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Parameterizing and validating existing algorithms for identifying out-of-bed time using hip-worn accelerometer data from older women

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ABSTRACT

Objective: To parameterize and validate two existing algorithms for identifying out-of-bed time using 24-hour hip-worn accelerometer data from older women.

Approach: Overall, 628 women (80±6 years old) wore ActiGraph GT3X+ accelerometers 24 hours/day for up to 7 days and concurrently completed sleep-logs. Trained staff used a validated visual analysis protocol to measure in-bed periods on accelerometer tracings (criterion). The Tracy and McVeigh algorithms were adapted for optimal use in older adults. A training set of 314 women was used to choose two key thresholds by maximizing the sum of sensitivity and specificity for each algorithm and data (vertical axis, VA, and vector magnitude, VM) combination. Data from the remaining 314 women were then used to test agreement in *waking wear time* (i.e., out-of-bed time while wearing the accelerometer) by computing sensitivity, specificity, and kappa comparing the algorithm output with the criterion. Waking wear time-adjusted means of sedentary time, light-intensity physical activity (light PA) and moderate-to-vigorous-intensity physical activity (MVPA) were then estimated and compared.

Main results: Waking wear time agreement with the criterion was high for Tracy_$_{VA}$, Tracy_$_{VM}$, McVeigh_$_{VA}$, and highest for McVeigh_$_{VM}$. Compared to the criterion, McVeigh_$_{VM}$ had mean sensitivity=0.92, specificity=0.87, kappa=0.80, and overall mean difference (±SD) of-0.04±2.5 hours/day. Minutes of sedentary time, light PA, and MVPA adjusted for waking wear time using the criterion measure and McVeigh_$_{VM}$ were not statistically different (p >0.43 | all).

Significance: The McVeigh algorithm with optimal parameters using VM performed best compared to criterion sleep-log assisted visual analysis and is suitable for automated identification of waking wear time in older women when visual analysis is not feasible.

INTRODUCTION

Accelerometers have been used to measure human movement beginning in 1983 (Montoye *et al* 1983) and have since become the most used sensor in physical activity research (Chen *et al* 2012). Early research protocols required accelerometers be worn only while awake, often requiring participants to remove devices when they were likely to get wet (e.g., during showers or while swimming), and while sleeping [eg, (Diaz *et al* 2017)]. One problem with this waking-wear protocol is that taking devices off before bed and putting them on after waking presents opportunities for participants to forget to wear devices while awake, which can result in incomplete assessment of physical activity and sedentary times (Troiano *et al* 2014). This non-wear results in missing data (Tudor-Locke *et al* 2015) that is more likely to occur just before and just after sleep—a pattern that is not missing at random. Furthermore, systematically requiring device removal creates missed opportunities to assess sleep duration and several other dimensions of sleep that can be measured using hip-worn or wrist-worn accelerometers, though accuracy of some sleep dimensions measured with hip-worn accelerometry remains unclear (Zinkhan *et al* 2014, Weiss *et al* 2010).

For the assessment of time spent in physical activity, accelerometers are commonly worn on the hip to measure whole-body acceleration in three dimensions 30 to 100 times per second (Migueles *et al* 2017). Raw acceleration data are summarized to manageable sampling time intervals, or “epochs” (commonly 1 minute) using proprietary algorithms built into manufacturer-provided software resulting in activity measures known as “counts per minute” (cpm). The resulting cpm data can be used to classify each minute of the day into one of four categories: sedentary behavior; physical activity (light, moderate, vigorous); sleep; or non-wear.

Data processing techniques for classifying sedentary behavior and physical activity that rely solely on cpm data are widely used (Freedson *et al* 1998, Troiano *et al* 2008, Matthews *et al* 2008). These techniques use cpm thresholds, also called "cutpoints", that are established often in laboratory studies that calibrate cpm data to directly measured energy expenditure (e.g., oxygen uptake) while participants perform various tasks such as walking on a treadmill, folding laundry, mopping, and watching TV (Evenson *et al* 2015). Automated algorithms to classify non-wear time (Choi *et al* 2011) are also pervasively used. The identification of in-bed time (sometimes a proxy for sleep duration) using automated algorithms is common when accelerometers are worn on the wrist (Ancoli-Israel *et al* 2003). Identifying in-bed time using data from hip-worn accelerometers is more challenging because differences in whole-body movement patterns between sedentary behavior and sleep are not as clearly distinct as those observed on wrist-worn accelerometers. Despite the added difficulty, several automated in-bed detection algorithms for hip-worn accelerometer data have been developed and validated against whole-room calorimetry (Tracy *et al* 2014), parent-reported sleep logs (Barreira *et al* 2015) and expert visual analysis of cpm data (Tudor-locke *et al* 2014, McVeigh *et al* 2016a). Two of the algorithms—Tracy et al.'s bed-rest algorithm (referred to as the "Tracy algorithm") and McVeigh et al.'s waking wear time algorithm (referred to as the "McVeigh algorithm)—rely solely on cpm output from ActiGraph accelerometers (McVeigh *et al* 2016a, Tracy *et al* 2014). The simplicity of the cpm algorithms makes their application in large epidemiologic studies more feasible than other time intensive approaches.

Algorithms designed to categorize out-of-bed time from hip-worn accelerometry rely on temporal patterns of whole-body physical activity that occur while out of bed and while in bed/asleep. The algorithms are heavily influenced by physical activity profiles during the waking period. For example, a person who is consistently active throughout their out-of-bed period will have cpm readings that are distinctly different than the cpm readings during their in-bed period, making the distinction between the two periods clear. For someone who spends the vast majority of their out-of-bed periods sedentary (e.g., sitting at a computer, watching television), distinctions between in-bed and out-of-bed periods would be more difficult to ascertain. The Tracy and McVeigh algorithms were developed and validated using data from youth aged 10-18 and young adults aged ~22 years, respectively. Since sleep patterns (Yoon *et al* 2003) and activity intensity profiles (Troiano *et al* 2008) are highly variable by age, there is good reason to believe that the algorithms developed for adolescents and young adults are not directly generalizable to older adults (McVeigh *et al* 2016a). However, both the Tracy and McVeigh algorithms were originally designed with parameters that could be modified to fit different population subgroups.

The first objective of this study was to identify parameter values that optimized the Tracy and McVeigh algorithms for identifying waking wear time in older women. Waking wear time was defined as the daily out-of-bed time during accelerometer wear, and is the key variable used for adjustment in studies of physical activity and sedentary behavior that collect data over the 24-hour day. The second objective was to validate both algorithms in a separate sample of older women using the newly-identified optimal parameters. An algorithm parameterized for older adults, if sufficiently valid, could measurably reduce the resource burden of data processing, making it more feasible for large epidemiologic studies to include 24-hour accelerometry measures.

METHODS

Sample

Accelerometer and sleep log data from a subsample of Women's Health Initiative (WHI) participants who enrolled in the WHI Long Life Study (2012-2013) and the ancillary Objective Physical Activity and Cardiovascular Health Study (OPACH) were used (LaCroix *et al* 2017). Participants were between 63 and 99 years old (average age 79 ± 7 years), community-living, ambulatory, and cognitively able to both provide consent to the Long Life Study home examination, during which accelerometers were deployed in the majority of women, and provide consent into OAPCH. About half (49.4%) were non-Hispanic white, 33.7% were non-Hispanic black, and 16.9% were Hispanic/Latina. ActiGraph GT3X+ accelerometers were worn over the right hip for 24 hours per day (removed only when showering or swimming) over a 7-day measurement period. Sleep logs were concurrently distributed to collect in-bed and out-of-bed times during accelerometer wear; the sleep logs have been published elsewhere (Rillamas-Sun *et al* 2015). Of the 6489 women who wore accelerometers for at least one day, 6114 (94%) also completed sleep logs for at least one day.

The first 628 participants whose accelerometer data went through a validated sleep log-assisted visual inspection (described below) were included in the present study. Participants were randomly assigned to either a "parameterization subsample" that was used to determine optimal parameters or a "validation subsample" that was a separate sample used only to evaluate the optimal parameters.

Parameters for the Tracy and the McVeigh algorithms were largely dependent on in-bed and out-of-bed body movement. Sleep duration (short <7 hr/night, average 7-9 hr/night, and long >9 hr/night) and total physical activity (high and low, determined by a median split to accelerometer cpm) were used as proxies for this movement. To ensure sufficient variation in sleep and physical activity patterns in the parameterization and validation subsamples, the 628 women were stratified into the 6 mutually exclusive categories based on sleep duration and total physical activity. Then 50% of women from each category were randomly sampled without replacement for the parameterization subsample; the remaining women formed the validation subsample. The parameterization and validation subsamples each had 18 high activity short sleepers, 119 high activity average sleepers, 21 high activity long sleepers, 15 low activity average sleepers, 96 low activity average sleepers, and 45 low activity long sleepers.

Accelerometer data processing

ActiGraph GT3X+ accelerometers measured acceleration at 30 Hz. Raw acceleration data were converted into counts per 15-second epoch using the low frequency filter in ActiLife v6.11. This filter was used by McVeigh and colleagues and is designed so that activity at the lower end of the activity intensity spectrum can be detected with similar consistency as older ActiGraph accelerometer models such as those used by Tracy and colleagues (Tracy *et al* 2014, McVeigh *et al* 2016a, ActiGraphcorp.com 2015). Data were then aggregated to 1-minute epochs to represent cpm. Vector magnitude counts for each 1-minute epoch was computed as the square root of the sum of the vertical axis cpm squared, the horizontal axis cpm squared, and the perpendicular axis cpm squared. Non-wear time was identified by a commonly used automated algorithm which identified periods with ≥ 90 minutes of consecutive vector magnitude cpm of zero, allowing for up to 2 consecutive minutes of nonzero counts (to account for movement of the unworn device) conditional on there being 30 minute windows of zero cpm before and after the device was moved (Choi *et al* 2011, 2012).

Sleep log-assisted visual analysis

Similar to the procedures used by McVeigh et al., two raters were trained to visually identify in-bed periods by systematically observing cpm data on accelerometer tracings in the context of self-reported in-bed periods. Using ActiLife V6.11.8, raters created 60-sec condensed AGD files and scored each participant's 24-hour accelerometer data using the software's sleep analysis tab. Raters identified in-bed periods by inputting self-reported in-bed and out-of-bed times from completed sleep logs into the software and visually inspecting the accelerometer tracings (in cpm) for changes in physical activity that would indicate that the participant transitioned from in-bed to out-of-bed or vice versa. If the visually identified transition was different from the self-reported time by ≥ 15 minutes, then the self-reported sleep period was adjusted based on the observed accelerometer data. The 15-minute requirement was determined by raters and investigators during the protocol development process in part to give the self-reported times priority when raters' and reporters' times were 'close' and as pragmatic step to reduce coder burden. Raters identified the start of the in-bed period as the first zero count following a significant and persistent reduction in activity (<100 cpm) and defined the end of the in-bed period as a significant and persistent increase in activity (>100 cpm). The resulting in-bed periods, from visual inspection, were used as the criterion for algorithm parameterization and for validation. This protocol was developed based on a method used by sleep researchers shown previously to have high inter-rater reliability with mean absolute differences between raters and experts of 3.4±5.4 minutes and interclass correlations ranging from 0.84 to 0.99 (Blackwell *et al* 2005).

For 20 participants, a second rater coded data for the same days. The double-coded data were used to assess the degree to which the criterion data was reliable by computing percent agreement allowing for in-bed and out-of-bed times to differ by ±5 minutes. The inter-rater agreement was 88.2%.

The Tracy and McVeigh algorithms

Generally, both the Tracy and McVeigh algorithms work by first identifying long periods of relatively low intensity activity, to operationalize an in-bed period. The algorithms then search the beginning and end of each period for a more precise in-bed and out-of-bed time. Both steps rely on cpm cutpoints that were applied to data from the vertical axis only. Our study extends this by also using data from all three axes, summarized as the vector magnitude.

The Tracy and McVeigh algorithms were designed with modifiable parameters enabling them to be tuned to work in samples different from those used in their development and validation. Both algorithms are described in detail elsewhere (McVeigh *et al* 2016a, Tracy *et al* 2014). The Tracy algorithm has three modifiable parameters (CP0, CP1, and CP2), with CP1 and CP2 having the largest influence on the accuracy of the algorithm. CP1 is the cpm cutpoint that differentiates high from low intensity activity and is used to identify what the authors call "bedtime rest periods". CP2 is the cpm cutpoint used to find a more precise end time for the bed rest period. The validated cpm cutpoints supplied by the authors—determined by examining receiver operation curves for different options and optimizing for sensitivity and specificity—for CP1 and CP2 were 20 cpm and 500 cpm, respectively (Tracy *et al* 2014). CP0 – a parameter to identify precise start times for the bedtime rest period – was fixed at 50 cpm. The McVeigh algorithm had five modifiable parameters (slthres, prslthresh1, prslthresh2, prwkthresh1, and prwkthresh2), with slthres and prwkthresh2 being central to its functioning. Slthres was used to define period of prolonged low activity that indicated participants were either in bed or the device was not being worn (called in-bed/non-wear [BNW] periods); McVeigh et al. set this equal to 88 cpm. Prslthresh1 and prslthresh2 are parameters used to identify the precise beginning time for a BNW, while prwkthresh1 and prwkthresh2 are parameters used to identify the precise ending time of a BNW. McVeigh et al determined the parameter values by repeatedly changing values, graphing the results, then visually inspecting the results in relation to their criterion. McVeigh et al. set the parameters as follows: prslthresh1=89, prslthresh2=50, prwkthresh1=91, prwkthresh2=200 (McVeigh *et al* 2016a).

Selecting optimal parameters for each algorithm

For the Tracy and McVeigh algorithms, optimal parameters were selected separately using both the vertical axis (VA) and the vector magnitude (VM) data. A range of possible cpm cutpoints was prespecified for the two key modifiable parameters for each algorithm. We then choose 10 to 50 grid points within the plausible range for each parameter. The ranges of plausible values [low:high, by gridpoint] were [VA=10:120, by 10; VM=90:300, by 10] for CP_1, [VA=60:200, by 20; VM=200:700, by 50] for CP_2, [VA=50:150, by 10; VM=150:300, by 10] for slthres, and [VA=120:400, by 40; VM=300:700, by 50] for prwkthresh2, based on the literature (Evenson *et al* 2015, Tracy *et al* 2014) and our practical experiences.

Each combination of parameters was applied to data from participants in the parameterization subsample, one participant at a time, to implement the Tracy and McVeigh algorithms. One-minute epochs were classified as either out-of-bed or in-bed and/or non-wear time. After each implementation, the newly classified minutes were compared with minutes classified using the criterion sleep-log guided visual inspection method by computing sensitivity and specificity. Sensitivity was defined as the proportion of algorithm-identified out-of-bed minutes in agreement with out-of-bed minutes classified using the criterion method. Specificity was defined as the proportion of algorithm-identified in-bed minutes in agreement with in-bed minutes classified using the criterion method. The above procedures were repeated for all unique combinations of modifiable parameters. Sensitivity and specificity were computed for each participant first, and then the medians across all participants were calculated. The parameter combination with the *highest median sensitivity plus specificity* was selected.

To reduce the computational resources needed for the parameterization process, the following parameters, which based on our experience from systematically deconstructing both algorithms and on results from early exploratory sensitivity analyses were determined to be less influential for algorithm accuracy than the varied parameters, were fixed for all analytic steps: CP_0=50 cpm; prslthresh2=50 cpm; prslthresh1=slthresh+1; and prwkthresh1=slthresh+10.

Validation

The parameterization process resulted in 4 optimal cpm cutpoint combinations: $Tracy\_{VA}$; $Tracy\_{VM}$; $McVeigh\_{VA}$; and $McVeigh\_{VM}$. The Tracy and McVeigh algorithms were then implemented on data from the validation sample using the 4 optimal cutpoint combinations and the two originally validated cutpoint combinations supplied by the authors ($Tracy\_{original}$ and $McVeigh\_{original}$). Agreement in daily out-of-bed time between the criterion measure and all 6 implementations of the algorithms was assessed using sensitivity, specificity, and Cohen's kappa.

For each participant and each algorithm implementation, waking wear time was computed as the average number of out-of-bed minutes per day. Agreement in waking wear time was assessed by computing mean bias (i.e., the overall mean difference) and 95% limits of agreement. Bland-Altman plots displayed differences in waking wear time between the algorithm-identified measures and the criterion measure.

Each epoch of waking wear time was separated into "activity measure" categories identified as sedentary behavior, light intensity physical activity (light PA), and moderate-to-vigorous intensity physical activity (MVPA) using vector magnitude cutpoints previously established in the OPACH Calibration Study (sedentary time <39 counts/15-seconds, light PA

40-573 counts/15-seconds, MVPA > 573 counts/15-seconds) (Evenson *et al* 2015). A confusion matrix comparing activity measures for data processed using the criterion method to data processed using all 6 algorithm implementations was then tabulated to identify where misclassification occurred.

Estimates of sedentary time, light PA, and MVPA were computed for the validation sample after adjusting for waking wear time, which is consistent with the analytic method used by many studies of accelerometer-measured physical activity and sedentary behavior. The residuals method (Willett and Stampfer 1986) was used to adjust the activity measures for differences in waking wear time, and differences were analyzed using generalized estimating equations.

Simple linear regression was used to assess how the waking wear time computation method influenced associations between waking wear time-adjusted activity measures and health-related characteristics. The health-related characteristics at the time of accelerometry included age, body mass index (BMI) calculated from measured height and weight, physical functioning assessed using the short physical performance battery (SPPB), and resting blood pressure. The SPPB is a series of three timed tests—balance in three standing position, one 4-meter usual gait speed test, and 5 unassisted chair stands—that are each given a score from 0 to 4 based on previously validated thresholds and are summarized to a score ranging from 0 to 12 with 12 being highly functioning (Guralnik *et al* 1994). Beta coefficients from regression models were compared using the Horton method (Horton and Fitzmaurice 2004) with and without Bonforoni correction for multiple testing.

All analyses were conducted in R (R Foundation for Statistical Computing; Vienna, Austria) using two-tailed statistical tests with $p<0.05$ considered statistically significant.

RESULTS

The parameterization and validation subsamples had similar ages (mean=80±6 years; p=0.75) and similar racial-ethnic variation with the majority of each sample being White (60% and 57%; p=0.71). BMI was slightly higher in the parameterization subsample (29 vs 27 kg/m^2; p=0.01), while SPPB and blood pressure were slightly higher in the validation subsample (Table 1; p-values all > 0.05).

Table 1. Participant characteristics by subsample

	Parameterization subsample (n=314)	Validation Subsample (n=314)	p-value
Age (years)	80 ± 6	80 ± 6	0.75
Race-ethnicity, %			0.71
White	60%	57%	
Black	23%	24%	
Hispanic	17%	19%	
BMI (kg/m^2)	29 ± 6	27 ± 6	0.01
SPPB	8.0 ± 2.6	8.2 ± 2.5	0.37
Diastolic BP (mmHg)	71 ± 8	72 ± 9	0.38
Systolic BP (mmHg)	125 ± 14	127 ± 15	0.10

Abbreviations: BMI = body mass index; SPPB = short physical performance battery; BP = blood pressure
Data are mean ± sd for continuous variables, percentages for categorical variables

For all analyses, only days with complete accelerometer data and self-reported sleep logs were used, resulting in 314 women with 1436 days in the parameterization subsample and 307 women with 1402 days in the validation subsample. The ROC curves show joint distributions of sensitivity and (1-specificity) for each combination of algorithm parameters (Supplemental Figure 1). Optimal (CP_1, CP_2) cutpoints (cpm) maximizing the sum of sensitivity and specificity were (60, 100) for Tracy_$_{VA}$ and (210, 350) for Tracy_$_{VM}$, and optimal McVeigh (slthres, prwkthresh2) cutpoints were (90, 280) for McVeigh_$_{VA}$ and (210, 600) for McVeigh_$_{VM}$.

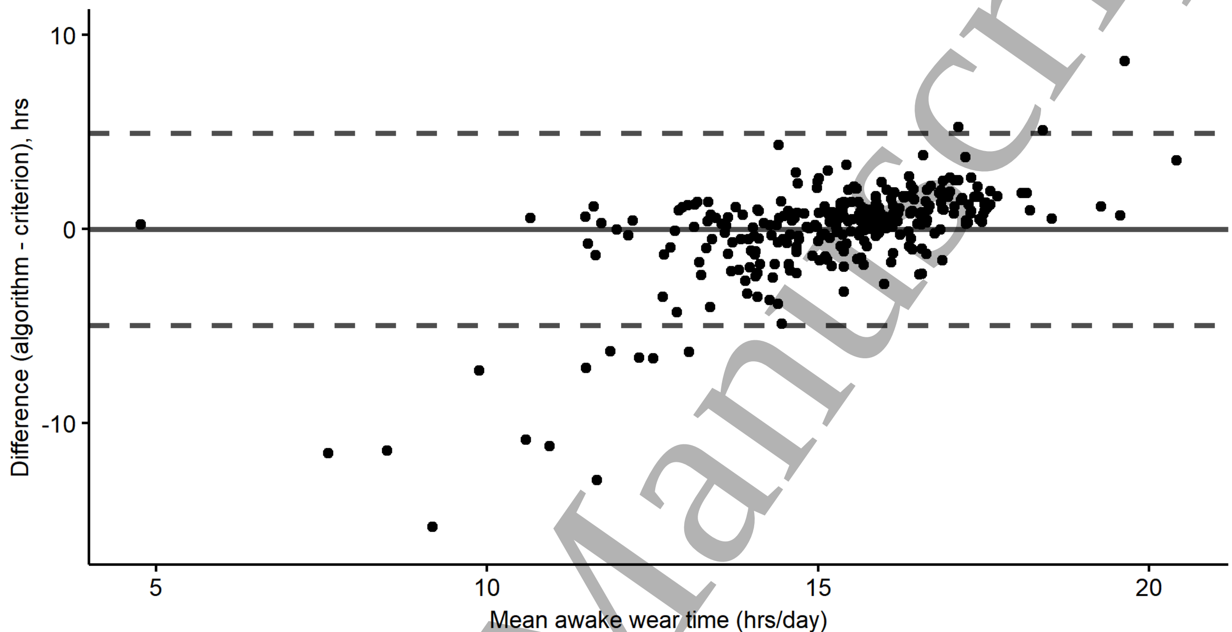
Agreement in waking wear time comparing the criterion method to the Tracy and McVeigh algorithms implemented using the original, optimal VA and optimal VM thresholds for each calendar day in the validation subsample are in Table 2. In general, agreement was high with day-level agreements across all algorithm implementations ranging from 84 to 91% agreement, 85 to 92% for sensitivity, 81 to 89% for specificity, and 67 to 80 for kappa. Between 87 and 94% of all calendar days, on average, had moderate to excellent kappa values.

For nearly all agreement metrics, the McVeigh_$_{VM}$ performed best. Seventy-two percent of days had excellent kappa values. When average waking wear times were computed, the mean bias was near zero (-0.04 hours/day) with 95% levels of agreement ranging from -5.0 hours/day to 4.9 hours/day. The Bland-Altman plot of waking wear time agreement between the McVeigh_$_{VM}$ and the visual analysis approach is show in Figure 1. Bland-Altman plots for all algorithm implementations are in Supplemental Figure 2.

Table 2: Agreement in awake wear time relative to sleep log-assisted visual analysis; validation subsample (1402 days from 307 women)

	Tracy original	**Tracy VA**	**Tracy VM**	**McVeigh original**	**McVeigh VA**	**McVeigh VM**
Day-level agreement						
Percent agreement, *mean (sd)*	84.8 (11.7)	85.3 (12.2)	87.0 (11.5)	86.3 (14.9)	86.0 (15.0)	90.5 (11.1)
Sensitivity, *mean (sd)*	0.87 (0.2)	0.85 (0.2)	0.86 (0.2)	0.86 (0.2)	0.85 (0.2)	0.92 (0.2)
Specificity, *mean (sd)*	0.81 (0.2)	0.86 (0.2)	0.89 (0.1)	0.87 (0.2)	0.87 (0.2)	0.87 (0.2)
Kappa, *mean (sd)*	0.67 (0.2)	0.69 (0.2)	0.73 (0.2)	0.72 (0.3)	0.71 (0.3)	0.80 (0.2)
Kappa category						
Poor (<0.4), *n (%)*	184 (13%)	169 (12%)	110 (8%)	179 (13%)	186 (13%)	86 (6%)
Moderate (0.4-0.75), *n (%)*	590 (42%)	560 (40%)	517 (37%)	403 (29%)	400 (29%)	310 (22%)
Excellent (>0.75), *n (%)*	626 (45%)	671 (48%)	773 (55%)	818 (58%)	814 (58%)	1004 (72%)
Person-level agreement						
Mean bias (hr/day), *mean (sd)*	-0.28 (2.5)	-1.06 (2.6)	-1.28 (2.5)	-1.00 (3.3)	-1.20 (3.4)	-0.04 (2.5)
95% Limits of agreement	-4.9, 4.8	-5.2, 5.1	-5.0, 4.9	-6.5, 6.5	-6.6, 6.5	-5.0, 4.9

Figure 1. Bland-Altman plot of agreement in average daily waking wear time for each participant in the validation subsample. The mean difference (solid line) was computed by subtracting the average daily waking wear time measured by criterion method from the average daily waking wear time measured by the McVeigh algorithm using the optimal vector magnitude (VM) cutpoints; upper and lower limits of agreement are shown with dotted lines. The x-axis is the average waking wear time between criterion method and McVeigh$_{_VM}$.



The confusion matrix in Table 3 shows minute-level epoch classifications for the McVeigh$_{_VM}$ implementation and the criterion method. Matrices for all other algorithm implementations are in the Supplemental Tables 1-5. Cells on the downward-sloping diagonal indicated perfect agreement for 90.5% of all 1-minute epochs in the validation subsample. Nearly all misclassification occurred between the in-bed/non-wear classifications and sedentary time. For 4.3% of the 1-minute epochs, sedentary time was classified as in-bed/non-wear by the McVeigh$_{_VM}$. Similarly, 4.1% of the 1-minute epochs that were classified as in-bed/non-wear by the criterion method were classified as sedentary time by the McVeigh$_{_VM}$. Few light PA or MVPA 1-minute epochs were differentially classified, less than 2% of all epochs in total.

Table 3. Confusion matrix for the McVeigh algorithm implemented using the optimal vector magnitude cutpoints showing activity measures and in-bed/non wear. Data are the number of 1-minute epochs (percentages). Validation subsample (n=307).

	Sleep-log-assisted visual inspection (criterion method)			
	In-bed / non wear time	**Sedentary time**	**Light PA**	**MVPA**
In-bed / non wear time	635540 (31.6)	85865 (4.3)	10738 (0.5)	967 (0.0)
Sedentary time	81812 (4.1)	716989 (35.6)	0 (0.0)	0 (0.0)
Light PA	10009 (0.5)	0 (0.0)	390413 (19.4)	0 (0.0)
MVPA	1754 (0.1)	0 (0.0)	0 (0.0)	77830 (3.9)

Abbreviations: PA = Physical activity, MVPA = Moderate-to-vigorous intensity physical activity

The average number of minutes per day spent in sedentary time, light PA, and MVPA were adjusted for waking wear time, as is typically done in studies of sedentary time and physical activity (Table 4). Women in the validation sample were sedentary for 574 minutes/day, in light PA for 286 minutes/day, and were in MVPA for 56 minutes/day. Across the 6 algorithm implementations, the magnitude of mean differences was highest for sedentary time and lowest for MVPA. Activity time estimates were most similar between the McVeigh$_{VM}$ and the criterion method, with no significant differences for sedentary time (p=0.43), light PA (p=0.82), or MVPA (p=0.51). MVPA estimates adjusted for awake wear time computed using all 6 algorithms were not significantly different from MVPA adjusted using the criterion method (p >0.27 | all).

Table 4: Average minutes per day spent in sedentary time, light physical activity (PA), and moderate to vigorous physical activity (PA) after adjustment for awake wear time. Validation subsample (n=307).

	Criterion method	Tracy original	Tracy VA	Tracy VM	McVeigh original	McVeigh VA	McVeigh VM
Sedentary time[a]	574 (99)	559 (86)	513 (79)	499 (71)	529 (82)	519 (81)	572 (82)
mean difference	-	-15.1	-61.2	-75.2	-45.6	-54.7	-2.3
95% CI	-	(-20.5, -9.7)	(-67.3, -55.0)	(-82.5, -67.9)	(-51.5, -39.7)	(-60.8, -48.7)	(-8.1, 3.4)
p-value	-	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	0.428
light PA[a]	286 (75)	283 (66)	282 (62)	283 (56)	271 (65)	269 (64)	285 (64)
mean difference	-	-2.7	-3.2	-2.4	-14.2	-16.6	-0.5
95% CI	-	(-6.6, 1.1)	(-7.5, 1.1)	(-7.7, 2.8)	(-18.2, -10.3)	(-20.7, -12.6)	(-4.6, 3.6)
p-value	-	0.162	0.140	0.361	**<.001**	**<.001**	0.820
MVPA[a]	56 (41)	56 (38)	57 (37)	56 (36)	55 (36)	55 (36)	56 (38)
mean difference	-	0.8	1.1	0.5	-0.3	-0.5	0.6
95% CI	-	(-0.8, 2.4)	(-0.8, 3.0)	(-1.6, 2.6)	(-2.3, 1.8)	(-2.6, 1.6)	(-1.1, 2.3)
p-value	-	0.347	0.275	0.612	0.808	0.638	0.508

[a] Data are mean (sd)

Inferences about the statistical significance and, when significant, the direction of associations between sedentary time and age, BMI, SPPB, and diastolic blood pressure were similar when sedentary time was adjusted for waking wear time using the criterion method and all 6 implementations of the Tracy and McVeigh algorithms (Table 5). Qualitatively, the magnitude of associations with health-related characteristics were generally most similar when sedentary time was adjusted for the waking wear time computed using the criterion method and McVeigh_VM. Quantitatively, the beta coefficients for *age* estimated using all algorithm-derived waking wear times were different from the beta coefficients adjusted for waking wear time computed using the criterion method ($p<0.05$ | all) with and without Bonforoni correction. When using the Bonforoni method to correct for possible inflation of Type 1 error due to multiple testing, the beta coefficients for BMI, SPPB, and diastolic blood pressure estimated using all algorithm-derived waking wear times were not significantly different from the beta coefficients estimated using the criterion method (except Tracy_VM and BMI). Similar patterns were observed for associations with light PA and with MVPA (Supplemental Tables 6 and 7). Analyses were repeated for systolic blood pressure and results were similar to those for diastolic blood pressure (data not shown).

Table 5: Simple linear regression results for associations between 1 hour of sedentary time (adjusted for awake wear time) and health-related characteristics. Validation subsample (n=307).

	Criterion method (1)	**Tracy original (2)**	**Tracy VA (3)**	**Tracy VM (4)**	**McVeigh original (5)**	**McVeigh VA (6)**	**McVeigh VM (7)**
Age (years)							
beta	0.86	0.57	0.52	0.55	0.64	0.65	0.76
95% CI	(0.48,1.24)	(0.12,1.02)	(0.03,1.01)	(0.00,1.10)	(0.17,1.11)	(0.18,1.13)	(0.29,1.23)
p-value	**<.001**	**0.013**	**0.037**	0.050	**0.008**	**0.007**	**0.002**
Δ beta[a]	2,3,4,5,6,7	1	1,7	1,7	1	1	1,3,4
Δ beta (corrected)[b]	2,3,4,5,6,7	1	1,7	1,7	1	1	1,3,4
BMI (kg/m^2)							
beta	1.10	1.36	1.47	1.26	1.54	1.53	1.21
95% CI	(0.75,1.46)	(0.95,1.76)	(1.03,1.91)	(0.75,1.76)	(1.12,1.97)	(1.10,1.96)	(0.77,1.65)
p-value	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**
Δ beta[a]	4,7	4,7	4	1,2,3,5,6,7	4,6,7	4,5,7	1,2,4,5,6
Δ beta (corrected)[b]	4	4	4	1,2,3,5,6,7	4,6,7	4,5,7	4,5,6
SPPB							
beta	-0.35	-0.41	-0.35	-0.33	-0.30	-0.30	-0.30
95% CI	(-0.54,-0.17)	(-0.63,-0.20)	(-0.58,-0.12)	(-0.60,-0.07)	(-0.53,-0.08)	(-0.53,-0.07)	(-0.52,-0.07)
p-value	**<.001**	**<.001**	**0.003**	**0.013**	**0.009**	**0.012**	**0.010**
Δ beta[a]	4,5,6,7	3,4,5,6,7	2,4	1,2,3	1,2	1,2	1,2
Δ beta (corrected)[b]	-	3,4,6	2	2	-	2	-
Diastolic BP (mmHg)							
beta	-0.10	0.05	-0.15	0.08	-0.10	-0.10	-0.10
95% CI	(-0.70,0.50)	(-0.64,0.74)	(-0.90,0.59)	(-0.75,0.92)	(-0.81,0.62)	(-0.82,0.62)	(-0.83,0.62)
p-value	0.740	0.882	0.683	0.848	0.788	0.792	0.777
Δ beta[a]	-	-	-	-	-	-	-
Δ beta (corrected)[b]	-	-	-	-	-	-	-

Abbreviations: CI = confidence interval; BMI = body mass index; SPPB = short physical performance battery; BP = blood pressure

[a] Differences between betas tested using the Horton method with $p<0.05$ considered significant.

[b] Differences between betas tested using the Horton method with p-values corrected for multiple tests using the Bonforoni method (i.e., $p<0.05/7$ considered significant).

DISCUSSION

This project intended to parameterize and validate two existing algorithms to identify in-bed time to accurately measure waking wear time using data from hip-worn accelerometers worn 24 hours/day by older adults. Automation reduces errors from human visual inspection and drastically reduces the resources needed to process accelerometer data collected using a 24-hour wear protocol, making these approaches more scalable. Our results showed an overall high agreement between the criterion visual inspection method and all 6 implementations of the Tracy and McVeigh automated algorithms, with the highest agreement achieved by the McVeigh_$_{VM}$ with optimized parameters. The McVeigh_$_{VM}$ implementation provided unbiased estimates of average waking wear time though with high variation around the mean (±5 hours). Other implementations had mean biases ranging from -0.28 to -1.28 hours. Sedentary time was the activity most often misclassified by the algorithms, with fewer instances of misclassification on light PA and MVPA. After adjusting sedentary time, light PA, and MVPA for waking wear time, there were no differences in average estimates between the criterion method and McVeigh_$_{VM}$, but other implementations including the McVeigh_$_{original}$ significantly underestimated sedentary time and, in some instances, light PA as well. Similar overall inferences were generally made between health-related characteristics and sedentary time, light PA, and MVPA regardless of the method used to quantify awake wear time. In most tests, estimates based on McVeigh_$_{VM}$ were closest to those based on the criterion method than all other implementations, although there were few significant differences between algorithm implementations. Of particular note, the direction of associations were similar between the criterion method and McVeigh_$_{VM}$ for all health-related variables, and there was statistically significant differences in the magnitude of associations of sedentary time, light PA, and MVPA only with age.

Similar to McVeigh and colleagues, our study objective was to advance available methods for accurate and efficient identification of waking accelerometer wear time. The objective of Tracy and colleagues was to identify bedrest time which they measured directly using energy expenditure from whole-room calorimetry and movement-related mechanical work measured using a force plate in the floor of the whole room calorimeter. This focus on bedrest, which the authors note has also been referred to as sleep or sleep-period, could account for why the McVeigh algorithm outperformed the Tracy algorithm when compared to our criterion measure. Tracy et al. reported bedrest time sensitivity and specificity in their adolescent validation sample (n=40) of 0.97 and 0.97, respectively. The authors subsequently adapted their algorithm to function using data from adults (using a sample of 141 men and women aged 40±14) and achieved bedrest time sensitivity and specificity of 0.82 and 0.97, respectively (Tracy *et al* 2018). McVeigh et al. reported waking wear time sensitivity and specificity in their validation sample (n=97) of 0.97 and 0.96, respectively. The mean bias and 95% limits of agreement reported in their study was (3.6 min/day and -2.3 to 2.5 h/day). The waking wear time sensitivity and specificity observed in our study for the best performing algorithm implementation ($McVeigh\_{VM}$) was comparable, although lower, at 0.92 and 0.87, respectively, and $McVeigh\_{VM}$ mean bias and 95% limits of agreement were (0 min/day and -5 to 4.9 h/day). It is noteworthy that $McVeigh\_{VM}$ outperformed the $McVeigh\_{original}$ demonstrating that parameterizing for older adults and/or using signals from the vector magnitude was an improvement over using only the vertical axis .

Our criterion method was similar to the one used to develop and validate the McVeigh algorithm and is the approach commonly used by researchers when processing sleep-related actigraphy data from wrist-worn devices. The protocol used was originally developed for systematic visual inspection of raw data from wrist-worn accelerometers to determine in-bed periods (Blackwell *et al* 2005) and was modified for use on hip-worn accelerometers; the full protocol is available upon request. While visual inspection is the standard method in the field of sleep research, it is resource intensive, taking approximately 15 minutes per participant in the present study, and can lead to error. In our analysis, the error was small with inter-rater agreement of 88%. Furthermore, in our sleep-log assisted visual analysis, when the in-bed and out-of-bed time appeared to be within 15 minutes of the participants' self-reported in-bed or out-of-bed time, the in-bed period was defined by self-report. This protocol decision was made, in part, to reduce rater burden. The 15-minute buffer combined with the inter-rater error could account for some of the observed differences in waking wear time observed between the criterion method and all 6 algorithm implementations.

The use of automated algorithms can greatly reduce the resources needed to accomplish repetitive tasks in a large scale study setting, especially when set-up time, which sometimes can be long, is reduced by the availability of ready-to-use software. When working with intensive longitudinal data, it is always good practice to visually inspect how algorithms perform (Bolger and Laurenceau 2013). This can be accomplished for a randomly chosen subset of data and/or for the days with unusually long and unusually short waking wear times. In some instances, manually correcting the data following algorithm implementation may be needed. In the present study, we did not manually correct any data. However, we strongly recommend that all researchers implementing this algorithm visually inspect the results. In practice, an example workflow would be to implement the Choi algorithm to identify non-wear, then the McVeigh_VM algorithm to identify awake wear time, plot the results of both overlaid on the VM cpm data for each valid day, then make modifications to the McVeigh_VM results as needed. The McVeigh_VM algorithm can also be used to perform sensitivity analyses when other in-bed period imputation methods are used such as mean imputation [eg, (Bellettiere *et al* 2019)]. If desired, the McVeigh_$_{VM}$ parameters can be further changed to improve the algorithms' accuracy for different samples.

This study is not without limitations. Our focus was on identifying waking wear time and not sleep, primarily because sleep is a construct characterized by physiologic states that is difficult to proxy using only accelerometer data from hip-worn devices. In-bed time (a proxy for sleep duration) is output by the McVeigh algorithm, but this was not the focus of our parameterization or validation. The algorithms were originally designed then newly optimized and validated using data from ActiGraph accelerometers; caution should be taken when applying them to accelerometer data from other devices. New algorithms were published after the design and implementation of our study protocol and were therefore not evaluated [eg, (Tracy *et al* 2018)]. Our study was conducted among older community-living, ambulatory women and we are not sure whether the results can be generalized to the entire older adult population. Finally, we modified only two parameters for each algorithm to conserve computational resources. It is unlikely that this had an appreciable negative effect on parameterization, considering the overall waking wear time agreement was relatively high and that some optimal parameters (specifically the McVeigh_$_{VM}$) tended to outperform the original parameters.

Strengths of our study include the sample size that was more than twice the size of other comparative studies. We had sufficient numbers to parameterize and validate the optimal parameters on two separate datasets, each with over 300 participants. We also parameterized and compared algorithm performance to data from a sleep-log assisted visualization process that is thought to be better than using un-augmented self-reported bed times (Lockley *et al* 1999).

Using only hip-worn accelerometer data collected 24-hours/day from older women, the McVeigh algorithm with the optimal VM parameters provided unbiased estimates of waking wear time. Adjustment for waking wear time computed using McVeigh_$_{VM}$ can introduce error into measures of sedentary time, light PA, and MVPA, which could lead to biased associations with health indicators or other factors of interest. However, most of the associations tested in the validation subsample were not qualitatively different when adjusting for waking wear time computed using the criterion method or McVeigh_$_{VM}$. We also observed unbiased estimates of wear time-adjusted sedentary time, light PA, and MVPA when the McVeigh_$_{VM}$ implementation was used. We therefore conclude that the McVeigh_$_{VM}$ implementation is suitable for identifying awake wear time among older adults. Caution should be used when implementing automated algorithms on intensive longitudinal data, and users of this algorithm should take appropriate precautions, such as visually inspecting the results as needed and manually making changes where appropriate.

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REFERENCES

ActiGraphcorp.com 2015 *ActiGraph White Paper Low Frequency Extension Filter* Online: http://actigraphcorp.com/wp-content/uploads/2015/06/Low-Frequency-Extension-Filter.pdf

Ancoli-Israel S, Cole R, Alessi C, Chambers M, Moorcroft W and Pollak C P 2003 The role of actigraphy in the study of sleep and circadian rhythms. *Sleep* **26** 342–92

Barreira T V., Schuna J M, Mire E F, Katzmarzyk P T, Chaput J P, Leduc G and Tudor-Locke C 2015 Identifying children's nocturnal sleep using 24-h waist accelerometry *Med. Sci. Sports Exerc.* **47** 937–43

Bellettiere J, LaMonte M J, Evenson K R, Rillamas-Sun E, Kerr J, Lee I-M, Di C, Rosenberg D E, Stefanick M L, Buchner D M, Hovell M F, LaCroix A Z 2019 Sedentary Behavior and Cardiovascular Disease in Older Women *Circulation* **139** 1036–46 Online: https://www.ahajournals.org/doi/10.1161/CIRCULATIONAHA.118.035312

Blackwell T, Ancoli-Israel S, Gehrman P R, Schneider J L, Pedula K L and Stone K L 2005 Actigraphy scoring reliability in the study of osteoporotic fractures *Sleep* **28** 1599–605

Bolger N and Laurenceau J-P 2013 *Intensive longitudinal methods: an introduction to diary and experience sampling research* ed D A Kenny (Guilford Press)

Chen K Y, Janz K F, Zhu W and Brychta R J 2012 Redefining the roles of sensors in objective physical activity monitoring *Med. Sci. Sport Exerc.* **44** 13–23

Choi L, Liu Z, Matthews C E and Buchowski M S 2011 Validation of accelerometer wear and nonwear time classification algorithm *Med. Sci. Sports Exerc.* **43** 357–64

Choi L, Ward S C, Schnelle J F and Buchowski M S 2012 Assessment of wear/nonwear time classification algorithms for triaxial accelerometer *Med. Sci. Sports Exerc.* **44** 2009–16

Diaz K M, Goldsmith J, Greenlee H, Strizich G, Qi Q, Mossavar-Rahmani Y, Vidot D C, Buelna C, Brintz C E, Elfassy T, Gallo L C, Daviglus M L, Sotres-Alvarez D and Kaplan R 2017 Prolonged, uninterrupted sedentary behavior and glycemic biomarkers among US Hispanic/Latino adults : The Hispanic Community Health Study/Study of Latinos (HCHS/SOL) *Circulation* **136** 1362–73

Evenson K R, Wen F, Herring A H, Di C, LaMonte M J, Tinker L F, Lee I M, Rillamas-Sun E, LaCroix A Z and Buchner D M 2015 Calibrating physical activity intensity for hip-worn accelerometry in women age 60 to 91years: The Women's Health Initiative OPACH Calibration Study *Prev. Med. Reports* **2** 750–6 Online: http://dx.doi.org/10.1016/j.pmedr.2015.08.021

Freedson P S, Melanson E and Sirard J 1998 Calibration of the Computer Science and Applications, Inc. accelerometer. *Med. Sci. Sports Exerc.* **30** 777–81

Guralnik J M, Simonsick E M, Ferrucci L, Glynn R J, Berkman L F, Blazer D G, Scherr P a. and Wallace R B 1994 A short physical performance battery assessing lower extremi *J. Gerontol.* **49** 85–94

Horton N J and Fitzmaurice G M 2004 TUTORIAL IN BIOSTATISTICS Regression analysis of multiple source and multiple informant data from complex survey samples **2933** 2911–33

LaCroix A Z A Z, Rillamas-Sun E, Buchner D, Evenson K R K R, Di C, Lee I-M I-M, Marshall S, LaMonte M J M J, Hunt J, Tinker L F L F, Stefanick M, Lewis C E C E, Bellettiere J and Herring A H A H 2017 The Objective Physical Activity and Cardiovascular Disease Health in Older Women (OPACH) Study *BMC Public Health* **17** Online: http://bmcpublichealth.biomedcentral.com/articles/10.1186/s12889-017-4065-6

LaMonte M J, Lewis C E, Buchner D M, Evenson K R, Sun E R-, Di C, Lee I-M, Bellettiere J, Stefanick M L, Eaton C B, Howard B V., Bird C and LaCroix A Z 2017 Both light intensity and moderate-to-vigorous physical activity measured by accelerometry are favorably associated with cardiometabolic risk factors in older women: The Objective Physical Activity and Cardiovascular Health (OPACH) Study *J. Am. Heart Assoc.* **6** e007064

Lockley S W, Skene D J and Arendt J 1999 Comparison between subjective and actigraphic measurement of sleep and sleep rhythms *J. Sleep Res.* **8** 175–83

Matthews C E, Chen K Y, Freedson P S, Buchowski M S, Beech B M, Pate R R and Troiano R P 2008 Amount of time spent in sedentary behaviors in the United States, 2003-2004. *Am. J. Epidemiol.* **167** 875–81 Online: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3527832&tool=pmcentrez&rendertype=abstract

McVeigh J A, Winkler E A H, Healy G N, Slater J, Eastwood P R and Straker L M 2016a Validity of an automated algorithm to identify waking and in-bed wear time in hip-worn accelerometer data collected with a 24-hour wear protocol in young adults *Physiol. Meas.* **37** 1636–52

McVeigh J A, Winkler E A H, Howie E K, Tremblay M S, Smith A, Abbott R A, Eastwood P R, Healy G N and Straker L M 2016b Objectively measured patterns of sedentary time and physical activity in young adults of the Raine study cohort *Int. J. Behav. Nutr. Phys. Act.* **13** 41 Online: http://ijbnpa.biomedcentral.com/articles/10.1186/s12966-016-0363-0

Migueles J H, Cadenas-Sanchez C, Ekelund U, Delisle Nystrom C, Mora-Gonzalez J, Lof M, Labayen I, Ruiz J R and Ortega F B 2017 Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations *Sport. Med.* **47** 1821–45

Montoye H J, Washburn R, Servias S, Ertl A, Webster J G and Nagle F J 1983 Estimation of energy expenditure by a portable accelerometer *Med. Sci. Sport Exerc.* **15** 403–7

Rillamas-Sun E, Buchner D M, Di C, Evenson K R and LaCroix A Z 2015 Development and application of an automated algorithm to identify a window of consecutive days of accelerometer wear for large-scale studies *BMC Res Notes* **8** 270

Tracy D J, Xu Z, Choi L, Acra S, Chen K Y and Buchowski M S 2014 Separating bedtime rest from activity using waist or wrist-worn accelerometers in youth *PLoS One* **9**

Tracy J D, Acra S, Chen K Y and Buchowski M S 2018 Identifying bedrest using 24-h waist or wrist accelerometry in adults *PLoS One* **13** 1–16

Troiano R P, McClain J J, Brychta R J and Chen K Y 2014 Evolution of accelerometer methods for physical activity research *Br J Sport. Med* **48** 1019–23 Online: http://www.ncbi.nlm.nih.gov/pubmed/24782483

Troiano R R P, Berrigan D, Dodd K W K, Masse L, Tilert T, McDowell M, Mâsse L C, Tilert T and McDowell M 2008 Physical activity in the United States measured by accelerometer. *Med. Sci. Sports Exerc.* **40** 181–8 Online: http://www.researchgate.net/publication/5757920_Physical_activity_in_the_United_States_measured_by_accelerometer/file/9fcfd50a2830d51ac9.pdf

Tudor-Locke C, Barreira T V, Schuna J M, Mire E F, Chaput J-P, Fogelholm M, Hu G, Kuriyan R, Kurpad A, Lambert E V, Maher C, Maia J, Matsudo V, Olds T, Onywera V, Sarmiento O L, Standage M, Tremblay M S, Zhao P, Church T S, Katzmarzyk P T and ISCOLE Research Group 2015 Improving wear time compliance with a 24-hour waist-worn accelerometer protocol in the International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE). *Int. J. Behav. Nutr. Phys. Act.* **12** 11 Online: http://www.scopus.com/inward/record.url?eid=2-s2.0-84924584808&partnerID=tZOtx3y1%5Cnhttp://www.ncbi.nlm.nih.gov/pubmed/25881074%5Cnhttp://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4328595

Tudor-locke C, Barreira T V, Schuna J M, Mire E and Katzmarzyk P T 2014 Fully automated waist - worn accelerometer algorithm for detecting children ' s sleep period time separate from 24 - hour physical activity or sedentary behaviors *Appl. Physiol. Nutr. Metab.* **39** 53–7

Weiss A R, Johnson N L, Berger N A and Redline S 2010 Validity of activity-based devices to estimate sleep *J. Clin. Sleep Med.* **6** 336–42

Willett W and Stampfer M J 1986 Total energy intake: implications for epidemiologic analyses. *Am. J. Epidemiol.* **124** 17–27

Yoon I Y, Kripke D F, Youngstedt S D and Elliott J A 2003 Actigraphy suggests age-related differences in napping and nocturnal sleep *J. Sleep Res.* **12** 87–93

Zinkhan M, Berger K, Hense S, Nagel M, Obst A, Koch B, Penzel T, Fietze I, Ahrens W, Young P, Happe S, Kantelhardt J W, Kluttig A, Schmidt-Pokrzywniak A, Pillmann F and Stang A 2014 Agreement of different methods for assessing sleep characteristics: A comparison of two actigraphs, wrist and hip placement, and self-report with polysomnography *Sleep Med.* **15** 1107–14 Online: http://dx.doi.org/10.1016/j.sleep.2014.04.015