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Agreement of Step-Based Metrics From ActiGraph and ActivPAL Accelerometers Worn Concurrently Among Older Adults

Eric T. Hyde[1], **Steve Nguyen**[1], **Fatima Tuz-Zahra**[1], **Christopher C. Moore**[2], **Mikael Anne Greenwood-Hickman**[3], **Rod L. Walker**[3], **Loki Natarajan**[1], **Dori Rosenberg**[3], **John Bellettiere**[1]

[1]Herbert Wertheim School of Public Health and Human Longevity Science, University of California San Diego, La Jolla, CA, USA

[2]Department of Epidemiology, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA

[3]Kaiser Permanente Washington Health Research Institute, Seattle, WA, USA

Abstract

Purpose: Our study evaluated the agreement of mean daily step counts, peak 1-min cadence, and peak 30-min cadence between the hip-worn ActiGraph GT3X+ accelerometer, using the normal filter (AG_N) and the low frequency extension (AG_{LFE}), and the thigh-worn activPAL3 micro (AP) accelerometer among older adults.

Methods: Nine-hundred and fifty-three older adults (≥65 years) were recruited to wear the ActiGraph device concurrently with the AP for 4–7 days beginning in 2016. Using the AP as the reference measure, device agreement for each step-based metric was assessed using mean differences (AG_N – AP and AG_{LFE} – AP), mean absolute percentage error (MAPE), and Pearson and concordance correlation coefficients.

Results: For AG_N – AP, the mean differences and MAPE were: daily steps −1,851 steps/day and 27.2%, peak 1-min cadence −16.2 steps/min and 16.3%, and peak 30-min cadence −17.7 steps/min and 24.0%. Pearson coefficients were .94, .85, and .91 and concordance coefficients were .81, .65, and .73, respectively. For AG_{LFE} – AP, the mean differences and MAPE were: daily steps 4,968 steps/day and 72.7%, peak 1-min cadence −1.4 steps/min and 4.7%, and peak 30-min cadence 1.4 steps/min and 7.0%. Pearson coefficients were .91, .91, and .95 and concordance coefficients were .49, .91, and .94, respectively.

Conclusions: Compared with estimates from the AP, the AG_N underestimated daily step counts by approximately 1,800 steps/day, while the AG_{LFE} overestimated by approximately 5,000 steps/day. However, peak step cadence estimates generated from the AG_{LFE} and AP had high agreement (MAPE ≤ 7.0%). Additional convergent validation studies of step-based metrics from concurrently worn accelerometers are needed for improved understanding of between-device agreement.

Keywords

cadence; wearable devices; gait; physical activity

corresponding author ehyde@health.ucsd.edu.

Step counting is a simple and accessible measurement of physical activity that is available on a multitude of wearable devices from smartphones to fitness trackers (Bassett et al., 2017). Unlike measurement of meeting the current U.S. adult aerobic physical activity guideline (PAG) of at least 150 min/week of moderate- to vigorous-intensity physical activity (U.S. Department of Health and Human Services, 2018), daily step counts may be more easily understood and measured by the general population (Kraus et al., 2019). In addition, steps can be taken at all intensity levels (i.e., light, moderate, and vigorous intensity), which allows for participation across most ages and physical fitness levels and is particularly important for older adults who often face declining physical function and aerobic capacity with age, limiting ability to engage in more intense movement (Kraus et al., 2019; Maula et al., 2019; Newman et al., 2016; Ortlieb et al., 2014). The popularity and accessibility of steps-based metrics further reflects their utility for translating research findings into public health recommendations, policies, and programs (Bassett et al., 2017; Kraus et al., 2019). For these reasons, the 2018 PAG Advisory Committee examined the relationships between daily step volume (i.e., daily step counts) and several health outcomes (2018 Physical Activity Guidelines Advisory Committee, 2018), and insufficient evidence was available for providing a daily step volume recommendation. In response to this conclusion, a number of studies have since reported a protective association between steps and cardiovascular disease, dysglycemia, and all-cause mortality (Hall et al., 2020; Lee et al., 2019; Paluch et al., 2021; Saint-Maurice et al., 2020).

The 2018 PAG Advisory Committee also concluded future studies should also examine the role of stepping intensity (i.e., cadence [steps/minute]) in these relationships (2018 Physical Activity Guidelines Advisory Committee, 2018) and directly called for studies to evaluate the agreement between steps-based metrics derived from different wearable devices to enable assimilation of dose–response relationships across studies and devices (Kraus et al., 2019). For example, ActiGraph, commonly worn on the hip or wrist, has been the brand of accelerometer used in over 50% of published studies (Wijndaele et al., 2015). However, over the past decade, use of thigh-worn devices like the activPAL (PAL Technologies Ltd.) has increased due to their ability to detect posture and greater step count accuracy at slow treadmill walking speeds (but above 0.5 m/s) and during free living (Edwardson et al., 2017; Harrington et al., 2011; Ryan et al., 2006; Toth et al., 2018).

Recent meta-analyses have helped illuminate the previously unclear associations between physical activity and all-cause mortality through harmonization of accelerometer-measured physical activity data from different accelerometer devices across several prospective cohort studies (Ekelund et al., 2019, 2020). Similar analyses have not been done using step-based metrics inpart due to insufficient literature on the agreement of accelerometer-measured step-based metrics across various devices and heterogeneity of study designs (Hall et al., 2020). An improved understanding of the agreement for steps-based metrics across multiple devices is an important step toward facilitating well-powered and harmonized meta-analyses to evaluate the dose–response associations between steps-based metrics with several health outcomes. Comparison of step-based surveillance estimates across different populations and time points would also be enhanced (Tudor-Locke et al., 2009). The present study evaluated the agreement of three steps-based metrics (mean daily step counts, peak 1-min cadence, and peak 30-min cadence) between the hip-worn ActiGraph GT3X+ accelerometer, processed with the normal filter (AG_N) and the low frequency extension (AG_{LFE}), and the thigh-worn activPAL3 micro accelerometer (AP) in a large sample of community-based older adults who wore both devices concurrently.

Methods

Study Population

The Adult Changes in Thought (ACT) study (Kukull et al., 2002) is a longitudinal cohort study of aging and dementia. In 1994, Seattle area members of Kaiser Permanente Washington (previously Group Health) who were 65 years or older without dementia were randomly selected to participate in the ACT study. Consenting study participants undergo biennial follow-up visits to screen for incident dementia. An expansion cohort was included in 2000 and starting in 2004 a cohort refreshment protocol was implemented using the same inclusion criteria to replace attrition from dementia, dropout, and death. In April 2016, ACT participants were consented to wear an ActiGraph GT3X+ and/or an AP accelerometer (Rosenberg et al., 2020). Participants who were wheelchair bound, receiving hospice or care for a critical illness, residing in a nursing home, or, if memory problems became evident during testing were not eligible to participate (Rosenberg et al., 2020). Among 1,688 eligible and approached ACT participants, 1,151 consented to wear the ActiGraph and 1,088 returned devices with four or more adherent days (defined as days with at least 10 hr of awake wear time), and 1,135 participants consented to wear the AP, of which 1,039 returned devices with at least four adherent days. In total, the analytic sample for our study comprised of 953 men and women who wore both devices concurrently for at least four adherent days. Overall, participants consenting to wear devices were generally younger and healthier than those who did not consent (Rosenberg et al., 2020). For example, about 21% of participants who did not consent to wear devices were age 90+ years, while only about 6% of consenting participants were age 90+ years (Rosenberg et al., 2020). Further details on the ACT study and the accelerometry methods used are provided elsewhere (Kukull et al., 2002; Rosenberg et al., 2020). Study procedures were approved by the Kaiser Permanente Washington institutional review board, and participants provided written informed consent.

Accelerometers and Step Measurement

Participants who consented were asked to wear both devices for the same seven calendar days and were encouraged to wear them for 24 hr/day except when risking submersion in water (e.g., swimming or bathing) for the ActiGraph device (ActiGraph LLC). Participants were asked to keep sleep logs each night of accelerometer wear to document their in-bed and out-of-bed times, along with notes regarding any removal of the ActiGraph device for reasons other than bathing or showering. Sleep and wear logs were double entered into a database to protect against transcription errors and was quality checked for completeness and accuracy, and missing sleep log data were imputed using person-specific means if available or sample means otherwise ($N = 37$). Recorded in-bed and out-of-bed times were used to identify awake time for processing data from both devices.

The ActiGraph was worn on an elastic belt secured around the waist so the device rests on the right hip at the level of the suprailiac crest. To minimize nonwear and increase total concurrent wear, participants were asked to wear the ActiGraph 24 hr/day, except while swimming or bathing. Using ActiLife software (version 6.13.3), data were collected at 30 Hz, aggregated into 60 s, time-stamped epochs, and device nonwear time was determined using the Choi algorithm (Choi et al., 2011, 2012). Steps were ascertained using the ActiGraph manufacturer's step algorithm using two data processing filters: (a) the normal filter and (b) the LFE filter. Per the ActiGraph website, the LFE:

> … allows users to capture data previously unavailable. By adjusting filter criteria to allow more data to be retained in low activity and/or low frequency environments, elderly or other slow-moving subjects can be studied. This filter significantly improves response to both activity as well as step counts.
>
> (ActiGraph Corp., 2017)

Several (Feito et al., 2017; Hickey et al., 2016; Toth et al., 2018; Tudor-Locke et al., 2015; Wanner et al., 2013) studies have shown that using the LFE filter leads to more steps being registered over the exact same timeframe than if data were processed using the normal filter, which is the factory default. Our study is the first that we know of to assess agreement of step cadence measures using steps ascertained using both the normal filter and the LFE.

The AP was packaged in a waterproof casing and secured to the center of the participants' right thigh using a medical grade adhesive tape to avoid removal for bathing, showering, or swimming to improve compliance (Dall et al., 2018). Data from these devices were converted to event-level files using the default setting in PALbatch (version 7.2.32, PAL Technologies) and were visually compared to heat maps that had sleep log and ActiGraph data superimposed to identify potential anomalies. Similar to the method of measuring steps by the ActiGraph, the AP device uses proprietary algorithms to identify stepping events (defined as a single reciprocal leg movement, generating two steps). Steps accumulated in all stepping events in a given period of time (e.g., 1 min, day) were manually totaled to generate step summaries.

For each participant, daily wear time was determined by subtracting nonwear time (determined by the Choi algorithm; Choi et al., 2011, 2012) from awake wear time. Mean step volume was calculated by summing steps across all adherent days and dividing by number of adherent days. To assess stepping intensity, two commonly used measures were calculated: peak 1-min cadence and peak 30-min cadence (Lee et al., 2019; Paluch et al., 2021; Saint-Maurice et al., 2020; Tudor-Locke & Aguiar, 2019; Tudor-Locke & Rowe, 2012). Peak cadence is a simple indicator of a person's best natural ambulatory effort in a free-living environment (Tudor-Locke et al., 2018; Tudor-Locke & Rowe, 2012). Steps measured by the AP, AG_{N}, and AG_{LFE}, were stored in 1-min epochs and rank ordered within each adherent day. Peak 1-min cadence is the highest single recorded minute of steps in a day. Peak 30-min cadence is the mean steps per minute of the 30 highest 1-min epochs, which are not required to be consecutive (Tudor-Locke et al., 2018). Both peak 1-min and peak 30-min cadences were then averaged over adherent days.

Covariates

When participants were fitted with the accelerometers, participants' age, gender, race/ethnicity, education level, self-rated health, and difficulty walking 0.5 miles were ascertained via a questionnaire. Self-rated health was assessed using the following question from the RAND 36 questionnaire (Ware, 2000; Ware & Sherbourne, 1992), "In general, would you say your health is: excellent, very good, good, fair, poor?" Difficulty walking 0.5 miles was assessed with a single question asking, "Does your health now limit you in walking half a mile and if so, how much?" Response options included yes, limited a lot; yes, limited a little; and no, not limited at all. Lastly, participants' height and weight were measured by trained staff using a tape measure and the clinic scale. Body mass index was computed as weight (in kilograms) divided by height^2 (in square meters).

Statistical Analysis

All statistical analyses were carried out in R (version 4.0.2). Mean and *SD*, or counts and proportions, were calculated to describe participant characteristics. Body mass index, self-rated health, and difficulty walking 0.5 miles were dichotomized as <30 versus ≥30; very good or excellent versus good, fair, or very poor; and no difficulty versus some difficulty, respectively. Due to mounting evidence that the AP may have higher accuracy in estimating step counts than the ActiGraph (Bassett et al., 2017; Kooiman et al., 2015; Moore et al., 2020; Toth et al., 2018), the AP was considered the reference (not necessarily criterion) measure in our analyses. Histograms were plotted to show distributions for step-based metrics (mean daily step counts, peak 1-min cadence, and peak 30-min cadence) for the AG_N, AG_{LFE}, and AP devices. We calculated mean paired differences (AG_N – AP and AG_{LFE} – AP). Mean absolute percentage error (MAPE) is a commonly used statistic to quantify measurement agreement between devices and was calculated for each step-based metric as follows (Moore et al., 2020):

$$\left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{AG}_i - \mathrm{AP}_i}{\mathrm{AP}_i}\right|\right) \times 100\,\%,$$

where n is the number of participants (here, $n = 953$), which are indexed by i. Different thresholds (such as MAPE ≤ 10% and MAPE ≤ 5%) have been used for determining the accuracy of step-counting devices, though empirical evidence supporting these cut points are lacking (Moore et al., 2020). Next, we utilized the Bland–Altman approach to illustrate potential associations between measurement bias and magnitude (Bland & Altman, 2007). Assigning the AP as the reference measure, we calculated 95% limits of agreement (LOA) using linear regression of the difference between the AG and AP regressed on the AP-measured step-based metric and visually assessed agreement via Bland–Altman plots. Lastly, we calculated Pearson correlation coefficients to describe the between-device linear associations for each step-based metric, and Lin' s concordance correlation coefficients to assess the degree to which the between-device associations were linear and aligned with the 45° line for each step-based metric. Table 1 further describes each metric of agreement used in this analysis (Koo & Li, 2016).

Results

Study Population Characteristics

For the 953 ACT participants included in the analytic sample, the mean (*SD*) age was 77.0 (6.6) years, 55.8% were female, 89.5% were non-Hispanic White, 74.7% completed college, 22.2% had a body mass index of 30 or above, 62.9% reported very good or excellent health, and 76.2% reported no difficulty walking 0.5 miles (Table 2). Average daily wear time for the AG_N was 915.2 min/day, 920.0 min/day for the AG_{LFE}, and 926.8 min/day for the AP.

Steps Agreement

Mean daily steps as measured with the AP were 6,832 (Table 3). Mean daily steps measured with the AG_N was 4,981 and a MAPE of 27.2% compared with the AP, resulting in a mean difference of −1,851 steps/day (95% confidence interval [CI] [−1,928, −1,773]; 95% LOA [−3,799, 97]). Mean daily steps measured with the AG_{LFE} was 11,800 with a MAPE of 72.7% compared with the AP, resulting in a mean difference of 4,968 steps/day (95% CI [4,853, 5,083]; 95% LOA [1,629, 8,307]). Pearson correlation coefficients for mean daily steps were .94 for AG_N – AP and .91 for AG_{LFE} – AP, while the concordance correlation coefficients were .81 for AG_N – AP and .49 for AG_{LFE} – AP.

The mean peak 1-min cadence as measured with the AP was 101.7 steps/min. Mean peak 1-min cadence as measured with the AG_N (85.5 steps/min) had a MAPE of 16.3% compared with the AP, resulting in a mean difference of −16.2 steps/min (95% CI [−17.2, −15.1]; 95% LOA [−46.0, 13.7]). Mean peak 1-min cadence as measured with the AG_{LFE} (100.3 steps/min) had a MAPE of 4.7% compared with the AP, resulting in a mean difference of −1.42 steps/min (95% CI [−1.93, −0.91]; 95% LOA [−13.7, 10.9]). Pearson correlation coefficients for peak 1-min cadence were .85 for AG_N – AP and .91 for AG_{LFE} – AP, while the concordance correlation coefficients were .65 for AG_N – AP and .91 for AG_{LFE} – AP.

The mean peak 30-min cadence as measured with the AP was 74.3 steps/min. Mean peak 30-min cadence as measured with the AG_N (56.6 steps/min) had a MAPE of 24.0% compared with the AP, resulting in a mean difference of −17.7 steps/min (95% CI [−18.5, −16.9]; 95% LOA [−38.7, 3.3]). Mean peak 30-min cadence as measured with the AG_{LFE} (75.7 steps/min) had a MAPE of 7.0% compared with the AP, resulting in a mean difference of 1.44 steps/min (95% CI [0.95, 1.92]; 95% LOA [−9.6, 12.5]). Pearson correlation coefficients for peak 30-min cadence were .91 for AG_N – AP and .94 for AG_{LFE} – AP, while the concordance correlation coefficients were .73 for AG_N – AP and .94 for AG_{LFE} – AP.

Histograms and Bland–Altman plots comparing steps-based metrics from the AG_N to the AP are shown in Figure 1. For all three steps-based metrics, there was considerable overlap in the histograms with average values of the AG_N consistently lower than the AP. The Bland–Altman plot for mean daily step counts and mean peak 30-min cadence shows stronger agreement at lower values that weakens with increasing AP-measured step-based metrics beginning at approximately 12,000 steps/day (Figure 1b) and about 75 steps/min (Figure 1f). The 95% LOA for mean peak 1-min cadence were consistent across the distribution of AP-measured mean peak 1-min cadence values.

Figure 2 shows the histograms and Bland–Altman plots comparing steps-based metrics from the AG_{LFE} with the AP. There is a notable nonoverlap between the histograms for mean daily steps with the AG_{LFE} overestimating mean daily steps compared with the AP (Figure 2a), and the Bland–Altman plot shows wide 95% LOA that slightly increase with increasing AP-measured mean daily steps (Figure 2b). The histograms for mean peak 1-min cadence and mean peak 30-min cadence almost entirely overlap across the distribution of these metrics (Figure 2c and 2e). The Bland–Altman plots also show narrow 95% LOA that remain mostly consistent across the distribution of AP-measured values (Figure 2d and 2f).

Discussion

In this investigation of agreement in steps-based metrics between the hip-worn ActiGraph GT3X+ and thigh-worn AP accelerometers worn concurrently by community-based older adults, we observed discrepancies in daily step count estimates across the AG_N, AG_{LFE}, and AP. In terms of agreement, the AG_N underestimated daily step counts compared with the AP by an average of 1,851 steps/day, while the AG_{LFE} overestimated daily step counts by an average of 4,968 steps/day. While consistency was high between devices (Pearson correlation coefficient > .90), the concordance correlation coefficient was strong for AG_N – AP (.81) and only moderate for AG_{LFE} – AP (.49). The overall results suggest that the AG_N may provide more comparable estimates of daily step counts to the AP than the AG_{LFE}. In addition, our study identified high agreement in peak step cadence estimates between the AG_{LFE} and AP. The agreement for peak 1-min and peak 30-min cadences was less than 1.5 steps/min, and the Pearson and concordance correlation coefficients were greater than .90. These findings indicate that peak step cadence estimates generated from the AG_{LFE} and the AP have high agreement. As such, studies that measure step cadence using these devices and processing settings may be suitable for comparison. Overall, the results from our study help clarify the agreement of step-based metrics measured from two widely used research-grade accelerometers and could inform research as the basis for future national step-based PAGs and surveillance of steps-based metrics. Studies incorporating steps-based metrics measured from multiple devices should consider between-device differences to avoid errors in estimations. For example, our results suggest that in older adults, the daily step count estimates from the AP may be approximately 5,000 steps/day lower than the AG_{LFE} and approximately 1,800 steps/day higher than the AG_N solely due to differences in measurement properties. However, between-device agreement of peak cadence measures is higher when using the AG_{LFE}. More studies are needed to quantify how the between-device differences in steps measures impact their prospective associations with health outcomes.

To our knowledge, this is the first report to evaluate agreement in step-based metrics between the hip-worn ActiGraph GT3X+ and AP worn concurrently by a large cohort of older adults in a community-based environment. Toth et al. (2018) evaluated the step counting accuracy of the hip-worn AG and AP among 12 adults (mean age = 35 ± 13 years) under free-living conditions for a 1-day period and had similar findings—the AG_N underestimated daily step counts compared with the AP (mean difference = −830 steps/day, Pearson correlation coefficient = .94) while the AG_{LFE} overestimated daily step counts (mean difference = 5,542 steps/day, Pearson correlation coefficient = .94). Park et al. (2021) compared daily step counts of 48 adults (28 ± 12 years) for 2 days and reported similar findings (AG_N – AP: mean difference = −784 step/day, Pearson correlation coefficient = .88; AG_{LFE} – AP: mean difference = 4,272 steps/day, Pearson correlation coefficient = .91). However, when using video recordings as the criterion measure, Toth et al. (2018) reported the following mean differences and MAPEs for each device: −2,661 steps/day and 23.1% (AP), −3,491 steps/day and 30.8% (AG_N), and 2,881 steps/day and 28.1% (AG_{LFE}). When using the StepWatch—an ankle-worn research-grade accelerometer that has very high agreement with direct observation (Toth et al., 2018)—as the criterion measure, Park et al. (2021) reported similar results: −1,567 steps/day and 20.8% (AP), −2,259 steps/day and 24.0% (AG_N), and 2,797 steps/day and 28.6% (AG_{LFE}). Altogether, the results from the present study echo the findings of previous studies that the AG_N has higher agreement in daily step count estimates with the AP than the AG_{LFE}. However, further research is needed to clarify whether estimates from AG_N align more closely with "true" daily step count values than estimates from the AG_{LFE}.

The present study showed low agreement in daily step count estimates derived from the AG_{LFE} compared with AP (MAPE = 72.7%). This finding was expected given the purpose of the LFE filter is to retain more data during low intensity movement than the AG_N (ActiGraph Corp., 2017) and several previous studies have shown that the AG_{LFE} records substantially higher step counts than either the AG_N or AP (Feito et al., 2017; Hickey et al., 2016; Toth et al., 2018; Tudor-Locke et al., 2015; Wanner et al., 2013). However, the LFE may have utility for comparing physical activity estimates across different generations of ActiGraph devices. For example, one study found that enabling the LFE option may decrease differences in physical activity measures at lower intensities between the ActiGraph GT3X+ and older ActiGraph models, though daily step counts were not examined (Ried-Larsen et al., 2012). Another study comparing the older ActiGraph 7164 with the newer AG_N and AG_{LFE} found that the AG_N recorded fewer daily step counts by 2,041 steps/day while the AG_{LFE} recorded an average of 3,597 more steps/day (Cain et al., 2013). While the authors of this study concluded that newer generation ActiGraph models (with either the normal filter or LFE) do not produce comparable daily step count estimates to the older generation devices, their results suggested that the AG_{LFE} produced comparable estimates of other physical activity measures (such as minutes per day of sedentary time, light-, moderate-, and vigorous-intensity activity) to the older 7,164 model (Cain et al., 2013). A third study of 35 older adults completing a timed 100-m walk found that the AG_{LFE} was more accurate in estimating step counts than the AG_N while acknowledging that this was not a free-living environment that did not include any low-cadence walking, sitting, or sit–stand transitions (Korpan et al., 2015). Given the agreement of the AG_{LFE} to older ActiGraph models for estimates of other physical activity metrics except daily step counts (Cain et al., 2013; Ried-Larsen et al., 2012), there is clear utility for processing physical activity data from the ActiGraph GT3X+ using both the normal filter and the LFE enabled. However, more research is needed to clarify the role of the LFE in estimating daily step counts from cohort studies, particularly those that include older adults, and on the comparability of daily step counts estimated from different ActiGraph models and filter settings.

Among other considerations, gait speed and device wear location have important implications for step counting measurement among older adults (Bassett et al., 2017). A study using a treadmill protocol (n = 20; age = 26.7 ± 4.9 years; 40% female) found that the hip-worn AG_N undercounted steps relative to manually counted steps at all walking speeds and the difference was higher at slower speeds (range: −39 steps/min at 2.0 mph to −11 steps/min at 4.0 mph; John et al., 2018). Another study comparing the accuracy of measuring daily step counts between the hip-worn AG_N and AP analyzed data from two 100-step walking trials in a sample of 43 older adults aged ≥ 65 years (Hergenroeder et al., 2018). Using direct observation as the criterion measure, the authors estimated the percent of observed steps that were counted by devices was 93.7% (±11.1%) for the AP and 51.4% (±35.7%) for the AG_N, and the AG_N was substantially less accurate at slower speeds (14.1% at <0.6 m/s and 85.1% at >1.0 m/s) whereas the accuracy of the AP was less affected by gait speed (86.8% at <0.6 m/s and 95.1% at >1.0 m/s; Hergenroeder et al., 2018). This pattern in accuracy differences by gait speed is commonly observed for hip-worn versus thigh-worn devices (Moore et al., 2020). A study of 19 participants (mean age = 33 ± 12 years) measured for five average days found high agreement in estimates generated by the thigh-worn AG_N (9,920 ± 3,097 steps/day) to the AP micro4 (9,827 ± 2,971 steps/day; Crowley et al., 2019). Both devices were taped to participants' right thigh, which may help explain the higher agreement in estimates when compared to our study (Crowley et al., 2019). Our study compared two accelerometers placed at different wear locations, and the degree to which the device location, and not the devices themselves, contributed to the differences in step-based metrics cannot be determined. Reconciling differences in step-based metrics across devices that arise from differing participant gait speeds and device wear locations will be critical for developing and translating future public health step-based guidelines.

To our knowledge, our study is the first to compare step cadence estimates from the AG_{LFE} to the AP. We observed high agreement in peak cadence metrics between AG_{LFE} and AP, which could be due to both devices retaining more data during low frequency movements compared to the AG_N (ActiGraph Corp., 2017; Edwardson et al., 2017; Harrington et al., 2011; Toth et al., 2018). Our findings of high agreement in peak cadence metrics but low agreement in daily step counts between the AG_{LFE} and AP could be due to the different constructs being measured. Peak cadence is a measure of peak stepping intensity, which may be a reflection of more purposeful walking compared with total step counts (Tudor-Locke et al., 2018). In light of this, a more sensitive device that would capture each step would be favored, and the LFE is more sensitive than the normal filter (ActiGraph Corp., 2017). However, a drawback to enabling the LFE is the decreased specificity, which is illustrated by the substantially higher daily step counts when compared with the AP. Researchers using the ActiGraph device should consider these trade-offs when deciding which device settings to use for the desired step-based metrics.

At least two studies have compared step cadence estimates from the AP to video observation and found the AP to be a valid and reliable measure of step cadence (Harrington et al., 2011; Ryan et al., 2006). Therefore, the results of the present study suggest the associations of step cadence measures with health outcomes in older adults may be evaluated across studies that used the AG_{LFE} or AP with little differential classification due to the demonstrated agreement between the two devices. However, there is a need for criterion validation studies to examine agreement in step cadence estimates across multiple devices with video or direct observation as the criterion measure similar to the Toth et al. validation study of daily step counts (Toth et al., 2018).

The ability to conduct large meta-analytical studies of the prospective associations between step-based metrics and health outcomes has been hampered by lack of evidence regarding the agreement of these metrics across various devices (Kraus et al., 2019). A recent systematic review of longitudinal data consistently observed that taking an additional 1,000 steps/day can help lower the risk of all-cause mortality, cardiovascular disease mortality, and cardiovascular disease in adults; however, several limitations, including the use of different wearable devices by the included studies, restricted the study authors' ability to assess dose–response relationships across studies (Hall et al., 2020). The present study addresses gaps identified by the 2018 PAG Advisory Committee Scientific Report with regard to evaluating agreement of step-based metrics across devices, which could inform efforts to harmonize accelerometer-measured step-based metrics across studies to carry out more generalizable and statistically powerful meta-analyses for associations with health outcomes (2018 Physical Activity Guidelines Advisory Committee, 2018; Kraus et al., 2019). By evaluating the agreement between the hip-worn ActiGraph and AP, the present study represents an initial step toward updating future PAGs to include recommendations for step-based metrics for health promotion in older adults.

Our study has several strengths. Data were collected from a large sample of community-based older adults, an understudied population. We investigated three step-based metrics to better understand the extent of agreement between two commonly used research-grade accelerometers, the thigh-worn AP, and the hip-worn ActiGraph. Participants wore devices for up to 7 days, allowing for extensive data collection. We also acknowledge several limitations. First, as stated previously, estimates of daily step counts from activPAL have high agreement with direct observation (Toth et al., 2018), but not without error. Therefore, while we have shown convergent and concurrent validity, future research should further examine criterion validity. Second, the study sample consisted mainly of non-Hispanic White older adults, so the results of the present study may not generalize to other race ethnicity groups. Third, while the ActiGraph has traditionally been placed on the hip or waist in research settings (Wijndaele et al., 2015), the present study could not assess agreement of step-based metrics when ActiGraph devices are worn in other locations (e.g., thigh, ankle, wrist). However, a previous study has shown when the ActiGraph is worn on the thigh, agreement between AP and AG_N is very high (Crowley et al., 2019). Fourth, while participants were asked to wear both devices 24 hr/day, the ActiGraph device was removed for water-based activities (e.g., swimming, bathing) and average daily wear time differed between devices by less than 15 min. While we believe that most step-based activities would be captured by both devices, this is a source of error in our comparisons. Last, both the ActiGraph and the AP devices use proprietary analysis algorithms to determine steps and step timing, which limits our ability to investigate whether differences in agreement of steps-based metrics are at least partially due to differences in hardware, software, or data processing methods.

Conclusion

This study examined the agreement in estimates of three step-based metrics estimated by the AG_N, AG_{LFE}, and AP worn concurrently for up to 7 days by a cohort of older adults in a community-based setting. The results show that agreement in daily step count estimates between the ActiGraph and AP differs substantially by the filter setting used for the ActiGraph, though the AG_N may provide higher agreement in estimates than the AG_{LFE} compared with the AP, and extent literature (Kooiman et al., 2015; Toth et al., 2018) shows that AG_N estimates are similar to those from commonly used consumer wearables. For step cadence, our findings suggest that the estimates from the AG_{LFE} have high agreement with estimates from the AP. Evidence on the agreement of step cadence estimates generated from different devices is lacking. In order to harmonize step-based metrics from various cohort studies, further research is needed on the comparability of these metrics across different accelerometers, brand-specific models, filter settings, and device locations. Future measurement studies of step-based metrics can strengthen the evidence base by examining demographically diverse cohorts in free-living environments, using direct or video observation as the criterion measure, and including >1-day measurement period. Improved understanding of the agreement of step-based metrics across commonly used research-grade accelerometers and reconciling them with step-based metrics from consumer wearables can help facilitate pooled analyses of these metrics and their associations with health outcomes that will inform future PAGs (Kraus et al., 2019).

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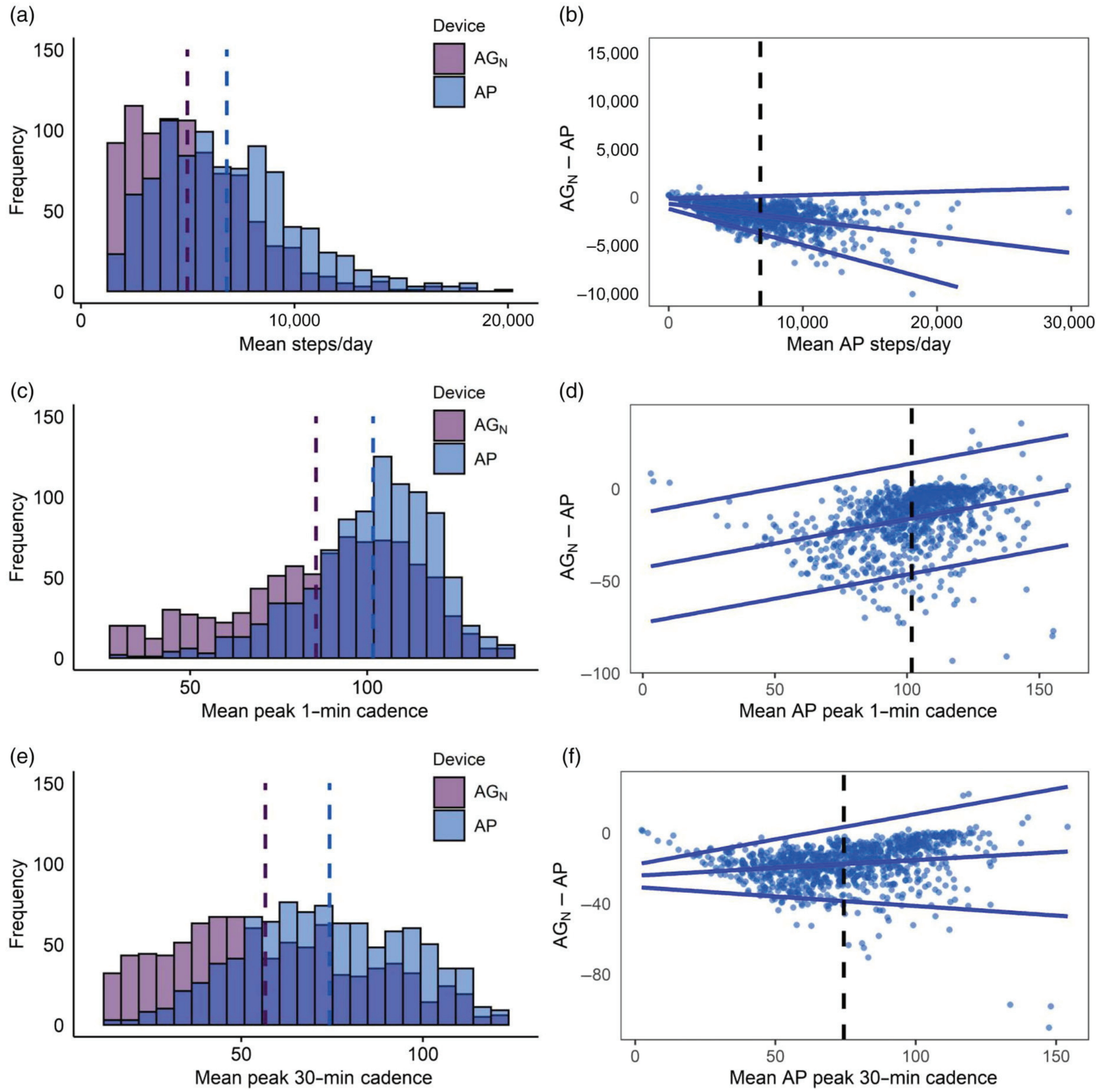

Figure 1 —.

Histograms and Bland–Altman plots comparing mean daily step counts (a and b), peak 1-min cadence (c and d), and peak 30-min cadence (e and f) for metrics derived using data from concurrently worn AP and AG_N. For the histograms (a, c, and e), the darker blue shade (darker black shade in printed versions) represents overlap in distributions and dashed lines represent the arithmetic mean of each distribution from both devices. For Bland–Altman plots (b, d, and f), dashed black lines represent the arithmetic mean of the step-based metric measured by the AP. The middle blue line represents the predicted difference (AG – AP) and 95% LOA were calculated as predicted difference ±1.96 times the *SD*. LOA = limits of agreement; AP = activPAL3 micro accelerometer; AG_N = ActiGraph GT3X+ with data processed using the normal filter; AG = ActiGraph GT3X+ accelerometer.

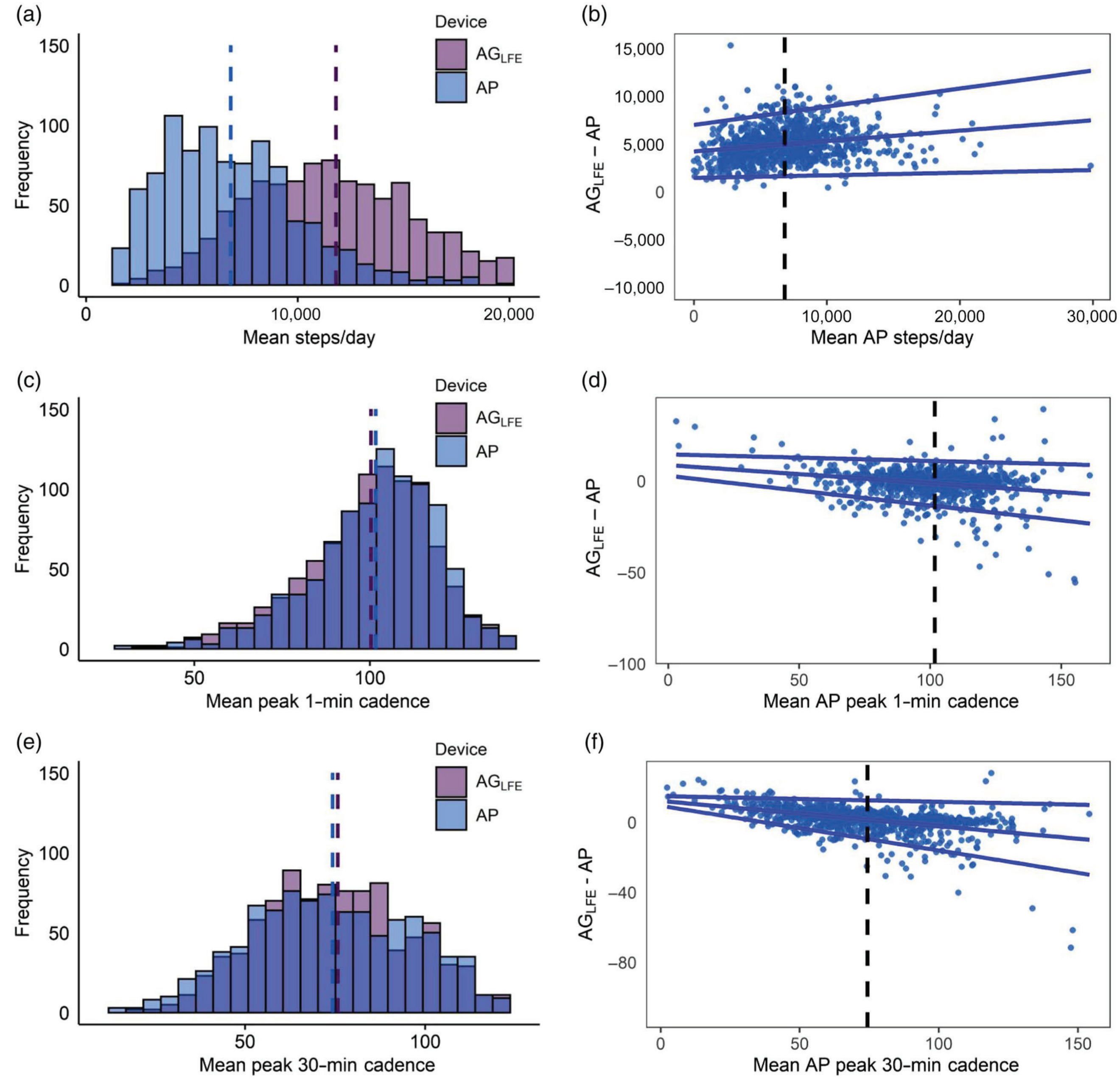

Figure 2 —.

Histograms and Bland–Altman plots comparing mean daily step counts (a and b), peak 1-min cadence (c and d), and peak 30-min cadence (e and f) for metrics derived using data from concurrently worn AP and AG_{LFE}. For the histograms (a, c, and e), the darker blue shade (darker black shade in printed versions) represents overlap in distributions and dashed lines represent the arithmetic mean of each distribution from both devices. For Bland–Altman plots (b, d, and f), dashed black lines represent the arithmetic mean of the step-based metric measured by the AP. The middle blue line represents the predicted difference (AG – AP) and 95% LOA were calculated as predicted difference ±1.96 times the *SD*. LOA = limits of agreement; AP = activPAL3 micro accelerometer; AG_{LFE} = ActiGraph

GT3X+ devices with data processed using the low frequency extension; AG = ActiGraph GT3X+ accelerometer.

Table 1

Explanation of Metrics of Agreement

Metric	Explanation
Mean difference	Measure of absolute agreement, indicates tendency of measures to differ to a particular direction
95% LOA	Measure of absolute agreement, indicates tendency of measures to differ to a particular direction
MAPE	Measure of absolute agreement, indicates overall agreement regardless of direction
Concordance correlation	Measure of absolute agreement, indicates degree to which pairs of observations fall on the 45° line through the origin
Pearson correlation	Measure of consistency, indicates degree to which measures rank individuals in a similar order

Note. LOA = limits of agreement; MAPE = mean absolute percentage error.

Table 2

Characteristics of Participants in the ACT Study Who Wore the ActiGraph GT3X+ and AP Accelerometers Concurrently (N = 953)

Age (years), mean (*SD*)	77.0 (6.6)
Gender, *n* (%)	
Male	421 (44.2)
Female	532 (55.8)
Race and ethnicity,[a] *n* (%)	
Hispanic or non-White	97 (10.2)
Non-Hispanic White	853 (89.5)
Education, *n* (%)	
Less than high school	15 (1.6)
Completed high school	74 (7.8)
Some college	152 (16.0)
Completed college	712 (74.7)
BMI (kg/m^2),[a] *n* (%)	
BMI below 30	722 (75.8)
BMI 30 or above	212 (22.2)
Self-rated health, *n* (%)	
Very good or excellent	599 (62.9)
Good, fair, or very poor	354 (37.1)
Difficulty in walking 0.5 miles, *n* (%)	
None	726 (76.2)
Some	227 (23.8)
Device wear time (min/day), mean (*SD*)	
AG_N	915.2 (66.7)
AG_{LFE}	920.0 (66.8)
AP	926.8 (64.1)

Note. ACT = Adult Changes in Thought; BMI = body mass index; AG_N = ActiGraph GT3X+ processed with the normal filer; AG_{LFE} = ActiGraph GT3X+ processed with the low frequency extension; AP = activPAL3 micro.

[a]Totals for race/ethnicity and BMI presented in the table deviate due to missingness. N (%) missing for each covariate: race and ethnicity, 3 (0.3%); BMI, 19 (2.0%).

Table 3

Summary and Agreement Results for Daily Step Counts and Peak Cadence Measured Using the AP, the AG_N, and the AG_{LFE} Among ACT Study Participants ($N = 953$)

	Daily step counts	Peak 1-min cadence	Peak 30-min cadence
Device, mean (*SD*)			
AP	6,832 (3,507)	101.7 (19.5)	74.3 (24.0)
AG_N	4,981 (3,099)	85.5 (29.0)	56.6 (28.7)
AG_{LFE}	11,800 (4,273)	100.3 (19.2)	75.7 (21.6)
AG_N vs. AP			
Mean differences (95% CI)	−1,851 (−1,928, −1,773)	−16.16 (−17.18, −15.14)	−17.68 (−18.45, −16.92)
95% LOA	−3,799, 97	−46.0, 13.7	−38.7, 3.3
Mean absolute error percent	27.2%	16.3%	24.0%
Pearson correlation (95% CI)	.94 (.93, .95)	.85 (.83, .87)	.91 (.90, .92)
Concordance correlation (95% CI)	.81 (.79, .82)	.65 (.62, .68)	.73 (.71, .75)
AG_{LFE} vs. AP			
Mean differences (95% CI)	4,968 (4,853, 5,083)	−1.42 (−1.93, −0.91)	1.44 (0.95, 1.92)
95% LOA	1,629, 8,307	−13.7, 10.9	−9.6, 12.5
Mean absolute error percent	72.7%	4.7%	7.0%
Pearson correlation (95% CI)	.91 (.90, .92)	.91 (.90, .92)	.95 (.94, .96)
Concordance correlation (95% CI)	.49 (.47, .52)	.91 (.90, .92)	.94 (.94, .95)

Note. ACT = Adult Changes in Thought; AP = activPAL3 micro; AG_N = ActiGraph GT3X+ with the normal filter; AG_{LFE} = ActiGraph GT3X+ with the low frequency extension; CI = confidence interval; LOA = limits of agreement.