Are we missing the sitting? Agreement between accelerometer non-wear time validation methods used with older adults' data

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Abstract

We used Bland Altman plots to compare agreement between a self-report diary and five different non-wear time algorithms [an algorithm that uses 60 min of consecutive zeroes (Troiano) and four variations of an algorithm that uses 90 min of consecutive zeroes to define a non-wear period] for estimating community-dwelling older adults' ($n = 106$) sedentary behaviour and wear time (min/day) as measured by accelerometry. We found that the Troiano algorithm may overestimate sedentary behaviour and wear time by 30 min/day. Algorithms that use 90 min of continuous zeroes more closely approximate participants' sedentary behaviour and wear time. Across the self-report diary vs. 90 min algorithm comparisons, mean differences ranged between −4.4 to 8.1 min/day for estimates of sedentary behaviour and between −10.8 to 1.0 min/day for estimates of wear time; all 95% confidence intervals for mean differences crossed zero. We also found that 95% limits of agreement were wide for all comparisons, highlighting the large variation in estimates of sedentary behaviour and wear time. Given the importance of reducing sedentary behaviour and encouraging physical activity for older adult health, we conclude that it is critical to establish accurate approaches for measurement.

Keywords

sedentary behaviour; physical activity; Bland Altman; limits of agreement; accelerometry

Subjects

Statistics; Physical Activity and Health; Gerontology

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1. Introduction

Sedentary behaviour is ubiquitous in our daily lives and evidence is emerging that it contributes to public health concerns. Distinct from physical *inactivity* (not meeting physical activity guidelines), sedentary behaviour is defined as any waking behaviour involving 1.5 metabolic equivalents (METs) while sitting or reclining (Sedentary Behaviour Research Network, 2012). Objective population-level data from Canada (Colley et al., 2011) and the United States (Evenson, Buchner, & Morland, 2012) highlight that time spent in sedentary behaviour increases with age; older adults spending the majority of their day (8–10 h) sitting. Time spent in sedentary behaviour is independently associated with reduced muscle mass (Gianoudis, Bailey, & Daly, 2015), metabolic syndrome, waist circumference, overweight/obesity and all-cause mortality in older adults (de Rezende, Rey-Lopez, Matsudo, & Luiz, 2014). Consequently, reducing sedentary behaviour among older adults is an important public health priority.

Characterizing sedentary behaviour is essential to develop age and ability-specific solutions to counter prolonged sitting. While self-report measures offer many benefits, they are susceptible to response bias (e.g. under-reporting of sedentary behaviour due to social desirability) and recall bias (i.e. inaccurate recollection of past activity) (Dishman, Washburn, & Schoeller, 2001; Sallis & Saelens, 2000). This measurement bias is of concern in studies of older adults as they are more likely than adults to underestimate sedentary behaviour (Dyrstad, Hansen, Holme, & Anderssen, 2014). Objective measurement of activity patterns (via accelerometry) provides a reliable approach to assess time spent in sedentary behaviour and physical activity (Matthews, Hagströmer, Pober, & Bowles, 2012) and may overcome limitations of questionnaires (Esliger, Copeland, Barnes, & Tremblay, 2005; Murphy, 2009). One of the benefits (but also a challenge) afforded by accelerometry is the large volume of raw data. To analyze and interpret physical activity data, researchers must systematically process output. However, evidence-based standards for sedentary time are lacking in general, and specifically for defining sedentary time in older adults (Gorman et al., 2014; Ward, Evenson, Vaughn, Rodgers, & Troiano, 2005).

Accelerometers measure accelerations caused by body movement to provide estimates of movement intensity. Another challenge is to identify whether data reflect sedentary behaviour. That is, it is difficult to differentiate sedentary behaviour during wear time from non-wear time (e.g. participant did not wear the accelerometer) as both are derived from periods where raw data are zero counts. Self-report diaries may be used to differentiate between wear time and non-wear time (Esliger et al., 2005). However, they increase participant (data collection) and researcher (data processing) burden, especially with large data sets. Older adults in particular are prone to recall bias and results are dependent on cognitive abilities (Dishman et al., 2001; Rikli, 2000). Consequently, standard algorithms are often used to distinguish between wear time and non-wear time.

The most common algorithm used to identify non-wear time for adult and older adult accelerometer studies was established by Troiano et al. (2008). It defines non-wear time as 60 min of consecutive zero counts, but allows 1–2 min of counts between 1–100 (Troiano et al., 2008). However, generally speaking, older adults tend to be sedentary for longer

periods of time compared with adults (Matthews et al., 2008). These sedentary behaviours likely involve non-movement that lasts for relatively long periods. Thus, longer periods of consecutive zero counts may be legitimate measures of sedentary behaviour and more appropriately differentiate it from non-wear time in this population. That said, the algorithm selected can alter the number of hours and days of wear time. Specifically, this subjective choice will change the proportion of the day spent in non-wear time and sedentary behaviour. The shorter the period of allowable zeros to classify non-wear time, the more likely to eliminate wear time. That is, by applying the same assumptions to older adults that we apply to younger populations, we may inadvertently exclude and thus misclassify, prolonged sedentary behaviour. Although studies evaluated different wear time validation criteria, to our knowledge, only three evaluated criteria 60 min of consecutive zero counts in general (i.e. non-clinical) adult and older adult populations (Choi, Ward, Schnelle, & Buchowski, 2012; Hutto et al., 2013; Keadle, Shiroma, Freedson, & Lee, 2014); only one of these focused on older adults aged 65 years (Choi et al., 2012).

Therefore, our primary objective was to measure the agreement between a self-report diary and five different non-wear time algorithms in estimating community-dwelling older adults' time spent in sedentary behaviour (min/day). These algorithms include the ones developed by Troiano et al. (2008) and four variations of an algorithm that uses 90 min of consecutive zeroes to define a non-wear period. Our secondary objectives were to measure the agreement between a self-report diary, and five different non-wear time algorithms for estimating community-dwelling older adults' total wear time (min/day). We hypothesize that the algorithms that use 90 min of consecutive zeroes to define non-wear periods will more closely estimate sedentary behaviour and wear time than the algorithm developed by Troiano et al. (2008).

2. Methods

We used data from Walk the Talk: Transforming the Built Environment to Enhance Mobility in Seniors, a cross-sectional study that explored associations between the built environment, mobility and health in older adults living on low-income. Study methods are published elsewhere Chudyk, Sims-Gould, Ashe, Winters, and McKay (2017); Chudyk, McKay, Winters, Sims-Gould, and Ashe (in press); however, below we provide a summary of methods relevant to this manuscript.

2.1. Participants

We collaborated with a provincial crown organization, BC Housing, to identify eligible participants, defined as community-dwelling older adult (aged 65 years) residents of Metro Vancouver, British Columbia (BC) in receipt of a Shelter Aid for Senior Renters (SAFER) rental subsidy through BC Housing. We sampled using a random stratified design based on neighbourhood walkability as determined by Walk Score® (www.walkscore.com). We excluded older adults with a diagnosis of dementia (self-report), or who could not communicate in or understand English. Those who used a mobility aid (e.g. a walker) were eligible to participate, but had to be able to walk 10 m with or without a mobility aid (self-report), participate in a mobility assessment involving a four meter walk, and leave their

home 1 in a typical week (self-report). One hundred and sixty-one older adults took part in measurement sessions during March–May 2012. Relevant to this study, participants were asked to fill out a soci-odemographic questionnaire and we measured gait speed as part of the four-meter walk component (usual pace) of the Short Physical Performance Battery (Guralnik, Ferrucci, Simonsick, Salive, & Wallace, 1995). Prior to participation, all participants provided written informed consent. They received a $20 honorarium for their participation. The University of British Columbia Clinical Research Ethics Board approved this study (certificate: H10-02913).

2.2. Accelerometry

We used the ActiGraph GT3X+ accelerometer (LLC, Pensacola, FL) to measure sedentary behaviour and physical activity. The GT3X+ measures time varying accelerations in a magnitude of ±6 g through a micro-electro-mechanical system. Acceleration data are transformed from analog to digital by a 12-bit converter to a sampling rate of 30–100 Hz (user specified), and are stored directly in raw format into flash memory. Raw data are downloaded and analyzed, or filtered and integrated into a user specified epoch.

We requested that participants wear their accelerometers on their right hip from the time they woke up until they went to sleep, for 7 days. As the GT3X+ is water resistant, not water proof, we asked participants to remove the monitor during water based activities (e.g. bathing, swimming). We asked participants to record in a self-report diary each instance they removed their accelerometer for >10 min (referred to as "off time;" e.g. for water based activities, to sleep) and each instance they put the accelerometer back on (referred to as "on time;" e.g. after water based activities, after waking up in the morning).

2.2.1. Cleaning and processing of accelerometry data—We used ActiLife software (6.11.8) (LLC, Pensacola, FL) to initialize, download, and process accelerometry data. We included data from participants who wore the monitor three or more days for a minimum of eight hours per day (Ward et al., 2005). We manually selected the first 7 valid days of wear time during the wear time validation stage of processing. To correct for participants ($n = 8$) who wore the accelerometer past midnight on the 7th day of wear, we converted each participant's file to a .csv format, deleted the cells beyond midnight on the 7th day and reintegrated the file for analysis. We specified a sampling rate 30 Hz and integrated the raw data to 60 s epochs. We used a single axis (vertical) when analyzing the data. To determine sedentary behaviour and physical activity patterns, we batch-scored accelerometry data with ActiLife software, using pre-established cut points. We defined sedentary time as <100 counts/min (Matthews et al., 2008), light activity as 100–1951 counts/min, and moderate to vigorous physical activity (MVPA) as 1952 counts/min (Freedson, Melanson, & Sirard, 1998). We scored accelerometry data using six non-wear time algorithms:

1. Self-report diary: We used participants' self-report diaries to identify non-wear time (>10 min). This was our criterion standard.

2. Troiano: We considered 60 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time (Troiano et al., 2008).

3. Choi: We considered ≤ 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi, Liu, Matthews, & Buchowski, 2011).

4. We considered ≤ 90 min of continuous zeroes, without any allowances for interruptions, as non-wear time.

5. We considered ≤ 90 min of continuous zeroes, while allowing for up to 2 min of counts ≤ 50 counts as non-wear time.

6. We considered ≤ 90 min of continuous zeroes, while allowing for up to 2 min of counts ≤ 100 counts as non-wear time.

We investigated the algorithm developed by Troiano et al. (2008) as it is the most commonly used non-wear time algorithm for older adults. We investigated four variations of an algorithm that uses ≤ 90 min of consecutive zeroes to define a non-wear period because of the emerging evidence of the appropriateness of ≤ 90 min algorithms for estimating older adults' sedentary behaviour (Choi et al., 2012; Keadle et al., 2014). Within these four algorithms, we investigated the algorithm developed by Choi et al. (2011) in an attempt to replicate findings regarding the increased accuracy of this algorithm over Troiano's algorithm for estimates of older adults' sedentary behaviour and wear time (Choi et al., 2012); we investigated the effect of the extent of interruptions that are allowed within a 90 min non-wear period (algorithms 4–6) as choice of interruptions within Troiano's algorithm has been shown by Winkler et al. (2012) to impact estimates of adults' sedentary behaviour and wear time.

2.3. Self-report diaries

We asked participants to complete paper-based diaries over the 7-day period that they wore their accelerometer. Participants reported data on: (1) accelerometer on/off time at the beginning/end of the day, (2) accelerometer off/on time throughout the day, and (3) date.

2.3.1. Processing and cleaning of self-report diaries for ActiLife format—A research assistant entered data from self-report diaries into Excel; we established data entry quality by checking a random sample of 10% entered values. One author (HKC) checked the accuracy of participants' entries by identifying instances where a participant had: (1) missing dates, (2) missing data for an entire day, (3) missing on/off time at the beginning/end of the day, (4) noted an off time during the day without a corresponding on time (and no mention that accelerometer was off for the remainder of the day), (5) noted an on time during the day that was not preceded by an off time, (6) on/off times that did not correspond (e.g. accelerometer put back on before it was taken off), and (7) noted an off time during the day after already indicating that he/she had taken the accelerometer off for the day. We refer to these instances as mislogs. A mislog on a given day resulted in that day's data no longer being valid. After identifying mislogs, one author (HKC) compiled a list of number of valid wear days by participant, and excluded data from participants with fewer than three valid days ($n = 44$).

We entered self-report data (.csv format) into ActiLife software using the diary filter. The filter classifies non-wear time based on participants' self-report diary data. The software then applies the aforementioned cut points to participants' accelerometry data to determine time spent in sedentary behaviour and physical activity and also estimates wear time. Following analysis and export of data into Excel, we manually excluded days where wear time was less than eight hours. After removal of these days, we excluded participants that did not wear the accelerometer for three or more days for a minimum of eight hours per day ($n = 9$).

2.4. Statistical analyses

We describe participants' characteristics and physical activity (min/day, as estimated by the self-report diary algorithm), using means [standard deviations (SD)]; the exception is MVPA, which we describe using medians [p25, p75 as these data were skewed. We use the self-report diary algorithm to describe participants' physical activity as this is our criterion standard algorithm and estimates of physical activity did not vary by algorithm (data not shown). We describe participants' sedentary behaviour (min/day) and wear time (min/day) (as estimated by all six algorithms) using means (SD). We treated accelerometry data as continuous and compared agreement between algorithms for estimates (min/day) of sedentary behaviour and wear time using Bland Altman Plots (Bland & Altman, 2007; Ludbrook, 2010). We report mean differences [95% confidence intervals (CI)] and 95% limits of agreement. The mean difference represents the average difference between two non-wear time criteria. The 95% limits of agreement represent the 95% distribution for the individual discrepancy values. We investigated the presence of proportional and heterogeneity of biases with a visual inspection of the data. All statistical analyses were completed with Stata version 13.1 (Stata, College Station TX).

3. Results

Figure 1 presents the flow of participants into the study. One hundred and six participants (76 women and 30 men) provided at least three days of valid data using all six algorithms.

Participants were 74.1 (SD = 6.4) years old and, on average, had a gait speed [1.0 (SD = 0.3) m/s] that supported community ambulation [=0.8 m/s, (Fritz & Lusardi, 2009)]. They spent an average of 219 (SD = 81) min/day in light activity and a median of 11.8 [p25, p75 = 2.6, 30.3] min/day in MVPA. Participants' mean sedentary behaviour (across algorithms) ranged between 549.7–591.6 min/day and mean wear time (across algorithms) ranged between 795.9–836.8 min/day (Table 1).

Table 2 displays agreement between non-wear time algorithms for estimates of sedentary behaviour and wear time. Figures 2 and 3 display Bland Altman plots of non-wear time algorithms for estimates of sedentary behaviour and wear time. For estimates of sedentary behaviour, the mean difference was greatest for the self-report diary vs. Troiano comparison (37.5 min/day, 95% CI = 25.7, 49.3). The mean difference ranged between –4.4 min/day (95% CI = –14.6, 5.8) and 8.1 min/day (95% CI = –2.3, 18.5) across the four other comparisons and all 95% CIs crossed zero. For estimates of wear time, the mean difference was also greatest for the self-report diary vs. Troiano comparison (30.0 min/day, 95% CI =

18.2, 41.8). The mean difference was -10.8 min/day (95% CI = −21.4, −0.2) for the self-report diary vs. Algorithm 4 comparison. The mean difference ranged between −1.3 min/day (95% CI = −12.0, 9.3) and 1.0 min/day (95% CI = −9.7, 11.7) across the three other comparisons; all 95% CIs crossed zero. 95% Limits of agreement were wide for all sedentary behaviour and wear time comparisons.

4. Discussion

In this study we extend the field by confirming the results of Choi et al. (2012) with more participants and those with greater capacity to be mobile (as measured by gait speed). We also test three other variations of algorithms that use 90 min of consecutive zeroes to define a non-wear period. Overall, we found that bias was greatest for estimates of sedentary behaviour and wear time for the algorithm developed by Troiano et al. (2008). We also found that the algorithms that use 90 min of consecutive zeroes to define non wear periods provided similar estimates of sedentary behaviour and wear time; the 95% CIs of the mean differences crossed zero for all comparisons that involved the 90 min algorithms. However, 95% limits of agreement were wide for all comparisons, highlighting the large variation in estimates of sedentary behaviour and wear time.

Accuracy of algorithms for classification of non-wear time (vs. actual sedentary behaviour) is likely age and population (e.g. general vs. clinical) specific (Janssen & Cliff, 2015). Among older adults aged 56 years, Hutto et al. (2013) reported that a non-wear time criterion of 120 min of continuous zeroes may provide the most dependable population-based estimates of non-wear time, sedentary behaviour, and physical activity. However, Choi et al. (2012) and Keadle et al. (2014) reported that a 90 min criterion may be most appropriate. Despite this, the majority of studies of older adult physical activity classify non-wear time using a 60 min of continuous zeroes criterion (Gorman et al., 2014). This implies that the older adults may be spending even more time in sedentary behaviour than estimated by 60 min non-wear time criteria. Further, given that estimates of sedentary behaviour vary widely across non-wear time criteria, it is pertinent that researchers adopt a uniform system for the classification of sedentary behaviour when analyzing accelerometry data (Young et al., 2016).

We acknowledge the strengths of our study in that we address an important methodological issue for accelerometry (especially for older adults). Further, we systematically and rigorously approached data cleaning and management, and compared estimates among the most commonly used classification criteria for non-wear time (60 and 90 min of continuous zeroes). However, despite our best efforts, we note some limitations. We excluded data from 44 participants who had missing information. Also, we had a select group of older adults who were quite active and their data may not be generalizable to all older adults. Finally, self-report measures are susceptible to response bias (e.g. under-reporting of sedentary behaviour due to social desirability) and recall bias (i.e. inaccurate recollection of past activity) (Dishman et al., 2001; Sallis & Saelens, 2000). Since we asked participants to fill out their self-report diaries daily, these data are less susceptible to recall bias than methods that rely on participants' recall of past behaviour (Dishman et al., 2001).

5. Conclusion

The algorithm most commonly used to classify accelerometry non-wear time in older adults may overestimate sedentary behaviour and wear time by 30 min/day. Algorithms that use 90 min of continuous zeroes to identify non-wear time may more closely approximate participants' self-reported sedentary behaviour and wear time, although estimates showed wide variation within each comparison. In our view this is a significant finding with important implications. As efforts globally need to focus on reducing sedentary behaviour and encouraging physical activity for older adult health, it is critical to accurately represent these behaviours. In addition, valid measures are essential for population-level surveillance of sedentary behaviour and physical activity levels and to appropriately design studies that aim to decrease sedentary behaviour and/or increase physical activity in older adults.

Acknowledgments

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Biography

Anna M. Chudyk obtained a BHSc Honours Specialization in Health Sciences (2006) and MSc in Epidemiology and Biostatistics (2008) from the University of Western of Western Ontario. She obtained a PhD in Experimental Medicine from the University of British Columbia in 2016. Anna's research focuses on the association between the built environment (the human-made infrastructure that comprises the areas where we live, work, and play) and older adults' health and mobility (namely, physical activity and travel behaviour). Anna will apply the findings of this paper to inform the analysis of accelerometry data that she collects from older adult study participants, and hopes that you will too!

PUBLIC INTEREST STATEMENT

Sedentary behaviour refers to activities that require little energy expenditure. Accelerometers are small devices that measure accelerations caused by body movements. Researchers frequently use accelerometers to measure sedentary behaviour in the everyday life of study participants. We conducted a study that investigated the impact of different accelerometry analysis algorithms on estimates of sedentary behaviour and wear time (how long participants wore accelerometers for) in community-dwelling older adults. We found that the most commonly used algorithm in older adult sedentary behaviour research may overestimate sedentary behaviour and wear time by 30 min/day. Variations of algorithms that classify sedentary behaviour as little-to-no movement in 90 min intervals provided estimates of sedentary behaviour and wear time that more closely approximated participants' self-reported behaviour. Given the importance of reducing sedentary behaviour and encouraging physical activity for older adult health, we conclude that it is critical to establish accurate approaches for measurement.
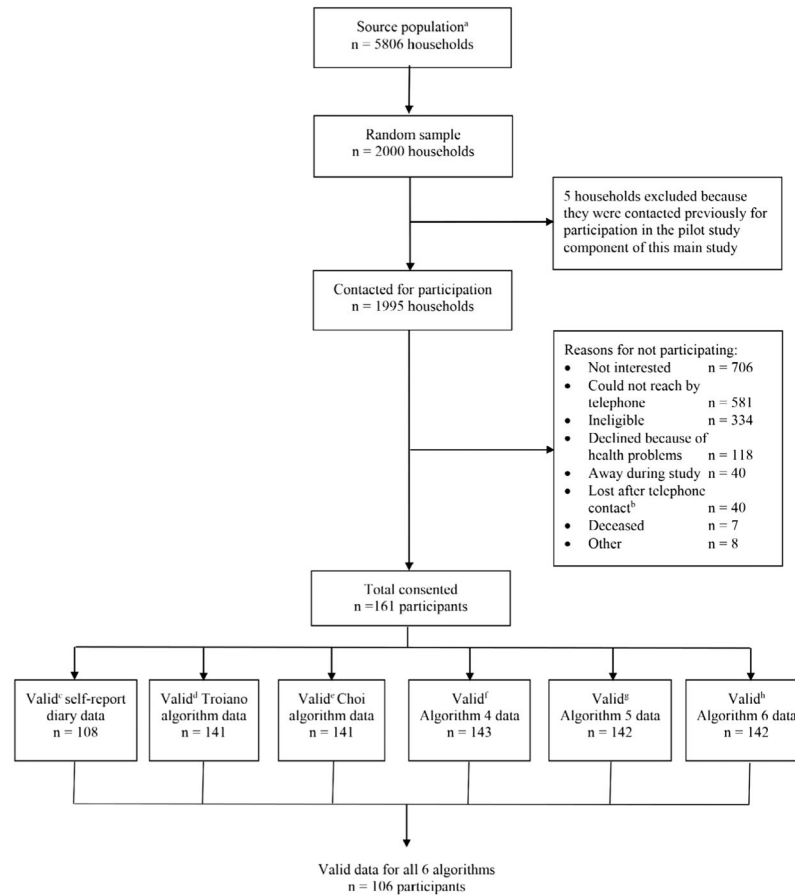
Figure 1. Flow of study participants

[a] Households in our study area (Burnaby, New Westminister, North Vancouver, Richmond, Surrey, Vancouver, West Vancouver, White Rock) that receive a Shelter Aid for Elderly Renters rental subsidy from BC Housing, have a head of household aged 65 years, and a telephone number on file with BC Housing. [b]Could not be reached again after expression of interests in study participation. [c]As measured by self-report diary, based on 3 days with 480 min/day valid wear time; non-wear time determined by self-report. [d]As measured by accelerometry (ActiGraph GT3X+, 60 s epochs), based on 3 days with 480 min/day valid wear time; non wear time defined as 60 min of continuous zeroes, allowing for up to 2 min of counts 100 (Troiano et al., 2008). [e]As measured by accelerometry (ActiGraph GT3X+, 60 s epochs), based on 3 days with 480 min/day valid wear time; non wear time defined as 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi et al., 2011). [f]As measured by accelerometry (ActiGraph GT3X+, 60 s epochs), based on 3 days with 480 min/day valid wear time; non wear time defined as 90 min of continuous zeroes, without any allowance for interruptions. [g]As measured by accelerometry (ActiGraph GT3X+, 60 s epochs), based on 3 days with 480 min/day valid wear time; non wear time defined as 90 min of continuous zeroes, while allowing for up to 2 min of counts <50 counts. [h]As measured by accelerometry (ActiGraph GT3X+, 60 s

epochs), based on 3 days with 480 min/day valid wear time; non wear time defined as 90 min of continuous zeroes, while allowing for up to 2 min of counts <100 counts.
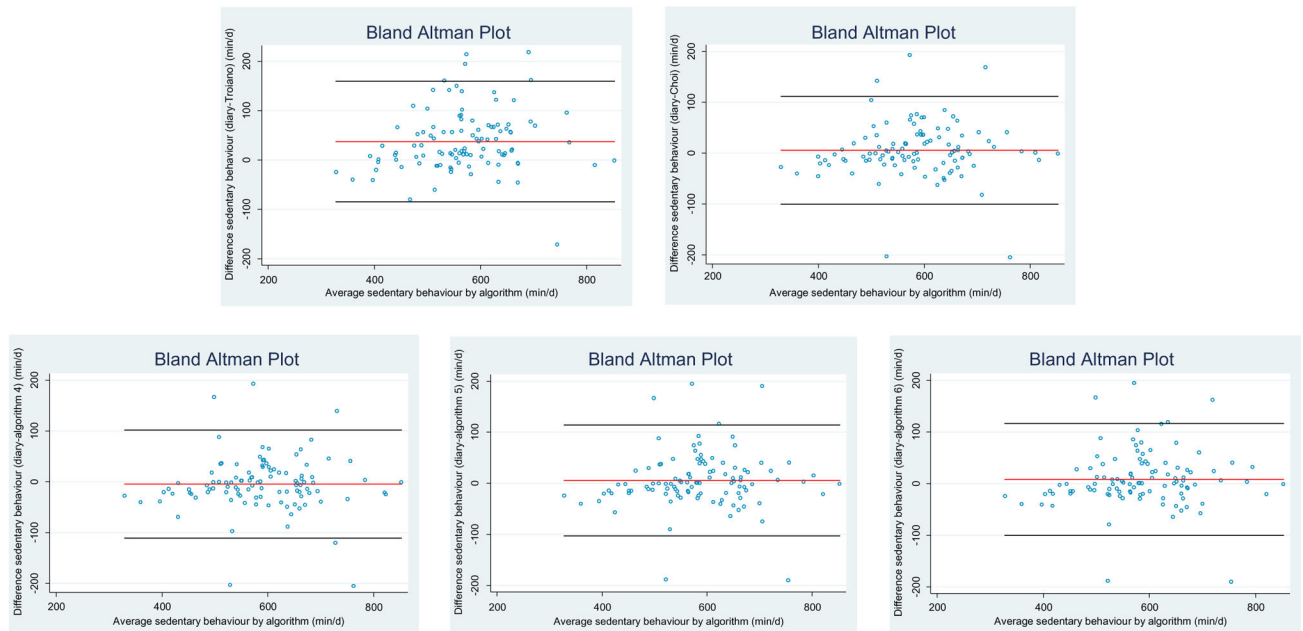
Figure 2. Bland Altman plots of non-wear time algorithm comparisons for estimates of sedentary behaviour (min/day)

Diary: We used participants' self-report diaries to identify non-wear time (>10 min); Troiano: We considered 60 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time (Troiano et al., 2008); Choi: We considered 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi et al., 2011); Algorithm 4: We considered 90 min of continuous zeroes, without any allowances for interruptions, as non-wear time; Algorithm 5: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 50 counts as non-wear time; Algorithm 6: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time.
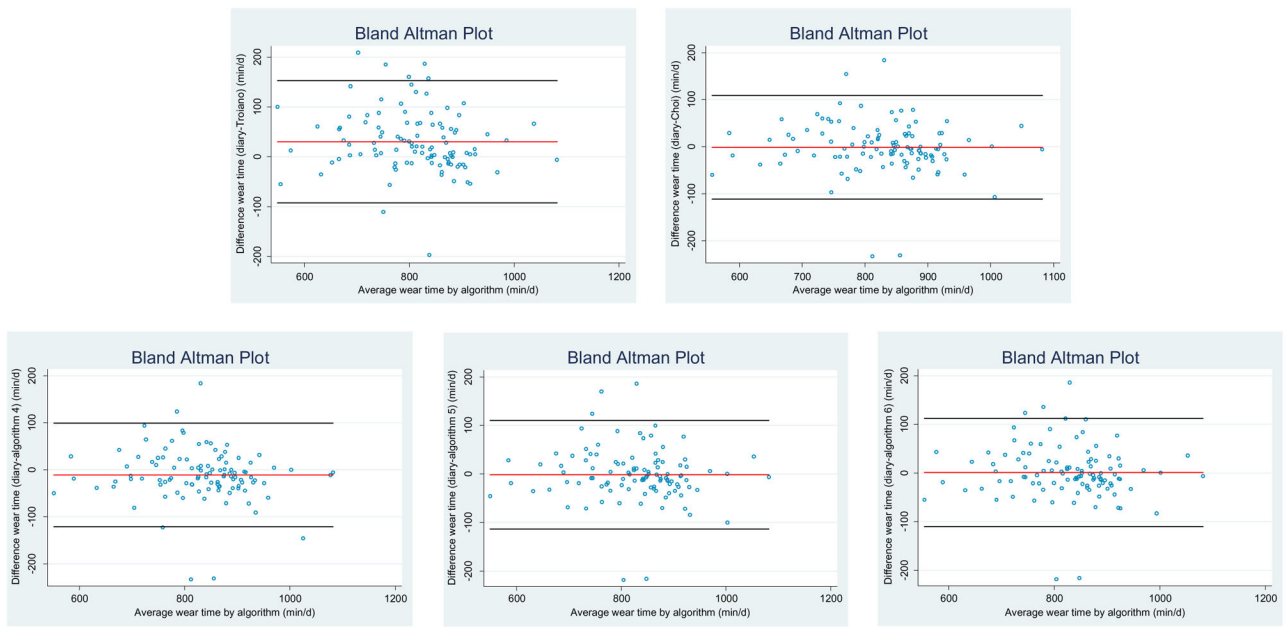
Figure 3. Bland Altman plots of non-wear time algorithm comparisons for estimates of wear time (min/day)

Diary: We used participants' self-report diaries to identify non-wear time (>10 min); Troiano: We considered 60 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time (Troiano et al., 2008); Choi: We considered 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi et al., 2011); Algorithm 4: We considered 90 min of continuous zeroes, without any allowances for interruptions, as non-wear time; Algorithm 5: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 50 counts as non-wear time; Algorithm 6: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time.

Table 1

Estimates of sedentary behaviour and wear time (min/day), by non-wear time algorithm

Algorithm[a]	Sedentary behaviour [mean, (SD)]	Wear time [mean, (SD)]
Self-report diary	587.2 (102.9)	825.9 (95.1)
Troiano	549.7 (94.0)	795.9 (103.7)
Choi	581.4 (100.9)	827.2 (99.6)
4	591.6 (102.3)	836.8 (101.3)
5	581.7 (99.9)	827.4 (100.2)
6	579.1 (99.7)	824.9 (100.0)

[a]Self-report diary: We used participants' self-report diaries to identify non-wear time (>10 min); Troiano: We considered 60 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time (Troiano et al., 2008); Choi: We considered 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi, et al., 2011); 4: We considered 90 min of continuous zeroes, without any allowances for interruptions, as non-wear time; 5: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 50 counts as non-wear time; 6: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time.

Table 2

Agreement between non-wear time criteria for estimates of sedentary behaviour and wear time (min/day)

Comparison[a]	Sedentary behaviour		Wear time	
	Mean differences (95% CI)	95% Limits of agreement	Mean differences (95% CI)	95% Limits of agreement
Diary vs. Troiano	37.5 (25.7, 49.3)	−84.6, 159.6	30.0 (18.2, 41.8)	−92.4, 152.5
Diary vs. Choi	5.8 (−4.4, 16.0)	−100.2, 111.8	−1.3 (−12.0, 9.3)	−111.7, 109.0
Diary vs. Algorithm 4	−4.4 (−14.6, 5.8)	−110.5, 101.8	−10.8 (−21.4, −0.2)	−120.9, 99.2
Diary vs. Algorithm 5	5.5 (−4.9, 15.9)	−103.0, 114.0	−1.5 (−12.2, 9.3)	−113.1, 110.1
Diary vs. Algorithm 6	8.1 (−2.3, 18.5)	−100.2, 116.4	1.0 (−9.7, 11.7)	−110.0, 112.0

[a]Diary: We used participants' self-report diaries to identify non-wear time (>10 min); Troiano: We considered 60 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time (Troiano et al., 2008); Choi: We considered 90 min of consecutive zeroes, while allowing for up to 2 min of non-zero counts if the interruption was accompanied by 30 consecutive minutes of 0 counts either upstream or downstream (Choi, et al., 2011); Algorithm 4: We considered 90 min of continuous zeroes, without any allowances for interruptions, as non-wear time; Algorithm 5: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 50 counts as non-wear time; Algorithm 6: We considered 90 min of continuous zeroes, while allowing for up to 2 min of counts 100 counts as non-wear time.