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Review

Assessment of Physical Activity in Adults Using Wrist Accelerometers

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The health benefits of physical activity (PA) have been widely recognized, yet traditional measures of PA, including questionnaires and category-based assessments of volume and intensity, provide only broad estimates of daily activities. Accelerometers have advanced epidemiologic research on PA by providing objective and continuous measurement of PA in free-living conditions. Wrist-worn accelerometers have become especially popular because of low participant burden. However, the validity and reliability of wrist-worn devices for adults have yet to be summarized. Moreover, accelerometer data provide rich information on how PA is accumulated throughout the day, but only a small portion of these rich data have been used by researchers. Last, new methodological developments are emerging that aim to overcome some of the limitations of accelerometers. In this review, we provide an overview of accelerometry research, with a special focus on wrist-worn accelerometers. We describe briefly how accelerometers work; summarize the validity and reliability of wrist-worn accelerometers; discuss the benefits of accelerometers, including measuring light-intensity PA; and discuss pattern metrics of daily PA recently introduced in the literature. A summary of large-scale cohort studies and randomized trials that implemented wrist-worn accelerometry is provided. We conclude the review by discussing new developments and directions of research using accelerometers, with a focus on wrist-worn accelerometers.

accelerometry; bias; epidemiologic studies; exercise; sedentary behavior

Abbreviations: AC, activity count; LPA, light-intensity physical activity; MET, metabolic equivalent of task; MPA, moderate-intensity physical activity; MVPA, moderate to vigorous physical activity; PA, physical activity; PAEE, physical activity energy expenditure; SB, sedentary behavior; VPA, vigorous physical activity.

The health benefits of engaging in physical activity (PA) have been widely recognized (1). Accurately quantifying trends in PA is vital to defining public health guidelines and gauging population-level risk for a wide range of diseases, chronic conditions, and functional outcomes. PA is defined as bodily movement that results in energy expenditure above a resting state (2). PA volume is "the total amount of activity accumulated over a specific period of time" (3, p. 354). According to the energy required for a given task, PA can be categorized into different intensity levels, from sedentary behavior (SB) to vigorous PA (VPA). SB refers to any activities with energy expenditure of not more than 1.5 metabolic equivalents (METs) while sitting, reclining, or lying down (1). Though the definition of SB excludes standing quietly, SB derived by wrist- or hip-worn accelerometers does not make the distinction between sitting or lying down and standing, because most devices do not provide information on body posture. Light PA (LPA), moderate-intensity PA (MPA), and VPA require 1.6–2.9, 3.0–5.9, and at least 6.0 METs, respectively (1).

The gold standard for measuring PA energy expenditure (PAEE) is doubly labeled water, a technique that quantifies total daily energy expenditure in free-living conditions (4). PAEE is estimated by subtracting dietary-induced thermogenesis and laboratory-measured resting metabolic rate from total energy expenditure (5). However, the technique is rarely used in large-scale epidemiologic studies, because of the expensive and complex procedures. PA questionnaires are instruments that can be administered to many participants at low cost. Although PA questionnaires provide context, such as the type of PA being performed and/or the location in which PA is performed (6), there are measurement

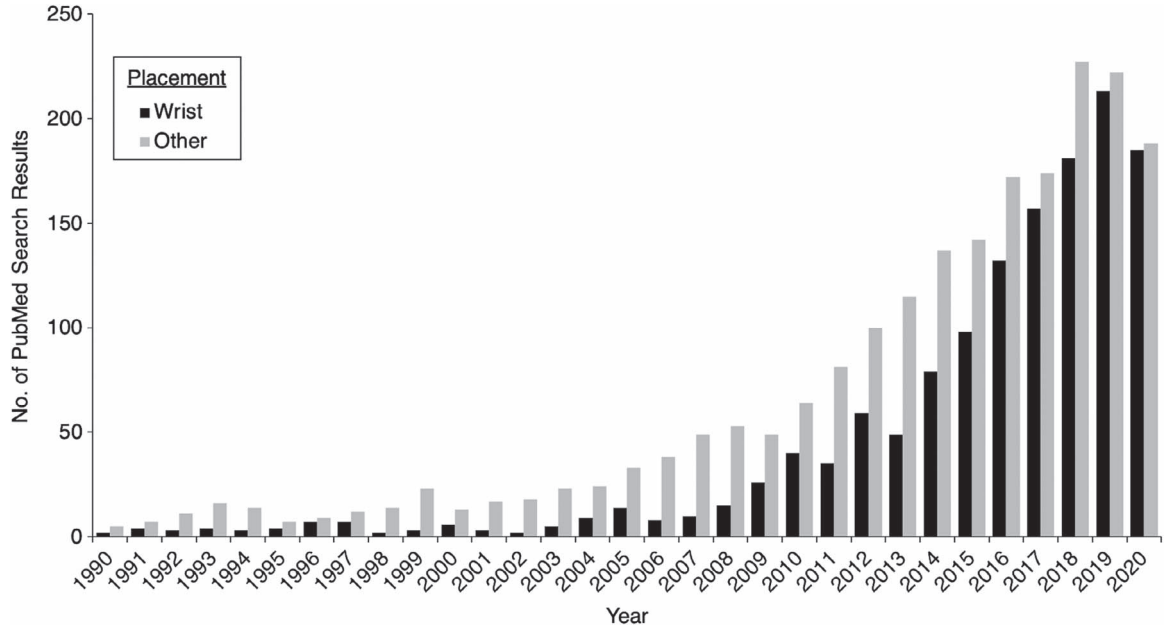

Figure 1. Number of PubMed search results for wrist accelerometers and accelerometers worn at other body locations.

and methodological challenges, including recall biases, variability in individual perception of activity intensity, and difficulty quantifying time spent in LPA (7–11).

The desire to overcome some of the limitations associated with self-report has led to the increasing use of wearable accelerometers over the past 2 decades. Accelerometers measure PA by quantifying movement, which is highly proportional to PAEE (12–15). Accelerometers are small and noninvasive, with sampling frequencies that can reach 100 observations/second (Hz) in habitual PA research, providing an objective assessment of movement-based PA across the entire intensity spectrum (from zero to maximal exertion). Large memory space and long battery life also facilitate continuous, sub-second measurement for weeks. When used in research, accelerometers are fitted to a specific body location, most commonly the hip, chest, thigh, lower back, and wrist. Wrist-worn devices have gained increasing popularity in recent years (Figure 1) in efforts to reduce participant burden and improve compliance (13, 16), and have been used to estimate PA in the National Health and Nutrition Examination Survey (NHANES), UK Biobank, and other large epidemiologic studies (16).

A few reviews have been published on accelerometers and their use in epidemiologic studies (5, 16–21); these give comprehensive overviews of many practical considerations when using accelerometers. However, new trends in accelerometry research warrant another review. First, wrist-worn accelerometers are becoming more prevalent in research (Figure 1), but previous reviews mainly focused on hip-worn accelerometers (5, 19, 21). Second, accelerometer use has generally centered on quantifying total amount of daily PA, classifying activity intensity, and estimating PAEE. Although these estimates are important for understanding the health benefits of PA and compliance with PA guidelines (1), they reduce the high-frequency time-series nature of accelerometer data to basic summary variables (e.g., active minutes/day). Thus, the enormous potential to understand the link between movement and health at a much deeper level using these rich data has yet to be fully realized (22). The recent development of novel accelerometry metrics that capture how and when PA is accumulated throughout the day have the potential to add new dimensions to PA epidemiologic research, beyond volume and intensity. Last, several methods have been developed in recent years to address several limitations of accelerometers, primarily related to recognizing certain body posture(s) and/or types of PA (e.g., sitting vs. lying or walking vs. climbing stairs) (9, 16, 20).

In this review, first we describe how accelerometers work and what they measure. Second, we summarize studies examining validity and reliability of wrist-worn accelerometers. Third, we review innovative metrics of PA that go beyond volume, intensity, and energy expenditure, using the data on a wider scale. Next, we summarize epidemiologic studies in which wrist-worn accelerometers were implemented in their study protocols. Lastly, we discuss limitations of accelerometers and efforts of the scientific community to overcome them and then conclude with future directions. The scope of this review is limited to research conducted with adults.

ACCELEROMETER MEASUREMENT

As indicated by the name, accelerometers measure time-stamped accelerations of the movement of the body part to which they are attached in *g*'s in 1 to 3 orthogonal planes (23). Because accelerations due to gravity and movement are recorded by the devices, the effects of gravity should to be removed when processing accelerometer data for PA

measurement (24). Euclidian norm minus one and sum of vector magnitudes with gravity subtracted are 2 common acceleration metrics. Both Euclidian norm minus one and sum of vector magnitudes with gravity subtracted remove gravity from the vector magnitude, an aggregate of the accelerations from the 3 axes. Euclidian norm-minus-one rounds negative values of gravity-subtracted vector magnitude to zero and averages the values within a user-specified time window, or an epoch, whereas sum of vector magnitudes with gravity subtracted takes the absolute values and sums the values within an epoch.

The acceleration data from some accelerometer brands (e.g., ActiGraph, Pensacola, Florida), can also be processed into summary measures such as activity counts (ACs) within an epoch (e.g., ACs per minute), using the proprietary software of the device manufacturer (25). Compared with acceleration, ACs are less comparable across device brands but require less storage space on the device (26). This advantage is disappearing with the expansion of memory on the device that can store weeks of raw acceleration data. As a result, use of raw acceleration metrics is increasing.

Both accelerations and ACs are difficult to interpret clinically. Therefore, their values over a defined epoch are frequently classified into time spent in sedentary, light, moderate, or vigorous intensities, or used to estimate energy expenditure on a continuous scale. Steps per hour or day are another metrics that are widely understood by both researchers and the general public. However, using software algorithms to convert accelerometer data to steps may pose validity issues, potentially leading to over- or underestimation of steps per day (27–32). For example, differences in leg length and gait mechanics make step estimation using a single algorithm problematic (33). Also, the vibration from riding in a motorized vehicle may be incorrectly classified as steps (34).

Earlier versions of accelerometers tended to be worn on the trunk of the body and typically measured accelerations using vertical axis only to best capture the up-and-down movements consistent with ambulation. More recently, accelerometers have been upgraded to triaxial designs (vertical, medio-lateral, and anterior–posterior axes) to capture a wider range of movement. The primary benefit of the additional axes is believed to be better discrimination of LPA (35–37) and nonambulatory activities such as yoga (38, 39). Table 1 summarizes the number of axes, available acceleration data, and processing software for a few common research-grade accelerometer brands.

Wrist accelerometers facilitate 24-hour wear which includes sleep time. However, sleep periods may be misclassified as SB if not properly identified. Participant sleep diaries traditionally have been used to record sleep periods, but some devices, such as ActiGraph and Actiwatch (Philips Respironics, Bend, Oregon), have built-in sleep-detection features in their respective software programs. Open-source methods are also available to detect sleep periods, using raw acceleration data (40). Another threat to the accurate estimation of SB is nonwear time, periods when the accelerometer is collecting data but is not attached to the participant. Days on which nonwear time exceeds a threshold (e.g., 10% of 24 hours) are called nonvalid

Table 1. Common Research-Grade Wrist-Worn Accelerometers by Brand, Number of Axes, Data Type, Processing Software, and Company Website

Brand	Current Models	Axis	Data Type	Processing Software	Company Website
ActiGraph	Centerpoint Insight Watch; GT9X; wGT3X-BT	Triaxial	ACs/*g*	Proprietary ActiLife software/open-source software	https://actigraphcorp.com/
GENEActiv		Triaxial	*g*	Open-source software	https://www.activinsights.com/products/geneactiv/
Axivity	AX3; AX6	Triaxial	*g*	Open-source software	https://axivity.com/
Actiwatch	Actiwatch 2; Actiwatch Spectrum PRO; Actiwatch Spectrum Plus	Uniaxial	ACs	Proprietary Actiware software	https://www.usa.philips.com/healthcare/sites/actigraphy
Actical		Omnidirectional	ACs	Proprietary Actical software	Discontinued
MotionWatch	MotionWatch 8; MotionWatch Rugged	Triaxial	ACs	Proprietary MotionWare software	https://www.camntech.com/motionwatch-8/
Ambulatory Monitoring Actigraph		Uniaxial	ACs	Proprietary software	http://www.ambulatory-monitoring.com
CSA		Uniaxial	ACs	Proprietary software	Discontinued

Abbreviations: AC, activity count; CSA, Computer Science and Applications.

Table 2. PubMed Search Terms Used in This Review

Concept[a]	MeSH[b]	Key Words[b]
Figure		
Physical activity	"Exercise"	"physical activity" (tiab) OR "activity" (tiab) OR "exercise" (tiab)
Accelerometer	"Acceleration" OR "Actigraphy" OR "Accelerometry"	"acceler*" (tiab)
Wrist worn	"wrist"	"wrist-worn" (tiab) OR "wrist*" (tiab)
Other placements	"Hip" OR "Thigh"	"hip-worn" (tiab) OR "hip" (tiab) OR chest-worn" (tiab) OR "chest" (tiab) OR "thigh-worn" (tiab) OR "thigh" (tiab) OR "lower back" (tiab)
Validity		
Physical activity	"Exercise"	"physical activity" (tiab) OR "activity" (tiab) OR "exercise" (tiab)
Accelerometer	"Acceleration" OR "Actigraphy" OR "Accelerometry"	"acceler*" (tiab)
Validity		"doubly labeled water" (tiab) OR "indirect calorimetry" (tiab) OR valid* (tiab) OR "sensitivity" (tiab) OR "specificity" (tiab) OR "accuracy" (tiab) OR "precision" (tiab)
Wrist worn	"wrist"	"wrist-worn" (tw) OR "wrist*" (tw)
Reliability		
Physical activity	"Exercise"	"physical activity" (tiab) OR "activity" (tiab) OR "exercise" (tiab)
Accelerometer	"Acceleration" OR "Actigraphy" OR "Accelerometry"	"acceler*" (tiab)
Reliability		"reliab*" (tiab)
Wrist worn	"wrist"	"wrist-worn" (tw) OR "wrist*" (tw)

Abbreviations: MeSH, Medical Subject Headings; tiab, title and abstract; tw, text word.
[a] Concepts were combined by Boolean operator AND, except for wrist-worn and hip-worn concepts for Figure 1, which were not combined.
[b] MeSH terms and key words of the same concept were combined by Boolean operator OR.

days and are excluded from analysis (41). On days with acceptable nonwear time, missing data can be imputed.

Though wrist-worn accelerometers can improve compliance in research and clinical settings (13, 16) and are the focus of this review, other placement locations may be more advantageous in terms of measurement accuracy, depending on the PA metric of interest. For example, ankle placement may be more accurate for step estimation (27), and thigh placement may better distinguish postures and activity types (42). Yet, evidence on the effect of placement for estimating energy expenditure is mixed. Some studies found the hip or thigh provided better estimates than the wrist (43–45), whereas others found the body locations were comparable (46) or the wrist to be more advantageous with certain algorithms for energy expenditure prediction (47). Different placements also may be differentially sensitive to intensities and types of PAs. Placement at the ankle and hip may be better for measuring moderate to vigorous physical activity (MVPA) (48), whereas wrist placement may be better for detecting daily tasks with more upper-body movement, such as household tasks (49). Therefore, careful consideration of placement and the desired outcome measure is warranted.

VALIDITY OF ACCELEROMETERS

Evaluation of validity and reliability of accelerometers should be specific to accelerometer output (uniaxial or multiaxial), placement, and the population in which they will be deployed (50). Models and algorithms add another layer of complexity to how accurately accelerometer data can be used to estimate energy expenditure and classify intensity and activity types. Finally, epoch length used for accelerometer data processing (e.g., 10 seconds, 30 seconds) can also affect intensity classification (51–54).

To review the validity of wrist-worn accelerometers, we searched PubMed using the search terms listed in Table 2. A total of 406 records were retrieved on July 6, 2020, and the titles and abstracts were screened for relevance. We limited inclusion to studies in which doubly labeled water and indirect calorimetry (the standard laboratory method for measuring energy expenditure) (55) were used as criterion methods. Studies of populations with specific diseases or disabilities were excluded. A total of 25 relevant papers were identified (13, 14, 43, 45–48, 56–73). These papers validated 2 basic uses of accelerometer data: total PA and intensity classification.

Validity of estimating total PA

Of the 25 included papers, 17 discussed the validity of total PA measured by accelerometers against energy expenditure measured by doubly labeled water or indirect calorimetry (13, 14, 43, 45–48, 56–65). Another 3 papers were identified from other sources (44, 74, 75). The findings

Table 3. Validity Studies Compared With Doubly Labeled Water and Indirect Calorimetry

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Neil-Sztramko, 2017 (59)	Actiwatch 2 (uniaxial, unspecified, 15 seconds, nondominant wrist)	30 female participants	40 (14.9)[a]	Treadmill walk/run at 2.0 mph, 3.0–3.5 mph, and fast self-selected speed; self-paced indoor walk at slow, medium, and fast speeds; stair ascend and descend; and a lift-and-carry task	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	None	Correlation between ACs and METs: $r = 0.69$
Lee, 2019 (57)	Actiwatch 2 (uniaxial, unspecified, 1 minute, both wrists)	27 young adults	18–26	Treadmill run at 4, 6, 8, 10, and 12 km/h	METs calculated from V_{O_2} measured by indirect calorimetry	METs estimated by regression models including ACs and quadratic terms of ACs	Correlation between AC and METs: right wrist, $r = 0.73$; left wrist, $r = 0.72$. No significant biases between estimated and criterion METs
Chen, 2003 (63)	Actiwatch 64 (uniaxial, unspecified, 1 minute, dominant wrist)	60 women	20–52	Structured exercise, including walking periods with average speeds of 0.6, 0.9, and 1.2 m/second and stepping periods with average speed of 12 steps/10 seconds, 18 steps/10 seconds, and 24 steps/minute. Laboratory-based spontaneous activities, including sitting, television viewing, deskwork, walking around the room, and voluntary exercises	EE (kcal) calculated from V_{O_2} and V_{CO_2} measured by indirect calorimetry	EE estimated by nonlinear model including ACs	Correlation between AC and criterion EE: $r = 0.646$. Significant underestimation between estimated and criterion EE

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Neil-Sztramko, 2017 (59)	ActiGraph GT3X+ (triaxial, unspecified, 15 seconds, nondominant wrist)	30 female participants	40 (14.9)[a]	Treadmill walk/run at 2.0 mph, 3.0–3.5 mph, and fast self-selected speed; self-paced indoor walk at slow, medium, and fast speeds; stair ascend and descend; and a lift-and-carry task	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	None	Correlation between AC and METs: $r = 0.69$
Lee, 2019 (57)	ActiGraph wGT3X (triaxial, unspecified, 1 minute, both wrists)	27 young adults	18–26	Treadmill run at 4, 6, 8, 10, and 12 km/hour	METs calculated from V_{O_2} measured by indirect calorimetry	METs estimated by regression models including AC and quadratic terms of AC	Correlation between AC and METs: right wrist, $r = 0.73$; left wrist, $r = 0.74$ No significant biases between estimated and criterion METs
Ho, 2019 (58)	ActiGraph GT9X (triaxial, 30 Hz, 10-s, non-dominant wrist)	90 adults	22.9 (4.15)[a]	Treadmill walk/run at 4.8, 6.4, 8.0, 9.7, and 11.3 km/hour	EE (kcal/min) calculated from V_{O_2} (L/min) and V_{CO_2} (L/min) measured by indirect calorimetry	1) EE estimated by Freedson VM3 Combination (2011) available with ActiLife software 2) EE estimated by a linear model including AC, body weight, and heart rate	1) The Freedson VM3 Combination model explained 38.4% of the variance in criterion EE and underestimated energy expenditure at each speed. 2) The linear model explained 80.2% of variance in criterion EE. Bias was not specified.

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Ellingson, 2017 (61)	ActiGraph GT3X+ (triaxial, 100 Hz, 1 second and 15 seconds, right wrist)	51 adults	18–40	Laboratory-based activities including supine resting, sitting reading a book, sitting typing, sitting fidgeting, standing reading a book, standing typing, standing fidgeting, climbing stairs, throwing/catching a ball, stationary biking, walking on a treadmill at 2 mph and 3 mph, walking at 3 mph typing, and running on a treadmill at 4.5 and 5.5 mph	METs calculated from VO_2 (mL/kg/minute) measured by indirect calorimetry	METs estimated from the Hildebrand linear method (43), Hildebrand nonlinear method, Staudenmayer linear method (47), and Staudenmayer random forest method (47) using acceleration	For the average across activities of all intensities, only the Hildebrand linear method was equivalent with the criterion METs. None of the methods was equivalent to the criterion METs within each intensity level.
Staudenmayer, 2015 (47)	ActiGraph GT3X+ (triaxial, 80 Hz, 15 seconds, dominant wrist)	20 adults	20–39	Treadmill walk/run at 3.0 mph (5% grade), 4.0 mph (5% grade), and 5.5 mph laboratory-based free-living activities including stairs, tennis, shooting, fast walk, stacking boxes, raking, walking while carrying groceries, self-paced walk, golfing (swinging), slow walk, vacuuming, gardening, laundry, dusting, driving, office work	METs calculated from VO_2 (mL/kg/minute) measured by indirect calorimetry	METs estimated from linear model and machine-learning models (ANN, SVM, and RF) using acceleration	Cross-validation showed that linear, ANN, and RF models were unbiased and had good agreement with overall criterion METs. All models tended to overestimate METs when the actual METs were low and underestimated them when actual METs were high.

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Stec, 2012 (44)	ActiGraph GT3X+ (triaxial, unspecified, 1-s, right wrist)	30 adults	21.7 (1.0)[a]	Resistance exercises, including machine bench press, machine shoulder press, machine squat, leg extension, leg curl, latissimus dorsi pull-down, triceps push down, and barbell biceps curl	EE (kcal) calculated from V_{O_2} measured by indirect calorimetry	None	Criterion EE only correlated with AC on the horizontal axis ($r = -0.40$), but not with AC on the other 2 axes or the sum of AC
Ellis, 2014 (46)	ActiGraph GT3X+ (triaxial, 30 Hz, 1 minute, nondominant wrist)	40 adults	35.8 (12.1)[a]	Laboratory-based household activities including laundry, window washing, dusting, dishes, and sweeping. Locomotion activities including stairs, slow walk, brisk walk, and jog	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	METs estimated from RF machine-learning model	No significant biases between estimated and criterion METs
Strath, 2015 (62)	ActiGraph GT3X+ (triaxial, unspecified, 1 second, nondominant wrist)	99 adults	≥18	Treadmill walk with speed from 40.2 to 107.2 m/minute in increments of 13.4 m/minute. Laboratory-based daily activities, including computer work, vacuuming, mopping/sweeping, carrying box of 3 weights, and walking with intermittent stair climbing	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	METs estimated from TR machine-learning model using n-gram–based feature (unigrams)	No bias between estimated and criterion METs by leave-one-out validation. Nonsignificant increase in biases and overall error when applying model for 18–39 years age group to 40–64 years age group or ≥65 years age group

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Hildebrand, 2014 (43)	ActiGraph GT3X+ (triaxial, 60 Hz, 1 second, nondominant wrist)	30 adults	18–65	Laboratory-based activities, including lying supine, sitting, standing, taking off shoes, standing, moving 8 items on a bookshelf, writing a sentence, putting a paper in an envelope, sitting down, treadmill walk/run at 3, 5, and 8 km/hour, and stepping	V_{O_2} (mL/kg/minute) measured by indirect calorimetry	V_{O_2} estimated from linear regression model including the ENMO only	ENMO explained 75% of the variance in V_{O_2}
Melanson, 1995 (75)	CSA (uniaxial, unspecified, 5 seconds, nondominant wrist)	28 adults	21.0 (1.0)[a] for male participants; 21.0 (1.1)[a] for female participants	Treadmill walk/run at speeds of 4.8, 6.4, and 8.1 km/hour and 0%, 3%, and 6% grade	V_{O_2} (mL/kg/minute) from indirect calorimetry, EE (kcal/min) calculated from V_{O_2} (L/min)	EE estimated using linear regression model including AC and body weight	Significant correlation between AC and V_{O_2} and EE: $r = 0.89$ and 0.81, respectively Linear regression model with $R^2 = 0.86$; small mean difference between estimated and criterion EE by cross-validation
Swartz, 2000 (60)	CSA (uniaxial, unspecified, 60 seconds, dominant wrist)	70 adults	19–74	Laboratory-based yard work, occupational, housework, family care, conditioning and recreational activities	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	None	Significant correlation between AC and criterion METs: $r = 0.181$
Hildebrand, 2014 (43)	GENEActiv (triaxial, 60 Hz, 1 second, nondominant wrist)	30 adults	18–65	Laboratory-based activities, including lying supine, sitting, standing; taking off shoes; standing; moving 8 items on a bookshelf; writing a sentence; putting a paper in an envelope; sitting down; treadmill walk/run at 3, 5, and 8 km/hour; and stepping	V_{O_2} (mL/kg/minute) measured by indirect calorimetry	V_{O_2} estimated from linear regression model including the ENMO only	ENMO explained 76% of the variance in V_{O_2}

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
Duncan, 2020 (48)	GENEActiv (triaxial, 80 Hz, 1 second, both wrists)	23 adults	55–77	Laboratory-based activities, including lying supine, seated reading, slow walking, medium walking, fast walking, folding laundry, sweeping the floor, and cycling	METs calculated from VO_2 (mL/kg/minute) measured by indirect calorimetry	None	Significant correlations between ENMO and criterion METs for nondominant wrist: r = 0.188 or 0.259 with cycling removed Significant correlations between ENMO and criterion METs for dominant wrist: r = 0.174 or 0.270 with cycling removed
Montoye, 2015 (45)	GENEActiv (triaxial, 20 Hz, 30 seconds, both wrists)	39 adults	22.1 (4.3)[a]	Laboratory-based free-living activities, including lying down, reading, playing a computer game, standing, laundry, sweeping, walking slowly, walking fast, jogging, cycling, stair use, biceps curls, squats	METs calculated from VO_2 (mL/kg/minute) measured by indirect calorimetry	METs estimated by ANN machine-learning model using 4 different feature sets	Significant correlation between estimated and criterion METs by leave-one-out cross-validation: r = 0.84 to 0.87 No statistically significant bias between estimated and criterion METs
Sirichana, 2017 (65)	GENEActiv (triaxial, 40 Hz, 60 seconds, both wrists)	20 adults	21 (1)[a]	Laboratory-based activities, including lying on back; sitting and reading a book; siting and doing computer work; washing dishes; sweeping; stacking and organizing chairs; treadmill walk at 1.5, 3, 4, and 6 mph and 0%, 3%, and 8% grade	METs calculated from VO_2 (mL/kg/minute) measured by indirect calorimetry	Piecewise linear regression model with SVMgs as dependent variable and METs as independent variable (linear spline at 6 METs)	Significant correlations between SVMgs and METs by regression model: nondominant wrist, R^2 = 0.85; dominant wrist, R^2 = 0.86

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
van Hees, 2011 (13)	GENEA (triaxial, 40 Hz, 1 second, each wrist for half of the participants)	30 pregnant and 65 nonpregnant women	20–35	Free-living conditions for 10 days	PAEE (MJ/day) derived from doubly labeled water	PAEE estimated from regression models using raw acceleration	Leave-one-out cross-validation showed acceleration explained 19% of the variance in criterion PAEE for nonpregnant women No statistically significant biases between estimated and criterion PAEE for nonpregnant women Nonsignificant correlation between acceleration and criterion PAEE for pregnant women
Esliger, 2011 (64)	GENEA (triaxial, 80 Hz, 1 minute, both wrists)	60 adults	40–65	Laboratory-based activities, including lateral recumbent; seated computer work; standing; window washing; washing dishes; shelf stacking; sweeping; treadmill walk/run at 4, 5, 6, 8, 10, and 12 km/hour; stair ascent/descent at 80 steps/minute; and brisk and medium free-living walk	METs calculated from V_{O_2} (mL/kg/minute) measured by indirect calorimetry	None	Correlation between SVMgs and METs: left wrist, $r = 0.86$; right wrist, $r = 0.83$
Correa, 2016 (74)	Actical (omnidirectional, 32 Hz, 1 minute, dominant wrist)	70 adults	42 (13)[a]	Free-living conditions for 1 week	PAEE (kcal/day) derived from doubly labeled water	PAEE estimates from Actical	Significantly overestimation between estimated and criterion PAEE

Table continues

Table 3. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Activity	Criterion	Algorithms	Findings
White, 2019 (14)	Axivity AX3 (triaxial, 100 Hz, 5 seconds, both wrists)	193 adults	40–66	Free-living conditions for 9–14 days	PAEE (kJ/day/kg) derived from doubly labeled water	PAEE estimated from 4 models developed by White et al., 2016 (15)	Correlation between estimated and criterion PAEE: dominant wrist, r = 0.61 to 0.65; nondominant wrist, r = 0.63 to 0.68 No statistically significant biases between estimated and criterion PAEE
Patterson, 1993 (56)	Ambulatory monitoring actigraph (uniaxial, 10 Hz, unspecified, nondominant wrist)	15 adults	22–38	Sedentary activities, including mental arithmetic task, self-paced reading, self-paced typing, and video game using a joy stick Graded activities, including treadmill walk/run at 5% grade and at 30%, 60%, 75%, and 90% of individual VO_{2max}; stepping at 20 and 36 steps/minute, and knee bends at 28 and 48 bends/minute	VO_2 (mL/kg/minute) from indirect calorimetry	None	Significant correlation between AC and VO_2: physical activity, r = 0.73; sedentary activity, r = 0.46

Abbreviations: AC, activity count; ANN, artificial neural network; CSA, Computer Science and Applications; EE, energy expenditure; ENMO, Euclidian norm minus one; MET, metabolic equivalent; PAEE, physical activity energy expenditure; RF, random forest; SVM, support vector machine; SVMgs, sum of vector magnitudes with gravity subtracted; TR, decision tree; VO_2, oxygen consumption.

[a] Values are expressed as mean (standard deviation).

from these 20 papers are summarized in Table 3. Eleven studies examined ActiGraph and Computer Science and Applications devices, the predecessor of ActiGraph (19); 6 studies validated GENEA/GENEActiv (Activinsights Ltd., Cambridge, United Kingdom); 3 studies tested Actiwatch; and Actical (Philips Respironics), Axivity (Axivity, Newcastle upon Tyne, United Kingdom), and Ambulatory Monitoring Actigraph (Ambulatory Monitoring Inc., Ardsley, New York) were examined by 1 study each. Eight and 11 papers used ACs and acceleration metrics for validation, respectively. Only 3 studies were conducted under free-living conditions. Five studies deployed leave-one-out cross-validations for their energy-expenditure prediction models, and 3 studies validated previously published models.

All brands except Actical (74) had some validity in measuring total PA, especially when total PA was of interest, but a wide range of correlations with the criterion methods was reported (0.17 to 0.93) due to the wide range of AC and acceleration metrics used, differing energy-expenditure prediction models used, inclusion of other variables such as body weight, and the diverse ranges of activities performed. Results of 2 studies suggested that the validity differed by intensity of PA (47, 61). Stec and Rawson (44) showed that ACs from ActiGraph were not correlated with energy expenditure during resistance exercise (r = –0.01 to –0.40), suggesting limitations for this type of exercise. No evidence suggested the superiority of one brand over another. In 2 studies, authors found similar correlations with criterion energy expenditure between Actiwatch and ActiGraph (r = 0.69 to 0.74) (57, 59), and similar correlations were found in another study between ActiGraph and GENEActiv (R^2 = 75% and 76%, respectively) (43).

It was unclear whether AC or acceleration was better for estimating total PA. Hildebrand et al. (43) reported a higher correlation with energy expenditure by indirect calorimetry, using Euclidian norm minus one in ActiGraph (r = 0.87), than did the correlations reported by Lee and Tse (r = 0.72 to 0.74) (57) and Neil-Sztramko e al. (r = 0.69) (59) using AC in ActiGraph.

The method used to compare AC and acceleration with criterion energy expenditure varied. In some studies, researchers used correlation or linear regression models with AC or accelerations alone, whereas others added body weight, heart rate, or nonlinear terms for acceleration in the regression models. Models including heart rate and linear splines for acceleration (58, 65, 75) reported higher R^2 values (range, 0.80 to 0.86) than AC- or acceleration-only models (range, 0.03 to 0.76) (43, 48, 57, 59, 63). However, body weight and quadratic terms for accelerations explained little additional variance in criterion energy expenditure (13, 14, 75). Machine-learning models were used in 5 studies (45–47, 61, 62) to predict energy expenditure, using accelerometry features such as means, standard deviations, percentiles, and angles of acceleration. Good validity for machine-learning models was reported by 4 studies (45–47, 62), but bias was found for a published random forest method in 1 study (61). Two of these 5 studies also included linear models in their analyses and did not find that machine-learning models improved prediction (47, 61).

No included studies compared the performance of accelerometers in free-living environment and laboratory conditions. However, the correlations with criterion energy expenditure reported in studies in free-living conditions (r = 0.44 to 0.65) (13, 14) were comparable to the correlations reported by authors of several laboratory studies (r = 0.46 to 0.73) (56, 58, 59, 63).

Studies using leave-one-out cross-validation all demonstrated unbiased estimation of energy expenditure by accelerometers (13, 47, 62, 73, 75). However, validations of published energy-expenditure prediction models in different populations were less promising. Ellingson et al. (61) found good validity for the linear model developed by Hildebrand et al. (43) and but biased estimation for the models developed by Staudenmayer et al. (47). Ho et al. (58) applied the Freedson VM3 Combination (2011) model (76) available in the ActiGraph software and found underestimation of energy expenditure during treadmill walking. Four models previously developed using GENEActiv worn on the nondominant wrist (15) produced unbiased estimation of PAEE, using Axivity on the nondominant and dominant wrists in a different sample (14).

Validity of PA intensity classification

Eight of the 25 included papers established intensity cutpoints using indirect calorimetry as the criterion (43, 48, 57, 59, 64, 66–68). These papers are listed in Table 4. All the reported cutpoints were for absolute PA intensity, given that the criterion was energy expenditure (1). There was substantial variability in the intensity cutpoints, even within the same accelerometer brand and model. This may be due to a combination of factors, including methods used to identify cutpoints (i.e., receiver operating characteristic analysis vs. linear regression) (77), activities performed (78), and epoch length (51–54). None of the papers considered relative intensity, which is defined in reference to individual's aerobic capacity (e.g., percent heart-rate reserve, percent maximal oxygen consumption, lactate thresholds, and/or Borg rate of perceived exertion) (1).

Validation on published cutpoints was conducted by authors of 4 of the 25 studies (Table 5) (48, 69–71). Three of the published cutpoints (79–81) were not included in Table 3 because activPAL (PAL Technologies Ltd., Glasgow, United Kingdom), a thigh-worn accelerometer that detects sitting and lying-like behaviors versus standing than other body locations (82) was used as the criterion for SB. In general, both sensitivity and specificity were worse in the validation population than in the population from whom the cutpoints were developed.

Ellingson et al. (61) validated another approach of classifying PA intensity. Accelerometer data were used to estimate METs using linear and nonlinear equations and grouped into intensity categories. Three equations were evaluated, and all were found to have excellent sensitivity and specificity for VPA (98%, 89%, and 98% sensitivity, respectively; and 99% specificity for all 3 equations) but not for SB (0%, 89%, and 39% sensitivity; 100%, 60%, and 90% specificity, respectively), LPA (67%, 21%, and 45% sensitivity; 37%, 90%, and 64% specificity, respectively), and moderate-intensity

Table 4. Studies Included in This Review and that Defined the Intensity Cutpoints

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Method	Cutpoints	Sensitivity and Specificity	Discrimination AUC
Lee, 2019 (57)	Actiwatch 2 (uniaxial, unspecified, 1 minute, both wrists)	27 young adults	18–26	Cutpoints were identified using linear regression models.	Right wrist SB–LPA: 61 cpm; LPA–MPA: 450 cpm; MPA–VPA: 1,322 cpm Left wrist SB–LPA: 58 cpm; LPA–MPA: 399 cpm; MPA–VPA: 1,404 cpm	Right wrist SB: NA; LPA: 93.7% SE, 55.2% SP; MPA: 77.3% SE, 81.9% SP; VPA: 61.7% SE, 91.6% SP Left wrist SB: NA; LPA: 96.2% SE, 49.1% SP; MPA: 79.9% SE, 76.5% SP; VPA: 42.4% SE, 90.7% SP	Right wrist: SB: NA; LPA: 86.5%; MPA: 86.4%; VPA: 84.5% Left wrist: SB: NA; LPA: 88.7%; MPA: 83.6%; VPA: 78.5%
Neil-Sztramko, 2017 (59)	Actiwatch 2 (uniaxial, unspecified, 15 seconds, nondominant wrist)	30 female participants	40 (14.9)[a]	Cutpoints were identified by maximizing SE and SP.	SB–LPA: 145 cpm; LPA–MPA: 274 cpm MPA–VPA: 597 cpm	SB: 100% SE, 92.2% SP; LPA: NA; MPA: 97.3% SE, 81.6% SP; VPA: 73.0% SE, 66.9% SP	SB: 0.96; LPA: NA; MPA: 0.92; VPA: 0.77
Lee, 2019 (57)	ActiGraph wGT3X (triaxial, unspecified, 1 minute, both wrists)	27 young adults	18–26;	Cutpoints were identified using linear regression models.	Right wrist SB–LPA: 418 cpm, LPA–MPA: 4,793 cpm, MPA–VPA: 15,696 cpm Left wrist SB–LPA: 232 cpm, LPA–MPA: 4,515 cpm, MPA–VPA: 15,044 cpm	Right wrist SB: NA; LPA: 92.4% SE, 48.9% SP; MPA: 76.4% SE, 88.0% SP; VPA: 61.1% SE, 90.9% SP Left wrist SB: NA; LPA: 95.2% SE, 39.3% SP; MPA: 74.5% SE, 88.1% SP; VPA: 60.9% SE, 89.7% SP	Right wrist: SB: NA, LPA: 85.4%, MPA: 87.1%, VPA: 85.7% Left wrist: SB: NA, LPA: 84.7%, MPA: 86.5%, VPA: 85.3%
Neil-Sztramko, 2017 (59)	ActiGraph GT3X+ (triaxial, unspecified, 15 seconds, nondominant wrist)	30 female participants	40 (14.9)[a]	Cutpoints were identified by maximizing se and sp.	SB–LPA: 1,514 cpm LPA–MPA: 2,199 cpm MPA–VPA: 4,712 cpm	SB: 100% SE, 92.2% SP LPA: NA MPA: 94.5% SE, 83.8% SP VPA: 89.2% SE, 56.3% SP	SB: 0.96; LPA: NA; MPA: 0.95; VPA: 0.79
Rhudy, 2020 (66)	ActiGraph GT9X Link (triaxial, unspecified, 1 minute, left wrists)	44 adults	26.1 (9.65)[a]	Cutpoints were identified by maximizing se and sp.	SB–LPA: NA; LPA–MPA: 4,836 cpm; MPA–VPA: 8,453 cpm	SB: NA; LPA: NA; MPA: 86.4% SE, 89.7% SP; VPA: 93.0% SE, 91.6% SP	SB: NA; LPA: NA; MPA: 0.93; VPA: 0.96
Hildebrand, 2014 (43)	ActiGraph GT3X+ (triaxial, 60 Hz, 1 second, unspecified)	30 adults	34.2 (10.7)[a]	Cutpoints were identified using linear regression models.	SB–LPA: undefined; LPA–MPA: ENMO = 100.6 mg; MPA–VPA: ENMO = 428.8 mg	SB: NA; LPA: NA; MPA: 54%–59% classification accuracy; VPA: 89%–92% classification accuracy	Unspecified

Table continues

Table 4. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Method	Cutpoints	Sensitivity and Specificity	Discrimination AUC
Hildebrand, 2014 (43)	GENEActiv (triaxial, 60 Hz, 1 second, unspecified)	30 adults	34.2 (10.7)[a]	Cutpoints were identified using linear regression models	SB–LPA: undefined; LPA–MPA: ENMO = 93.2 mg; MPA–VPA: ENMO = 418.3 mg	SB: NA; LPA: NA; MPA: 54%–59% classification accuracy; VPA: 89%–92% classification accuracy	Unspecified
Duncan, 2020 (48)	GENEActiv (triaxial, 80 Hz, 1 second, both wrists)	23 adults	55–77	Cutpoints were identified by maximizing se and sp	Nondominant wrist: SB–LPA: ENMO = 17.5 mg and 19.2 mg (cycling activity removed); LPA–MPA: ENMO = 121.9 mg and 89.8 mg (cycling activity removed); MPA–VPA: NA Dominant wrist SB–LPA: ENMO = 10.1 mg; ENMO = 20.2 mg (cycling activity removed); LPA–MPA: ENMO = 18.2 g and 113.9 g (cycling activity removed); MPA–VPA: NA	Nondominant wrist— SB: 78.1% SE, 78.9% SP; 73.8% SE, 80.7% SP (cycling activity removed); LPA: NA; MVPA: 86.6% SE, 64.6% SP 67.4% SE, 80.6% SP (cycling activity removed). Dominant wrist— SB: 88.2% SE, 83.8% SP 77.2% SE, 88.1% SP (cycling activity removed) LPA: NA MVPA: 79.0% SE, 60.3% SP 64.8% SE, 79.8% SP (cycling activity removed)	Nondominant wrist SB: 0.821 and 0.814 (cycling activity removed); MVPA: 0.659 and 0.912 (cycling activity removed) Dominant wrist: SB: 0.910 and 0.977 (cycling activity removed); MVPA: 0.692 and 0.715 (cycling activity removed)
Esliger, 2011 (64)	GENEA (triaxial, 80 Hz, 1 minute, both wrists)	60 adults	40–65	Cutpoints were identified by maximizing SE and SP	Right wrist SB–LPA: SVMgs = 386 $g \times$ min; LPA–MPA: SVMgs = 440 $g \times$ min; MPA–VPA: SVMgs = 2,098 $g \times$ min Left wrist SB–LPA: SVMgs = 217 $g \times$ min; LPA–MPA: SVMgs = 645 $g \times$ min; MPA–VPA: SVMgs = 1,810 $g \times$ min	Right wrist SB: 99% SE, 96% SP; LPA: NA; MPA: 100% SE, 56% SP; VPA: 78% SE, 97% SP Left wrist SB: 97% SE, 95% SP; LPA: NA; MPA: 95% SE, 72% SP; VPA: 78% SE, 98% SP	Right wrist: SB: 0.98; LPA: NA; MPA: 0.84; VPA: 0.89 Left wrist: SB: 0.98; LPA: NA; MPA: 0.91; VPA: 0.91

Table continues

Table 4. Continued

First Author, Year (Reference No.)	Device (Axis, Frequency, Epoch, Placement)	Study Population	Age Range, Years	Method	Cutpoints	Sensitivity and Specificity	Discrimination AUC
Landry, 2015 (67)	MotionWatch 8 (triaxial, unspecified, 1 minute, nondominant wrist)	23 adults	57–80	Cutpoints were identified by minimizing the distance to (0, 1) on ROC curve given sp $>$ 0.90 for MVPA	SB–LPA: 178.5 cpm; LPA–MPA: 562.5 cpm; MPA–VPA: NA	SB: 78% SE, 70% SP; LPA: NA; MVPA: 34% SE, 90% SP	SB: 0.81; MVPA: 0.79
Diaz, 2018 (68)	Actical (omnidirectional, 32 Hz, 1 minute, nondominant wrist)	24 adults	20–54	Cutpoints were identified for 99%, 95%, 90%, 85%, 80%, and 75% of se and by maximizing SE and SP	Maximizing SE and SP: SB–LPA: NA; LPA–MPA: 1,031 cpm; MPA–VPA: 3,589 cpm	Maximizing SE and SP: SB: NA; LPA: NA; MPA: 85.6% SE, 87.5% SP; VPA: 88.0% SE, 98.7% SP	MPA: 0.93; VPA: 0.96

Abbreviations: AUC, area under the ROC curve; cpm, count per minute; ENMO, Euclidean norm minus one; LPA, light physical activity; MPA, moderate physical activity; MVPA, moderate to vigorous physical activity; NA, not applicable; ROC, receiver operating characteristic; SB, sedentary behavior; SE, sensitivity; SP, specificity; SVMgs, sum of vector magnitudes with gravity subtracted; VPA, vigorous physical activity.

[a] Values are expressed as mean (standard deviation).

Table 5. Validation Studies on Published Cutpoints or Algorithm

First Author, Year (Reference No.) for Validation Studies	First Author, Year (Reference No.) for Published Cutpoint or Algorithm	Age Range of Development Population,	Age Range of Validation Population,	Accuracy in Development Population	Accuracy in Validation Population
Welch, 2013 (69)	Esliger, 2011 (64)	40–65	20–60	Left wrist: SB: 97%, SE, 95% SP; LPA: unspecified; MPA: 95% SE, 72% SP; VPA: 78% SE, 98% SP	Left wrist: SB: 69.7% SE, 85.7% SP; LPA: 44.9% SE, 82.5% SP; MPA: 46.2% SE, 74.3% SP; VPA: 70.7% SE, 69.9% SP
Ellis, 2016 (71)	Hildebrand, 2014 (43)	34.2 (10.7)[a]	55.2 (15.3)[a]	Cutpoint of ENMO = 100 mg for MPA Classification accuracy: MPA: 54%–59%; VPA: 89%–92%	The study validated classification of MVPA only: significant underestimation of mean minutes/day in MVPA
Duncan, 2020 (48)	Hildebrand, 2014 (43)	34.2 (10.7)[a]	63.2 (6.5)[a]	Cutpoint of ENMO = 100 mg for MPA Classification accuracy: MPA: 54%–59%; VPA: 89%–92%	Nondominant wrist MVPA: 79% SE, 59% SP Dominant wrist MVPA: 76% SE, 61% SP
Duncan, 2020 (48)	Hildebrand, 2017 (81)	34.2 (10.7)[a]	63.2 (6.5)[a]	Cutpoint of ENMO = 44.8 mg for SB SB: 98% SE, 74% SP	Nondominant wrist SB: 51% SE, 91% SP Dominant wrist SB: 51% SE, 93% SP
Duncan, 2020 (48)	Sanders, 2019 (79)	60–86	55–77	Cutpoint at ENMO = 6 mg for SB, 19 mg for MVPA; SB: 62% SE, 93% SP; LPA: unspecified; MVPA: 86% SE, 89% SP	Nondominant wrist SB: 71% SE, 80% SP; MVPA: 59% SE, 64% SP Dominant wrist SB: 79% SE, 89% SP; MVPA: 62% SE, 59% SP
Marcotte, 2020 (70)	Koster, 2016 (80)	70–92	18–25	Cutpoint at 1,853 cpm for SB SB: 81.5% SE, 76.6% SP Cutpoint at 376 counts/15 seconds for SB SB: 75.2% SE, 74.1% SP	Cutpoint at 1,853 cpm: 72.8% SE, 84.5% SP Cutpoint at 376 counts/15 seconds: 66.0% SE, 81.2% SP Significant underestimation by both cutpoints of time spent in SB
Marcotte, 2020 (70)	Hildebrand, 2017 (81)	34.2 (10.7)[a]	20.4 (1.3)[a]	Cutpoint of ENMO = 44.8 mg for SB SB: 98% SE, 74% SP	89.0% SE, 57.5% SP. Significant overestimation of time spent in SB

Abbreviations: cpm, count per minute; ENMO, Euclidean norm minus one; LPA, light physical activity; MPA, moderate physical activity; MVPA, moderate to vigorous physical activity; SB, sedentary behavior; SE, sensitivity; SP, specificity; VPA, vigorous physical activity.

[a] Values are expressed as mean (standard deviation).

Table 6. Machine-Learning Approaches for Physical Activity Intensity Classification

First Author, Year (Reference No.)	Features	Device	Findings
		Artificial Neural Network	
Staudenmayer, 2015 (47)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to vertical on the device	ActiGraph GT3X+ (80 Hz, 15-second epoch, dominant wrist)	Leave-one-out cross-validated classification accuracy for LPA, MPA, and VPA was approximately 72% (no values given in the article; approximation from figure)
Montoye, 2016 (72)	10th, 25th, 50th, 75th, and 90th percentiles of raw acceleration	GENEActiv (20 Hz, 30-second epoch, both wrists)	Leave-one-out cross validation results as follows: Left wrist: SB: 97.5%, SE, 99.2% SP; LPA: 99.0%, se, 99.3% SP; MVPA: 90.8% SE, 95.4% SP Overall classification accuracy was 95.9% Significant overestimation of time spent in LPA (2.2 minutes) Significant underestimation of time spent in MVPA (1.9 minutes) Right wrist: SB: 93.1%, SE, 97.6% SP; LPA: 97.8% SE, 98.7% SP; MVPA: 65.7% SE, 84.1% SP SP Overall classification accuracy was 85.4% Significant overestimation of time spent in SB (1.2 minutes) and LPA (7.4 minutes) Significant underestimation of time spent in MVPA (8.6 minutes)
Montoye, 2018 (73)	Tested 6 feature sets. Feature that performed the best in out-of-sample validation: *3 sets of statistics for 3 axes:* mean, SD, minimum, maximum, 10th, 25th, 50th, 75th, and 90th percentiles of acceleration signal	GENEActiv (20 and 60 Hz, 30-second epoch, left wrist)	Two out-of-sample validated classification accuracies were 77.0% and 77.7%.
		Random Forest	
Staudenmayer, 2015 (47)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to vertical on the device	ActiGraph GT3X+ (80 Hz, 15-second epoch, dominant wrist)	Leave-one-out cross-validated classification accuracy for LPA, MPA, and VPA was 75%
Ellingson, 2017 (61)	*VM statistics:* mean and SD *Angle statistics:* mean and SD of angle of acceleration *Other:* features derived from fast Fourier transform analysis of the signal	ActiGraph GT3X+ (100 Hz, 15-second epoch, right wrist)	Validation of the model developed by Staudenmayer (47): SB: 43% SE, 93% SP; LPA: 48% SE, 60% SP; MPA: 48% SE, 81% SP; VPA: 99% SE, 99% SP Overall classification accuracy was 53.5%

Table continues

Table 6. Continued

First Author, Year (Reference No.)	Features	Device	Findings
Marcotte, 2020 (70)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to the vertical axis on the device	ActiGraph GT3X-BT (100 Hz, 15-second epoch, nondominant wrist)	The study validated classification of SB only using model developed by Staudenmayer (47): 61.3% SE and 84.2% SP; classification accuracy, 70.6%; significant underestimation of time spent in SB
Montoye, 2018 (73)	Tested 6 feature sets. Feature that performed the best in out-of-sample validation: *3 sets of statistics for 3 axes*: mean, SD, minimum, maximum, 10th, 25th, 50th, 75th, and 90th percentiles of acceleration signal	GENEActiv (20 and 60 Hz, 30-second epoch, left wrist)	Two out-of-sample validated classification accuracies were 77.3% and 78.5%.
	Support Vector Machine		
Staudenmayer, 2015 (47)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to vertical on the device	ActiGraph GT3X+ (80 Hz, 15-second epoch, dominant wrist)	Leave-one-out cross-validated classification accuracy for LPA, MPA, and VPA was approximately 73% (no values given in the article; approximation from figure)
Montoye, 2018 (73)	Tested 6 feature sets. Feature that performed the best in out-of-sample validation: *3 sets of statistics for 3 axes*: mean, SD, minimum, maximum, 10th, 25th, 50th, 75th, and 90th percentiles of acceleration signal	GENEActiv (20 and 60 Hz, 30-second epoch, left wrist)	Two out-of-sample validated classification accuracies were 76.1% and 70.9%.
	Decision Tree		
Staudenmayer, 2015 (47)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to vertical on the device	ActiGraph GT3X+ (80 Hz, 15-second epoch, dominant wrist)	Leave-one-out cross-validated classification accuracy for LPA, MPA, and VPA was 74%
Marcotte, 2020 (70)	*VM statistics:* mean, SD, percentage of the power in 0.6–2.5 Hz, dominant frequency, fraction of power at the dominant frequency *Angle statistics:* mean and SD of angle of acceleration relative to the vertical axis on the device	ActiGraph GT3X-BT (100 Hz, 15-second epoch, nondominant wrist)	The study validated classification of SB only using model developed by Staudenmayer (47): 70.0% Se and 81.7% Sp; classification accuracy, 74.7%; significant underestimation of time spent in SB
Montoye, 2018 (73)	Tested 6 feature sets. Features that performed the best in out-of-sample validation: *3 sets of statistics for 3 axes*: mean, SD, minimum, maximum, 10th, 25th, 50th, 75th, and 90th percentiles of acceleration signal	GENEActiv (20 and 60 Hz, 30-second epoch, left wrist)	Two out-of-sample validated classification accuracies were 76.4% and 75.7%.

Abbreviations: LPA, light physical activity; MPA, moderate physical activity; MVPA, moderate to vigorous physical activity; SB, sedentary behavior; SD, standard deviation; SE, sensitivity; SP, specificity; VM, vector magnitude; VPA, vigorous physical activity.

PA (40%, 37%, and 44% sensitivity; 84%, 86%, and 74% specificity, respectively) (61).

Table 6 summarizes common machine-learning approaches for intensity classification. In 5 of the 25 studies, 4 approaches were evaluated: artificial neural network, random forest, support vector machine, and decision tree (47, 61, 70, 72, 73). The collection of accelerometry features used as input for the machine-learning models varied from study to study. Moderate to good accuracy (classification accuracy 53.5–78.5%) was reported in most studies, but Montoye et al. (72) found very good accuracy for both wrists (classification accuracy, 95.9% and 84.1%, respectively). It is unclear whether these complex methods are better than absolute cutpoints. Staudenmayer et al. (47) suggested that machine-learning methods outperformed the cutpoint method when comparing wrist machine-learning models with hip data cutpoints. Marcotte et al. (70), however, found similar classification accuracies using cutpoints and machine-learning methods at the wrist.

In conclusion, wrist-worn accelerometers are valid instruments for measuring total PA and classifying PA intensities. However, caution should be taken when applying published intensity cutpoints. Validation in the population of interest may be needed to understand the change in sensitivity and specificity and the potential impact on analysis.

RELIABILITY OF ACCELEROMETERS

Using the search terms listed in Table 2, we performed a separate search of PubMed for articles reporting on assessment of the reliability of wrist-worn accelerometers. Seven articles were identified from 92 results retrieved on July 10, 2020 (56, 67, 83–87). Four of these articles addressed the number of valid days needed for reliable measurement of PA. Dillon et al. (85) found 6 days of monitoring were necessary to achieve reliability greater than 0.80 for VPA and 2–3 days for other intensities among middle-aged adults wearing GENEActive (100 Hz; 1-minute epoch). Ricardo et al. (87) found 5 days were needed to achieve reliable estimates of LPA and MVPA for young adults (aged 18 and 30 years) for GENEActive (85.7 Hz; 5-second epoch). Falck et al. (84) found that the MotionWatch 8 (CamNtech, Cambridge, United Kingdom) (3–11 Hz; 1-minute epoch) needed 1–2 wear-days to achieve reliability of 0.80 for SB, LPA, and MVPA among older adults. The 1 study in which ActiGraph was used was conducted with pregnant women; at least 3 days were required to measure overall PA reliably, but 7 days were needed for MVPA (83). Despite different device brands, sampling frequency, and epoch lengths, the findings from these studies are consistent: more days are needed if activities of higher intensities are of interest.

PA may vary by season or by month (88, 89). Though a reliable measurement of PA can be achieved with 3–7 valid days, the PA measured may not be representative of yearly habitual PA. However, longer measurement periods may reduce participant compliance. Seven consecutive wear-days is typical of accelerometer studies.

Authors of 3 publications examined different types of reliability for ActiGraph, MotionWatch 8, and the Ambulatory Monitoring Actigraph. Ozemek et al. (86) tested the interdevice reliability of 2 ActiGraph GT3X+ monitors (100 Hz; 1-minute epoch) worn on the dominant wrist while activities of daily living were performed. A strong intraclass correlation coefficient of 0.989 was reported for the vector magnitude counts (86). Landry et al. (67) also found good interdevice reliability (intraclass correlation coefficient = 0.979) for MotionWatch 8 devices (unspecified hertz; 1-minute epoch) worn on the nondominant wrist. Patterson et al. (56) examined the test–retest reliability of the Ambulatory Monitoring Actigraph (10 Hz; unspecified epoch) using 2 measurements within 1 week from 4 adults. They found high correlation (0.97–0.99) between the 2 measurements.

EXPANSION OF ACCELEROMETRY RESEARCH

Accelerometers generally are thought to be more accurate and reliable than self-report in measuring volume, intensity, and frequency of PA, especially for LPAs and nonexercise activities of daily living in free-living conditions (9, 16, 20). This is paramount to accurately time-stamping and quantifying daily PA in a detailed manner, because these activities encompass the majority of the activities in which people engage (90). Several observational studies and randomized control trials have shown health benefits associated with these types of activity, but these have mainly been limited to accelerometers placed on the hip. In the NHANES and studies in other cohorts, LPAs were reported to have many health benefits, including lower cardiovascular risk factors (91–94), larger hippocampal volume (95), better health and well-being (96, 97), and lower mortality risk (91, 98, 99). In another recent NHANES study, researchers found that greater step intensity was not associated with lower mortality risk after adjusting for total steps per day (100). Nonexercise activity has been linked to death, as well (101, 102). Findings from randomized control trials also suggested that lifestyle activities such as walking, taking stairs, and low-intensity supervised exercise were beneficial to weight loss, reduction of cardiovascular risk factors, and improvement in physical function (103, 104). Studies should replicate these finding using wrist accelerometers, which may better capture light-intensity upper body movements than do hip accelerometers (49).

Another advantage of accelerometers over questionnaires is the ability to measure patterns of daily PA (20). This feature allows research to go beyond traditional PA metrics, characterizing how and when PA is accumulated throughout the day. Understanding these patterns may be important in lower-activity populations who engage in little to no MVPA and may highlight novel opportunities for intervention. Pattern metrics include sedentary and active bouts, breaks in sedentary time, the active-to-sedentary transition probability, and diurnal patterns. These metrics have mostly been assessed using hip- or chest-worn accelerometers, but studies using wrist accelerometers are emerging (41).

Sedentary and active bouts are defined as the consecutive minutes during which activity intensity falls in the range of SB or an active state (105). Studies have linked more prolonged sedentary bouts per day with incident metabolic syndrome in adults (106), abdominal obesity (107), and death in older adults (108). Time spent in longer MVPA

Table 7. Cohort Studies and Randomized Trials That Implemented Accelerometers

Study Name	Study Type	Device	Dates of Collection
NHANES	Population-based survey	ActiGraph GT3X+	2011–2014
BLSA	Prospective cohort study	ActiGraph GT9X Link	2015–ongoing
STURDY	Randomized control trial	ActiGraph GT9X Link	2015–2019
NSHAP	Population-based survey	Actiwatch Spectrum	2010–2011
UK Biobank	Prospective cohort study	Axivity AX3	2013–2015
The Fenland Study	Prospective cohort study	GENEActiv	2005–2015
Whitehall II	Prospective cohort study	GENEActiv	2012–2013
FinHealth 2017 Survey	Population-based survey	ActiGraph GT9X Link	2017
FIREA	Prospective cohort study	ActiGraph wActiSleep-BT	2014–ongoing
Pelotas (Brazil) birth cohorts	Birth cohorts	GENEActiv	2010–2013
		ActiGraph wGT3X-BT	2015–2017

Abbreviations: BLSA, Baltimore Longitudinal Study of Aging; FIREA, Finnish Retirement and Aging Study; NHANES, National Health and Nutrition Examination Survey; NSHAP, National Social Life, Health and Aging Project; STURDY, Study to Understand Fall Reduction and Vitamin D in You.

bouts (≥5 minutes and ≥10 minutes) decreased with age, beginning in early adulthood (109–111). Older adults who more frequently engaged in short active bouts (<5 minutes) had elevated mortality risk but not those who engaged in longer active bouts (≥5 minutes) (112). However, more time spent in MVPA was associated with higher odds of successful aging, whether it was spent in short (<10 minutes) or long bouts (≥10 minutes) (113).

Sedentary and active bouts have also been used in randomized clinical trials. For example, the Lifestyle Interventions and Independence for Elders study was a randomized clinical trial completed in 2014 that demonstrated an MPA intervention reduced the risk of major mobility disability compared with a health education program in older adults (114). At baseline, a larger percentage of wake time spent in active bouts of ≥2 minutes and ≥5 minutes, but not total active time, was associated with better performance on memory tests (115). Over 24 months, participants in the PA intervention spent less time in sedentary bouts of ≥10 minutes and ≥30 minutes (116), and spent more time in active bouts of ≥5 minutes and ≥10 minutes than did participants in the health education group (117).

Breaks in SB are defined as "a non-sedentary bout in between two sedentary bouts" by the Sedentary Behavior Research Network (105, p. 9). Operationally, studies often define breaks in SB as the number of interruptions of activity (≥1 minute) when in a sedentary state. More breaks in sedentary time were beneficially associated with cardiometabolic risk factors (118, 119) and lower likelihood of impairment in activities of daily living and instrumental activities of daily living (120, 121).

In contrast to sedentary breaks, the active-to-sedentary transition probability is the probability (range, 0–1) of transitioning from an active state to a sedentary state (122). It is calculated as the reciprocal of the average active-bout duration. Higher active-to-sedentary transition probability is conceptualized as a more fragmented pattern of daily PA. Higher active-to-sedentary transition probability has been associated with lower physical function (122), higher perceived fatigability and performance fatigability (122, 123), and greater risk of death (112, 124), even after adjusting for total volume of activity. Moreover, cancer survivors and patients with glaucoma with higher degrees of visual-field damage also had a more fragmented PA pattern (125, 126).

Diurnal patterns of PA measure PA within multiple time windows throughout the day. They can help assess changes in PA over time of day, understand rest-activity rhythms, and identify the ideal time of day to target for intervention. Several researchers have found more pronounced declines in PA in the afternoon than in the morning with higher age (127–132), though authors of 1 study found the decline in PA with age was similar through the day (133). Different patterns throughout working days were associated with various health measures, including body composition and cardiorespiratory fitness (134). Moreover, LPA in the morning and afternoon benefitted sleep, whereas PA of any intensity after 8:00 PM adversely affected sleep (135). A few factors, including falls (136), more severe visual damage (126), and higher level of fatigability (137), were linked to less PA during waking hours. Retirement delayed the time when activity was initiated and reduced the number of activity peaks during the day (138).

LARGE-SCALE WRIST-ACCELEROMETRY RESEARCH

Many large epidemiologic studies have implemented accelerometers, and major studies that used hip- or chest-worn accelerometers have been reviewed in a few review articles (9, 16). We complement these reviews by providing an overview of studies that adopted wrist-worn protocols (Table 7).

NHANES is a stratified, multistaged, probabilistic sample representative of the civilian, noninstitutionalized US

population (139). NHANES participants wore the ActiGraph GT3X+ on the nondominant wrist for 7 days in the 2011–2012 and 2013–2014 cycles (6). NHANES wrist-accelerometer data were released in November 2020.

The Baltimore Longitudinal Study of Aging is a study of human aging, established in 1958. The procedures for participant enrollment and the inclusion criteria have been described elsewhere (140). A 7-day wear protocol of the ActiGraph GT9X Link on the nondominant wrist was implemented in 2015, replacing a previous protocol using a chest-worn monitor (Actiheart; CamNtech) (141). As of March 2020, data from 780 participants had been collected.

The National Social Life, Health and Aging Project is a longitudinal, population-based survey representative of older adults born between 1920 and 1947. The study aims to "understand the well-being of older, community-dwelling Americans by examining the interactions among physical health and illness, medication use, cognitive function, emotional health, sensory function, health behaviors, social connectedness, sexuality, and relationship quality." (142) Participants were recruited in 2005–2006 (wave 1) and followed up in 2010–2011 (wave 2). A subset of wave 2 participants (n = 738) was asked to wear an Actiwatch Spectrum on their nondominant wrist for 3 days (143).

The Healthy Aging in Neighborhoods of Diversity Across the Life Span study is a cohort study of adults (White and Black) aged 30–64 years at enrollment. Participants are followed up every 4–5 years. A subset (n = 760) of wave 4 (2013–2017) participants wore the ActiGraph GT3X+ on their wrist for 1 week (144).

The Study to Understand Fall Reduction and Vitamin D in You is a recently completed randomized control trial of the use of vitamin D supplementation for fall prevention in older adults. The primary outcome of the trial was time to first fall or death (145). PA was 1 of the secondary outcomes and was measured using the ActiGraph GT9X Link on the nondominant wrist for 7 days at baseline, 3, 12, and 24 months (146). Data were collected on 664 participants.

Many other large US studies have implemented wrist accelerometry in their ongoing research protocols. For example, wrist accelerometry has been introduced in the Atherosclerosis Risk in Communities Study (147), the Peripheral Artery Disease Study of Study of Latinos, which is an ancillary study to the Hispanic Community Cohort Study/Study of Latinos (148), the Multicenter AIDS Cohort Study (149), the National Health and Aging Trends Study (150), and the Aging and Cognitive Health Evaluation in Elders Study (151) (J.A.S., personal communication). The protocol details are not yet published for these studies and therefore are excluded from Table 7.

Studies conducted in the United Kingdom also collected wrist-worn accelerometer data. The UK Biobank is a large, prospective cohort study with 500,000 participants residing in the United Kingdom. The goal of the study is to investigate genetic and nongenetic determinants of diseases in middle and old age. Researchers implemented wrist-worn Axivity AX3 for 7-day wear for 103,578 participants between 2013 and 2015 (132). Repeated measures are available for 2,500 participants (152). The Fenland Study is an ongoing study in the United Kingdom that recruited volunteers born between 1950 and 1975. The study is designed to investigate the interaction between genetic and lifestyle factors and obesity and related metabolic disorders. Phase 1 of the study was completed between 2005 and 2015. All participants were asked to wear a chest-mounted Actiheart, and a subsample of 2,100 participants also wore a GENEActiv accelerometer on the nondominant wrist simultaneously for 6 days (153). The Whitehall II Study is a cohort of UK civil servants established in the mid to late 1980s (1985–1988) that was designed to investigate health inequality between social classes. A total of 4,029 participants provided valid accelerometer data measured by the GENEActiv device worn on the nondominant wrist over 9 days during the 2012–2013 wave (154).

Two studies in Finland introduced wrist-worn accelerometry: the FinHealth 2017 Survey and the Finnish Retirement and Aging Study. The FinHealth 2017 Survey is a 2-stage cluster sample representative of adults older than 18 years in Finland; 933 participants in the cohort also participated in a "physical activity and sleep" substudy and wore a ActiGraph GT9X Link on their nondominant wrist for 7 days (131). The Finnish Retirement and Aging Study is a cohort study established in 2013 in which researchers aim to examine change in health behaviors during the retirement transition and the health and functional consequences of work and retirement (155). A subsample of the cohort was invited to participate in an activity substudy during which they were asked to wear the triaxial ActiGraph wActiSleep-BT for 7 days. Assessments before retirement were available for 903 participants (156), and repeated measurements were available for 527 participants as of March 2019 (157).

Several birth cohorts in Pelotas, Brazil, have also collected wrist-worn, accelerometer-assessed PA data. Participants of the 1982, 1993 and 2004 cohorts (n = 10,029) wore GENEActiv accelerometers on their nondominant wrist for 4–7 days, including at least 1 weekend day, between 2010 and 2013 (110). For the 2015 cohort, participants of the antenatal substudy during 16 to 24 weeks of gestation, fathers at 12-month follow-up, and mothers at 24-month follow-up after birth, entered a 7-day accelerometer protocol wearing the triaxial ActiGraph wGT3X-BT (158). Accelerometer data were collected from 2,620 pregnant women (109).

CHALLENGES WITH ACCELEROMETRY RESEARCH

Accelerometers, despite their many advantages and increasing popularity, also come with measurement and interpretation challenges. Some of these challenges are inherent limitations. For example, wrist-worn accelerometers may not adequately measure certain types of low-impact PAs such as cycling, yoga, and strength training (16) or capture the motion of certain activities, such as carrying groceries while walking or pushing a stroller (20).

Other challenges are methodological. Posture detection is currently difficult using wrist-worn accelerometers (9). Though devices worn on the thigh can better differentiate sitting or lying down and standing and stepping (42), they cannot differentiate sitting from lying down (159). The inclinometer built into some ActiGraph models can distinguish sitting and standing postures when worn on the thigh

(85.7%–100% correct) (160), but the accuracy was not good on the waist or wrist (mean absolute percent error > 44%) (161). Several methods have been developed to address this limitation. A second activPAL fixed to the chest in addition to the thigh can perfectly discriminate sitting and lying (159). Machine-learning and threshold-based methods were also developed to improve posture classification. Clark et al. (162) reviewed such studies with various placement locations, including the wrist. The majority of these studies had very small sample sizes and were conducted in structured or semi-structured conditions, with mixed results; in some studies, researchers found inaccurate classification of lying down, sitting, and standing, even in semi-controlled conditions (163–166), but others reported good accuracy (71, 167–171).

Last, wrist-worn accelerometers do not provide straightforward information on the types of PA performed. Overcoming this challenge would greatly advance PA research by providing more details about PA as a behavior and providing new insights toward health surveillance and outcomes. Machine-learning models to classify activity types (162, 166, 169–173) have been proposed for wrist-worn accelerometers. However, most of the studies published to date have mainly focused on method validation. Applications in research to characterize free-living PA types and investigate associations with health outcomes are limited (174).

FUTURE DIRECTIONS

Over the past several years, PA research has expanded beyond volume- and intensity-based metrics to patterns, posture, and activity types to maximize the use of the rich information contained in high-frequency accelerometer data. Yet to date, posture and activity-type classification methods have generally been limited to small sample sizes and laboratory environments. Validation in free-living conditions with more representative samples are needed to further understand the utility of these novel methods in epidemiologic research, because they hold considerable promise for advancing the science of PA.

Accelerometers can also be used to measure biomechanics such as physical function in free-living conditions. For example, gait speed, an important predictor of disability and death (175–177), is commonly assessed in the laboratory using a usual paced 4-m or 6-m walk. However, standardized gait speed measured in the laboratory may not adequately reflect free-living gait speed or variability (178). Methods to extract gait parameters, such as cadence and stride, are emerging (179–181). Studies are needed to investigate whether free-living gait parameters provide more insights into health and functional status than do laboratory-based gait assessments.

We have reviewed the validity of several published, absolute intensity cutpoints, but it is debatable whether absolute or relative cutpoints are the best approach to classify activity intensity, because individuals vary greatly by cardiorespiratory fitness levels (182). Time spent in MVPA estimated using relative cutpoints differed markedly from the estimates generated using absolute cutpoints using hip- or chest-worn accelerometers in several studies (183–185). Yet to date, studies that apply relative cutpoints for wrist accelerometers are few (186).

Finally, accelerometers have been used in many large-scale epidemiologic studies around the world. Multicohort harmonization of data will facilitate global PA research. However, different device brands and data collection and processing protocols impose challenges in pooling studies (16). Several recommendations have been proposed for data harmonization (187). For previously collected data, it has been suggested that raw acceleration data (measured in *g*'s) should be made available, and the types of monitors whose data can be pooled should be determined (187). Moreover, a new accelerometer data metric, Monitor-Independent Movement Summary, has been proposed to improve the pooling of the data from different accelerometer brands (188), but it has not be widely used. Work to process and harmonize raw data across device brands, placement, and data collection protocols is warranted.

CONCLUSION

Accelerometers have transformed PA epidemiologic research by making it possible to objectively and continuously measure PA in free-living conditions in large populations. In recent years, wrist-worn accelerometers have become increasingly popular due to better participant compliance and the ability to measure activity and sleep over a 24-hour protocol. To date, research suggests wrist accelerometers provide good validity and reliability, including quantifying total amount of PA, estimating energy expenditure, and classifying activity intensities. However, though clinically important, the traditional uses of accelerometer data reduce the rich information collected. Emerging pattern metrics of daily PA provide fairly simple ways to use data in a greater scope. Small studies have demonstrated promise in measuring posture, identifying activity types, and extracting free-living gait parameters. The potential utility of these measures to provide more sensitive information about health and functional status warrants additional investigation. Last, much data has been, and continues to be, collected in large-scale epidemiologic studies around the world. Because movement and health are intrinsically linked, data harmonization across these studies would greatly facilitate movement-based health research, providing a platform to refine and enhance public health recommendations and intervention efforts.

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