Agreement of Sedentary Behavior Metrics Derived From Hip- and Thigh-Worn Accelerometers Among Older Adults: With Implications for Studying Physical and Cognitive Health

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Little is known about how sedentary behavior (SB) metrics derived from hip- and thigh-worn accelerometers agree for older adults. Thigh-worn activPAL (AP) micro monitors were concurrently worn with hip-worn ActiGraph (AG) GT3X+ accelerometers (with SB measured using the 100 counts per minute [cpm] cut point; AG_{100cpm}) by 953 older adults (age 77 ± 6.6 , 54% women) for 4–7 days. Device agreement for sedentary time and five SB pattern metrics was assessed using mean error and correlations. Logistic regression tested associations with four health outcomes using standardized (i.e., *z* scores) and unstandardized SB metrics. Mean errors (AP – AG_{100cpm}) and 95% limits of agreement were: sedentary time –54.7 [–223.4, 113.9] min/day; time in 30+ min bouts 77.6 [–74.8, 230.1] min/day; mean bout duration 5.9 [0.5, 11.4] min; usual bout duration 15.2 [0.4, 30] min; breaks in sedentary time –35.4 [–63.1, –7.6] breaks/day; and alpha –.5 [–.6, –.4]. Respective Pearson correlations were: .66, .78, .73, .79, .51, and .40. Concordance correlations were: .57, .67, .40, .50, .14, and .02. The statistical significance and direction of associations were identical for AG_{100cpm} and AP metrics in 46 of 48 tests, though significant differences in the magnitude of odds ratios were observed among 13 of 24 tests for unstandardized and five of 24 for standardized SB metrics. Caution is needed when interpreting SB metrics and associations with health from AG_{100cpm} due to the tendency for it to overestimate breaks in sedentary time relative to AP. However, high correlations between AP and AG_{100cpm} measures and similar standardized associations with health outcomes suggest that studies using AG_{100cpm} are useful, though not ideal, for studying SB in older adults.

Keywords: frailty and physical function, physical activity, sedentary accumulation patterns, sedentary behavior patterns, sitting time

Sedentary behavior is increasing in modern society, and among older adults, it is the most prevalent behavior among sleep, sedentary behavior, and physical activity. (Diaz et al., 2016; Du et al., 2019; Jefferis et al., 2015; Matthews et al., 2012; Yang et al., 2019) By consensus, sedentary behavior has been defined as all

waking behaviors while in a seated or lying posture that result in an energy expenditure ≤ 1.5 metabolic equivalents (Tremblay et al., 2017). When measured using ActiGraph (AG) accelerometers worn around the participant's hip, sedentary time is estimated based on lack of movement and does not factor in posture. To obtain device-based measures of sedentary behavior derived from both posture and movement, the most common approach is to attach an activPAL (AP) monitor—an inclinometer/accelerometer specifically designed as a thigh-worn device capable of assessing posture and thus capturing sitting/lying—to the participant's thigh (Edwardson et al., 2016). This approach is often viewed as the device-based standard for the measurement of sedentary behavior.

Accelerometers produce time-stamped data, making it possible to identify when during the day activity occurs (Glazer et al., 2013; Lord et al., 2011), as well as the patterns in which behaviors are accumulated (Chastin & Granat, 2010). These patterns include the timing, frequency, and duration of sedentary bouts and breaks throughout the day (Tremblay et al., 2017). While there has been an

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increase in the number of studies examining sedentary patterns and their associations with health (e.g., Brocklebank, Falconer, Page, Perry, & Cooper, 2015; Jefferis et al., 2019), the Physical Activity Guidelines for Americans, 2nd edition (U.S. Department of Health and Human Services, 2018), and the update (Katzmarzyk et al., 2019) both highlighted that further research using prospective cohorts to study sedentary patterns in relation to mortality and other health outcomes is needed.

One challenge to updating this literature is that most prospective cohort studies use hip-worn AG accelerometers rather than the thigh-worn AP monitor (Lee & Shiroma, 2014), and the measurement of sedentary bouts and breaks using hip-worn accelerometers and standard data processing techniques (Miguelles et al., 2017) is not accurate (Barreira, Zderic, Schuna, Hamilton, & Tudor-Locke, 2015). For example, when compared with direct observation of sit-to-stand transitions during usual free-living conditions, one study of 13 adults reported 0.3% bias for thigh-worn AP-measured transitions and 98.6% bias for hip-worn AG-measured transitions (Lyden, Kozey Keadle, Staudenmayer, & Freedson, 2012). Despite the inaccuracy, the authors reported correlation coefficients compared with direct observation of .97 for the AP-measured transitions and .92 for the AG-measured transitions (Lyden et al., 2012). There has also been evidence of convergent validity in several labs and cohorts around the world that showed AG-derived measures of sedentary patterns were associated with various health outcomes in the expected direction (Bellettiere et al., 2019; Brocklebank et al., 2015; Diaz, Goldsmith, et al., 2017; Diaz, Howard, et al., 2017). Given the historical and continuing use of AG accelerometers in prospective cohorts, understanding the agreement between AG- and posture-based measures for assessing sedentary behavior, including accumulation patterns, is critical for advancing the field.

The aim of this study was to assess agreement between the most commonly used hip-worn AG measures of volumes and patterns of sedentary time and thigh-worn AP measures in a well-characterized cohort of older adults and determine how any measurement error may bias associations of sedentary behavior with physical or cognitive health.

Methods

In 1994, adults over 65 without dementia were randomly sampled from the King County membership of Group Health Cooperative of Puget Sound (now Kaiser Permanente Washington) to join the Adult Changes in Thought (ACT) study, a longitudinal cohort study of aging and incident dementia. An expansion cohort was enrolled starting in 2000. In 2005, a cohort refreshment protocol to maintain a constant 2000 participants was initiated by enrolling new members to replace those who died, were diagnosed with dementia, or dropped out of the study. Beginning in April 2016, enrolled participants were given the option to wear an AG GT3X+ accelerometer (ActiGraph LLC, Pensacola, FL) and/or an AP micro (PAL Technologies, Glasgow, Scotland, United Kingdom). Of the 1688 eligible participants who were able to and asked to wear devices, 1,151 wore the AG (1,088 returned devices with four or more adherent days, which for both devices were defined as days having 10 or more hours of awake wear), and 1,135 wore the AP (1,039 returned devices with at least four adherent days). The 953 men and women who wore both devices concurrently for at least four adherent days comprised our study population. Details on the ACT cohort and accelerometer deployment are published elsewhere (Rosenberg et al., 2020). Ethics approval was obtained from

the Kaiser Permanente Washington Institutional Review Board, and all participants provided written informed consent.

Accelerometers

Participants were asked to wear devices for the same 7 days and to complete sleep logs each night of wear to document their in-bed and out-of-bed times. Sleep-log data were double entered to protect against transcription errors. Missing data were imputed using person-specific means if available and ACT sample means otherwise. Recorded in-bed and out-of-bed times were used to identify awake time for processing data from both devices.

The AG GT3X+ was worn 24 hr/day on an elastic waistband at the right hip region with data collected at 30 Hz. Using ActiLife (version 6.13.3; ActiGraph LLC, Pensacola, FL), 15-s epoch data were generated using the normal filter then aggregated to 1-min epochs. Device nonwear was determined using the Choi algorithm (Choi, Liu, Matthews, & Buchowski, 2011; Choi, Ward, Schnelle, & Buchowski, 2012) applied to vector magnitude counts per minute (CPM) using a 90-min window, 30-min streamframe, and 2-min tolerance. To classify awake-wear-time epochs as sedentary, the most common cut point (100 CPM) was applied to the vertical axis (Miguelles et al., 2017). Sedentary bouts were then derived as consecutive waking sedentary time epochs with no minimum and no tolerance.

The AP3 micro was placed in a waterproof casing and secured to the center of the right thigh using Tegaderm adhesive tape (3M, St. Paul, MN). Using the default setting in palBatch (version 7.2.32; PAL Technologies, Glasgow, Scotland, UK), data were converted to event-level files which were then visually inspected for anomalies using heat maps that had sleep-log and AG data superimposed. Sitting events that occurred while participants were awake (a.k.a., sitting bouts) were used to compute sedentary behavior metrics.

Sedentary Behavior Metrics

Sedentary behavior metrics were computed using only adherent days on which both devices were worn. Total sedentary time was averaged across all adherent days for each device. Five of the most commonly used sedentary accumulation pattern metrics were evaluated. Time spent in 30+ min bouts was computed as the average sedentary time per day that was accumulated in bouts that were 30 min in duration or greater. Mean bout duration was computed as the sum of all sedentary bout durations divided by the number of bouts. The usual bout duration (UBD) and alpha were computed using the methods described by Chastin and colleagues (Chastin & Granat, 2010; Chastin et al., 2015). UBD is the midpoint of the cumulative distribution of sedentary bout durations, computed using nonlinear regression. UBD indicates the bout duration above which half of all sedentary time is accumulated—higher values indicate a more prolonged accumulation pattern. Alpha characterizes the shape of the sedentary bout duration distribution for each person with lower alphas reflecting frequent long bouts with few short bouts and higher alphas reflecting frequent short bouts with few long bouts (see [Supplementary Figure 1](#) in our earlier publication for more details [Bellettiere et al., 2017]). The number of breaks was computed as the average number of sedentary bouts per day over all adherent days. In this regard, sedentary breaks represented the number of times per day there was a transition from a sedentary bout to movement above the 100 cpm cut point, while sitting breaks represented the number of

times per day there was a transition from a sitting/lying posture to standing or stepping.

Outcomes

At the ACT study visit when accelerometers were distributed, participants' height and weight were measured by trained staff using a tape measure and the clinic scale. Body mass index (BMI) was computed as the weight (in kilogram) divided by height (in meter square). Participants also completed questionnaires. From the RAND 36 questionnaire (Ware, 2000; Ware & Sherbourn, 1992), self-rated health was assessed with a single item asking "In general, would you say your health is: excellent, very good, good, fair, poor?"; difficulty walking half a mile was assessed with a single item asking "Does your health now limit you in walking half a mile and if so, how much?" Responses were yes, limited a lot; yes, limited a little; and no, not limited at all. Global cognitive performance was measured using the Cognitive Abilities Screening Instrument, which consists of a short series of tests that assess nine domains of cognitive impairment (Chiu, Yip, Woo, & Lin, 2019; De Oliveira et al., 2016; Teng et al., 1994). Resulting scores range from 0 to 100 (best functioning). Cognitive impairment was defined as having a score ≤ 86 on the Cognitive Abilities Screening Instrument and/or referral for additional diagnostic workup. For analyses, BMI, self-rated health, difficulty walking a half mile, and cognitive function—selected for analysis because of known or expected associations with sedentary behavior—were dichotomized as ≥ 30 versus <30 ; good, poor, and very poor versus very good and excellent; yes versus no; and cognitive impairment, yes versus no, respectively.

Statistical Methods

Summary statistics described distributions of participant characteristics. Histograms were plotted to show distributions of the six sedentary behavior metrics separately for AP and AG_{100cpm} measures. Then, AP and AG_{100cpm} measures of the six sedentary behavior metrics were compared at the person level by computing mean error (AP – AG_{100cpm}) and mean absolute error. Agreement between the two devices was visually assessed using the Bland–Altman approach, with 95% limits of agreement computed using regression analysis to test for and account for relationships between bias and magnitude (Bland & Altman, 2007). Pearson and Spearman correlation coefficients were used to describe the between-device linear relationship of the sedentary behavior metrics. Concordance correlation coefficients were used to assess the degree to which the between-device linear relationship aligns with the 45° line. To explore the epidemiologic implications of any potential measurement error, associations of the six sedentary behavior metrics with four indicators of health (self-rated health, BMI, difficulty walking half a mile, and cognitive impairment) were estimated using separate multivariable logistic regression models. Values for all sedentary behavior metrics were first converted to z scores to standardize the resulting beta coefficients. This enabled a distribution-based "apples-to-apples" between-device comparison of the size of the odds ratios (ORs) as the underlying unit of change in each z -score-converted sedentary behavior metric is identical (i.e., a 1 SD increment). Models were adjusted for age, gender, race/ethnicity (Hispanic or non-White vs. non-Hispanic White), and education (less than high school, completed high school, some college, or completed college). The resulting standardized ORs from models using AG_{100cpm} sedentary behavior

metrics were compared with the corresponding standardized ORs from models using AP metrics, according to the methods described by Horton and Fitzmaurice (2004). Results from analyses of sedentary behavior and health outcomes were also reported using unstandardized ORs, which were computed using sedentary behavior metrics that were not converted to z scores and instead remained in their original units of measure.

Following initial peer review, we reran agreement analyses after classifying sedentary behavior using alternate cut points of 200 cpm applied to the vector magnitude and 25 cpm applied to the vertical axis (Aguilar-Farías, Brown, & Peeters, 2014), cut points that were similar to those reported by Koster et al. (2016).

Analyses were conducted using R (R Foundation for Statistical Computing, Vienna, Austria) with two-tailed statistical tests and statistical significance set to $p < .05$.

Results

The 953 ACT participants included in this study were, on average, aged 77 ± 7 years, 54.3% female, 87.0% non-Hispanic White, and 72.7% completed college (Table 1).

Distributions for each sedentary behavior metric separately for AP and AG_{100cpm} measures are presented in [Supplementary](#)

Table 1 Participant Characteristics for Men and Women of the ACT Study Who Concurrently Wore AG and AP Accelerometers; N = 953

Quantitative variables, mean (SD)	
Age (years)	77 (6.6)
Categorical variables, n (%)	
Gender	
Men	421 (44.2%)
Women	532 (55.8%)
Race/ethnicity	
Hispanic or non-White	97 (10.2%)
non-Hispanic White	853 (89.5%)
Education	
Less than high school	15 (1.6%)
Completed high school	74 (7.8%)
Some college	152 (16.0%)
Completed college	712 (74.7%)
BMI	
BMI below 30	722 (75.8%)
BMI 30 or above	212 (22.2%)
Self-rated health	
Very good and excellent	599 (62.9%)
Good, poor, or very poor	354 (37.1%)
Difficulty in walking half a mile	
None	726 (76.2%)
Some	227 (23.8%)
Cognitive impairment	
Impaired	23 (2.4%)
Not impaired	930 (97.6%)

Note. AP = activPAL; AG = ActiGraph; ACT = Adult Changes in Thought; BMI = body mass index. Percentages may not sum to 100% due to rounding.

Table 2 Summary and Agreement Results for Sedentary Time and Patterns of Sedentary Time Measured Using AG GT3X+ and AP Micro Among ACT Participants; N = 953

Statistic	Total sedentary time (min/day)	Time spent in 30+ min bouts (min/day)	Mean bout duration (min)	UBD (min)	Number of breaks in sedentary time	Alpha
AP, mean (SD)	598.4 (116.1)	351.2 (135.5)	14.8 (6.6)	37.9 (17.8)	44.5 (12.8)	1.30 (.04)
AG, mean (SD)	653.2 (95.2)	273.6 (128.0)	8.9 (3.9)	22.7 (12.5)	79.9 (18.1)	1.79 (.13)
Person-level agreement						
Mean error (AP – AG)	–54.7	77.6	5.9	15.2	–35.4	–.49
95% LoA	[–223.4, 113.9]	[–74.8, 230.1]	[0.5, 11.4]	[0.4, 30.0]	[–63.1, –7.6]	[–.6, –.4]
Mean absolute error	80.1	92.9	6.1	15.7	35.3	.49
Pearson correlation	.66 [.62, .70]	.78 [.76, .81]	.73 [.7, .76]	.79 [.77, .82]	.51 [.46, .56]	.40 [.34, .45]
Concordance correlation	.57 [.53, .61]	.67 [.64, .70]	.40 [.37, .43]	.50 [.47, .53]	.14 [.12, .15]	.02 [.01, .02]

Note. ACT = Adult Changes in Thought; AP = activPAL; AG = ActiGraph; LoA = limits of agreement; UBD = usual bout duration.

Figure 1 (available online). Mean total sedentary time as measured by AG_{100cpm} (653 min/day) was 9.1% higher compared with the AP (598 min/day), resulting in a mean difference of 54.7 min/day (limit of agreement [LOA] = [–223.4, 113.9; Table 2]). There were nearly twice as many breaks in sedentary time detected by the AG_{100cpm} (mean = 79.9 breaks/day) than the AP (mean = 44.5 breaks/day; mean difference = 35.4 breaks/day; LOA = [–63.1, –7.6]). The higher number of breaks recorded using AG_{100cpm} resulted in 77.6 fewer minutes per day (LOA = [–74.8, 230.1]) by AG_{100cpm} than AP in time spent in 30+ min sedentary bouts. The mean difference in mean bout durations was 5.9 min (LOA = [0.5, 11.4] min), resulting in a 39.9% shorter mean when measured by AG_{100cpm} (8.9 min) than by AP (14.8 min). The mean difference in UBDs was 15.2 min (UBD_{AG} = 22.7 min, UBD_{AP} = 37.9 min), resulting in a 40.1% shorter mean. The higher frequency of and generally shorter duration of bouts detected by AG_{100cpm} resulted in a more rapid decay of the bout duration distribution and higher alpha values (alpha_{AG} = 1.3, alpha_{AP} = 1.8). Bland–Altman plots illustrating mean differences for each metric are shown in **Supplementary Figure 2** (available online).

Pearson correlations between AG_{100cpm} and AP for all sedentary behavior variables ranged between .40 and .79. Sedentary breaks and alpha had lower correlations ($r = .40$ and $r = .51$, respectively) than total sedentary time ($r = .66$), time in long bouts ($r = .78$), mean bout duration ($r = .73$), and UBD ($r = .79$). Spearman correlations produced similar results (data not shown). Concordance correlation coefficients followed a similar pattern ranging from .02 to .67. Alpha and sedentary breaks had lower concordance correlations (.02 and .14, respectively) compared with total sedentary time (.57), time in long bouts (.67), mean bout duration (.40), and UBD (.50).

Measures of total sedentary time using the Aguilar-Farías et al. (2014) cut points were, on average, lower than AP-measured sedentary time, with 95% limits of agreement contained the value of zero, and a slightly lower mean error (see **Supplementary Table 1** [available online]). Total sedentary time correlation coefficients for AG_{25cpm} ($r = .70$ and concordance correlation = .64) and AG_{200cpm} ($r = .80$ and concordance correlation = .77) were higher than those for AG_{100cpm} ($r = .66$ and concordance correlation = .57). Agreement for sedentary accumulation pattern metrics were not appreciably different when processing data using the Aguilar-Farías et al. (2014) cut points versus the 100 cpm cut point, though more similarities were observed for the 200 cpm vector magnitude cut point than for the 25 cpm vertical axis cut point.

Figure 1 shows standardized ORs and 95% confidence intervals (CIs) for associations between sedentary behavior and health. Lower self-rated health (i.e., good, poor, or very poor) was significantly related to all sedentary behavior metrics regardless of the device used, and there were no statistically significant differences between the computed ORs for AG_{100cpm} and AP measures. While not significantly different for all metrics, point estimates for ORs were generally stronger when computed using AP measures than when using AG_{100cpm} measures of total sedentary time, 30+ min bouts, mean bout duration, and UBD; OR point estimates were slightly larger when computed using AG_{100cpm} measures of alpha and sedentary breaks. The same general pattern was observed for associations with BMI, in that differences in ORs between AG and AP were significant for total sedentary time ($p < .001$), 30+ min bouts ($p \leq .001$), mean bout duration ($p = .01$), and usual bout duration ($p = .03$). For example, a 1 SD increment in total sedentary time measured by AP was associated with 1.94 times higher odds of BMI ≥ 30 compared with BMI < 30 (95% CI [1.63, 2.32]), whereas a 1 SD increment in AG_{100cpm} total sedentary time resulted in OR (95% CI) of 1.56 [1.32, 1.85]. Difficulty walking half a mile was associated with all six sedentary behavior metrics. The only significant difference between AG_{100cpm} and AP OR point estimates was observed for alpha ($p < .001$), with a greater magnitude OR for AG (OR = 0.55; 95% CI [0.46, 0.67]) than for AP (OR = 0.77; 95% CI [0.65, 0.91]). For cognitive impairment, there were no statistically significant associations with any of the sedentary behavior metrics and no significant differences in ORs between AG_{100cpm} and AP.

When metrics were not standardized, significant differences in ORs between AG_{100cpm} and AP measures were more common (**Figure 2**). For example, associations of all six sedentary behavior metrics with BMI differed significantly between devices. For all four health outcomes, the largest differences were observed for mean bout duration, with higher ORs for AG_{100cpm} measures than AP measures. Alpha was consistently differentially associated with three outcomes, with stronger ORs for AP than AG_{100cpm}.

Discussion

In this investigation of sedentary behavior metrics computed using data from concurrently worn AG and AP devices among older adults, agreement was generally highest for the two metrics that relied most heavily on the volume of sedentary behavior: total sedentary time and time in 30+ min bouts. Our data showed that the

(a) Associations with self-rated health (good, poor, and very poor vs. very good and excellent)

(b) Associations with body mass index (≥ 30 vs. < 30)

(c) Associations with difficulty walking half mile (any vs. none)

(d) Associations with cognitive impairment (impaired vs. not impaired)

Figure 1 — Forest plots for standardized (based on a 1 *SD* unit change in each metric) associations of AG_{100cpm} and AP sedentary behavior metrics with self-rated health (a), BMI (b), difficulty walking half mile (c), and cognitive impairment (d). All models are adjusted for age, sex, race/ethnicity, and education. The *p* value_{Horton} is from models testing the hypothesis that OR_{AG} and OR_{AP} are different. AP = activPAL; AG = ActiGraph; BMI = body mass index; CI = confidence interval; OR_{AP} = odds ratio and 95% CI for associations with AP-measured variables; OR_{AG} = odds ratio and 95% CI for associations with AG-measured variables.

AG_{100cpm} detected significantly more breaks in sedentary time than did the AP, which resulted in shorter sedentary bouts, on average. Estimates of AG_{100cpm} metrics thus reflected more frequently interrupted sedentary time accumulation than AP estimates, as shown by significantly shorter mean bout duration and UBD, and higher alpha. Studies that rely on AG_{100cpm} estimates of sedentary behavior patterns (e.g., descriptive epidemiology studies, dose-response analyses) should take these between-device differences into account, recognizing that AG_{100cpm}-derived metrics systematically misestimate sedentary behavior patterns. This will be particularly important for researchers working to establish sedentary behavior guidelines as

the values that might be considered “too sedentary” or “too prolonged of a sedentary behavior pattern” will differ depending on the device used. More studies are needed to quantify the between-device differences and their potential impact on future recommendations. Notably, the approximate 1 hr/day difference in total sedentary time and time in 30+ min bouts observed in this study highlight that the between-device differences are large enough that they could have important public health implications.

On the other hand, even with the between-device differences in estimates of sedentary behavior volume and patterns, we observed moderate to high linear relationships between sedentary behavior

(a) Associations with self-rated health (good, poor, and very poor vs. very good and excellent)

(b) Associations with body mass index (≥ 30 vs. < 30)

(c) Associations with difficulty walking half mile (any vs. none)

(d) Associations with cognitive impairment (impaired vs. not impaired)

Figure 2 — Forest plots for unstandardized associations between sedentary behavior measured using AG_{100cpm} and AP and self-rated health (a), BMI (b), difficulty walking half mile (c), and cognitive impairment (d). AP = activPAL; AG = ActiGraph; BMI = body mass index; CI = confidence interval; CPM = counts per minute; OR_{AP} = odds ratio and 95% CI for associations with AP-measured variables; OR_{AG} = odds ratio and 95% CI for associations with AG-measured variables; USD = usual bout duration. All models are adjusted for age, sex, race/ethnicity, and education. The *p* value_{Horton} is from models testing the hypothesis that OR_{AG} and OR_{AP} are different. Odds ratios are unstandardized, meaning that for AP and AG_{100cpm}, they are presented for the same increments for each sedentary behavior metric: 116 min/day for total sedentary time; 136 min/day for time in 30+ min bouts; 6.6 min for mean bout duration; 17.8 for USD; 12.8 for breaks in sedentary behavior; and .04 for alpha.

metrics measured by AG_{100cpm} and AP (except for breaks in sedentary time and alpha), which suggest that metrics from either device similarly ranked participants according to high versus low sedentary time, and according to prolonged versus frequently interrupted sedentary behavior patterns. And when the metrics were first standardized, inferences of associations between sedentary behavior and health outcomes were not appreciably different for AG_{100cpm} versus AP measures. Associations have three main components: direction, magnitude, and statistical significance. AG_{100cpm} and AP similarities in the magnitude of associations

were most apparent when sedentary behavior metrics were standardized (five associations out of 24 were significantly different) compared with when they were unstandardized (13 associations out of 24 were significantly different). Accuracy of the magnitude of associations are important because they enable more accurate computation of population attributable risk (or population attributable fraction), which are needed for efficiently allocating public health- and research-related resources. In addition and importantly, in all but one test, the statistical significance and the direction of associations were consistent between AG_{100cpm} and AP measures

as illustrated by the 95% confidence intervals. Taken together, *when interpreting associations using standardized (not unstandardized) metrics*, the two devices resulted in generally similar inferences about the relationship of sedentary behavior with physical and cognitive health.

Similar Findings From Other Studies

As far as we know, the only other studies that evaluate agreement of AG_{100cpm} and AP measures of sedentary behavior patterns among adults focus on the metric “breaks in sedentary time.” Breaks in sedentary time are the main component for measuring how sitting and sedentary time are accumulated because they define the beginning and end of each sedentary bout, and sedentary bouts are the underlying input for all sedentary behavior pattern metrics. In this study, we observed that significantly more breaks were counted by AG_{100cpm} compared with AP devices, leading to a high mean error and low concordance in the number of breaks measured per day, but a modest Pearson correlation coefficient of .51. These first findings among older adults, who accumulate sitting time differently than younger adults (Diaz et al., 2016), corroborate results from the previous studies discussed below that were conducted among adults (Barreira et al., 2015; Lyden et al., 2012) and children (Carlson et al., 2019).

Lyden et al. (2012) directly observed 13 participants between 20 and 60 years old (mean $\pm$ SD age 25 ± 5 years) on two 10-hr occasions, one during normal living, and another during a time when they were asked to reduce their sitting and to breakup sedentary time more frequently. The authors found that AP data provided accurate estimates of the number of breaks compared with direct observation. However, AG data, processed using the 100 cpm cut point, overestimated breaks by more than twofold. Despite the differences in accuracy, the correlation between AG_{100cpm} and direct observation was .86 during normal living and .64 during the treatment condition.

Barreira and colleagues compared breaks measured by AP to those measured by AG among 15 participants aged 28 ± 3 years. The number of AG_{100cpm} breaks were, on average, almost two times (90%) higher than AP breaks (Barreira et al., 2015). Most of the additional AG_{100cpm} breaks (52%) occurred when, according to the AP, participants were sitting. This demonstrates one source of error when measuring breaks in sedentary time using AG_{100cpm}: long sitting bouts are artificially broken into several shorter bouts when enough movement occurs (e.g., fidgeting or wiggling) that the 100 cpm threshold is breached. Barreira et al. (2015) also reported that 40% of the additional AG_{100cpm} breaks occurred while participants were standing. This demonstrates a second source of error when measuring breaks in sedentary time using AG_{100cpm}. AG_{100cpm} breaks reflect a transition from low levels of movement (i.e., movement below 100 cpm) to relatively more movement, and does not capture transitions in posture from sitting to standing. Therefore, AG_{100cpm} breaks can occur when a participant is standing with low level of movement then transitions to a higher level of movement (e.g., walking), or when they are engaging in a high level of movement and then stand sufficiently still before going back to a high level of movement. As this source of error will occur more often among people who stand more and standing has been associated with beneficial health outcomes (Katzmarzyk, 2014; Purva, 2021; Winkler et al., 2018), this might explain why, in this study, we observed marginally stronger associations with physical health outcomes for standardized AG_{100cpm}-measured breaks in sedentary time and alpha.

Among children, the most common accelerometer data processing protocol is to classify sedentary time using a 25 counts/15-s cut point. Using that protocol among 195 children aged 10.5 ($SD = 0.7$) years, Carlson et al. (2019) reported that AG_{25 counts} detected a 307% mean absolute increase in the number of breaks compared with AP. While they reported that the respective mean absolute increase was just 25% when using AG_{100cpm}, the interclass correlation between AG_{100cpm} and AP breaks was just .31. A deep dive into data revealed that despite similar averages (AG_{100cpm} = 89.9/day; AP = 82.8/day), the timing of the breaks was very different between the devices, with the AP detecting breaks that went undetected by AG_{100cpm}, and AG_{100cpm} detecting breaks that went undetected by the AP. Deviation in the timing of transitions resulted in a 57% and a 59% mean difference in UBD and alpha, respectively, and similar mean differences were observed in this study.

Similar to two smaller studies of agreement in measuring total sedentary time, AG_{100cpm} overestimated measures of daily sedentary time—by 55 min/day in this study compared with 107 min/day among 37 adults aged 74 ± 7 years (Aguilar-Farías et al., 2014) and to 114 min/day among 62 adults aged 78 ± 6 years (Koster et al., 2016). Like in the two previously mentioned studies, when alternate cut points were used, agreement with AP in total sedentary time improved and was underestimated by 45 min/day for AG_{200cpm} and 27 min/day AG_{25cpm}.

Strengths and Limitations

This study has several strengths. Data were collected from a large community-based cohort study of older men and women. We included five different measures of sedentary behavior patterns as there remains a lack of consensus concerning which metric might be best. In addition, our criterion measure (AP) has been shown to be as good as direct observation for identifying breaks in sedentary behavior, which is requisite for measuring sedentary behavior patterns.

As in all studies, our results should be interpreted within the context of study limitations. Generalizability would be enhanced by introducing more racial/ethnic diversity and by including more geographic variability. Our AG sedentary behavior metrics were derived from data processed with the normal filter within ActiLife, as we do not yet have data processed using the low-frequency extension filter. However, at least one previous study among adults showed that agreement between sedentary breaks measured using AG_{100cpm} and direct observation is nearly the same when data were processed using the low-frequency extension filter or the normal frequency filter (Lyden et al., 2012). The Choi algorithm classifies periods of 90 min or more with zero movement (and requiring a 30-min streamframe and 2-min tolerance) as nonwear time. The 90-min duration and streamframe criteria were developed specifically for older adults and help prevent misclassifying sedentary time as nonwear time (Choi et al., 2012). However, it is possible that differences in sedentary behavior metrics between devices could have been impacted by using this data processing protocol, which is the most commonly used protocol among studies of older adults (Miguelles et al., 2017). To test this, we repeated all analyses among the 596 adults who had four or more days without Choi-identified nonwear time, and the results were not appreciably changed (data not shown). While the AG GT3X+ is no longer sold by AG, the cross-generational accuracy with the currently available model (w-GT3X-BT) is exceptionally high (Miller, 2015). Finally, our study used data from the AP, which has very low error in comparison with gold standard direct observation (Lyden et al., 2012), but is not without error.

Conclusion

This study showed that using AG_{100cpm} led to an overestimation of breaks in sedentary time and systematically more interrupted sedentary behavior patterns than were observed using AP measures. For example, mean bout duration as measured by AP was 66% longer, on average, than duration as measured by AG_{100cpm} and breaks in sedentary time measured by AG_{100cpm} was nearly twice as large. As a result, caution should be used when interpreting estimates of sedentary behavior patterns from AG_{100cpm} and any associations that rely on those pattern metric estimates. When our metrics were first standardized based on their underlying distribution—we used the *SD*, but an interquartile range or comparing quartiles of the exposure are also distribution-based methods that would work—associations with physical and cognitive health using AG_{100cpm} and AP were similar *when the associations were interpreted using the distribution-based unit of analysis but not when the distribution-based units were converted back to the absolute unit of analysis*. For example, we strongly recommend reporting results for a 1 *SD* increment in mean bout duration instead of an *x*-minute increment in mean bout duration, where *x* is the *SD* of the mean bout duration. Whenever estimates of associations are presented using absolute units of sedentary behavior pattern measures (e.g., minute, minute/day, n/day), the magnitude of the association will differ according to which device is used in determining those pattern measures. Consequently, if physical activity guidelines were developed using research conducted only by AG_{100cpm}, the guidelines could be meaningfully different than if the same research were conducted using only AP. Future development of sedentary behavior guidelines will rely on accelerometer data from longitudinal studies. As many studies have already collected hip-worn AG data and many new studies will likely continue to employ the AG, research is needed to develop accelerometer data processing techniques (Kerr et al., 2018; Nakandala et al., 2021) or measurement error correction models (Sampson, Matthews, Freedman, Carroll, & Kipnis, 2016) to increase the accuracy of sedentary behavior pattern metrics derived from hip-worn devices. Until then, for studies assessing associations of sedentary behavior volumes and patterns with health using AG_{100cpm}, we recommend presenting results for standardized and unstandardized point estimates in AG_{100cpm}-based studies and *interpreting associations using units of the standardized metric rather than absolute units of sedentary behavior measures* (e.g., minute, minute/day, n/day). This will increase accuracy of the relative magnitude of associations between sedentary behavior and health and might help harmonize results from prospective cohort studies that use different activity monitors. Ultimately, such an approach will help to answer the 2018 Physical Activity Guidelines Advisory Committee's call to provide more data about associations of sedentary behavior patterns, including bouts and breaks, with health outcomes (U.S. Department of Health and Human Services, 2018).

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