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Estimating Sedentary Time from a Hip- and Wrist-worn Accelerometer

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Abstract

Purpose—Determine the validity of existing methods to estimate sedentary behavior (SB) under free-living conditions using ActiGraph GT3X+ accelerometers (AG)

Methods—Forty-eight young (18–25 yr) adults wore an AG on the right hip and non-dominant wrist and were video recorded during four 1-hour sessions in free-living settings (home, community, school, exercise). Direct observation videos were coded for postural orientation, activity type (e.g. walking), and METs derived from the Compendium of Physical Activities, which served as the criterion measure of SB (sitting or lying posture, METs < 1.5). Thirteen methods using cut-points from vertical counts/minute (CPM), counts/15-s (CP15s), and vector magnitude counts (vm) (e.g., CPM1853vm), raw acceleration and arm-angle (Sedentary Sphere), Euclidean norm corrected for gravity (ENMO, m*g*) thresholds, uni- or tri-axial Sojourn hybrid-machine learning models (Soj1x and Soj3x), random forest (RF) and decision tree (TR) models were used to estimate SB minutes from AG data. Method bias, mean absolute percent error (MAPE), and their 95% confidence-intervals were estimated using repeated measures linear mixed models

Results—On average, participants spent 34.1 minutes/session in SB. CPM100, CPM150, Soj1x, and Soj3x were the only methods to accurately estimate SB from the hip. Sedentary Sphere and ENMO44.8 over-estimated SB by 3.9 and 6.1 minutes, respectively, while the remaining wrist methods underestimated SB (range: 9.5–2.5 minutes). In general, MAPE was lower using hip methods compared to wrist methods

Conclusion—Accurate group-level estimates of SB from a hip-worn AG can be achieved using either simpler count-based approaches (CPM100, CPM150) or machine learning models (Soj1x, Soj3x). Wrist-methods did not provide accurate or precise estimates of SB. Development of large open source free-living calibration datasets may lead to improvements in SB estimates

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Disclosures

None of the authors have financial conflicts of interest with the device manufacturer or distributors. The results of the current study do not constitute endorsement by the ACSM. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation.

Keywords

ActiGraph; free-living behavior; validation; direct observation; signal processing

Introduction

Sedentary behavior (SB), defined by the Sedentary Behavior Research Network, is “any waking activities performed while in a sitting, reclining, or lying posture requiring an energy expenditure of 1.5 METs or less” (1). Time spent in SB has been associated with detrimental health outcomes such as all-cause mortality (2), type 2 diabetes (3), and cardiometabolic markers (4). As a result, many national health organizations have developed SB public health guidelines (5, 6), however these recommendations are broadly stated and not quantitative. This reflects the insufficient evidence-base to establish recommendations regarding the dose-response relationship of SB, warranting further investigations on the health implications of SB (7).

Much of the early associations between SB and health have been derived from self-report estimates of screen-time behaviors, but these approaches have been shown to display differential associations with cardiometabolic outcomes and underestimate SB by 40–60% compared to waist-worn accelerometers (6). A variety of data processing methods exist to estimate SB from an ActiGraph accelerometer for hip (8–12) and wrist wear-locations (12–15). A major study that derived an objective estimate of SB from a waist worn ActiGraph accelerometer was the National Health and Nutrition Examination Survey (NHANES) cohort (16). However, NHANES collected ActiGraph data from the non-dominant wrist in the most recent cohort (2011–2014) (17). If different monitor locations and/or methods are used to estimate SB, this makes it difficult to clarify the relationship between SB and health. To systematically develop the evidence-base for SB associations with health, comparability among different processing methods and accelerometer wear-locations is required (18).

Original approaches with the hip-worn ActiGraph used proprietary counts in linear regression models or receiver-operator characteristic analyses to identify thresholds to estimate SB (8, 11), while more complex approaches have used counts in machine learning models to identify bouts, or “sojourns”, of inactivity (10). Similar count-based threshold approaches have also been developed for the wrist (15). Novel data processing approaches have also been developed using raw acceleration to develop thresholds similar to the count-based approaches (12), thresholds in combination with arm-angle inclination (14), or machine learning models that use statistical features of the raw accelerations as predictors (13). The advantages of using raw acceleration over counts are the ability to capture high-frequency characteristics of movement and data processing methods that may be implemented with different accelerometer brands (14).

To date, the comparability and validity of the various ActiGraph data processing approaches with different wear locations in free-living conditions is not known. Thus, the primary purpose of this study was to concurrently validate existing data processing methods on an independent sample to estimate SB under free-living conditions using hip- and wrist-worn ActiGraph accelerometers to determine the most accurate and precise methods. The secondary purpose was to identify method-specific systematic errors that result in the misclassifications of SB, to provide insight to inform future development of accelerometer data processing methods.

Methods

A total of 48 participants volunteered to participate in the study. Participants were recruited via word of mouth, e-mail, or flyer distribution at the University of Massachusetts Amherst and the surrounding area of western Massachusetts. Participants were excluded if they had any physical or cognitive impairment that would prevent them from participating fully in the study protocol. All procedures were reviewed and approved by the Institutional Review Board at the University of Massachusetts Amherst and all participants provided written informed consent prior to participation in the study.

Study Design

Participants were recruited as part of a larger study, Movement Observation in Children and Adolescents (MOCA), and only the young adult sample was included in the present study. For the criterion measure, participants were continuously video recorded using a GoPro camera (San Mateo, CA, USA) during free-living activities in four settings while wearing two research-grade accelerometers; one on the right hip and one on the non-dominant wrist. The four 1-hour sessions took place at: a) Home - the participant's home, b) School/ Learning environment - classroom or place where participants completed school work, c) Community - public places (e.g. grocery store, shopping mall, community park), and d) Exercise - areas where participants were purposefully physically active (e.g. recreational area, basketball court, fitness center).

Measures

Direct Observation—Direct observation of the participant served as the criterion measure. At the beginning of each session, participants were asked to remain stationary for 15–30 seconds. At the beginning of the stationary period, a video recording with a GoPro was started, with the participant and current time visible in the camera's viewing field, and the video start time was recorded. The same laptop used to initialize the ActiGraph devices was also used to display the current time to ensure synchronization between the video and ActiGraph timestamps. When starting the camera, there is a slight delay between activating the recording and the actual recording. Thus, the 15- to 30-second delay between the video and session start times was included to account for any asynchrony between the video and accelerometer timestamps and ensure alignment of the data. The session began at the end of the stationary period at which time participants began their normal activities and the session start time was recorded.

After field-based data collection, video files were imported into the Noldus Observer XT software (version 14; Noldus Information Technology, Inc, Leesburg, VA) for direct observation coding. Direct observation coding using the Noldus Observer XT software has been used in previous accelerometer calibration and validation studies (19). The coding system used in the current study is an extension of the focal sampling coding system used by Lyden et al. (19), where a new observation or event is coded each time the observed individual changes to a different activity. Direct observation video coding was performed by trained research assistants who achieved at least 80% reliability with an expert coder using the MOCA method. Briefly, the MOCA direct observation coding system requires the coding of distinct body movements and behaviors that last at least 1-second in duration by assigning the following variables to each coded event: whole body movement or posture, activity type, MET value (based on the whole body movement or activity type), and locomotion (binary classifier). For example, an individual who is sitting while lifting weights would be coded as follows: sitting for the whole-body posture, lifting weights for the activity type, 4.3 METs, and no for locomotion. All activity types and corresponding MET values were derived from the Compendium of Physical Activities (20).

The activity type variable serves as a contextual descriptor to the observed behaviors, however there are periods when the participant is not engaging in the coded activity type. Using the aforementioned example, the participant may be in the context of lifting weights, but there are rest periods when the participant is not actively interacting with the weights. During these periods, all of the coded variables would remain the same except for the coded MET value, which would be coded as 1.5 METs during the rest period instead of 4.3 METs during the active lifting weights period.

To ensure reliability and consistency across coded observations, each video file was extensively inspected (Figure 1). Coded observations were initially visually inspected for errors by a trained coder who was different from the original coder. If there were no errors identified in the coded observations, the observation data were exported from the Noldus Observer software. Otherwise, the coder identified and recorded details on the errors associated with the coded observations. Then, a third expert coder inspected the video, added comments if additional errors were found, and verified whether errors identified in the first visual inspection were valid or not. Finally, an expert coder examined the errors recorded from both rounds of visual inspection to amend the coded observations prior to exporting the data.

After data were exported, all coded combinations of behavior, activity type, and MET value were visually inspected by three trained research assistants (RM, MC, GP). Coded combinations were examined for incompatible whole-body movement and activity-type pairs (e.g. sitting while standing), coded MET values that didn’t match the compendium MET values for either the behavior or activity type, or coded MET values did not follow the MOCA coding scheme rules (i.e. coded MET value will be associated with the behavior unless the activity type better represents the intensity level). Of the 9,677.2 total observation minutes, 283.9 minutes (2.9%) contained coded MET value abnormalities which were corrected to the proper MET values. There were 4.9 minutes (0.05%) that contained incompatible behavior and activity type combination errors which were excluded from the analyses.

Accelerometer—The ActiGraph GT3X-BT (ActiGraph, Pensacola FL) is a small, lightweight, water-resistant wearable accelerometer that records and stores raw acceleration data. The primary accelerometer can be initialized to sample between 30–100 Hz and measures accelerations in the dynamic range of ± 8*g*'s. For the current study, ActiGraphs were initialized using ActiLife (version 6.13.3) to sample at 80 Hz. ActiGraph devices were placed on the body using manufacturer-provided straps and elastic belts. For the right hip, the ActiGraph was secured medial to the anterior supra-iliac crest with the USB cap on the superior aspect of the device, so that the Y-axis was the vertical axis. For the non-dominant wrist, the ActiGraph was secured midway between the radial and ulnar styloid processes with the USB cap on the inferior aspect of the device closest to the hand, so that the Y-axis of the device was parallel to the long axis of the forearm.

Procedures

At the first data collection session, participants provided informed consent and height and weight were measured using a portable stadiometer (Weigh and Measure, LLC, Olney, MD) and calibrated weight scale (SECA Model 876), respectively, with shoes off. Height and weight were measured twice, however if measurements were not within 1 cm or 0.5 kg for height and weight, respectively, a third measurement was taken, and the outlier disregarded. These measures were averaged across the two measurements.

Data Processing

Direct observation files (output from the video coding process) were imported and processed using custom R functions (21). Direct observation timestamps were converted to hundredths of seconds to allow for identification of the main body movement and activity type coded for the majority of a 1-second window. The main body movement and activity type coded for the majority of each 1-second window (>0.5 seconds) were recorded as the criterion behavior and activity type for that second. For the purpose of this study, SB was defined as any observation that was coded with sitting or lying as the main body movement (1) with the exception of seated activities that are >1.5 METs (e.g. lifting weights).

The data processing methods examined in this study relied on either raw acceleration or count data. Therefore, raw and 1-second epoch data (normal and low-frequency extension (LFE) filters) were downloaded from ActiGraph devices using ActiLife (version 6.13.3) resulting in three data formats exported from each device. For count-based methods that were developed on larger epochs, 1-second count data were re-integrated to the required epoch length using a custom R-script. The results from this custom R-program produced identical values as the ActiLife reintegration process in a sample of participants (n = 5; data not shown). ActiGraph data files were then trimmed to include only the wear-time periods between the start and end of the sessions, not including the 15–30 second stationary period.

Estimates of sedentary time were calculated by applying 13 different processing methods (Table 1). For the hip-worn ActiGraph, we applied the following methods: 100 counts/minute (CPM100) (8), 150 counts/min (CPM150) (9), 200 counts/min using vector magnitude (CPM200vm) (11), Sojourn-1x (Soj1x), Sojourn-3x (Soj3x) (10), and 47.4 m*g* threshold using Euclidean norm minus one (ENMO) (ENMO44.8) (12). LFE-enabled counts were used for three of the hip methods (CPM100, CPM150, CPM200vm) to maximize backward compatibility with methods developed using older generations of ActiGraph (22) and reproduce original calibration study methods (9, 11). For the wrist-worn ActiGraph, we applied two vector magnitude count-based methods [1853 counts/min (CPM1853vm) and 376 counts/15sec (CP15s376vm)] (15), two ENMO-based thresholds (ENMO27.9, ENMO44.8) (12, 23), the Sedentary Sphere (14), and two machine learning algorithms [random forest (WristRF) and decision tree (WristTR)] (13).

For Soj1x and Soj3x, 1-second count data were used to identify sojourns of inactivity and activity using the methods of Lyden et al. (10). Briefly, MET values were applied to the various sojourn types (i.e. Type 1 sitting still: 1.0 METs, Type 2 sitting with movement: 1.2 METs, Type 3 standing still: 1.5 METs, Type 4 standing with small movements: 1.7 METs) and activity sojourn METs were estimated using the previously trained neural networks. Soj1x and Soj3x sedentary times were estimated as the amount of time accumulated below 1.5 METs.

For the methods requiring vector magnitude (VM; $\sqrt{x^2 + y^2 + z^2}$), the VM of count and raw acceleration data were calculated for the hip and wrist. Two additional VM were calculated for raw acceleration: VM corrected for gravity (VM-*g*; $\left|\sqrt{x^2 + y^2 + z^2} - 1\right|$) and ENMO [$(\sqrt{x^2 + y^2 + z^2}) - 1$]. The x-, y-, and z-axes data used to calculate ENMO were auto-calibrated using the non-movement periods within each accelerometer file (24). If there were not enough non-movement periods present, the average of derived auto-calibration coefficients for accelerometer files from the devices with the same serial number were used instead. Auto-calibrated acceleration that were <0 *g* was replaced with 0 *g*. For ENMO47.4 and ENMO44.8 (12), data were collapsed into 1-second windows by calculating the average of ENMO acceleration. Sedentary time was estimated as the amount of time accumulated in 1-second windows <47.4 or 44.8 m*g*. The same approach was used for ENMO27.9 with the exception that a 5-second window was used instead (23).

For the Sedentary Sphere (14), VM-*g* data were collapsed into 15-second windows. Consistent with the published procedures, the statistics calculated for each 15-second window were the average acceleration for the x-, y-, and z-axes; sum of VM-*g*; and mean arm angle [$\sin^{-1}(\overline{\text{y-axis}}) * (\frac{180}{\pi})$]. If the mean y-axis acceleration per 15-sec window was > 1 *g* or < −1 *g*, the mean y-axis acceleration for arm angle calculations was set to 1 *g* or −1 *g*, respectively. Thus, arm angles could only exist between the range of −90° to 90° relative to the horizontal. 15-second windows were classified as sedentary if the VM-*g* was < 489 *g* and the arm angle was higher than −15° below the horizontal.

For the WristRF and WristTR models (13), the signal features calculated for each 15-second window were the mean of VM, standard deviation of VM, percent of the power of the VM within the range of 0.6 to 2.5 Hz, dominant frequency of the VM, fraction of power in VM at the dominant frequency, mean angle of acceleration relative to the vertical axis on the device, and the standard deviation of the angle of acceleration relative to the vertical on the device (18). Computed statistics were included as covariates in the previously trained models to classify each 15-second window as sedentary or non-sedentary.

To align the sedentary classifications of each method with 1-second direct observation data, each epoch or sojourn classification was repeated for the duration of that epoch. For example, using CPM100, if a 60-second epoch was classified as sedentary, the sedentary classification was expanded to sixty 1-second sedentary classifications to enable second-by-second comparison with the corresponding direct observation data.

Statistical Analyses

All statistical analyses, including the pre-processing of direct observation and accelerometer data and implementation of processing methods, were performed using R-software (version 3.4.1). Time spent in SB (minutes/session) were used in repeated measures linear mixed-models to estimate method bias (estimate-directly observed SB) and the 95% confidence interval around the bias. This is a group level summary, and significant bias was identified when zero was not included within the 95% confidence interval. Bias is used as a measure of accuracy, and the relative widths of the confidence intervals around the biases assess precision. We assessed individual-level errors by computing the mean absolute percent error (MAPE) for each method. Second-by-second agreement between direct observation and estimated SB and the sensitivity and specificity of each method were assessed also. Following that, behaviors or activities during the misclassified periods of SB were examined to identify method specific systematic errors.

Results

Descriptive characteristics of participants are shown in Table 2. Of the 48 participants who volunteered to be in the study, 38 completed all four sessions. Of those who did not finish all sessions, four completed only one, five completed two, and one completed three sessions. As a result, 169 sessions had complete direct observation and accelerometer data. Table 3 presents a summary of the sessions included for analysis.

Figure 2 shows the overall bias and MAPE of hip and wrist method estimates of SB. For the hip, there were no significant biases for Soj3x, Soj1x, CPM100, or CPM150. Time spent in SB was underestimated using CPM200vm by −5.5 minutes ($p < 0.001$) and overestimated using ENMO47.4 by 12.2 minutes ($p < 0.001$). For the wrist, all of the methods examined were biased. Time spent in SB was underestimated using Wrist RF, CPM15s376vm, Wrist TR, and CPM1853vm, and ENMO27.9, ranging from −9.5 to −2.5 minutes ($p < 0.001$), and overestimated using the Sedentary Sphere and ENMO44.8 (3.9 and 6.1 minutes, respectively; $p < 0.001$). The lowest individual level error for hip and wrist methods was observed using Soj3x and ENMO44.8 with a MAPE of 14.3% and 28.7%, respectively (see Figure, Supplemental Digital Content 1, Estimated vs criterion sedentary time for hip and wrist methods). Except for ENMO47.4, all hip-derived estimates of SB displayed lower MAPE values compared to the wrist-methods.

There was no distinct pattern for hip-method bias when error was examined within a given environmental setting see Figure, Supplemental Digital Content 2, Bias and MAPE for hip- and wrist-method estimated sedentary time by session). However, sedentary time was generally underestimated using wrist methods in environmental settings where participants were primarily sedentary (home, school and community). MAPE values were generally highest within the home setting across hip- and wrist-methods.

In general, SB classification accuracy was greater using hip methods compared to wrist (Table 4). Regardless of method or wear location, the majority of false positive misclassifications occurred during standing and cycling behaviors, ranging from 60.4% to 93.5%. The majority of false negative misclassifications occurred during sitting behaviors (>91.5% across methods) and activities of daily living (e.g. computer work, texting, driving) see Table, Supplemental Digital Content 3, Percent contribution of activities to false positive and negative classifications).

Discussion

Hip-worn accelerometers have been used to estimate time spent in SB, however the recent shift in data-collection procedures to the wrist location poses a barrier to the validity and comparability across studies. This comprehensive validation on an independent sample in free-living environments contributes to the existing literature by evaluating the accuracy of data processing methods to estimate SB for both hip and wrist locations and identifying systematic errors in SB misclassifications. For the hip, we observed no significant biases for SB estimates using either simpler count-based thresholds (CPM100, CPM150) or machine-learning (Soj1x, Soj3x) approaches. However, all of the examined wrist methods produced biased estimates of SB. The majority of SB misclassifications affecting all methodological approaches were due to various lifestyle activities during sitting and standing, such as driving, computer work, or shopping, or bicycling behaviors. As mentioned before, our analyses focused on bias to evaluate method performance, and we note that bias is a group level performance metric; it describes the accuracy of the method compared to the criteria on average over participants and time. Individual-level error was evaluated using MAPE, which was lower using hip-derived estimates compared to the wrist.

The results from the current study reinforce previous assertions that free-living device calibrations may lead to improved estimates of free-living behaviors (25). Although some of the methods were developed on an older adult population (11, 15), which may have an impact on their validity in the current sample, many of the biased models were derived from lab-based protocols that included only a few SB activities (12, 13). Based on the behaviors observed in the current study, over 34 different activities were performed during sitting or lying postures which would be often overlooked in lab-based protocols. Even when these activities are included in a lab-based protocol, the nature of how they're performed under the free-living conditions will likely vary depending on environmental contexts or constraints. This creates a problem whereby prediction models are created that lack exposure to the large diversity of the types of daily activities performed. Many of the unbiased methods have been modeled using some aspect of free-living data (9, 10), emphasizing that model performance is influenced by the calibration data sets that were used to develop them.

A lower proportion of false-positive misclassifications were observed during standing periods for methods that attempt to distinguish standing from sitting behavior (i.e. Soj3x and Sedentary Sphere), however systematic errors from standing or bicycling periods were still common across all methods. Recently, the Sedentary Behavior Research Network has proposed new terminology of *stationary behavior*, being distinct from SB, defined as, *"any waking behavior done while lying, reclining, sitting, or standing with no* *ambulation, irrespective of energy expenditure*" (1). Since the majority of misclassifications occurred during stationary behaviors, this calls into question whether the interpretation of accelerometer-derived estimates represent sedentary- or stationary behaviors as proposed in previous studies (6). When the analysis from the current study was repeated to include stationary behaviors in the criterion definition (i.e. standing, kneeling, squatting down), we observed a general increase in method bias for those which previously underestimated SB or were initially unbiased (i.e. CPM100 and CPM150) and a reduction in method bias for those that previously overestimated SB. However, the exceptions to these trends were methods that attempt to capture standing behaviors (Soj1x, Soj3x, and Sedentary Sphere; data not shown). The Sojourn models remained unbiased while the magnitude of overestimation increased for the Sedentary Sphere, which may be partially attributed to the laboratory-derived threshold as the only input to differentiate between stationary and active behaviors. Thus, it may be ill-advised to interpret estimates from existing methods as stationary behavior if they were originally calibrated to distinguish SB from activity. Future research is needed to develop and assess accelerometer data processing approaches to classify stationary behavior if the aim of research questions is to address the health implications of stationary behavior as distinct from sedentary behavior and physical activity.

To reflect the diversity in data processing approaches that exist for accelerometers, we included methods that utilized various metrics that can be derived from a single accelerometer (i.e. counts, raw accelerations, ENMO) or different data reduction approaches (i.e. thresholds, machine learning). However, given the paucity of available methods, the limitation of the observed underestimation of SB for methods included may be attributed to differences in sample characteristics, such as older adults (CPM200vm, CPM1853vm, CP15s376vm), or device wear location, such as the dominant wrist (Wrist TR and RF). The MET level was inferred using Compendium values for the coded behaviors unless the activity was of moderate-to-vigorous intensity, which may have had an effect on borderline sedentary-light activities (e.g. eating or drinking = 1.5 METs), however this approach is similar to previous studies using activPAL as a criterion (26), which determines postural orientation independent of energy expenditure. Bias was also assessed at the per-session level, which may not extrapolate to general performance during a full waking day. Despite its limitations, the strengths of this study include an evaluation under diverse free-living environments where a wide-spectrum of activities could be observed, external validity was assessed using a sample independent from the original calibration samples, and using direct observation as the criterion measure with a reliable coding system that provides insights on the contexts of human behavior.

Although the participant sample size was modest (N = 48), a strength of the current study lies in the amount of time observed across individuals (161.3 hours). In general, the number of participants is often used to determine the generalizability of a study's findings, however, it is also important to consider the amount of time observed for each participant, especially in free-living studies. To demonstrate this point, we used a random effect model to estimate both the within and across person variability of hip counts per second, while controlling for the session type with a fixed effect. The within person variance (i.e. the average variability over time for each participant) is approximately 12 times larger than the person-to-person variance. Using the general idea that it is important to take more samples where there is more variability, this indicates that there is a lot of value to collecting more data over time from each person as well as from more participants.

In conclusion, accurate group-level estimates of SB may be achieved using several hip-based methods (CPM100, CPM150, Soj3x, Soj1x). Hip-based methods also produced more precise individual-level estimates of SB compared to the wrist-methods examined in the current study. A majority of misclassification errors were from diverse activities which occurred during sitting and standing postures. Thus, future calibration efforts should shift to the free-living environment to improve model-exposure to a diverse spectrum of activities to potentially improve real-world external validity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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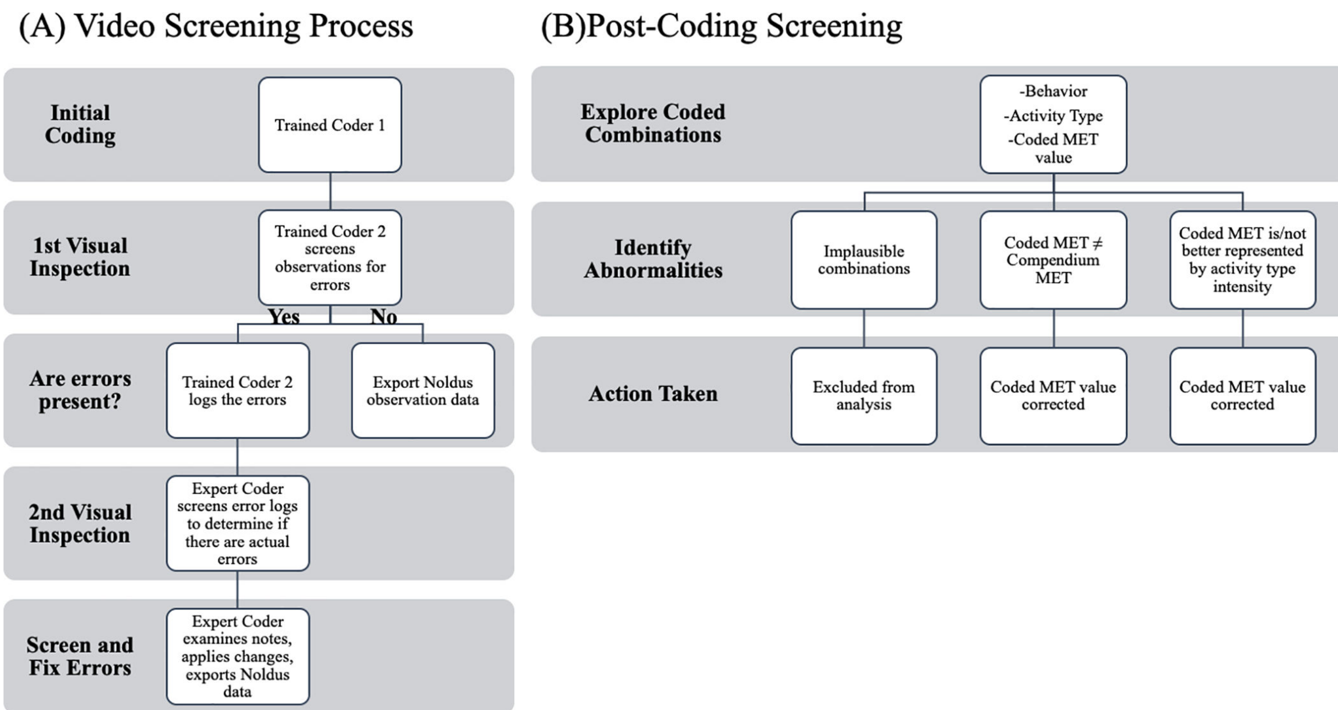

Figure 1.

Data quality assurance flow-chart for A) video and B) post-coding screening

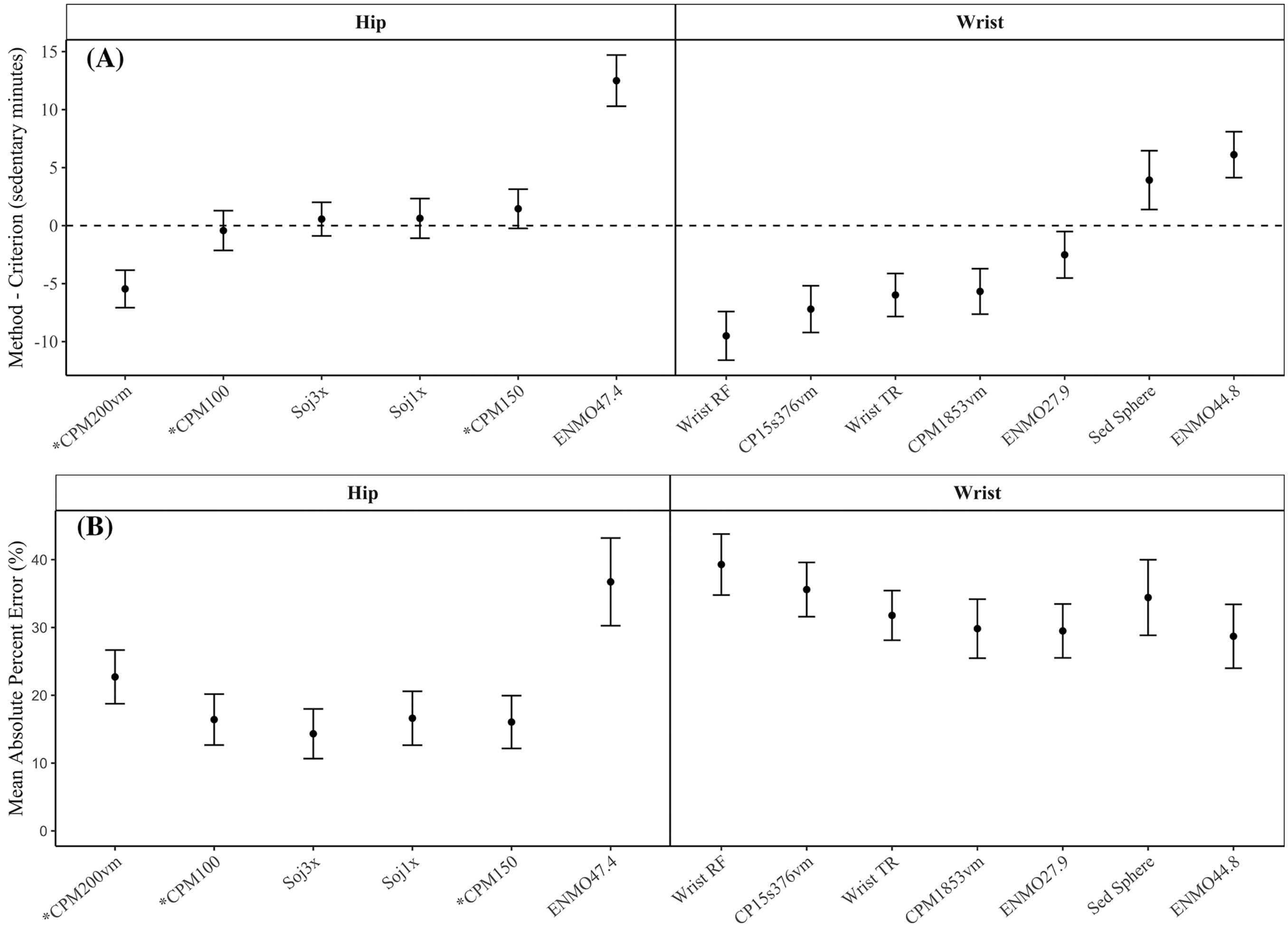

Figure 2.
A) Bias and B) mean absolute percent error for hip- and wrist- method estimated time spent in sedentary behavior. * indicates processed using LFE

Table 1:

Overview of accelerometer processing methods to estimate sedentary behavior

	Method	Metric	Approach	Epoch Window (seconds)	Reference
Hip	CPM100*	Vertical Axis Counts	Threshold (<100 counts)	60	(8)
	CPM150*	Vertical Axis Counts	Threshold (<150 counts)	60	(9)
	CPM200vm*	VM Counts	Threshold (<200 counts)	60	(11)
	Soj1x	Vertical Axis Counts	Hybrid Machine Learning	-	(10)
	Soj3x	Tri-Axial Counts	Hybrid Machine Learning	-	(10)
	ENMO47.4	ENMO	Threshold (<47.4 m*g*)	1	(12)
Wrist	CPM1853vm	VM Counts	Threshold (<1853 counts)	60	(15)
	CP15s376vm	VM Counts	Threshold (<376 counts)	15	(15)
	ENMO27.9	ENMO	Threshold (<27.9 m*g*)	5	(23)
	ENMO44.8	ENMO	Threshold (<44.8 m*g*)	1	(12)
	Sed Sphere	VM-*g*, arm angle	Threshold (<489 VM-*g* and >−15° arm angle)	15	(14)
	Wrist RF	VM Raw	Machine Learning (Random Forest)	15	(13)
	Wrist TR	VM Raw	Machine Learning (Decision Tree)	15	(13)

VM, vector magnitude; ENMO, Euclidean norm minus one; VM-*g*, vector magnitude corrected for gravity

*indicates processed using LFE

Table 2:

Demographic characteristics of sample (mean ± SD)

	Males	Females	Overall
N	22	26	48
Age (years)	20.6 ± 1.5	20.1 ± 1.2	20.4 ± 1.3
Height (cm)	178.9 ± 7.2	165.6 ± 5.7	171.7 ± 9.2
Weight (kg)	76.3 ± 16.5	62.9 ± 11.7	69.0 ± 15.5
BMI (kg/m^2)	23.7 ± 4.0	22.8 ± 3.1	23.2 ± 3.5

Table 3:

Description of session characteristics (mean ± SD)

	Number of Sessions	Session Duration (minutes)	Sedentary Time (minutes)
Overall	169	57.2 ± 8	34.1 ± 23.3
School	42	57.7 ± 4.4	54.5 ± 7.6
Home	44	58.4 ± 7.8	48.1 ± 17.8
Community	41	57.7 ± 6.9	26.6 ± 17.1
Exercise	42	55.1 ± 11.3	6.3 ± 8

Table 4:

Method percent agreement with direct observation, sensitivity, and specificity to classify sedentary behavior

		Percent Agreement	Sensitivity	Specificity
Hip	Soj3x	87.8	90.5	83.7
	Soj1x	86.0	89.2	81.4
	CPM150	85.7	90.2	79.2
	CPM100	85.2	87.0	81.4
	CPM200vm	83.7	78.3	91.5
	ENMO47.4	77.5	99.5	46.4
Wrist	CPM1853vm	77.5	72.8	84.5
	ENMO44.8	76.2	89.0	57.5
	Wrist TR	74.7	70.0	81.7
	ENMO27.9	74.6	75.0	74.1
	Sedentary Sphere	73.5	83.5	58.8
	CP15s376vm	72.2	66.0	81.2
	Wrist RF	70.6	61.3	84.2