514.0)	427.7 (320.5–571.0)
M10	513.4 (396.2–609.2)	532.9 (419.1–764.8)
M5	672.3 (517.9–847.9)	847.6 (637.6–1107.4)
M2	843.1 (651.5–1128.7)	1321.5 (949.0–1607.4)
M1	1039.0 (757.2–1301.9)	1721.0 (1250.0–2056.9)

Note: Data are presented as mean ± SD or median (25th −75th percentile).

Table 2. Agreement of physical activity metrics from the activPAL with the ActiGraph.

	MPE ± SD	MAPE ± SD	ICC (95%CI)
Average acceleration (mg/day)	−26.0 ± 16.6	27.6 ± 24.7	0.56 (−0.09,0.84)
Intensity Gradient (mg/day)	1.9 ± 28.1	5.5 ± 4.9	0.70 (0.53,0.82)
MX metrics (mg)			
M960	−64.5 ± 73.0	70.6 ± 80.8	−0.25 (−0.16, 0.15)
M720	−60.5 ± 69.0	60.2 ± 43.3	0.01 (−0.05,0.10)
M600	−59.4 ± 65.6	55.7 ± 17.6	0.01 (−0.04,0.09)
M480	−57.0 ± 58.7	54.4 ± 16.2	0.02 (−0.04,0.11)
M360	−53.5 ± 46.5	52.0 ± 14.5	0.08 (−0.05, 0.28)
M240	−45.3 ± 15.8	45.9 ± 13.8	0.22 (−0.06,0.57)
M120	−15.7 ± 54.9	25.2 ± 14.4	0.62 (0.10,0.83)
M60	10.6 ± 11.7	21.5 ± 21.0	0.78 (0.65,0.87)
M30	7.8 ± 25.3	23.8 ± 25.0	0.79 (0.61,0.88)
M20	−1.1 ± 31.8	21.2 ± 19.9	0.81 (0.69,0.89)
M15	−7.3 ± 34.7	18.8 ± 15.7	0.83 (0.72,0.90)
M10	−14.9 ± 36.5	18.0 ± 12.2	0.82 (0.64,0.91)
M5	−24.2 ± 38.2	22.2 ± 13.3	0.74 (0.03,0.91)
M2	−32.3 ± 36.9	30.6 ± 13.5	0.03 (−0.01,0.15)
M1	−36.6 ± 42.2	34.5 ± 13.2	0.51 (−0.08,0.82)

Note: MAPE, Mean Absolute Percent Error; MPE, Mean Percent Error; ICC, intraclass Correlation Coefficients; CI, confidence intervals.

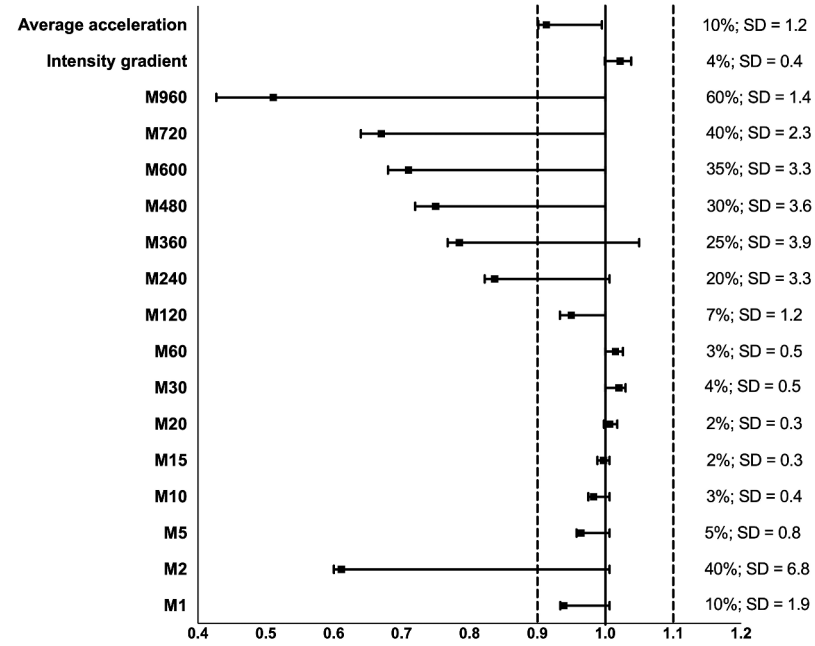

Figure 1. Equivalence between the activPAL and the ActiGraph for PA metrics. Dashed lines represent the 10% equivalence zone. To the right of the figure, the absolute zone needed to reach equivalence is provided as a %, alongside the zone necessary to achieve equivalence as a proportion of the SD. The ActiGraph was used as the reference device in all analyses.

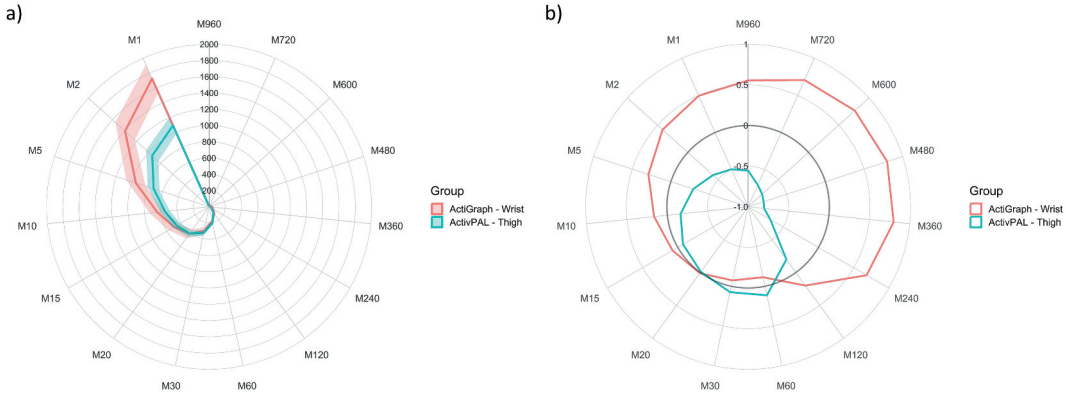

Figure 2. Radar plots illustrating the differences in MX metrics between devices. (a) Mean MX values ± SD (*mg*); (b) Standardized MX values.

34.5%). Agreement from the ICCs was poor for most MX metrics but moderate for M60, M30, M20, M15 and M10.

For average acceleration, the absolute zone needed to reach equivalence was 10%, which corresponded to a relative equivalence zone of 1.2 SDs (Figure 1). For the intensity gradient, the absolute zone needed to reach equivalence was 4%, which corresponded to a relative equivalence zone of 0.4 SDs. The absolute and relative zones needed to reach equivalence for M960, M720, M600, M480, M360, M240 and M2 were≥20% (range 20% – 60%) and≥1.4 SDs (range 1.4 SDs – 6.8 SDs). For M120, M60, M30, M20, M15, M10, M5 and M1 the absolute zone needed to reach equivalence was≤10% (range 2% to 10%) whereas the relative zone for these metrics were in the main≤0.5 SDs. As these MX metrics appear to demonstrate the greatest potential for data harmonization across the devices, alongside the intensity gradient, further equivalence tests were undertaken for these metrics with the activPAL used as the reference. Findings were broadly similar when the activPAL was used as the reference (Supplementary Figure S1). If using a threshold of≤10% and≤0.5 SDs for the absolute and relative zones needed to reach equivalence, the intensity gradient, M60, M30, M20, M15 and M10 appear to be the best candidates for harmonization across different studies. The acceleration values associated with these MX metrics are indicative of walking at varying intensities and jogging.

Discussion

As the ActiGraph is often used to capture PA metrics in children, the aim of this study was to explore whether the activPAL was able to provide comparable values. Our findings revealed that the intensity gradient compared well between the ActiGraph and activPAL but there was poor agreement for average acceleration between devices. For the MX metrics, differences

tended to decrease at both the group and individual level as the MX duration decreased up until M20 but increased thereafter. Agreement was evident for M60, M30, M20, M15 and M10 between devices. Regardless of the device used as the reference, equivalent estimates for the intensity gradient, M60, M30, M20, M15 and M10 were evident with relative equivalence zones being≤4% and absolute equivalence zones being≤0.5 SDs. Altogether, these findings suggest that the activPAL device worn on the thigh can provide comparable estimates to the ActiGraph worn on the non-dominant wrist for the intensity gradient as well as the M60, M30, M20, M15 and M10. These metrics appear good candidates for comparing activity data collected from the activPAL to that from the ActiGraph worn on the non-dominant wrist and may have important implications for data harmonization between studies.

Since the intensity gradient describes the pattern, rather than the magnitude of acceleration, the good agreement and equivalent outcomes between devices are consistent with the findings of others (Buchan, 2021; Edwardson et al., 2021; Rowlands, Plekhanova, et al., 2019). Previous studies deploying three accelerometer devices (ActiGraph, GENEActiv and Axivity) on both wrists found the intensity gradient to be equivalent between any combination of device and wrist location when applying a 10% equivalence zone (Buchan, 2021; Rowlands, Plekhanova, et al., 2019). Similar findings were also reported when four accelerometer (ActiGraph, GENEActiv, Axivity and activPAL) devices were worn on the thigh with equivalence evident across all pairings when applying a 10% equivalence zone (Edwardson et al., 2021). Although the use of a 10% equivalence zone is common in studies comparing activity metrics from accelerometer devices, the use of dichotomous thresholds can be problematic (O'brien, 2021). Take for instance a scenario whereby a measure falls slightly outside the 10% equivalence zone (i.e., ±10.1%) whereas another measure requires a zone of ±99% to reach equivalence. In such cases, both metrics are considered non-equivalent which doesn't fully reflect the equivalence of each metric. To overcome this issue, a strength of this study is the reporting of the required zone needed to reach equivalence. This is particularly important for the intensity gradient which has a narrow range of values and can lead to a 10% equivalence zone being lax. From our findings, the absolute and relative zones needed for the intensity gradient to reach equivalence was 4% and≤0.5 SDs which strengthens the physiological and clinical significance of the intensity gradient findings.

As expected, the average acceleration values tended to be lower from the activPAL in comparison to the ActiGraph. Wrist movements can be independent of body posture in certain instances when individuals are sitting down and moving their arms. Since the measurement period coincided with the participants attending school, this could have contributed to the differences observed in average acceleration between devices. Especially since children aged 7–12 years of age spend most of their time at school sedentary (McLellan et al., 2020). Moreover, the lower average acceleration values from the activPAL may also be due to the lower dynamic range (±4 *g* vs.±8 *g*) and sampling frequency (20 Hz vs. 80 Hz) of the device settings in comparison to the ActiGraph. In a recent study, healthy adults wore two Axivity accelerometers on the dominant wrist and two on the hip for 24 hours with one device initialized at each location with a sampling frequency of either 25 Hz or 100 Hz (Small et al., 2021). Findings revealed that average acceleration values were between 12% to 13% lower with 11% to 23% less time observed in MVPA, when using a reduced sampling rate. The differences in sampling rate between devices in this study therefore, may also explain the findings presented in Table 2 at both the group and individual level for most metrics. MAPE tends to be greater than MPE, but this isn't always evident when there is a consistent underestimate or overestimate from a device compared to the reference method. The direction of error, apart from M60 and M30, could suggest that the activPAL consistently underestimated average acceleration associated with most MX metrics compared to the ActiGraph. This underestimation could explain why the MPE and MAPE values were very similar for some metrics but for others, MPE was larger than MAPE. Alternatively, the findings could just reflect the activities being undertaken and the different sampling frequencies used between devices.

When you consider the findings for the lowest acceleration magnitude-based metrics (i.e., ≥ M240), the relative equivalence zones were high, the absolute equivalence zones were≥1 SDs and agreement was poor. A possible explanation for these discrepancies could relate to the nature of activity undertaken during these durations where there is a lack of lower limb movement (i.e., walking and running). To explore this hypothesis, we used PAL analysis to determine stepping time from the activPAL devices on the days used in the current analysis. The analysis revealed stepping time to be 121.2 ± 39.5 min/day. This suggests that of the acceleration values included within M240, ~ 50% of these activities were undertaken with the lower limbs typically stationary. It could be argued therefore, that the discrepancies in metrics ≥ M240 could be due to erroneous wrist movements whilst the lower limbs are typically stationary. When considering the findings from M60 and M30, the activPAL produced higher acceleration values to that from the ActiGraph which could be explained by the walking activities undertaken by the participants. It is plausible that most activities undertaken during M60 and M30 comprised walking, where higher acceleration values could be seen from the thigh versus the wrist. Especially if participants had their arms by their side or hands in their pockets whilst walking. We can also draw upon laboratory findings involving adults who were asked to walk on a treadmill for 5 mins at 4 mph whilst wearing ActiGraph accelerometers at the wrist to support this hypothesis (Buchan et al., 2020). Here the authors reported the median (25^{th} – 75^{th} percentile) acceleration values from the non-dominant wrist to be 234 m*g* (208–260 m*g*) which is broadly similar to M30, but lower than the M60, acceleration values (Table 1). Finally, the differences observed in metrics ≤ M10, which are over a shorter period, likely reflect the influence of the higher dynamic range and sampling frequency of the ActiGraph device.

Using the same processing methods, Edwardson et al. (Edwardson et al., 2021) reported a high MAPE of 63% and a lack of equivalence when comparing the M480 metric between the activPAL and ActiGraph. To the best of our knowledge, this is the only study to compare activity metrics from the activPAL

and ActiGraph using identical processing methods provided by the open-source software GGIR. The lack of additional MX metrics reported by Edwardson (Edwardson et al., 2021), other than M60 and M30, precludes further comparisons of MX metrics > M60 with our own findings. Nonetheless, our findings suggest that MX metrics >M60 are not comparable between devices and therefore may not be good candidates for data harmonization. Similar interpretations could also be made for M5, M2 and M1 where the highest acceleration values are provided with poor agreement, and mainly high relative and absolute equivalence zones evident.

In this study we have to extend the work of Edwardson et al. (Edwardson et al., 2021) by reporting additional GGIR-derived MX metrics from the activPAL and for the first time from children. The lack of agreement and equivalence between many of the acceleration magnitude-based metrics reported here is unsurprising given the differences in device settings and wear location. As others have also observed poor agreement and a lack of equivalence for acceleration magnitude-based MX metrics between the activPAL and either the ActiGraph, Axivity or GENEActiv when all were worn on the thigh and processed identically (Edwardson et al., 2021), differences in device settings likely explain these findings. Yet, without a criterion measure, it is not possible to ascertain which monitor performed best, nor which sampling frequency and/or dynamic range is the most appropriate for accurately capturing activity and SB movement patterns. Nonetheless, previous studies have established the activPAL as the gold standard for measuring SB (Kozey-Keadle et al., 2011; Sellers et al., 2016). The primary use of the activPAL device is to classify posture as well as time spent upright, stepping and in SB unlike other accelerometer devices such as the ActiGraph, Axivity and GENEActiv. Moreover, findings suggest that accelerometers worn on the thigh demonstrate superior accuracy over accelerometers placed on other locations (i.e., both wrists and the hip) for predicting time spent in activity categories and for predicting the number of breaks in SB against direct observation in a laboratory setting (Montoye et al., 2016).

In the study by Edwardson et al (Edwardson et al., 2021), the aim was to compare postural and activity metrics across different accelerometers worn on the thigh during free living, therefore acceleration values indicative of standard activities were not provided. Nor have there been any laboratory-based validation studies undertaken with the aim of providing MVPA cut-points for the activPAL worn on the thigh which are specific for the ENMO metric. Future research should therefore consider addressing these evidence gaps to aid post-hoc interpretations. Doing so may encourage the use of a single device (i.e., activPAL) to provide data that can offer important insights into both activity and SB movement patterns and facilitate comparisons with other studies that have deployed wrist worn accelerometers.

Strengths of this study include the use of the open-source software GGIR to process data collected from activPAL and ActiGraph after 7 days of free-living in an identical manner. Furthermore, devices were worn in accordance with the manufacturer's recommendations. Finally, presenting the required absolute and relative zones needed to reach equivalence for several acceleration magnitude-based metrics is a particular strength and can facilitate future between-study comparisons. Limitations of this study include the narrow age range of participants recruited from one geographical area which may limit the generalizability of our findings. Another limitation of this study is the removal of a large number of participants from subsequent analysis for failing to meet the inclusion criteria. Furthermore, participants were required to provide a full 24 h of wear time to be included in subsequent analysis. We felt it was important to compare identical time periods to ensure differences were only due to the differences between wear location, dynamic range, and sampling frequency and not due to comparing asynchronous timeframes. Whilst we believe this stringent quality control was important for this analysis, future work may wish to explore whether comparable findings are evident in independent data sets which cover different time periods (i.e., the school day, waking hours).

In summary, acceleration magnitude-based metrics tended to be lower from the activPAL in comparison to the ActiGraph, with the magnitude of differences increasing as the MX duration increases above 60 minutes. Yet, our findings do suggest that the intensity gradients M60, M30, M20, M15 and M10 are comparable between the activPAL worn on the thigh and the ActiGraph when worn on the non-dominant wrist. This is an important finding and may allow future research to generate PA metrics from the activPAL to enable comparisons between other studies and at the same time, report on sedentary behaviours.

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