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Validation of the ActiGraph GT3X and activPAL Accelerometers for the Assessment of Sedentary Behavior

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This study examined (a) the validity of two accelerometers (ActiGraph GT3X [ActiGraph LLC, Pensacola, FL, USA] and activPAL [PAL Technologies Ltd., Glasgow, Scotland]) for the assessment of sedentary behavior; and (b) the variations in assessment accuracy by setting minimum sedentary bout durations against a proxy for direct observation using an automated wearable camera in free-living environments. Time spent in sedentary behavior estimated from the GT3X, with varying identification methods (i.e., a hybrid machine learning algorithm, *Sojourn*, and activity count thresholds), and the activPAL were compared to the criterion measure with and without applying minimum sedentary bout durations. The activPAL assessed sedentary behavior most accurately followed by GT3X with the Sojourn method. The performance of the GT3X is improved when identifying sedentary bouts ≥ 15 min with the Sojourn method or a threshold of < 150 cpm. The activPAL should be considered for studies focusing on sedentary behavior. The ability of the GT3X to assess sedentary behavior is improved when focusing on sedentary bouts ≥ 15 min using the Sojourn method or the threshold of < 150 cpm.

Keywords: accelerometry, ActiGraph, activPAL, measurement, physical activity

Sedentary behavior (SB), which is conceptually defined as any behavior requiring low energy expenditure [< 1.5 metabolic equivalents (METs)] with a sitting or reclining posture during waking hours (Sedentary Behavior Research Network, 2012), has become a major health risk behavior in modern society. Rapidly growing evidence demonstrates the negative impacts of SB on various health outcomes including, but not limited to, cardiovascular disease risk factors and chronic disease morbidity and mortality (Bankoski et al., 2011; Healy, Matthews, Dunstan, Winkler, & Owen, 2011b; Katzmarzyk & Lee, 2012; Koster et al., 2012; Wijndaele et al., 2011). Of the various SB assessment methods, objective assessments (i.e., accelerometers) have been broadly used in studies ranging from clinical trials to large-scale observational studies with greater reliability and validity compared to subjective methods (Atkin et al., 2012; Healy et al., 2011a). Several accelerometers developed by different manufacturers can generally be classified into two broad categories (i.e., energy-expenditure classification devices and postural classification devices) based on functional features as to how they capture human movements (Granat, 2012).

Energy-expenditure classification devices typically measure the frequency and amplitude of accelerations generated from ambulatory movements. These raw accelerations are analyzed with the manufacturer's software to provide outputs in the form of activity counts for user-defined time

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intervals (i.e., epochs). A number of activity count thresholds have been proposed for different intensity levels of physical activity (PA) across accelerometers (Freedson, Melanson, & Sirard, 1998). For example, in one frequently used energy-expenditure device, the ActiGraph (ActiGraph LLC, Pensacola, FL, USA) accelerometer, the activity count threshold for identifying SB is < 100 counts per minute (cpm) (Matthews et al., 2008), which approximately corresponds to the energy cost of < 1.5 METs. Postural classification devices like the activPAL (PAL Technologies Ltd., Glasgow, Scotland) use an inclinometer to detect postural information (e.g., lying, sitting, or standing), of which lying/sitting during waking hours is commonly considered SB (Harrington, Dowd, Bourke, & Donnelly, 2011; Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011).

Although there are promising aspects of using objective methods to characterize SB in health outcome research, several measurement criticisms have been raised for each type of monitoring device (Atkin et al., 2012; Granat, 2012; Marshall & Merchant, 2013). Most of the criticisms, in general, are related to operationalizing SB in a way that is congruent with the conceptual definition, particularly focusing on the components of energy expenditure (< 1.5 METs) and posture (sitting). For instance, researchers examining SB using energy classification devices may have to make an arbitrary assumption regarding body posture (i.e., sitting or lying) when energy expenditure estimates are less than the SB threshold. Conversely, postural classification devices may fail to account for energy expenditure when classifying lying/sitting to SB. However, previous validation studies examining SB through different accelerometers in both laboratory and free-living settings generally concluded that the posture classification device (i.e., activPAL) provides better estimates of time spent in SB with less bias and higher accuracy while the use of energy expenditure classification devices (e.g., ActiGraph) based on a fixed activity count threshold may introduce significantly larger random errors, potentially altering study outcomes (Kozey-Keadle et al., 2011; Lyden, Kozey-Keadle, Staudenmayer, & Freedson, 2012).

A continuous effort has been made to improve the performance of energy-expenditure classification devices in assessing SB. A number of activity count thresholds of SB have been established in different experimental settings, and triaxial accelerometers (e.g., ActiGraph GT3X) have become equipped with a built in inclinometer function estimating postural information when the device is worn on the hip and is perfectly vertical. However, there is still little consensus on which threshold provides the best estimates of SB while minimizing misclassification errors of light-intensity PA in free-living settings (Carr & Mahar, 2012; Kozey-Keadle et al., 2011; Lyden et al., 2012). Furthermore, validity of postural information estimated from energy-expenditure classification devices is not well understood (Carr & Mahar, 2012; Hänggi, Phillips, & Rowlands, 2012). In addition, one aspect that has not been well understood in evaluating the performance of energy-expenditure classification devices for the assessment of SB may be related to the impact of setting minimum detectable sedentary bout durations during the accelerometer data processing phase to minimize possible misclassification of light-intensity PA. Although energy-expenditure classification devices are not able to distinguish between light-intensity PA and SB using fixed thresholds of SB at a given epoch (i.e., ≤ 1 min), light-intensity PA with minimal movements (e.g., standing still) featuring low energy expenditure of < 1.5 METs may likely be intermittent with short durations in a free-living environment. Thus, it is presumable that the misclassification of light-intensity PA as SB may possibly be reduced by focusing on extracting persistent SB (i.e., SB without frequent interruptions) with a given minimum sedentary bout duration from the accelerometer data (Kim, Welk, Braun, & Kang, 2015).

Meanwhile advanced statistical techniques based on machine learning classification have also been employed to develop optimized algorithms to better classify posture from energy expenditure classification devices. Lyden, Kozey-Keadle, Staudenmayer, and Freedson (2014) recently developed a method called *Sojourn*, which is a hybrid machine learning algorithm that combines an artificial neural network with a hand-built decision tree analysis. The algorithm was validated among seven healthy adults in a free-living environment and significantly improved the performance of the GT3X accelerometer for classifying SB compared with direct observation; however, the performance of the Sojourn method needs further evaluation in a different sample.

The overarching goal of this study was, therefore, to examine the performance of two types of accelerometers in assessing SB in a free-living environment. The specific purposes include: (a) to examine the validity of the GT3X with different approaches (i.e., thresholds, Sojourn, and inclinometer) and the activPAL for identifying time spent in overall SB and (b) to examine the validity of those accelerometers in identifying time spent in persistent SB after setting the minimum detectable sedentary bout durations in the data processing phase compared with a direct observation proxy, the Autographer (Oxford Metrics Group, PLC., Oxford, UK) wearable camera.

METHODS

Participants and Procedures

A convenience sample of 11 adults (male = 8) was recruited from a community in the mid-southern region of the United

TABLE 1
Demographic Characteristics of the Participants

	Total (n = 11)	*Male (n = 8)*	*Female (n = 3)*
Age (yr)	30.67 (7.24)	29.51 (12.59)	33.76 (7.92)
Height (cm)	173.27 (8.86)	178.25 (6.83)	160.00 (3.00)
Weight (kg)	76.70 (17.81)	83.11 (27.63)	59.59 (5.56)
BMI (kg/m^2)	25.36 (4.57)	26.15 (9.64)	23.26 (1.65)
Monitoring period (min)	366.54 (21.47)	373.36 (20.49)	348.35 (12.34)

Note: Values are presented as mean (*SD*).

TABLE 2
Characteristics of the Accelerometer Measures

Device	*Output*	*SB Identification*	*Measure*
ActiGraph GT3X	Activity counts for 1-sec epoch	Sojourn method (vertical axis)	GT3X-Soj1x
		Sojourn method (three axis)	GT3X-Soj3x
		Inclinometer	GT3X-Incli-1s
	Activity counts for 10-sec epoch	< 8 counts	GT3X-< 8 cnts/10s
		Inclinometer	GT3X-Incli-10s
	Activity counts for 60-sec epoch	< 50 cpm	GT3X-< 50 cpm
		< 100 cpm	GT3X-< 100 cpm
		< 150 cpm	GT3X-< 150 cpm
		Inclinometer	GT3X-Incli-60s
activPAL	Activity events (time with seconds)	Lying/sitting	activPAL
Autographer (Criterion)	Images (time with seconds)	Standardized coding protocol (Kerr et al., 2013)	Autographer

Note: All measures were synchronized to a 1-sec data; SB = sedentary behavior, cpm = counts per minute.

States. Healthy adults between 20 and 60 years of age who do not have physical disabilities or medical conditions that may hinder normal daily activities were invited to participate (see Table 1). All participants attended an initial meeting where they signed an Institute Review Board-approved informed consent. During this time, a careful explanation about the potential risk and privacy issues associated with using a wearable camera was provided in consultation with the guidelines suggested by Kelly et al. (2013). Demographic information, including birthdate, gender, smoking status, and self-reported height (cm) and body weight (kg), were also obtained.

Upon completion of the informed consent form, the participants were asked to wear two accelerometers (ActiGraph GT3X and activPAL) and an Autographer wearable camera on designated body locations for the respective devices (waist over the right hip for GT3X accelerometer, mid-anterior position on right thigh for activPAL, and around the neck using a lanyard for Autographer). The measurement period was approximately 6 hr in a single monitoring day, that is, until the Autographer automatically turned off due to battery limitations (mean monitoring period = 366.54 ± 21.47 min). The aim was to observe any naturally occurring SB without taking consideration of specific contexts of SB by different characteristics of the participants (e.g., job status), the participants were instructed to perform normal daily activities without any behavior modification, such as reducing SB or increasing PA during the measurement period.

Accelerometers and SB Identification Approaches (See Table 2)

ActiGraph

The GT3X accelerometer, which is a light and small (27 g; 3.8 cm × 3.7 cm × 1.8 cm) triaxial accelerometer capable of recording accelerations in three axes (vertical, antero-posterior, and medio-lateral), was used for this study. The GT3X measures accelerations ranging from 30-Hz sampling rate in response to the magnitude from ± 3 g, which is in turn, integrated over a user-defined epoch length as activity counts. For this study, the GT3X device was programmed to record accelerations in 1-sec (sec) epochs with low-frequency extension in order to increase the sensitivity to capture low-intensity movements including SB. The device was attached to an adjustable elastic belt. The participants were asked to wear the accelerometer on the waist over the right hip (perfectly vertical) in order to ensure the use of the inbuilt inclinometer function for posture classification (lying, sitting, standing, and off).

Actilife software version 5.10.0 (ActiGraph LLC, Pensacola, FL, USA) was used to initialize the device and to download the time-stamped accelerometer data by the second. Because there is no empirically proposed activity count threshold for SB in a 1-sec epoch, the data were collapsed into 60- and 10-sec epoch lengths to apply thresholds of < 50 cpm, < 100 cpm, and < 150 cpm for 60-sec and < 8 counts per 10 sec for 10-sec data (Crouter, Dellavalle, Haas, Frongillo, & Bassett, 2013; Kozey-Keadle et al., 2011; Lyden et al., 2012; Matthews et al., 2008). A time interval with vertical activity counts less than a threshold was considered sedentary time for that respective threshold. The inclinometer outputs from 1-sec and collapsed 60- and 10-sec data were also obtained. The inclinometer time intervals classified as lying or sitting were considered sedentary time.

Two different versions of the Sojourn method identified SB from the second-by-second GT3X accelerometer data (Lyden et al., 2014). The first version (Soj-1x) employs the hand-built decision tree approach identifying SB using activity counts from the vertical axis. Briefly, the decision tree classifies time intervals for two types of SB (i.e., "sitting or lying fairly still" and "sitting with minor movement") based on the characteristics of two classifier parameters (i.e., percentages and/or durations of non-zero activity counts) for the respective time intervals. The second version (Soj-3x) uses the second-by-second activity counts from three axes (vertical, antero-posterior, and medio-lateral). Similar classifier parameters (i.e., percentages and durations of non-zero activity counts from the vertical axis), with different criteria, are used in combination with an artificial neural network to identify the time intervals that may be featured with "sitting or lying fairly still" or "sitting with minor movement." A detailed description of the Sojourn method can be found in Lyden et al. (2014) and the entire Sojourn algorithm based on an open source R-language is available at www.math.umass.edu/~jstauden/SojournCode.zip.

activPAL

The activPAL is a light and small (15 g; 3.5 cm × 5.3 cm × .7 cm) triaxial accelerometer, worn on the mid-anterior position of the right thigh. The device measures accelerations of the thigh at a sampling frequency of 20 Hz, which is used to produce the signals related to thigh inclination. Using the proprietary algorithm in the manufacturer-provided software, the final output for body postures (lying/sitting, standing, and stepping) was provided. The activPAL software version 7.1.18 was used to initialize the device and to download data. The "event" data that provides the exact observed time with seconds when posture is changed was expanded to second-by-second data for later analyses. A time period in which the posture was classified as lying/sitting was considered sedentary time.

Autographer

The Autographer is a new generation of SenseCam, which was the first wearable camera used in lifelogging research (Doherty et al., 2011; Kerr et al., 2013). The device is light and small (58 g; 3.74 cm × 9.55 cm × 2.29 cm), and incorporates five sensors (triaxial accelerometer, magnetometer, ambient temperature, light level, and passive infrared) to determine the best moment to automatically capture images without user intervention. The device was set to capture images at high rate (approximately 10 images per minute) and participants were instructed to wear the Autographer around the neck using a lanyard.

The Autographer's custom-built software was used to upload, store, and review the time-stamped images taken during the measurement period. A standardized coding protocol developed by Kerr et al. (2013) for the SenseCam image data was used to determine the images featuring SB. A series of visual cues including the limb position (e.g., hands on or legs underneath a table), camera angles (e.g., lower than other persons who were standing), and the associated environments (e.g., not involved in the exercise-related environments such as bicycling, static stretching, yoga, or weight lifting) of each image were simultaneously considered to define the sedentary "event." Although automatically captured images provide a series of ample cues to determine the moment at which behavioral context is changed, the device, to the best of the authors' knowledge, has not been empirically validated against direct observation which is currently considered as a gold standard measure to identify SB in a free-living environment (Kozey-Keadle et al., 2011). Particularly, one challenging issue was that the exact time at which behaviors are changed from and to SB was not intuitively identifiable since the automatically captured, consecutive images had an interval of between approximately 5 and 10 sec. In such cases, the time at the median point between two consecutive images (from or to SB) was considered as the starting or ending time of SB. Intervals of 5–10 sec between images may fail to capture important behavioral changes between the images. However, to the best of the authors' knowledge, there is no empirical evidence indicating the minimum measurement time interval for detecting naturally occurring behavioral changes from or to SB in a free-living environment. Meanwhile, the majority of studies examining the validity of activPAL for the assessment of SB used the default setting of 10 sec for a minimum sitting/upright period (Alghaeed et al., 2013); that is, any postural changes < 10 sec are not registered as a new behavioral "event." In other words, behavioral changes from or to SB may be successfully identifiable using a minimum interval of 10 sec, which was assumed for the image data of this study.

In the preliminary calibration phase testing the sensitivity of the Autographer with standardized coding protocols to identify changes in behavior from or to SB against direct observation, a total of 11 sedentary events observed from two individuals during an approximately 1-hr period each in natural office environments were all correctly identified. In addition, the absolute mean differences in starting and ending time (in seconds) of sedentary events between direct observation and Autographer were 1.91 sec (SD = 1.51) with a maximum bias range of ± 5 sec, and thus Autographer image data was considered as a criterion measure of direct observation proxy.

Three observers independently coded the image data for all participants. Discrepancies across observers were resolved by comprehensive discussion until they reached a consensus. The SB starting and ending time identified from the Autographer image data were used to create the second-by-second time intervals of SB.

Data Analysis

All accelerometer data management and statistical analyses were performed using SAS version 9.3 (SAS Institute Inc., Cary, NC). A graphical representation of the results was performed using R-language (www.r-project.org). Descriptive statistics (mean [M] and 95% confidence interval [%CI]) of SB parameters, including total sedentary time, the number of SB bouts (i.e., events), and the average duration of SB were obtained for each accelerometer measure.

In order to examine the validity of different accelerometers for assessing SB, two approaches with different levels of focus (i.e., an aggregated level [total sedentary time] and a second-by-second level [sedentary time intervals in seconds]) were employed. First, mean differences in total sedentary time between the accelerometer estimates and the criterion were calculated to quantify the prediction errors of total sedentary time estimated from each accelerometer. Mean differences were presented by two statistical indices, namely mean absolute percentage error (MAPE, %) and percentage (%) of bias, in order to provide overall magnitude of the errors due to the bias and the direction of the bias (e.g., under- or over-estimation), respectively. A 95% CI associated with the percent of bias was also considered as a proxy indicator for precision of the estimates. Second, the second-by-second accelerometer data were compared with the time-matched, second-by-second criterion data with sedentary time intervals identified for each participant. The proportions of sedentary and non-sedentary time intervals obtained from the criterion data that were correctly classified as SB (true positive) and misclassified as SB (false positive) by the accelerometers were presented as sensitivity (%) and 1-specificity (%), respectively. Youden's index, which is ([sensitivity [%] + specificity [%]] – 100), was calculated as a relative approximation to the overall performance of each accelerometer measure to identify true sedentary time and presented as percentage (%). Mean sensitivity, 1-specificity, and Youden's index across all participants were calculated along with the associated 95% CIs. Phi coefficients were additionally obtained for each measure as an index of association with the criterion.

To address the second specific research question, SB with different minimum bout duration of ≥ 0 sec (no-minimum sedentary bout durations), ≥ 300 sec (5 min), ≥ 600 sec (10 min), ≥ 900 sec (15 min), and ≥ 1,200 sec (20 min) were extracted from all accelerometer measures including the criterion data to examine the performance of each accelerometer measure and identify persistent SB at given minimum sedentary bout durations. The changes in MAPE, percent of bias, sensitivity, and 1-specificity for each accelerometer were calculated across different bout durations.

Due to the small sample size with multiple outcome variables within each individual, parametric statistical tests were not employed to examine the mean differences in outcome variables with criterion. Alternatively, non-overlapping 95% CIs were considered only as a rough indication of meaningful difference (e.g., statistically significant at alpha level of .01 [Julious, 2004]) in outcome variables and effect size (Cohen's *d*) was calculated when possible.

RESULTS

Validity of Accelerometer Measures: Identifying Overall SB

Table 3 presents the descriptive statistics of SB parameters across the different accelerometer measures. The observed total sedentary time (min) from the criterion (*M* = 247.57; 95% CI = 181.63, 313.51) indicated that the participants generally spent a large amount (≈ 67.5%) of their monitoring period in SB. The estimated total sedentary time from the accelerometer measures was lowest for GT3X-Incli-60s (*M* = 189.33; 95% CI = 135.79, 242.87) and highest for GT3X-< 150 cpm (*M* = 264.98; 95% CI = 219.12, 310.83). The number of SB bouts and the average duration of SB bouts were meaningfully different from the criterion (*M* = 13.27; 95% CI = 9.44, 17.11; and *M* = 20.66; 95% CI = 13.77, 27.54, respectively). Larger numbers of SB bouts were observed across all measures compared with the criterion (Cohen's *d* ranges: 1.54–4.18) with the exceptions of GT3X-Soj3x, GT3X-Incli-60s, and activPAL. On average, smaller average SB durations were estimated compared with the criterion across all measures (Cohen's *d* ranges: .90–2.53) with the exceptions of GT3X-Soj3x, GT3X-< 100 cpm, GT3X-< 150 cpm, and activPAL.

The accuracy and precision of total sedentary time estimated from each accelerometer measure compared to the criterion are presented in Table 4. The results at the aggregated level indicated that the activPAL showed the most accurate estimate of total sedentary time with MAPE of 4.11% (95% CI = .00, 8.42) and percent of bias of −3.52% (95% CI = −8.08, 1.36), followed by GT3X-Soj3x with MAPE of 7.26% (95% CI = 2.28, 12.24) and percent of bias of −2.81% (95% CI = −9.67, 4.05). The GT3X inclinometer-based measures meaningfully underestimated the total sedentary time from the criterion which was evidenced by the negative limits of 95% CIs for GT3X-Incli-1s (percent of bias = −18.94; 95% CI = −32.73, −5.15; Cohen's *d* = .92), GT3X-Incli-10s (percent of bias = −19.32; 95% CI = −33.15, −5.49; Cohen's *d* = .94), and GT3X-Incli-60s (percent of bias = −19.91; 95% CI = −34.12, −5.70; Cohen's *d* = .94).

At the second-by-second level, activPAL demonstrated the best performance for the classification of sedentary time intervals compared with the criterion, which was evidenced by the highest phi-coefficient (.89; 95% CI = .81, .97), sensitivity (95.01%; 95% CI = 9.54, 99.47), and smallest 1-specificity (2.52; 95% CI = 1.54, 3.50). Youden's index was largest for activPAL (Youden's index = 92.48; 95% CI = 87.26, 97.70), followed by GT3X-Soj3x with Youden's index being 74.74 (95% CI = 68.05, 81.42).

TABLE 3
Descriptive Statistics of SB Parameters Across Accelerometer Measures

		GT3X 1-Sec Epoch			*GT3X 10-Sec Epoch*		*GT3X 60-Sec Epoch*				
	Autographer	*GT3X-Soj3x*	*GT3X-Soj1x*	*GT3X-Incli-1s*	*GT3X-< 8 cnts/10 s*	*GT3X-Incli-10s*	*GT3X-< 50 cpm*	*GT3X-< 100 cpm*	*GT3X < 150 cpm*	*GT3X-Incli-60s*	*activPAL*
Total sedentary time (min)	247.57	236.28	224.96	191.39	262.77	190.43	233.23	254.69	264.98	189.33	236.85
	(181.63, 313.51)	(172.89, 299.67)	(168.67, 281.26)	(138.54, 244.25)	(217.57, 307.96)	(137.78, 243.09)	(182.23, 284.23)	(207.64, 301.74)	(219.12, 310.83)	(135.79, 242.87)	(174.10, 299.61)
Number of SB	13.27	13.73	23.82	55.09	137.00	53.00	32.00	27.82	24.91	22.45	18.18
	(9.44, 17.11)	(10.24, 17.22)	(18.85, 28.79)	(35.60, 74.58)	(109.11, 164.89)	(34.53, 71.67)	(24.77, 39.23)	(22.11, 33.53)	(19.03, 30.79)	(14.92, 29.99)	(12.73, 23.64)
Average durations (min)	20.66	18.67	10.07	4.29	2.16	4.38	8.52	10.43	12.54	9.75	15.65
	(13.77, 27.54)	(12.70, 24.64)	(6.63, 13.51)	(2.76, 5.81)	(1.39, 2.93)	(2.86, 5.91)	(4.96, 12.08)	(6.48, 14.38)	(7.49, 17.58)	(7.00, 12.49)	(8.92, 22.37)

Note: Values are presented as mean (95% CI); SB = sedentary behavior.

TABLE 4
Validity of Accelerometer Measures for the Assessment of SB

	1-Sec Epoch			*10-Sec Epoch*		*60-Sec Epoch*				
		GT3X-Soj3x	*GT3X-Soj1x*	*GT3X-Incli-1s*	*GT3X-8 cnts < 10s*	*GT3X-Incli-10s*	*GT3X-< 50 cpm*	*GT3X-< 100 cpm*	*GT3X-< 150 cpm GT3X-Incli-60s*	*activPAL*
Aggregated level										
MAPE (%)	7.26	12.49	21.67	24.69	21.93	18.69	22.73	25.15	22.52	4.11
	(2.28, 12.24)	(5.60, 19.39)	(10.05, 33.29)	(0.00, 55.72)	(10.18, 33.67)	(1.73, 35.66)	(0.00, 53.68)	(0.00, 61.48)	(10.39, 34.65)	(0.00, 8.42)
Percent of bias	−2.81	−5.29	−18.94	21.14	−19.32	3.00	17.05	23.19	−19.91	−3.52
	(−9.67, 4.05)	(−15.83, 5.25)	(−32.73, −5.15)	(−11.17, 53.45)	(−33.15, -5.49)	(−18.38, 24.38)	(−15.66, 49.77)	(−13.78, 60.16)	(−34.12, -5.70)	(−8.08, 1.36)
Second-by-second level										
Phi-coefficient	0.72	0.60	0.54	0.54	0.54	0.57	0.60	0.61	0.54	0.89
	(0.64, 0.79)	(0.48, 0.72)	(0.36, 0.72)	(0.42, 0.67)	(0.36, 0.72)	(0.46, 0.69)	(0.48, 0.71)	(0.48, 0.74)	(0.36, 0.73)	(0.81, 0.97)
Sensitivity (%)	89.90	81.40	74.35	90.05	74.19	83.69	90.50	93.03	73.97	95.01
	(85.08, 94.72)	(72.18, 90.63)	(61.75, 86.95)	(86.43, 93.68)	(61.53, 86.84)	(78.12, 89.25)	(87.52, 93.48)	(90.83, 95.23)	(61.01, 86.92)	(90.54, 99.47)
1-Specificity (%)	15.16	15.44	14.19	35.07	13.70	21.26	28.70	32.20	13.50	2.52
	(8.15, 22.17)	(7.83, 23.06)	(5.15, 23.24)	(24.22, 45.92)	(4.90, 22.49)	(12.07, 30.45)	(16.59, 40.80)	(18.68, 45.71)	(4.46, 22.53)	(1.54, 3.50)
Youden's index (%)	74.74	65.96	60.16	54.98	60.49	62.42	61.80	60.83	60.47	92.48
	(68.05, 81.42)	(53.29, 78.63)	(43.08, 77.24)	(42.75, 67.21)	(43.57, 77.41)	(51.08, 73.77)	(49.99, 73.62)	(47.30, 74.36)	(43.45, 77.49)	(87.26, 97.70)

Note: Values are presented as *Mean* (95% CI); SB = sedentary behavior; MAPE = mean absolute percentage error (%).

Validity of Accelerometer Measures: Identifying Persistent SB

Figure 1 depicts the total sedentary time changes in percent of bias from each accelerometer compared with the criterion across different minimum bout durations. On average, most of GT3X-based SB measures (GT3X-Soj1x, GT3X-Incli-1s, GT3X-8cnts<10s, GT3X-Incli-10s, GT3X< 50 cpm, and GT3X-Incli-60s) underestimated total sedentary time compared with the criterion after accounting for minimum bout durations. GT3X-Soj3x showed the most accurate and stable estimates of total sedentary time across the bout durations, which was evidenced by the narrow range of 95% CIs that include absolute zero at given minimum bout durations.

Figure 2 depicts the changes in sensitivity, 1-specificity, and Youden's index across the bout durations. There was a reduction in 1-specificity as minimum bout durations of SB increased across all measures. Similarly, the increase in minimum bout durations resulted in decreases in sensitivity across all accelerometer measures, with the exceptions of GT3X-Soj3x, which demonstrated relatively stable levels of sensitivity across the bout durations.

DISCUSSION

The validity of two accelerometers (ActiGraph GT3X and activPAL) was investigated with different functional characteristics (i.e., posture classification and energy-expenditure classification) to identify the time spent in SB in a free-living environment compared with a direct observation proxy (i.e., an automated wearable camera). Results of the current study indicated that, on average, the total time estimates for SB from all accelerometers were comparable to the criterion in this modest sample size. However, the mean total sedentary time differences of each accelerometer measure at the individual level expressed as MAPE (%), ranged from the smallest of 4.11% for activPAL to the largest of 25.15% in GT3X-< 150 cpm. In addition, the inclinometer-based GT3X measures underestimated total sedentary time as measured by the criterion.

The present findings are generally aligned with previous reports suggesting that the activPAL is the most accurate and precise measure of SB among adults. Grant, Ryan, Tigbe, and Granat (2006) examined the validity of the activPAL accelerometer during everyday activities including SB (e.g., watching TV) and compared them with direct observation in controlled and daily living settings. The results highlighted that the activPAL correctly classified SB with high sensitivity in controlled (99.7%) and daily living settings (99.5%). Another recent study (Kozey-Keadle et al., 2011) comparing SB assessments via GT3X and activPAL accelerometers to a direct observation in a free-living environment also reported that the activPAL is an accurate and precise monitoring device sensitive enough to detect changes in total sedentary time.

However, the present findings, after setting a minimum sedentary bout duration in the data processing phase,

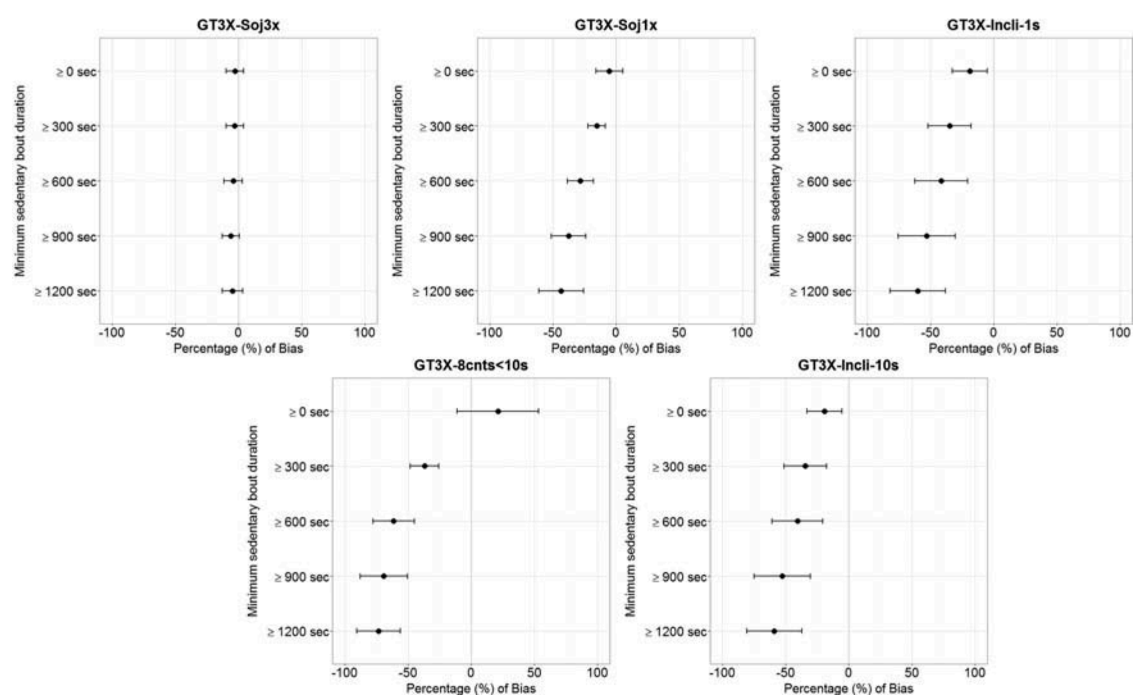

FIGURE 1 Illustrations of changes in % of bias (95% CI) on the estimated total sedentary time from accelerometer measures with and without application of minimum sedentary bout durations during the data processing phase.

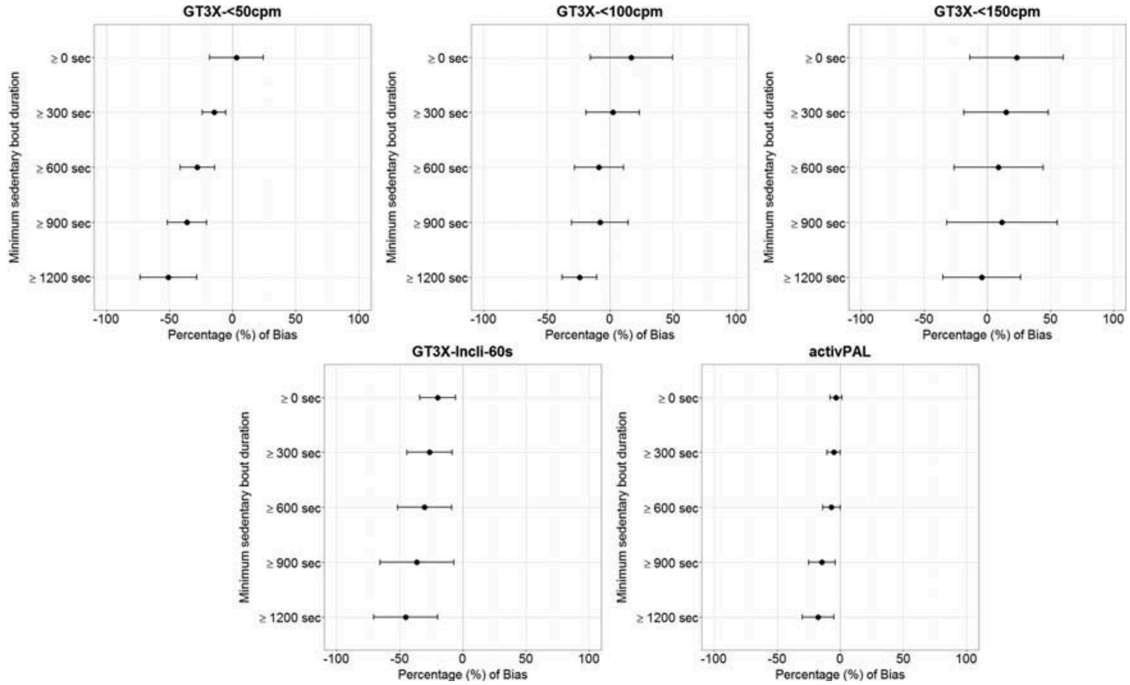

FIGURE 1 (continued) Illustrations of changes in % of bias (95% CI) on the estimated total sedentary time from accelerometer measures with and without application of minimum sedentary bout durations during the data processing phase.

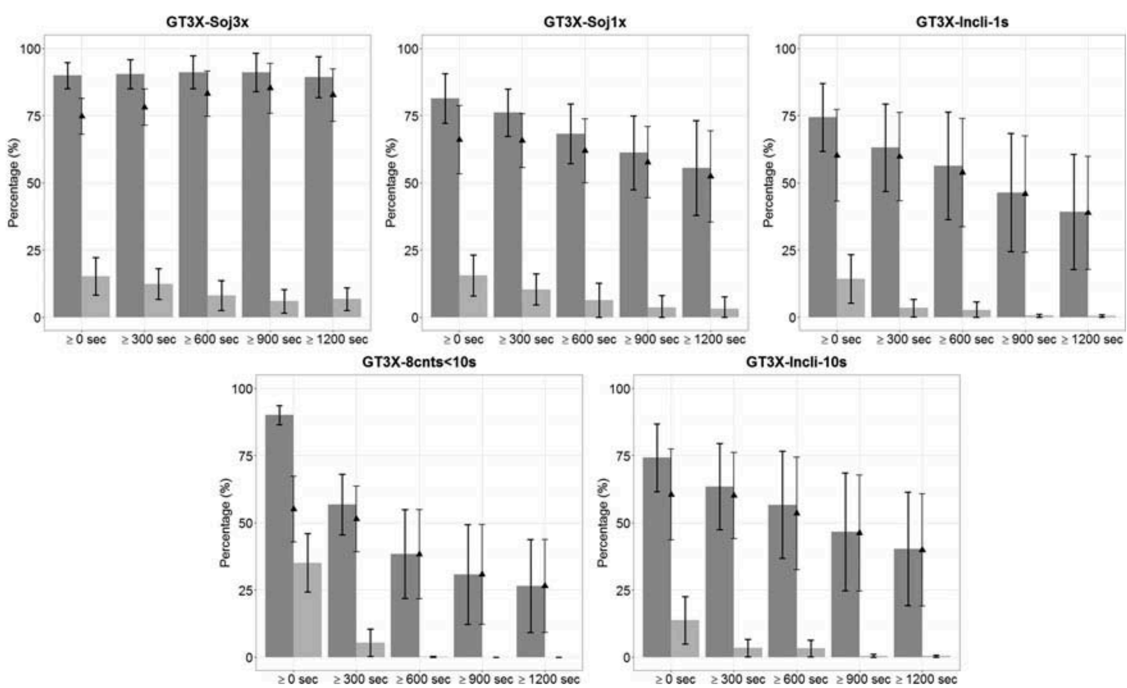

FIGURE 2 Illustrations of changes in sensitivity (dark grey on left), 1-specificity (light grey on right), and Youden's Index (black triangle in the middle) for accelerometer measures with and without application of minimum sedentary bout durations during the data processing phase.

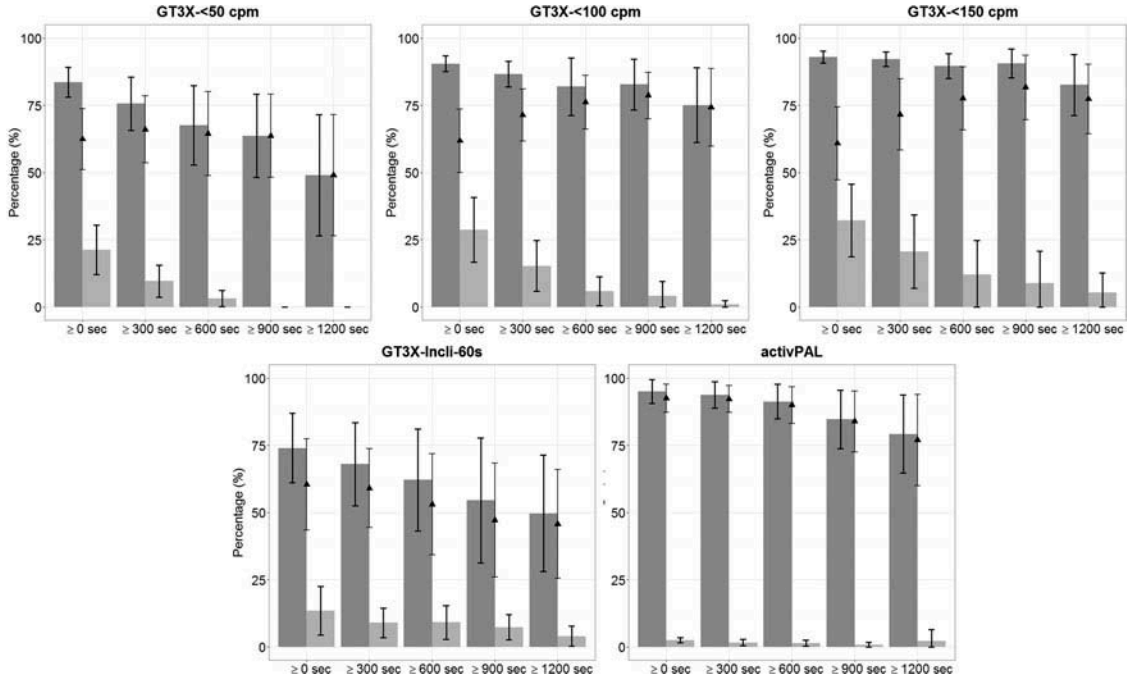

FIGURE 2 (continued) Illustrations of changes in % of bias (95% CI) on the estimated total sedentary time from accelerometer measures with and without application of minimum sedentary bout durations during the data processing phase.

showed reduced performance of the activPAL for correctly identifying intervals of persistent SB at given minimum bout durations. This could be of vital importance since the failure to detect true persistent SB might increase the number of sedentary events, one of the possible indicators to describe the patterns of how the sedentary time is accumulated. As shown in Table 3, the number of sedentary events from the activPAL (M = 18.18) was relatively greater than the criterion (M = 13.27) and hence, reduced the average duration of sedentary bout. However, considering high sensitivity and specificity of the activPAL and close estimates of total sedentary time compared with the criterion, it is legitimate to speculate that the duration of misclassification is relatively short and could possibly be minimized by increasing the minimum duration of upright period. The current results were based on the default setting of a minimum period of 10 sec (possible range from 1 through 100 sec) for both sitting and upright in activPAL. Changes in these parameters could possibly influence the performance of activPAL to correctly identify time spent in persistent SB, which may also affect the measured sedentary time accumulation pattern (Alghaeed et al., 2013).

A continuous effort has been made to refine the methods identifying SB using energy-expenditure classification devices. Specifically, several different thresholds have been proposed for the ActiGraph accelerometer, focusing on the vertical accelerations that might correspond to < 1.5 MET. However, the findings were generally inconsistent. For instance, the threshold of < 100 cpm has been extensively used for quantifying time spent in SB in studies ranging from clinical to large scale epidemiological studies (Healy et al., 2011b; Matthews et al., 2008). However, the findings from Kozey-Keadle et al. (2011) using the GT3X accelerometer with low-frequency extension, demonstrated that a threshold of < 150 cpm produced the most accurate estimate of total sedentary time (mean error 1.8%) compared with direct observation while a threshold of < 100 cpm showed underestimation (mean percent of bias −4.9%). Meanwhile, Crouter et al. (2013) reported that sedentary time estimated from the ActiGraph GT1M using the threshold of < 50 cpm underestimated measured sedentary time from indirect calorimetry (Cosmed K4b2; Cosmed, Srl., Italy) by 1.8% in a free-living setting. The authors also highlighted that the use of < 8 counts per 10 sec for the GT1M, which might be theoretically similar to < 50 cpm, resulted in greater underestimation (20.8%) of measured sedentary time from indirect calorimetry.

In the present study, it was found that the average total sedentary time estimated from threshold-based GT3X measures were comparable to each other. However, the accuracy of estimated sedentary time was relatively largely varied across individuals, as depicted by the relatively wide range of 95% CIs in MAPE and percent of bias for those measures. The present findings are aligned with the results from a study (Kozey-Keadle et al., 2011) that highlighted a large amount of random errors in sedentary time estimated from the GT3X.

This may imply that the ability of threshold-based GT3X measures to classify SB might be influenced by unidentified random error at the individual level, reducing the precision of the estimates. It is also worthwhile to note that the sensitivity of the GT3X was slightly improved by increasing the activity count threshold, which also resulted in an increased proportion of misclassification (1-specificity) of non-sedentary time. The findings suggest that increased thresholds would improve SB assessment of the GT3X accelerometer by identifying possible SB with minimal movements that might increase the accelerations in the vertical axis. However, it may also lead to tradeoffs in measurement errors due to the increased likelihood of misclassification of light-intensity PA (e.g., standing still) as SB.

The current study also extends these findings by applying a minimum duration of sedentary bout during the data processing phase in order to examine the performance of threshold-based GT3X measures to identify the time spent in persistent SB at given minimum bout durations. The findings indicate that an increased minimum sedentary bout duration resulted in reduced misclassification of non-sedentary time (Figure 2). Specifically, the minimum bout durations of ≥ 900 sec (≥ 15 min) for the GT3X < 150 cpm reduced the 1-specificity from 32.20% for ≥ 0 sec to 8.92% while the changes in sensitivity were minimal (i.e., 93.03% for ≥ 0 sec and 90.56% for ≥ 900 sec). It is widely acknowledged that a fixed activity count threshold for vertical movements may not be sensitive enough to distinguish SB from light intensity physical activities, such as standing still that involve minimal vertical movements (Granat, 2012; Lyden et al., 2012), increasing measurement error. However, the current findings imply that time intervals misclassified as SB were relatively short, which can possibly be minimized by focusing on persistent SB with a longer bout duration when extracting SB parameters from the accelerometer data. Such restrictions on minimum sedentary bout durations in the data processing phase may limit the operational definition of objectively measured sedentary time to be the time spent in persistent SB at a given minimum bout duration. However, considering the possible dose-response relationship of longer sedentary bouts and health outcomes are previously documented using the activPAL accelerometer (Chastin & Granat, 2010), it could be a legitimate approach to extract longer sedentary bouts from the GT3X when using the threshold approach in order to minimize measurement error.

Meanwhile, several updates have been made to the ActiGraph accelerometer. Specifically, the inclinometer function enables the GT3X device to detect postural information when the device is worn perfectly vertical on the hip. In the present study, the inclinometer-based GT3X measures underestimated total sedentary time regardless of the epoch length. Furthermore, while 1-specificity for all epoch lengths were relatively lower (13.50%–14.19%) compared to the threshold-based GT3X measures, sensitivity (73.97%–74.35%) was lower than GT3X-< 100 cpm (90.50%) and GT3X-< 150 cpm (93.03%). The current findings are aligned with the previous reports that indicated low accuracy of the inclinometer function in the GT3X. A controlled study validating the GT3X+ function (Carr & Mahar, 2012) highlighted the percentages of correctly classified SB as 66.7%, 63.4%, and 66.2% for lying down, sitting while watching TV, and sitting while working on a computer, respectively. Although the inbuilt inclinometer function in the GT3X device can be useful to estimate postural information, its low accuracy and precision should be of concern when measuring SB in a free-living setting.

Recently, an advanced statistical approach based on a machine learning technique has been increasingly applied to obtain accurate and precise PA levels including SB, from the accelerometer outputs. Lyden et al. (2014) proposed a hybrid machine learning method called Sojourn that combines artificial neural network with hand-built decision trees. The Sojourn-1x uses information about the percentage and duration of zero activity counts from the second-by-second vertical axis activity counts using the decision tree approach to determine time intervals for sitting/lying still and sitting with minimal movements separated from the standing still and standing with minimal movement. The Sojourn-3x uses the percentage of non-zero activity counts from the vertical axis to determine time intervals for inactivity. The neural network that was trained to distinguish SB from standing in a free-living setting is further applied to estimate time intervals with SB separated from light-intensity PA (i.e., standing still and standing with minimal movement) using the second-by-second activity counts from three axes (vertical, antero-posterior, and medio-lateral).

The Sojourn methods are primarily aimed to estimate METs from hip-mounted, ActiGraph accelerometer outputs; however, the previous validation results also highlighted that Sojourn methods significantly improved the performance of GT3X accelerometer in identifying time spent in SB (mean percent of bias of 8.8 and .5 for Sojourn-1x and -3x, respectively) compared to the threshold-based (< 100 cpm) GT3X measure (Lyden et al., 2014). In the present study, the accuracy and precision of the estimated total sedentary time using the Sojourn methods were relatively higher than other GT3X-measures. Specifically, the proportion of misclassification was relatively lower (1-specificity = 15.16% and 15.44% for GT3X-Soj3x and GT3X-Soj1x, respectively) and the overall performances to identify SB intervals were the second- and third-highest as shown by Youden's indices of 74.74% and 65.96% for GT3X-Soj3x and GT3X-Soj1x, respectively.

Although Sojourn methods showed relatively higher accuracy and precision compared to other GT3X measures, the overall performance expressed by Youden's index was lower compared to the activPAL (Youden's index of 92.48). However, it was also found that increases in minimum sedentary bout durations generally reduced the misclassification errors of the Sojourn method (i.e., GT3X-Soj3x) while maintaining relatively high and consistent sensitivity. This resulted in increased Youden's index for up to 85.14 under the ≥ 900 sec (15 min) of minimum bout durations, which is comparable to the values obtained from the activPAL (Youden's index = 83.87) at the given minimum bout durations. The current findings suggest that the use of the Sojourn method (Sojourn-3x) in combination with certain minimum sedentary bout duration (≥ 900 sec [15 min]) can improve the accuracy of estimating time spent in persistent SB while minimizing the misclassification of non-sedentary time in a free-living environment. Furthermore, considering that the training data used to distinguish SB from standing in the neural network analysis for Sojourn-3x was developed in a relatively small sample (six participants) (Lyden et al., 2014), training the neural network model with a larger sample size with varying patterns of habitual SB in a free-living setting would likely improve the performance of Sojourn-3x when assessing SB.

There are several limitations that need to be addressed when interpreting the results. First, the findings were based on a relatively small sample (11 participants) which might influence variation in the estimates due to sampling error. The measurement periods were relatively short (i.e., ≈ 6 hr) and may not be long enough to describe a whole spectrum of SB patterns in a day. Furthermore, the types of naturally occurring SB in the present sample were varied by different characteristic of the participants (e.g., occupation status, occupation category, and hours of measurement period). Although the goal was to examine the validity of two accelerometers to identify SB characterized by two main components (low energy expenditure and sitting or lying posture), regardless of specific domains (e.g., work-related, leisure time-related) or contexts (e.g., watching TV, working on a computer), the generalizability of the findings would be limited to the validity of the GT3X and activPAL for the assessment of specific types of SB across different domains. Second, the use of the Autographer automated wearable camera as the criterion measure might introduce a measurement error due to the time intervals between the images. Although it was assumed that the time intervals of approximately 5–10 sec between images would successfully describe the changes in behavioral contexts from or to SB, this might result in failure to detect important behavioral changes with short bout durations (e.g., < 5 sec). Furthermore, the coding scheme to extract the starting and ending time of SB from image data should be validated against direct observation in a natural environment. Finally, the current results for the ActiGraph GT3X measures were based on using the low frequency extension filter. The interpretation of the current findings should consider the possible variations in the performance of GT3X accelerometers for measuring SB in a free-living environment by different filtering options (Lyden et al., 2012).

CONCLUSIONS

In conclusion, the authors found that the activPAL was the most accurate monitoring device for the assessment of SB, and may accurately estimate SB parameters in a free-living environment. The GT3X measures based on the thresholds from the vertical axis and the inclinometer function may not be sensitive enough to detect postural information, increasing the likelihood of misclassification of non-sedentary time. The use of the Sojourn method using activity counts from three axes or the threshold of < 150 cpm from the vertical axis would improve the performance of the GT3X when only focusing on persistent SB with ≥ 15 min. However, it should be noted that such restriction may leave a critical gap in assessing total time spent in SB that may not be comprehensive enough to examine the potential health impact of naturally occurring SB in a free-living condition.

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