**Full title: Validating the Sedentary Sphere method in children: does wrist or accelerometer brand matter?**

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## Abstract

This study aimed to validate the Sedentary Sphere posture classification method from wrist-worn accelerometers in children. Twenty-seven 9-10-year-old children wore ActiGraph GT9X (AG) and GENEActiv (GA) accelerometers on both wrists, and activPAL on the thigh while completing prescribed activities: five sedentary activities, standing with phone, walking (criterion for all 7: observation) and ten minutes free-living play (criterion: activPAL). In an independent sample, 21 children wore AG and GA accelerometers on the non-dominant wrist and activPAL for two days of free-living. Percent accuracy, pairwise 95% equivalence tests (±10% equivalence zone) and intra-class correlation coefficients (ICC) analyses were completed. Accuracy was similar, for prescribed activities irrespective of brand (non-dominant wrist: 77%-78%; dominant wrist: 79%). Posture estimates were equivalent between wrists within brand (±6%, ICC>0.81, lower 95% CI≥0.75), between brands worn on the same wrist (±5%, ICC≥0.84, lower 95% CI≥0.80) and between brands worn on opposing wrists (±6%, ICC≥0.78, lower 95% CI≥0.72). Agreement with activPAL during free-living was 77%, but sedentary time was underestimated by 7% (GA) and 10% (AG). The Sedentary Sphere can be used to classify posture from wrist-worn AG and GA accelerometers for group-level estimates in children, but future work is needed to improve the algorithm for better individual-level results.



**Keywords: wearable technology, activity classification, sedentary behaviour**

## Introduction

In recent years sedentary behaviour in children has emerged as an independent risk factor for adverse health outcomes (Saunders, Chaput, & Tremblay, 2014) and has consequently become a target for future interventions (Lewis, Napolitano, Buman, Williams, & Nigg, 2017). Sedentary behaviour is defined as any waking *sitting*, *reclining* or *lying* behaviour with low energy expenditure (≤1.5 METs in adults (Tremblay et al., 2017), ≤2.0 METs in children (Saint-Maurice, Kim, Welk, & Gaesser, 2016)). Growing trends of children's sedentary behaviour are reason for concern (Carson et al., 2016), especially amidst the fast-paced advances of screen-based technologies occupying children's out-of-school hours, increasing their total sedentary time (Kiatrungrit and Hongsanguansri, 2014; Lane, Harrison, & Murphy, 2014; Olafsdottir et al., 2014). Despite this, research into children's sedentary behaviour is still in its infancy and requires valid and reliable measures (Carson, et al., 2016) for the field to advance towards effective epidemiological and intervention studies. Accurately measuring sedentary behaviour is vital to such research; however, it remains difficult to quantify sedentary behaviour due to the multiple contexts in which it occurs, the varied types of sedentary behaviour people engage in and the postural characteristics of the behaviour (Hardy et al., 2013).

Wrist- and hip-worn accelerometers are the most widely used objective measurement tools in children's physical activity research (Cain, Sallis, Conway, Van Dyck, & Calhoon, 2013). Although accelerometers have also been regularly used to quantify sedentary time, as characterised by an absence of or low levels of dynamic acceleration, this approach does not take into account the postural element of sedentary behaviour. Posture classification is vital in the measurement of sedentary behaviour and is central to its definition (Tremblay, et al., 2017). The ability to accurately classify sedentary behaviour and physical activity using one accelerometer would be advantageous to the discipline, as it would remove the requirement for additional devices that classify posture such as the activPAL. In turn, this would reduce participant burden, researcher processing time, and financial costs involved with running a study. Researchers have been calling for such a solution, i.e. a feasible method that would allow the use of one accelerometer able to classify posture as well as providing raw acceleration data (Boddy et al., 2018; Hildebrand, Hansen, van Hees, & Ekelund, 2016). In children, such a device should preferably be a wrist-worn monitor, as compliance is highest with wrist-worn devices (Fairclough et al., 2016) and children view it as more socially desirable than other devices or placements (McCann, Knowles, Fairclough, & Graves, 2016). Additionally, compliance with activPAL is low in adolescents, who reported the 7 days of wear time to be too long and would prefer not to wear it again (Shi et al., 2019).

Rowlands and colleagues first introduced the concept of the Sedentary Sphere in 2014 as a new method of analysing, identifying and visually presenting data from the wrist-worn GENEActiv accelerometer. The Sedentary Sphere uses arm elevation to classify the most likely posture in adult populations (Rowlands et al., 2014), thus providing a pragmatic solution to the lack of postural classification using the magnitude of acceleration intensity alone. During periods of inactivity, gravity provides the primary signal to the accelerometer and the Sedentary Sphere uses this gravitational component of the acceleration signal to determine the orientation of the monitor and therefore, the position of the wrist (Rowlands, et al., 2014). In a subsequent study, Rowlands and colleagues further validated this approach for posture classification using data from the widely used ActiGraph accelerometer worn on the wrist (Rowlands et al., 2016). The Sedentary Sphere represents a promising and feasible approach to measuring sedentary time that can be applied to the many large observational datasets using wrist-worn GENEActiv or ActiGraph accelerometers to assess children's physical behaviours (e.g. the Pelotas Birth

Cohort (da Silva et al., 2014), the Melbourne Child Health Checkpoint (Wake M et al., 2014), the Cork Children's Lifestyle Study (Li, Kearney, Keane, Harrington, & Fitzgerald, 2017), the National Health and Nutrition Examination Survey 2011-2014 (Troiano, McClain, Brychta, & Chen, 2014)). To date, application of the Sedentary Sphere concept has not been validated in children; therefore, this study aims to investigate whether the Sedentary Sphere method of classifying posture using GENEActiv and ActiGraph GT9X wrist-worn accelerometers, can be used in its current state in child populations.

## Methods

This is a secondary data analysis, and the methods have been published previously (Hurter et al., 2018). The first part of the analysis was taken from a calibration study, conducted in a school gymnasium while the second part came from a subsequent study to provide added free-living data. After obtaining ethical approval from the Research Ethics Committee of Liverpool John Moores University (16/SPS/056), 27 children (17 girls, 10 boys), aged 9-10 years old, were recruited from one primary school in Liverpool. Signed informed parental/carer consent and child assent forms were obtained from all participants prior to data collection. Data collection took place in January 2017.

Body mass was measured in light clothing without shoes, to the nearest 0.1 kg using an electronic scale (Seca, Birmingham, UK). Stature and sitting height were measured to the nearest 0.1 cm using a stadiometer (Leicester Height measure; Seca, Birmingham, UK). Waist circumference was measured at the midpoint between the bottom rib and the iliac crest, to the nearest 0.1 cm using a plastic non-elastic measuring tape (Seca, Birmingham, UK). Participants self-reported their dominant hand, and researchers confirmed this while participants were writing during the homework station of the calibration circuit.

Each participant wore five accelerometers: one ActiGraph GT9X (AG) and GENEActiv (GA) monitor on each of the dominant and non-dominant wrists (using the manufacturers' straps) and an activPAL monitor (attached with activPAL stickies) to the right anterior thigh. ActiGraph and GENEActiv monitors were placed next to each other on the wrist, but in no consistent or specific order. All monitors were worn throughout the testing protocol, which involved seven different 'stations' typically representative of sedentary behaviour and light physical activity. These were resting, television viewing, playing with a tablet, playing with lego, doing homework, standing while playing with mobile phone, and walking (see Table 1 for detailed description of the stations), with three participants per session rotating between the seven stations. The stations were designed to simulate, as accurately as possible, children's typical real life sedentary behaviours. Television viewing was always performed first, with the three participants watching together, in an effort to prevent the television from distracting participants during the other activities. The rest of the activities were completed individually, in no particular order. All activities were performed for five minutes, with each participant's start and end times observed with a Garmin Forerunner235 wristwatch and recorded onto a participant data collection sheet. The first author and two trained research assistants were present at each data collection session, observing the three participants completing the stations to confirm the posture was as described in Table 1. The first and last 30 seconds of data from each activity were excluded from the analysis, to remove any data from potential transitional movements. After each session in the school gymnasium, the participants continued to wear the monitors for at least 10 minutes outside, during school recess. Participants were instructed to play as they normally would during this time. Direct observation was used as the criterion for posture allocation for the seven sedentary and light activities. However, direct observation was not possible during recess due to the playground being very busy and not all movements/postures were visible to the researchers. Therefor the activPAL monitor was used as the criterion reference for posture allocation during school recess. Validation studies have shown almost perfect correlation between activPAL and direct observation ($r$ = 0.99) in both adults (Lyden, Kozey Keadle, Staudenmayer, & Freedson, 2012) and children (Aminian and Hinckson, 2012). While these studies used the older, uni-axial activPAL, its agreement with the tri-axial activPAL3 for characterising posture has proved to be high (>95%) (Sellers, Dall, Grant, & Stansfield, 2016).

In a subsequent study (ethical approval reference number: 17/SPS/034), an independent sample of 21 children (13 girls, 8 boys, 9-10 years old) was recruited from two primary schools to provide additional free-living data. Anthropometric measurements were taken as described above. The children wore three monitors in total for this part of the study: GENEActiv and ActiGraph accelerometers on their non-dominant wrist (AG distal to GA) and activPALs attached to their thigh. They wore the monitors for two consecutive days, and were requested to wear the thigh devices continually and only remove the wrist-worn devices for water-based activities. The activPAL monitors were waterproofed with small, flexible sleeves and attached with 10-15 cm Tegaderm adhesive. Participants were supplied with log sheets to record times when they removed the monitors.

[INSERT TABLE 1 NEAR HERE]

***Accelerometers and data processing***

The GENEActiv is a small, lightweight tri-axial accelerometer with a dynamic range of ±8$g$ (Activinsights Ltd., Cambridgeshire, UK). The monitors were initialised to collect data at a sampling frequency of 100 Hz. All GENEActiv data were downloaded using GENEActiv PC software version 3.1, saved in raw format as binary files before being converted to 15 s epoch .csv files, matching the format required for Sedentary Sphere analysis. The 15 s epoch files were then imported into custom-built Microsoft Excel spreadsheets (available from the authors on request), to facilitate computation of the most likely posture.

The ActiGraph GT9X is also a small, lightweight tri-axial accelerometer, with a dynamic range of ±8*g* (ActiGraph LLC, Pensacola, FL). Data were collected at a sampling frequency of 100 Hz, downloaded with ActiLife version 6.13.3, saved in raw format as .gt3x files, then converted to time-stamped .csv files containing *x*, *y* and *z* vectors. These 100 Hz .csv files were subsequently converted with a custom-built programme (GT9X-to-SedSphere) written in MATLAB (R2017b, The MathWorks Inc., Natick, MA, USA) to 15 s epochs with the orientation of each axis matched to those of the GENEActiv. Thus, this matched the format required for the analysis in the custom-built Excel spreadsheets. The resultant 15 s epoch files contained *x*, *y* and *z* vectors (mean acceleration over the epoch, retaining the gravity vector) and vector magnitude (VM) values (summed over each epoch and corrected for gravity).

The activPAL3c is a small, single-site lightweight, tri-axial activity monitor that uses proprietary algorithms to classify an individual’s activity into periods spent sitting, standing and walking (PAL Technologies Ltd., Glasgow, UK). Default settings were used during initialization, thus collecting data at 20 Hz. Data were downloaded using activPAL3 Professional Research Edition version 7.2.32, saved as .datx files and converted to 15 s epoch .csv files.

***Sedentary Sphere***

A detailed explanation of the use of the Sedentary Sphere for posture classification can be viewed elsewhere (Rowlands, et al., 2014). In short, the Sedentary Sphere calculates the most likely posture (sitting/reclining or upright) based on arm elevation and acceleration intensity. An arm elevation higher than 15º below the horizontal coupled with low intensity (<489 g·15 s (value is specific to data collected at 100 Hz over a 15 s epoch), or 326 m*g* (value is sampling frequency and epoch independent)) is indicative of a seated/reclining position (Rowlands, et al., 2016), thus classified as "sedentary". If the arm is hanging more vertically (lower than 15º below the horizontal), an "upright" (standing) posture is classified (Rowlands, et al., 2016). Moderate to vigorous physical activity intensities (>489g·15 s, or 326 m*g*) results in an "upright" classification, irrespective of wrist elevation (Rowlands, et al., 2016). During a free-living sample of 34 adults, agreement between GENEActiv (sedentary sphere) and activPAL was 85% (Rowlands, et al., 2014). Another free-living study in adults (Pavey, Gomersall, Clark, & Brown, 2016) found a strong, significant correlation (Pearson's $r = 0.81$ (95% CI 0.69-0.88)) between estimated sedentary time as measured by activPAL and GENEActiv (sedentary sphere).

### *Data analysis*

After applying the Sedentary Sphere method to both GENEActiv and ActiGraph data, the percentage of epochs correctly coded as sedentary and upright during the gymnasium protocol (criterion: direct observation) and school recess (criterion: activPAL) were calculated for both the dominant and the non-dominant wrists. Percentages (i.e. accuracy) were summarized and presented as means (95% CI) for each individual activity. Pairwise 95% equivalence tests (±10%) and intra-class correlation coefficients (ICC, single measures, absolute agreement) were used to evaluate agreement of posture estimates between wrists and between accelerometer brands.

During the subsequent free-living study, the Sedentary Sphere method was applied to all valid hours collected from GENEActiv and ActiGraph monitors between 07:00 and 21:00 on the second day of data collection and in the same way, compared to results from activPAL. Hours were deemed invalid if the monitors were removed for any number of minutes during that hour, according to the log sheets. Visual inspection of data files in GENEActiv, ActiGraph and activPAL software verified the recorded log sheet wear times (Rowlands, et al., 2016). Thirty-one hours were excluded due to non-wear, while two participants' activPALs fell off resulting in another 18 hours being excluded. A total of 245 free-living hours across the whole sample were included in the analysis. Intra-individual classification agreement across 15 s epochs was reported as percentage agreement, sensitivity and specificity, and limits of agreement were examined using Bland-Altman analysis. Due to the presence of heteroscedasticity, Bland-Altman analysis were re-run using logarithmic transformation (Bland and Altman, 1999). Equivalency analysis was performed to assess average group level equivalence between AG and GA sedentary estimates according to the sedentary sphere method with the criterion being sedentary time according to activPAL. An equivalence test was completed to establish whether the 90% confidence intervals for AG and GA sedentary time fell within the zone of equivalence, defined as ±10% of the activPAL mean (Dixon et al., 2018). Mean percent error (MPE) and Mean absolute percent error (MAPE) were calculated as described by DeShaw et al. (2018). In addition, for comparison we also applied a cut-point approach to classifying sedentary behaviour. All free-living seconds with a corresponding accelerometer output of less than 50 m*g* were coded as sedentary, with all other seconds coded as non-sedentary. The resultant sedentary times estimated by the 50 m*g* threshold for both GA and AG were compared with activPAL in the same way as the Sedentary Sphere results.

## Results

### *Sedentary stations and free-play during recess*

Descriptive data for all participants are presented in Table 2. Twenty-seven participants (17 girls, 10 boys; 3 left-handed) completed all the stations in the school gymnasium, while 10 minutes of school recess data for 25 participants were included in the analysis (two participants' activPALs fell off during school recess). Table 3 shows the mean (95% CI) percentage of 15 s epochs correctly coded as sedentary and upright for activities grouped by type and classification category, for each measurement method. During the protocol in the gymnasium, sedentary (lying and sitting) activities were correctly classified for the majority of the time (87-100%), except for Television viewing that had a slightly lower accuracy (66-71%).

Classification of walking as upright was accurate the vast majority of the time (87-90%), however 'standing while playing with a mobile phone' was misclassified as sitting for most of the time (≤12% accuracy). Free-living data during recess showed high classification accuracy (82-88%) relative to the activPAL. When the 'standing while playing with a mobile phone' activity was excluded from the analysis, accuracy increased across the board: from 77% to 87% for GENEActiv non-dominant wrist, 78% to 91% for GENEActiv dominant wrist, 78% to 90% for ActiGraph non-dominant wrist and from 79% to 91% for ActiGraph dominant wrist data (data not shown). During the observed activities, data from activPAL showed a 96.9% (SD = 4) agreement with direct observation.

Mean percent accuracy for the whole data collection period (observed and recess activities) was similar, irrespective of accelerometer brand, at 77%-78% for the non-dominant wrist and 79% for the dominant wrist. Posture estimates could be considered equivalent (Figure 1) between brands worn on the same wrist (±5%, ICC>0.84, lower 95% CI>0.80, top panel of

Figure 1), between wrists within brand (±6%, ICC>0.81, lower 95% CI≥0.75, middle panel of Figure 1) and between brands worn on opposing wrists (±6%, ICC≥0.78, lower 95% CI≥0.72, lower panel of Figure 1).

[INSERT TABLES 2 AND 3 NEAR HERE]

[INSERT FIGURE 1 NEAR HERE]

***Free-living sample***

Free-living data from 21 participants (13 girls, 8 boys; 3 left-handed) were included in the analysis (see Table 2 for descriptive data). Mean wear time was 700 ± 181 min (mean ± SD). Results from the various statistical analyses are presented in Table 4. According to activPAL, participants spent on average 67% of their time seated (468 ± 134 min). The corresponding estimates of sedentary time according to the Sedentary Sphere were both lower (GA: 60%, 415 ± 138 min and AG: 58%, 407 ± 131 min). Mean (95% confidence interval) intraindividual classification agreement between GA and activPAL across 15 s epochs was 77.3% (73.5, 81.1) with sensitivity at 77.2% (71.9, 82.6) and specificity 76.4% (72.2, 80.6). Figure 2 shows the log-transformed data: the mean bias of GA relative to activPAL was -0.06, with limits of agreement between -0.2 and 0.09 (Figure 2A). Back-transformation (antilog) of the log-transformed data revealed that the GA 95% limits of agreement were 37.4% lower to 22.5% higher than AP.

Agreement between AG and activPAL across 15 s epochs was similar, at 76.7% (74.5, 79), sensitivity 75.4% (71.8, 78.9) and specificity 78% (73.7, 82.4). Mean bias (Figure 2B) of log transformed data was also -0.06, but with narrower limits of agreement (-0.16 – 0.03, or 30.6%

lower to 5.9% higher than AP). Results from the equivalence testing are displayed in Figure 3. Estimates of sedentary time according to the Sedentary Sphere method applied to both GA and AG data could not be considered statistically equivalent when compared with the activPAL, on average at the group level. While both monitors underestimated time spent sedentary compared with activPAL, GA came closer than AG to achieving equivalency with activPAL. This is confirmed in the MPE indicating underestimations of -11.3% (GA) and -13.7% (AG) against activPAL, and MAPE (GA = 13.5%, AG = 15.3%). Table 4 and Figure 3 also display results from the comparison between activPAL and the 50m*g* threshold. Sedentary time according to the threshold were significantly higher compared with activPAL (GA: 72%, 505 ± 114 min, p = 0.001; AG: 72%, 504 ± 144 min, p = 0.002). Mean bias and limits of agreement of log-transformed GA and AG 50m*g* data relative to activPAL were similar (both with mean bias of 0.03, 95% limits of agreement 10% lower and 29% higher than AP).

[INSERT TABLE 4 NEAR HERE]

[INSERT FIGURE 2 NEAR HERE]

[INSERT FIGURE 3 NEAR HERE]

## Discussion

The aim of this study was to validate the Sedentary Sphere method of classifying posture using GENEActiv and ActiGraph GT9X wrist-worn accelerometers in children. Posture classification is vital to accurately measuring sedentary behaviour, though the majority of studies classify sedentary time using low levels or an absence of acceleration using threshold without considering posture. This study suggests that the Sedentary Sphere method can be used to classify the most likely posture in children (from either wrist-worn GENEActiv or ActiGraph accelerometers), but researchers should be cautious, knowing that the method is likely to underestimate sedentary time. Wrist-worn accelerometers are increasingly being used to measure children's physical activity  and sedentary behaviour (e.g. Keane et al., 2017), due to improved wear compliance in comparison to hip-worn devices (Fairclough, et al., 2016), therefore the ability to classify posture using one wrist-mounted accelerometer is advantageous to researchers and funders.

Posture classification accuracy was high for most observed activities, and during free-living recess and the longer free-living period, irrespective of monitor brand or dominance (mean around 78%). This is higher than the 69% agreement reported between the widely used ActiGraph hip cut-point for sedentary time (100 vertical-axis counts·min$^{-1}$) compared with activPAL sitting time during the school day (Ridgers et al., 2012). During free-living time, the Sedentary Sphere applied to AG and GA data both underestimated sitting time compared with activPAL, however, classification accuracy during this period was consistent with the observed activities. The free-living results showed smaller mean bias and limits of agreement than those reported by Hildebrand, et al. (2016) who compared sedentary cut-points with activPAL (smallest mean bias +30, LoA -226 to +287 min). While the activPAL has proven to be a valid tool to measure time spent sitting/lying, standing and walking (perfect correlation between activPAL and observation, $r$ = 1.00) in children (Aminian and Hinckson, 2012), the step count become increasingly inaccurate as physical activity intensity increases ($r$ = 0.21 to 0.34 for fast walking and running respectively) (Aminian and Hinckson, 2012). It is established that wrist-worn accelerometers can provide valid measures of physical activity in children (Chandler, Brazendale, Beets, & Mealing, 2016; Phillips, Parfitt, & Rowlands, 2013). This study showed that posture can also be classified using data from wrist-worn accelerometers during structured low intensity activities, a period of recess and free-living time. Further, this study shows that a wrist-worn GENEActiv or ActiGraph give equivalent estimates of sedentary time by using the

Sedentary Sphere method, irrespective of whether the monitor is worn on the dominant or non-dominant wrist. While previous research has shown acceleration magnitude for ActiGraph to be approximately 10% lower than that of GENEActiv (John, Sasaki, Staudenmayer, Mavilia, & Freedson, 2013; Rowlands et al., 2015), our findings are consistent with previous work suggesting that posture classification based on orientation of the gravitational component compare well, irrespective of monitor brand (Rowlands, et al., 2016).

'Standing while playing with a mobile phone', was rarely correctly classified. The reason for the misclassification lies in the nature of the activity itself. It is a known limitation of the posture classification algorithm that any activity requiring the arms to be elevated while standing will be misclassified as sitting (Rowlands, et al., 2016). This will have implications in free-living studies, the extent of which will depend on the prevalence of standing with arms raised. Similar findings were observed in adult studies, with activities like waitressing (Pavey, et al., 2016) or washing-up (Rowlands, et al., 2014) misclassified as sitting. Participants typically held the phone with both hands, resulting in the elevation of both arms, causing the misclassification on both wrists. Standing still is notoriously difficult to classify from the magnitude of acceleration alone, as noted by Lyden and colleagues (Lyden, Keadle, Staudenmayer, & Freedson, 2014), irrespective of whether counts per second or raw acceleration signals are examined, or whether laboratory or free-living settings are being investigated. As little or no dynamic acceleration is recorded during sedentary behaviour, devices cannot distinguish between sitting and standing still based on the magnitude of acceleration signals alone. To overcome large misclassifications, previous studies have chosen to group sitting and standing together (e.g. Ermes, Parkka, Mantyjarvi, & Korhonen, 2008; Mathie MJ, Celler BG, NH, & ACF, 2004), however, doing so contradicts the consensus definition of sedentary behaviour, that includes lying, reclining or sitting postures only

(Tremblay, et al., 2017). Notably, the Sedentary Sphere method accurately classifies standing still in adults (mean percentage accuracy = 100% for GENEActiv data, 95% for ActiGraph data) (Rowlands, et al., 2016), in structured conditions without the arms elevated.

During the recess period, where children did not have access to mobile phones, upright postures were classified accurately most of the time, as is evident via the high percentage agreement with activPAL (≥ 82%). The use of handheld devices, such as mobile phones, is prevalent; in a 2014 study, out of 8266 nine year old Irish children, 41% had their own mobile phones (Lane, et al., 2014) and access to mobile phones has increased dramatically over relatively short time periods (Kiatrungrit and Hongsanguansri, 2014). Potentially, mobile phone use could detrimentally effect the accuracy of the posture estimation; the impact of this will depend on whether children of this age spend a lot of time standing still with a mobile phone, or if they prefer to sit down or walk.

However, epoch-by-epoch agreement between both GENEActiv and ActiGraph non-dominant wrist data and activPAL during the subsequent free-living sample was the same (77%) as the accuracy reported during the observed activities and recess period, superior to published results from cut-points (Ridgers, et al., 2012). These are encouraging results, suggesting that the method performed equally well in an ecologically valid setting and in the controlled environment, where we aimed to mimic the typical range of activities children engage in during and after school hours. Equivalence testing, MPE and mean bias values of free-living data, however, showed that the method underestimated sedentary time compared with activPAL, suggesting that while this method seems promising, the algorithms may require refinement for use in children. While the Sedentary Sphere method underestimated sedentary time, the more traditional thresholds method slightly overestimated sedentary time compared with activPAL.

Our study has several strengths. The protocol included five different sedentary activities, one stationary activity and one light intensity physical activity as well as a recess period allowing free-play, thus a wide range of behaviours were represented. The independent free-living sample confirmed our observed activities had ecological validity, thus overcoming criticisms of previous validation studies. The participants wore five different monitors each, enabling us to validate the Sedentary Sphere method in both ActiGraph GT9X and GENEActiv monitors and across both wrists. We used direct observation as criterion measure for the protocol in the school gymnasium, with one trained researcher observing each participant. There were also some limitations. The small homogeneous sample of 9-10 year old children should not be considered representative of all ages, and further studies are needed for younger children and older adults. The monitors were placed next to each other on the wrist, in no consistent or specific order. Placing one brand consistently distal to the other might have resulted in slightly higher acceleration from that brand; however, no formal randomisation techniques were used and recent studies in adults suggest that results are consistent, regardless of placement (Rowlands et al., 2018). Though the stations were not performed in the same order no formal randomisation techniques were used, though unlike physical activity calibration studies, the sedentary and stationary nature of the stations should have avoided issues related to fatigue.

**Conclusions**

This is the first study to apply the Sedentary Sphere classification algorithm to children's data. The results suggest the method developed in adults can be applied to wrist-worn accelerometer data to predict the *most likely* posture in children, but the algorithm needs refining for child populations. Results found that the Sedentary Sphere was equally valid for GENEActiv and ActiGraph GT9X accelerometers, whether the monitor was worn on the dominant or non-dominant wrist, and agreement with activPAL was confirmed during the free-living sample. However, the method underestimated free-living sedentary time and future work should ideally use direct observation during free-living time, or simulated free living, to identify where misclassification occurs. This will allow further work on improving the algorithm for child populations in order to achieve better results on individual level estimates. Improvements might include adding new features like patterns of movement within angles, patterns of changes in angles or adding a frequency domain.

## Disclosure statement

The authors declare no conflict of interests.

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TABLE 1. Activities undertaken in the school gymnasium.

| Posture | | Activity |
|---|---|---|
| *Sedentary | Resting | Lying on a soft gym mat, in a supine position, asked to avoid bodily movements. |
| | TV | Sitting comfortably on a couch, watching TV. |
| | Tablet | Sitting comfortably on a couch, playing the Bike Race game on an iPad. |
| | Lego | Sitting at a table, playing with Lego. |
| | Homework | Sitting at a table, copying a piece of writing (mimicking homework). |
| *Upright | Phone | Standing while playing Subway Surf on a phone. |
| | Walking | Walking, at own pace, around a designated track. |
| †Free-living | Recess | 10 min free-living during break time (recess) at school. |

N.B. Each activity was performed for five minutes, in no particular order, but always starting with TV viewing

*Participants were directly observed to ensure the posture was as described

†The activPAL was worn to provide a criterion measure of posture

TABLE 2: Descriptive characteristics of the participants [Mean (SD)].

| | **Gymnasium protocol (n=27)** | **Free-living data (n=21)** |
|---|---|---|
| Age (years) | 10.2 (0.3) | 10.2 (0.3) |
| Stature (cm) | 141.5 (6.9) | 142.8 (7.4) |
| Sitting height (cm) | 70.9 (3.9) | 71.3 (3.3) |
| Waist circumference (cm) | 66.7 (10.9) | 70.3 (9.8) |
| Body mass (kg) | 37.3 (11.4) | 40.8 (10.6) |
| BMI (kg/m$^2$) | 18.3 (3.9) | 19.8 (4) |

TABLE 3. Mean (95% confidence interval) percentage of epochs correctly coded as sedentary (lying and sitting activities) and upright for each activity and method.

| **Activity Type** | **Individual Activities** | **Sedentary Sphere: GENEActiv data** | | **Sedentary Sphere: ActiGraph data** | |
|---|---|---|---|---|---|
| | | **Non-dominant** | **Dominant** | **Non-dominant** | **Dominant** |
| **Sedentary*** | Rest | 92.8 (85.4,100.0) | 88.0 (78.0,98.0) | 90.2 (81.7,98.7) | 86.9 (76.4,97.5) |
| | TV | 66.2 (49.9,82.5) | 68.8 (52.6,85.1) | 71.4 (55.6,87.2) | 71.4 (55.3,87.5) |
| | Tablet | 96.3 (89.1,100.0) | 99.8 (99.3,100) | 100 (100,100) | 99.8 (99.3,100.2) |
| | Lego | 92.2 (82.5,100.0) | 98.7 (96.5, 100) | 99.6 (98.7,100.0) | 100 (100,100) |
| | Homework | 89.8 (80.5,99.0) | 99.6 (98.7,100.4) | 93.9 (86.3,101.5) | 99.6 (98.7,100.0) |
| **Upright*** | Phone | 12.2 (0.1,24.3) | 0 (0,0) | 1.5 (0.0,3.5) | 1.5 (0.0,4.6) |
| | Walking | 87.4 (77.4,97.4) | 90.4 (82.9,97.9) | 86.5 (77.1,95.9) | 90.4 (84.7,96.1) |
| | **All observed activities** | **76.7 (71.2,82.2)** | **77.9 (72.3,83.5)** | **77.6 (72.1,83.1)** | **78.5 (73.0,84.0)** |
| **Recess†** | Recess | 81.6 (73.1,90.1) | 88.1 (83.3,92.9) | 86.1 (80.5,91.6) | 86.8 (81.3,92.3) |
| | **Recess and observed activities** | **77.3 (72.3,82.2)** | **79.1 (74.1,84.1)** | **78.6 (73.6,83.5)** | **79.5 (74.6,84.4)** |

*Participants were directly observed to ensure the posture was as described

†The activPAL was worn to provide a criterion measure of posture

TABLE 4: Sedentary time estimates according to the sedentary sphere applied to AG and GA free-living data compared with activPAL

| | Comparison | Mean (SD) minutes | Intraindividual classification agreement across 15s epochs [mean(95%CI)] | | | MAPE* (%) | MPE† (%) | Limits of Agreement† | | Equivalency Analysis (minutes) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Agreement (%) | Sensitivity (%) | Specificity (%) | | | Lower | Upper | |
| activPAL (sit/lie) | | 468 (134) | | | | | | | | Zone of Equivalence: 422 – 515 |
| | GENEActiv (Sed Sphere) | 415 (138) | 77.3 (73.5, 81.1) | 77.2 (71.9, 82.6) | 76.4 (72.2, 80.6) | 13.5 (11.3) | -11.3 (13.6) | 37.4% | 22.5% | 90% CI 389 – 441 |
| | ActiGraph (Sed Sphere) | 407 (131) | 76.7 (74.5 , 79) | 75.4 (71.8, 78.9) | 78 (73.7, 82.4) | 15.3 (6.9) | -13.7 (9.7) | 30.6% | 5.9% | 90% CI 389 – 424 |
| | GENEActiv (<50m*g*) | 505 (144) | | | | 9.6 (8.7) | 8.1 (10.2) | 10.2% | 28.9% | 90% CI 489 – 521 |
| | ActiGraph (<50m*g*) | 504 (144) | | | | 9.5 (8.9) | 7.8 (10.5) | 10.9% | 29.4% | 90% CI 488 – 520 |

*Mean absolute percent error †Mean percent error †Log-transformed data back-transformed (antilog) and reported as percentages

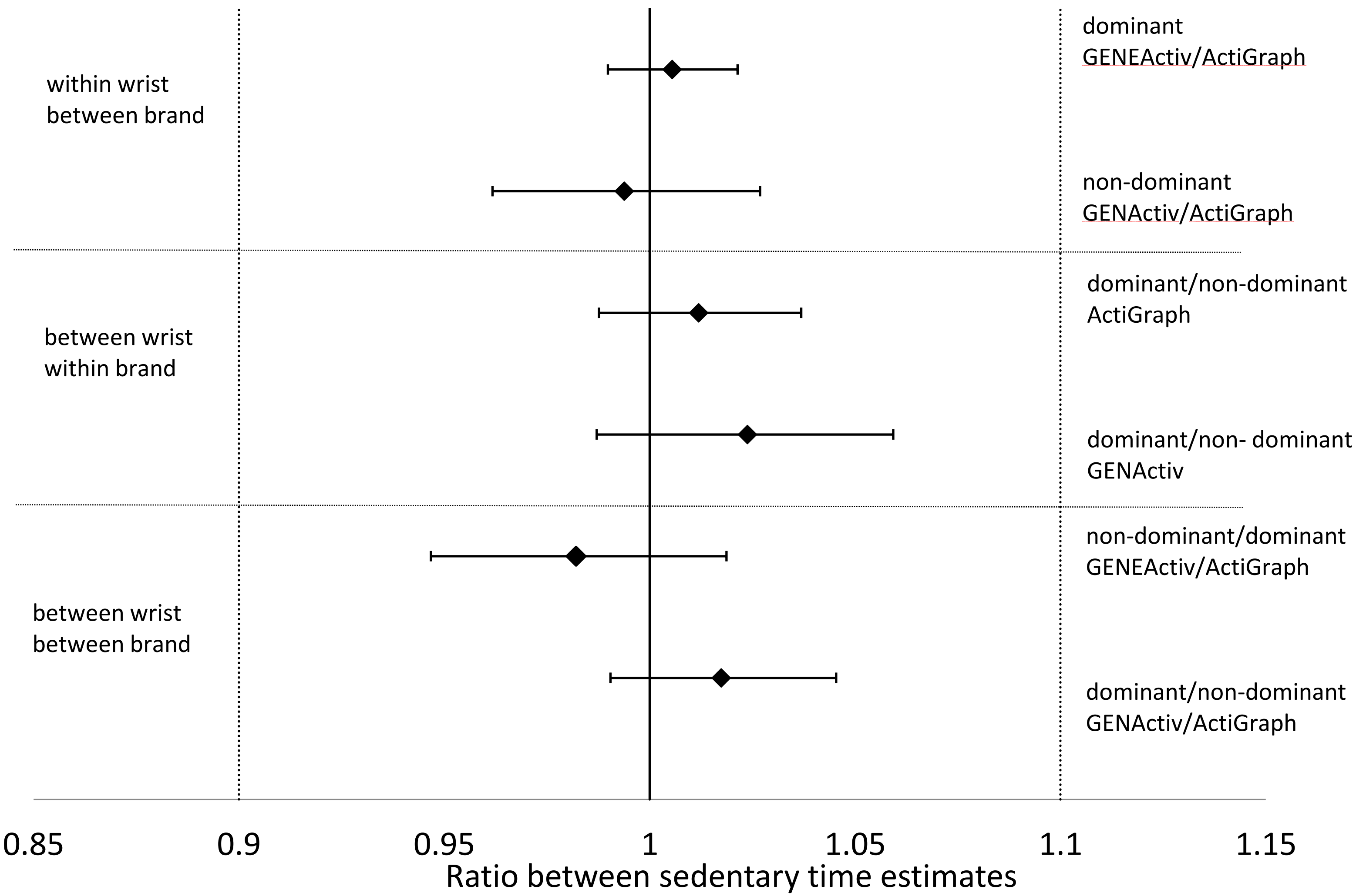



FIGURE 1: Equivalence between brands worn on the same wrist (top panel), between wrists within brand (middle panel) and between brands worn on opposing wrists (lower panel). Dashed vertical lines represent equivalence zone of ±10% of the mean.

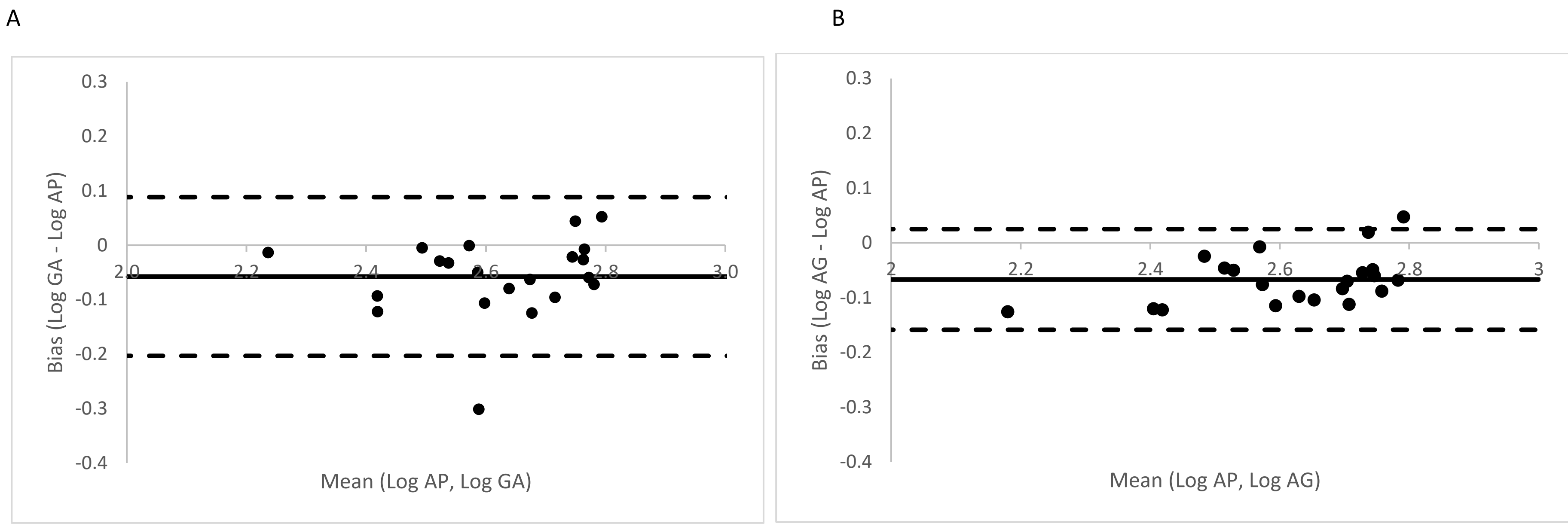
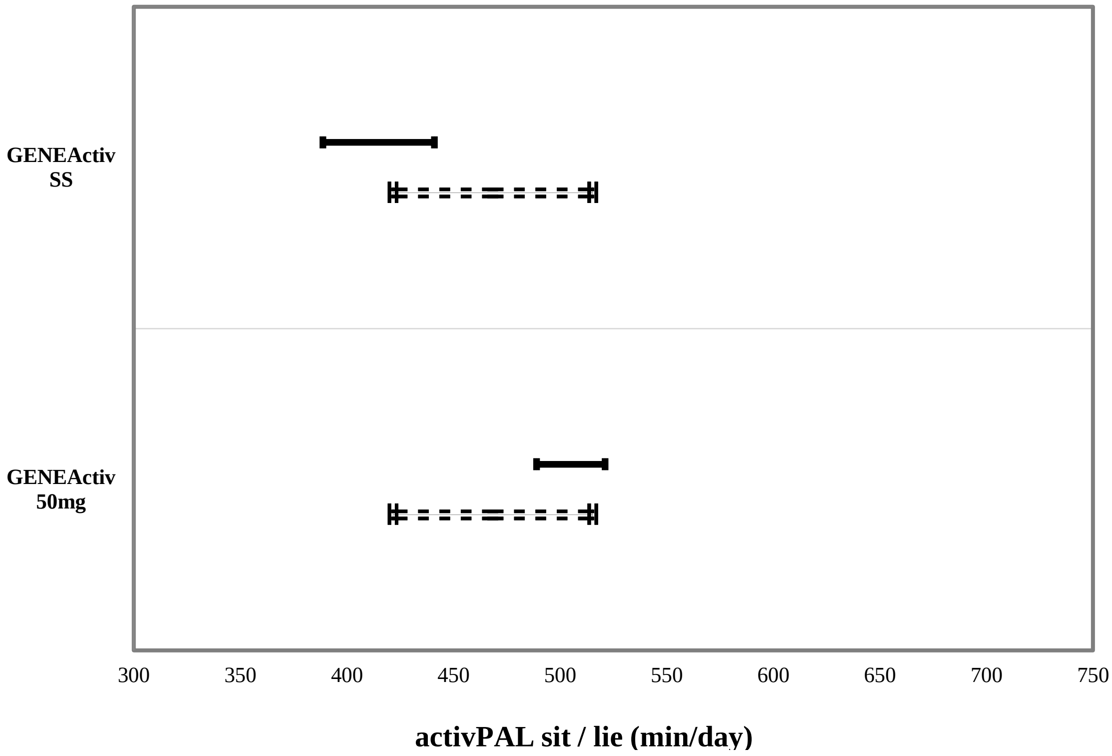



FIGURE 2: Mean bias (solid line) and 95% limits of agreement (dashed lines) for sedentary time estimated from the Sedentary Sphere posture algorithm applied to free-living GENEActiv (A) and ActiGraph log transformed data (B), relative to activPAL.



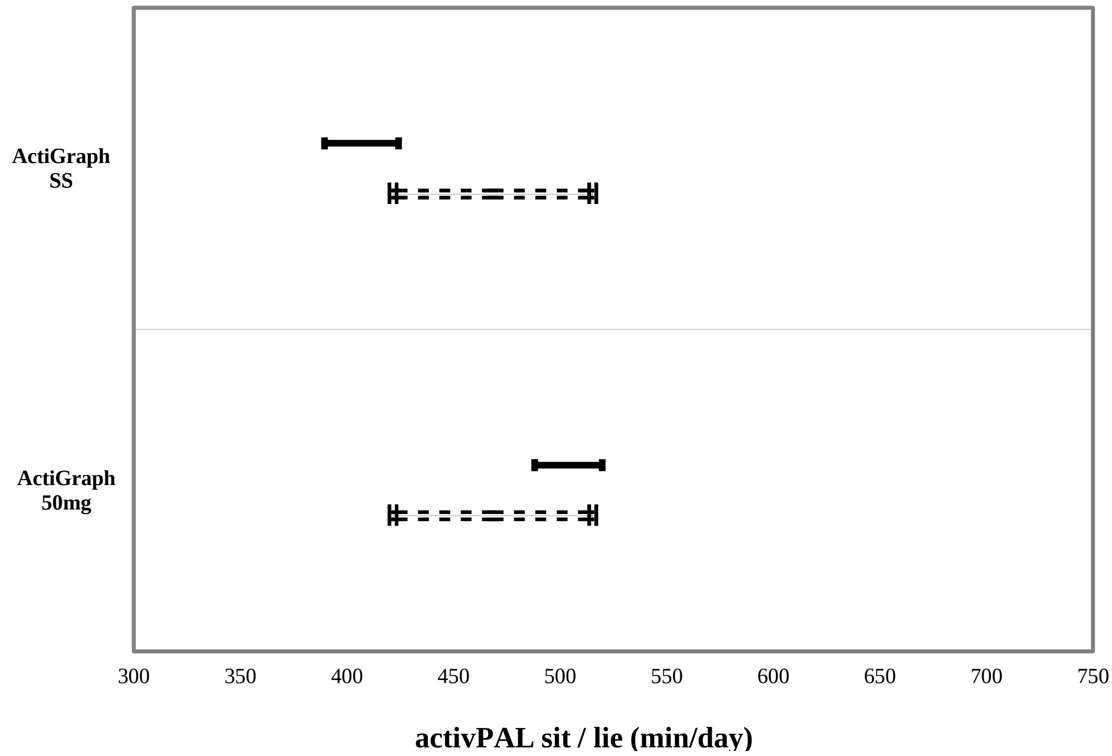




FIGURE 3: activPAL sedentary time zone of equivalence (dotted lines) and 90% confidence intervals for the GENEActiv (top) and ActiGraph (bottom) sedentary time estimates according to the sedentary sphere (SS) and threshold (50mg) methods.