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Review

Assessing Daily Physical Activity in Older Adults: Unraveling the Complexity of Monitors, Measures, and Methods

Jennifer A. Schrack,[1] Rachel Cooper,[2] Annemarie Koster,[3] Eric J. Shiroma,[4,5] Joanne M. Murabito,[6,7] W. Jack Rejeski,[8] Luigi Ferrucci,[9] and Tamara B. Harris[4]

[1]Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland. [2]MRC Unit for Lifelong Health and Ageing at UCL, London, UK. [3]Department of Social Medicine, CAPHRI School for Public Health and Primary Care, Maastricht University, The Netherlands. [4]Laboratory of Epidemiology and Population Sciences, National Institute on Aging, National Institutes of Health, Bethesda, Maryland. [5]Division of Preventive Medicine, Brigham and Women's Hospital, Harvard Medical School, Boston, Massachusetts. [6]Section of General Internal Medicine, Department of Medicine, Boston University School of Medicine and [7]National Heart, Lung, Blood Institute's Framingham Heart Study, Massachusetts. [8]Department of Health and Exercise Science, Wake Forest University, Winston-Salem, North Carolina. [9]Longitudinal Studies Section, Translational Gerontology Branch, National Institute on Aging, National Institutes of Health, Baltimore, Maryland.

Address correspondence to Jennifer A. Schrack, PhD, Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, 615 North Wolfe Street, E7144, Baltimore, MD 21205. E-mail: jschrac1@jhu.edu

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Abstract

At the 67th Gerontological Society of America Annual Meeting, a preconference workshop was convened to discuss the challenges of accurately assessing physical activity in older populations. The advent of wearable technology (eg, accelerometers) to monitor physical activity has created unprecedented opportunities to observe, quantify, and define physical activity in the real-world setting. These devices enable researchers to better understand the associations of physical activity with aging, and subsequent health outcomes. However, a consensus on proper methodological use of these devices in older populations has not been established. To date, much of the validation research regarding device type, placement, and data interpretation has been performed in younger, healthier populations, and translation of these methods to older populations remains problematic. A better understanding of these devices, their measurement properties, and the data generated is imperative to furthering our understanding of daily physical activity, its effects on the aging process, and vice versa. The purpose of this article is to provide an overview of the highlights of the preconference workshop, including properties of the different types of accelerometers, the methodological challenges of employing accelerometers in older study populations, a brief summary of ongoing aging-related research projects that utilize different types of accelerometers, and recommendations for future research directions.

Keywords: Physical activity—Exercise—Physical performance—Functional performance—Physical function

Physical Activity in Older Adults

Physical activity (PA) is an important modifiable risk factor for a wide range of diseases, chronic conditions, and functional outcomes (1–3), yet the simple question, "How active are you?" is difficult for participants to answer. PA questionnaires have been used for decades to increase our understanding of the individual, social, and environmental factors that facilitate—or impede—PA in daily life and guide public health recommendations. Although there are advantages to self-reported measures of PA, there are also many well-recognized challenges to accurately employing and interpreting PA questionnaires, some of which are particularly relevant for aging research.

PA questionnaires may be subject to a high level of recall bias, specifically light activities such as casual walking, stair climbing, and household tasks, which may be difficult to conceptualize and quantify as "physical activity" (4–6). High intensity activities are more easily recalled, yet very few older adults actually perform high

intensity, or moderate-to-vigorous PA (MVPA), on a regular basis (7–9). Estimates from the general population indicate that light activities account for 20%–31% of daily activity, and likely more in older populations (6,10); thus, much of the daily PA in which older adults engage may go unrecognized by self-reported methods (11).

Although questionnaires facilitate comparison of measured functional ability to daily functional engagement, for example, what participants are able to do (in the lab) versus what they actually do (in daily life), interpretation of questionnaire results can be problematic if results are classified into broad categories (eg, light, moderate, vigorous) or into metabolic equivalents (METs) to standardize results to a given intensity threshold (12). Given that most daily activities in which older adults engage are light intensity (ie, ≤3 METs), a tremendous amount of discriminatory power may be lost in this translation (12,13). Moreover, assignment of MET values to PAs fails to recognize age-related changes in speed of movement and metabolic function (14–16), or that METs of energy expenditure at age 40 may not be equivalent to METs of energy expenditure at age 80.

New Technology, New Challenges

Recent advances in PA monitoring (eg, accelerometers) provide researchers with unprecedented opportunities to increase and refine our understanding of the health benefits of PA by assessing daily quantities of activity, as well as circadian patterns and trends. Accelerometers use sensors to detect accelerations in one-to-three orthogonal planes; anterior–posterior, mediolateral, and vertical (17). They are relatively small in size, wireless, and noninvasive. Most models have a long battery life (30–45 days or more depending on sampling frequency), generating an objective comprehensive assessment of daily free-living PA across multiple levels of exertion (18). These features provide a wealth of opportunity to assess low levels of activity across the full range of intensity not captured by questionnaires and have the potential to greatly increase our knowledge base of PA in older populations beyond time spent in MVPA. Yet with this new technology come methodological challenges, including choosing a device best suited for an older study population, determining the ideal body placement, and learning how to handle, process, and analyze the massive volumes of data generated by this detailed level of monitoring (11,19–21).

Evolution of Wearable Activity Monitors (Accelerometers)

In the last decade, the popularity of PA monitors has exploded in both research and consumer settings. Recent estimates indicate the market for performance monitors—both consumer and research grade—is expected to exceed 60 million units by 2018 (22). Research publications on Scopus of studies using data from PA monitors/accelerometers have also shown tremendous growth from <50 publications in 1990 to >600 publications in 2013 (23). This has been accompanied by confusion surrounding which types of devices are best suited for addressing specific research questions, whether data from different research-grade devices are in any way comparable, and whether consumer monitors and smart phone applications are suitable surrogates for research-grade monitors (19).

Consumer or Research Grade?

Consumer grade devices are generally smaller, sleeker, and less expensive than research grade monitors. The better known brands include Apple iWatch, Microsoft Band, Nike Fuel Band, Fitbit, Samsung Gear Fit, Jawbone, and Garmin. They provide consumers with the ability to track data over time and usually provide an estimate of total daily step counts, caloric expenditure, and/or distance traveled. These devices are often released to the consumer market with little scientific evidence of validity, and the algorithms used to calculate steps, energy expenditure, and distance from measured acceleration are proprietary, with no access to the raw acceleration data. Recent attempts to validate consumer grade devices against energy expenditure or step counts are somewhat problematic because each device has its own method of calculating the desired output metrics (24–26). Moreover, without access to the raw acceleration data, it is very difficult to determine the accuracy and sensitivity of these devices, and whether they are suitable for use in research specific to older, more sedentary populations (19).

Research grade devices are generally bulkier and more expensive than consumer grade devices, and involve significant software costs. The better known brands include Actiheart, Actigraph, Actiwatch, GENEActiv, and ActivPal. These devices are well validated in the literature, although generally in small, tightly controlled laboratory settings with younger individuals (27–34). They provide researchers with detailed access to the data, usually in terms of individual activity counts or gravitational acceleration ("*g*") units for a given unit of time. Although the software packages that accompany these devices have the ability to derive estimates of energy expenditure and/or step counts, the algorithms used to generate these estimates are generally developed in young, healthy populations, with few populations including adults older than 60 years of age (27,29,35). Given the vast changes that occur in mobility and body composition with aging, general population level algorithms may not be suitable for older populations, and use of these estimates may thus lead to significant error and biased results (19,36).

Accelerometer Placement

Common placements for devices include the hip, wrist, thigh, chest, and ankle. However, there is great confusion about the "best" placement to accurately capture the many different types of activity that together contribute to total daily PA. The hip has traditionally been the most widely used placement site, because it is generally believed to capture the most movement associated with the larger muscles of the body, and thus correlate most strongly with energy expenditure (5,13,17). However, in some studies, the hip location has led to problems with compliance, as many participants remove the device to sleep or to shower and forget to replace it (23). Moreover, it is usually worn on an elasticized belt at the waist, which can shift greatly throughout the day, thus moving the device and contributing to greater measurement error.

The nondominant wrist is emerging as a popular alternative to the hip as it generally increases compliance and total wear time (23). Participants are generally asked to wear wrist worn devices at all times, thus enabling measurement of PA, sedentary time, and sleep. In older, more sedentary populations, this placement may also capture activities that are more consistent with the most commonly performed tasks of daily living (eg, cooking, dressing, light housework) and thus provide a more comprehensive picture of total daily activity (20,37). However, caution should be used when utilizing the wrist placement in populations using assistive devices such as walkers; the wrist often remains stationary when walking with assistive devices, particularly rolling walkers, and it is unknown how much movement the device registers under this scenario. Moreover, scoring methods to identify sleep and wake windows have not been defined; thus, use

of a sleep log may be required although programs to identify sedentary time and other functions are in development (38).

Methodological Challenges

Although wearable devices capture a wider range of different intensities of activity than self-reported methods they have limited ability to detect specific types of nonimpact activities, including bicycling, swimming, yoga, and strength training. They also provide little information on the context of the activity when not accompanied by a daily log. Although they give an idea of the magnitude of the activity, in counts per minute (CPM) or *g*-units, without in-lab calibration there is little to no context of the relative intensity of activity for a given individual. Moreover, use of cutpoints and MET thresholds to define activity intensities created in younger populations may prove problematic in older populations who demonstrate slower speed of movement and greater energy expenditure during specific tasks (39).

Investigators should have a research plan in place for the large volumes of data generated by wearable devices, particularly at higher-frequency sampling. Sampling at 80 Hz (the commonly used sampling frequency for wrist accelerometry) provides 80 observations per second, generating a massive raw data file. Even if the data are smoothed into larger time intervals, large studies may be overwhelmed by the amount of data to be stored, processed, cleaned, and analyzed. For example, 7 days of data smoothed into 1-minute intervals transforms to 10,080 data points per person (60 minutes * 24 hours * 7 days).

Interpreting these data into clinically meaningful results is also challenging. Although steps and energy expenditure provide contextual relevance, it is imperative to remember that neither steps nor energy expenditure is directly measured by the accelerometer. Cumulative activity count methodology is useful for determining total daily PA, and calculating mean activity CPM highlights circadian patterns, but both methods are based on proprietary manufacturer count algorithms (40). Some researchers have begun using the raw acceleration data for analyses to minimize the challenges associated with transforming acceleration data into interpretable metrics (23), yet the size and intensity of these data files make this option challenging, particularly in large-scale studies, and for those with limited data analysis resources.

Determining Wear Time

Determining the amount of time the accelerometer is actually worn is imperative for proper data interpretation and analysis. Automated wear time algorithms (13,41–43), participant wear logs (44), and visual inspection (43,45) have all been used to identify periods of nonwear. However, among older adults, different algorithms have been shown to predict varying amounts of wear time; resulting in differing estimates of PA, and particularly of sedentary time (44). Using a combination of wear-time logs and algorithms may improve reliability of estimates; however, participant logs are burdensome and may have large amounts of missing data. Visual inspection has been proposed as a replacement for wear-time logs when used in combination with wear algorithms (45); however, this method is also resource heavy and may be replaced by using a second algorithm for wear time (43).

Continuous or 24-hour wear protocols not only require detecting periods of nonwear but also ensure that nonwear is distinct from sleep time. Several studies have identified sleep periods using a participant-reported sleep/wake log, and studies among children and young adults have begun to examine fully automated algorithms to detect sleep (46). Other sensors such as heart rate and/or temperature sensors may help differentiate wear time from nonwear time, but these features are not universally available on all monitors. More research is needed to compare different sleep and wear time algorithms across body locations and particularly among older adults, who may have different activity and sleep patterns compared with younger populations.

Defining Thresholds of Intensity

Due to considerable heterogeneity in physical ability among older adults, efforts to define thresholds of activity have been challenging (47). Standardly defined moderate and vigorous intensity activities are difficult for many older adults to achieve and maintain for longer than a few minutes. Moreover, with increasing age and comorbidity burden, even simple tasks such as climbing stairs may become "vigorous activity" for the functionally challenged who have greatly reduced aerobic capacity. Recent analyses from the Lifestyle Interventions and Independence for Elders (LIFE) study showed that individually tailored cutpoints could be estimated using age and fast gait speed assessed during a 400-m walk test to avoid considerable underestimation or overestimation of actual minutes of PA achieved at the individual unit of analysis (47). Accordingly, this also raises concerns about conclusions related to the effects of MVPA on health outcomes from large epidemiological studies that apply fixed cutpoints to diverse populations, and suggests that researchers interested in defining MVPA in older populations should do so on an individualized basis (47).

Assessing sedentary behavior (SB), generally defined as activity between 1 and 1.5 METs while either sitting or lying down (48), is a growing area of interest in older populations. Because self-report of SB is unreliable, accelerometry is a particularly important methodological development for tracking SB (33). A common practice in the literature for hip-worn accelerometers has been to define activities below 100 CPM as SB; however, there is no solid empirical evidence to support this decision (33). Although recent work in sedentary adults suggests that a more appropriate cutpoint may be 150 CPM, it is unclear whether this cutpoint is appropriate for older adults (33), or whether using a single, vertical axis to define SB may be more informative (49). Other limitations in using cutpoints to define SB are that researchers are unable to identify different types of SB or the frequency of postural shifts, with recent evidence suggesting that this level of detail may be important in understanding health outcomes (50).

Accelerometer Use in Aging Studies

Although the challenges of using accelerometers in research are numerous, the benefits of measuring PA through movement hold the potential to substantially advance PA research. The following section provides a brief overview of several large studies of older populations that have employed accelerometers in their research efforts, a general overview of the data collected, and the pros and cons of the devices used (summarized in Tables 1 and 2).

Actiheart

The Actiheart device, a combined heart rate and uniaxial acceleration monitor (Actiheart, CamNtech Ltd, Papworth, UK), is attached in a standard position to the chest with two electrocardiogram

Table 1. The Devices Highlighted by the Aging Studies That Participated in the Workshop, Their Placements, Data Collection Frequencies, and the Pros and Cons of Each Device

Device	Study	Placement	Sampling Frequency (Hz)	Pros	Cons
Actiheart	BLSA, NSHD	Chest	32	Measures heart rate and movement Secure placement with electrodes prevents device shifting during wear time Heart rate provides validation of wear time Waterproof	Participants complained about skin irritation from the electrodes
ActivPAL	The Maastricht Study	Thigh	30	Accurate assessment of posture and postural changes Allows access to raw data files Waterproof wrapping and continuous wear are possible	Mild skin irritation may occur with continuous wear Not effective in assessing moderate to vigorous levels of physical activity
Actigraph	WHS, AGES, LIFE	Right hip	30–100	Wide comparability to other studies Allows access to raw data files Long battery life Large memory capacity	Participants removed belt for sleeping, some forgot to replace the belt the next day Some participants complained the belt was not "fashionable" Elastic belt shifted during wear time, which may lead to inconsistent measurement
Actical	Framingham	Right hip	32	Long battery life Delayed start option Waterproof Lightweight Low device failure rate	Participants removed belt for sleeping, some forgot to replace the belt the next day Some participants complained the belt was uncomfortable

electrodes. It has been used by the Baltimore Longitudinal Study of Aging (BLSA) and the Medical Research Council National Survey of Health and Development (NSHD). It was selected by these studies based on recommendations made by expert collaborators on the potential benefits of capturing data on both movement and heart rate.

BLSA

The BLSA is a study of normative human aging, established in 1958 and conducted by the National Institute on Aging Intramural Research Program. Participants are followed for life and undergo extensive testing every 1–4 years depending on age. The BLSA began using Actiheart in 2007. Participants are fitted with the device at the conclusion of their clinic visit and asked to wear the device for the following 7 days and return it via express mail. Data (heart rate and activity counts) are measured in 1-minute epochs. Detailed results from the BLSA Actiheart data have been previously reported (40). Briefly, in a sample of 611 participants aged 32–93 (mean age 67, 50% male), mean wear time was 6.2 days (range 2–8). PA declined 1.3% per year for each 1-year increase in age, and older participants engaged in significantly lower levels of afternoon and evening PA compared with younger individuals ($p < .01$). After adjusting for age, functional performance, nonworking status, and higher body mass index were independently associated with lower levels of PA ($p < .001$).

The device performed well in terms of data collection, but interpretation of the data into estimates of energy expenditure (kilocalories) using the company software has been problematic (36). Restricting analyses to the count per minute data enabled characterization of cumulative daily PA as well as daily PA patterns over multiple days (40). Participants complained about skin irritation and many are reluctant to wear the device at return visits, limiting its longitudinal appeal. Moreover, the device is uniaxial and does not provide access to the raw acceleration data, which may limit its utility as the field advances toward triaixal devices with raw data capabilities.

NSHD

The NSHD is a nationally representative British birth cohort that has been followed prospectively since birth in 1946 (51,52). The Actiheart was used in the NSHD in 2006–2011 when study participants were aged 60–64, as part of a major clinical assessment (N = 2,229) (52–54). Trained nurses attached the monitor to the participant's chest during the clinical assessment and participants were asked to wear the device for 5 days during which time heart rate and accelerometry counts were measured in 30-second epochs. At the end of the 5-day monitoring period, study participants were asked to return the monitors to the study team via mail for data download and processing. Mean wear time was 4.8 days, and of 1,829 participants who agreed to wear the device, 1,787 had 2 or more days of valid data available for inclusion in analyses (53).

Initial analyses have examined these data in relation to indicators of health status, sociodemographic factors, and other health-related

Table 2. A Summary of the Studies Highlighted in This Review

Study	Number With Valid Accelerometry Data	Age Range (y)	Device Type	Instructions for Wear	Wear Time Methods	% Return Rate	Epoch Used for Analysis
AGES-Reykjavik	671 total (589 with 4 or more days of requisite hours)	73–98	ActiGraph GT3X	Wear at all times. Remove only for sleeping, bathing, or swimming	4 or more days with ≥10 h Mean = 6.4 Nonwear time defined as 60 min of zero counts	99%	Minute level counts converted to intensity thresholds
BLSA	611 (data collection ongoing)	32–93	Actiheart	Wear at all times. Remove only for bathing or swimming	3 or more days with ≥22.5 h Mean = 6.2 d Nonwear time was identified using the heart rate data	96%	Minute level counts
Framingham*	2,684	24–83	Actical	Wear at all times. Remove only for bathing	5 or more days with ≥10 h Mean = 6.6 Nonwear time defined as 60 min of consecutive zero counts	96%	30-s counts converted to intensity thresholds
Framingham* Offspring/Omni Group 1	1,272	46–95	Actical	Wear at all times. Remove only while sleeping and bathing	5 or more days with > 10 h Mean = 6.3 Nonwear time defined as 60 min of consecutive zero counts	99%	30-s counts converted to intensity thresholds
LIFE	1,171 (baseline) 695 (24-month follow-up)	70–89	ActiGraph GT3X	Wear at all times. Remove only for sleeping, bathing, or swimming	5 or more days with ≥10 h Mean = NA† Nonwear time was defined as 90 min of consecutive zero counts	NA†	Minute level counts converted to intensity thresholds
The Maastricht Study	2,642 (data collection ongoing)	40–75	ActivPAL	Wear at all times	1 or more days with ≥14 h Mean = 6 d The device was worn continuously	99%	Time spent sitting, standing, and stepping
NSHD	1,787	60–64	Actiheart	Wear at all times. Remove only for bathing or swimming	2 or more days of continuous wear Mean = 4.8 d Nonwear time was identified using the heart rate data	99%	30-s counts
WHS	7,247	62–101	ActiGraph GT3X	Wear at all times. Remove only for sleeping, bathing, or swimming	4 or more days with ≥10 h Mean = 6.8 d Nonwear time was defined using a combination of participant logs and 90 min of consecutive zero counts	96%	Minute level counts converted to intensity thresholds

Notes: NA = not applicable.

*The complete database includes additional participants with at least one valid day of wear time, with a valid day defined as 10 or more hours of wear time (n = 247 in the Third generation/Omni Group 2 and n = 573 in the Offspring/Omni Group 1), who were not included in these analyses.

†The LIFE study was a clinical trial, and accelerometers were distributed and returned in person; thus, return rates are irrelevant. In the first 6 months of the study, 5 d of data were available on 88.5% of the participants originally randomized to treatment.

behaviors (53). Poorer health status and lower socioeconomic position were found to be associated with lower levels of activity and more time spent sedentary. In addition, those participants who had participated in leisure time PA earlier in adulthood were found to have higher levels of activity at 60–64 years than those participants who had been inactive, highlighting the value of tracking health behaviors over time. In further analyses, the activity data have been related to dual-energy X-ray absorptiometry measures of body composition at 60–64 and associations in the expected directions have been identified (55).

In light of recent findings, which highlight the need for caution when estimating energy expenditure using heart rate data (36) and when applying cutpoints to identify different intensities of activity, methods of modeling the accelerometry count data are now being utilized in collaboration with researchers who have already developed and applied these methods in the BLSA (40).

ActivPAL

The ActivPAL3 PA monitor (PAL Technologies, 60 Glasgow, UK) is a triaxial accelerometer that records movement in the vertical, anteroposterior, and mediolateral axes, and also determines posture (sitting or lying down, standing, and stepping) based on acceleration. The device is adhered to the body location that most accurately reflects the desired measurement properties (eg, walking, standing, arm swing, etc.). The thigh has been the most popular site as it allows the user to discriminate among activities such as sitting, standing, and lying down, thus providing better discrimination of SBs (33,49).

The Maastricht Study

The rationale and methodology of the Maastricht Study have been described previously (56). In brief, the study focuses on the etiology, pathophysiology, complications, and comorbidities of type 2 diabetes mellitus and is characterized by an extensive phenotyping of participants residing in the Netherlands. Data from 2,642 participants, aged 40–75 years, who completed the baseline survey between November 2010 and September 2013 and had worn an accelerometer, were available for the present analysis (57). The ActivPAL was attached directly to the skin on the front right thigh with transparent 3M Tegaderm tape, after the device was waterproofed using a nitrile sleeve. Participants were asked to wear the accelerometer for eight consecutive days, without removing the device at any time. To avoid inaccurately identifying nonwear time, participants were asked not to replace the device once removed. Data were uploaded using the ActivPAL software and processed using customized software written in MATLAB R2013b (MathWorks, Natick, MA). Data from the first day were excluded from the analysis because participants performed physical function tests at the research center after the device was attached. In addition, data from the final wear day providing ≤14 hours of data were excluded from the analysis. Participants were included if they provided at least 1 valid day (>14 hours of data).

Based on acceleration data, the total amount of time spent sitting/lying, standing, and/or stepping was assessed during waking time using an automated algorithm to identify wake and bed times on an individual level on multiple days (ie, different wake and bed times for each day for each participant) (58). The algorithm is based on the number and duration of sedentary periods to identify bed times, and on the number and duration of active periods (standing or stepping) to identify wake times.

Participants provided on average more than six valid days of data with an average waking time of almost 16 hours. On average, participants spent 60.0% of their waking time sedentary, 27.4% standing, and 12.6% stepping. Men spent significantly more time sedentary than women (63.0% ± 10.1% vs 55.8% ± 9.8%); standing and stepping time were significantly higher in women than in men (30.2% ± 7.8% vs 24.8% ± 7.5%; 13.0% ± 4.0% vs 12.2% ± 4.6%). With aging, sedentary time was significantly higher and standing time was significantly lower; no clear age-gradient in stepping time was found.

A major advantage of the ActivPAL PA monitor is that this device has been shown to be an accurate and precise monitor for measuring sedentary time and posture changes. Furthermore, the continuous wear protocol resulted in very good compliance. Removing the device after up to 8 days of continuous wear resulted in minor skin irritation for some participants. Another limitation included the limited capability of the ActivPAL software; in order to analyze the data beyond sitting/standing/stepping and changes in posture, more programing is required using customized software.

ActiGraph GT3X+

The ActiGraph GT3X+ (ActiGraph, Pensacola, FL) is a triaxial accelerometer that can be worn on the hip or wrist. It has been widely used in clinical research, including the most recent round of the National Health and Nutrition Examination Survey (NHANES), the Women's Health Study (WHS), and the Age, Gene/Environment Susceptibility-Reykjavik Study (AGES-Reykjavik) (8,9,23,59). The ActiGraph GT3X+ is an updated version of the 7160 and GT1M, which were used in earlier waves of NHANES (2003–2004 and 2005–2006) (13). The device collects and exports raw data as well as epoch (count) data using the manufacturer's software. The WHS and AGES-Reykjavik both chose the Actigraph device for its battery life, memory capacity, access to raw data, and wide use by other studies. Both studies asked participants to wear the device at the right hip using an elastic belt for 7 days during waking hours.

WHS

The WHS is a completed randomized control trial (1992–2004), which examined vitamin E and aspirin on the risk of cancer and cardiovascular disease, among 39,876 healthy women, aged ≥45 years (mean 71.6 ± 5.7 years) from across the United States (60,61). In 2011, data collection began for an ancillary study to examine PA using accelerometers and health outcomes among 18,000 women. The WHS accelerometer study used a direct mail study design (11). Women who agreed to participate were mailed an accelerometer, detailed instructions, and a wear log through first class mail.

Initial analyses focused on the challenges and methods of a direct mail study design as well as examining patterns of SB among older women (mean age = 71 at the time of accelerometer assessment) (11,44,59). There were considerable logistical challenges, including accelerometer return rates (>96% of participants returned accelerometers within 30 days) and observed "lost monitor" rates (~2% of all mailings that translates to >400 monitors lost) (8,11). In addition to logistical challenges, direct mail designs also require considerations for data reduction and wear time determination. Specifically, it is important to distinguish between when the participant is truly wearing the monitor and when the monitor is in the mail but may be producing a signal that looks like activity. A combination of using the data from the logs and the wear algorithms correctly identified the wear days. Patterns of SB among older women, such as bout frequency, bout length, and breaks in SB, were also examined (59). Results concluded that older women spent greater than two-thirds of their time in SB, but most of that behavior occurred in bouts of less than 30 minutes (59).

In general, participants tolerated the accelerometer well, with similar or better adherence to other studies. A few participants noted

the belt was not "fashionable" and the device would move throughout the day.

AGES-Reykjavik Study

The AGES-Reykjavik Study is a population cohort nested in the Reykjavik Study, a study of cardiovascular disease that was initiated to investigate the basis for the epidemic of cardiovascular disease in the 1960s in Iceland. In 2002, the Laboratory of Epidemiology and Population Sciences from the Intramural Research Program of the NIA, began a multidisciplinary follow-up of this cohort. In 2007, a follow-up study was initiated, and during this time, a substudy involving collection of objectively measured PA was initiated. The sample size included 671 older adults aged 73–98 years without cognitive impairment (Mini Mental State Examination ≥ 20) of whom 589 had four or more valid days of data (≥10 hours of wear time).

Data were downloaded in raw format (*g*) and in 1-minute count epochs. Results indicated that total PA declined with age, and as in the BLSA, older participants had significantly lower activity in the afternoon (8,40). In all participants, sedentary time was the largest component of total wear time (75%), followed by light PA (21%), and moderate to vigorous activity was <1% (40). Men had higher average daily PA than women, with more moderate to vigorous activity, but women had more light intensity activity and less sedentary time than men (8).

A number of substudies were conducted as part of this study. This included a 6-minute walk wearing an accelerometer and heart rate monitor for about half the participants to allow the development of a specific algorithm for relative moderate to vigorous activity. Other methods studies included a sleep study and a study of activity in summer–winter. Results from these substudies are in process.

Actical

The Actical (Philips Respironics, Bend, OR) is an omnidirectional accelerometer that can be worn on the hip, wrist, or ankle. It is waterproof, has a 6-month lithium battery, and a delayed start option. Data are collected at a sampling rate of 32 Hz and can be downloaded in raw data or count format.

Framingham Results

The Framingham Heart Study (FHS), funded by the National Heart Lung and Blood Institute, is an ongoing prospective community-based multigenerational family study initiated in 1948 to study cardiovascular disease and its risk factors and includes the Original cohort, Offspring cohort, and Third Generation cohort, and two multiethnic cohorts Omni groups 1 and 2 (62,63). Over the course of the study, investigator initiated grant funding expanded investigation beyond cardiovascular disease so that participants are deeply phenotyped including many age-related diseases, cognitive function, and physical performance. Participants undergo extensive research examinations every 2–8 years.

The FHS began using accelerometry in 2008. The Actical accelerometer (model no. 198-0200-00) was chosen after conferring with experts in the field and for the following features: waterproof, light weight, long battery life (6 months) delayed start option, and low device failure rate. Participants wore the device on a belt at the hip for 8 days to ensure seven full days of wear and they were provided with postage paid addressed envelopes to return the device to the FHS. A valid day was considered to be 10 or more hours of wear time. Data were downloaded and collected in 30-second epochs and raw data formats. Some participants reported difficulties with the belt or found wearing the device uncomfortable, whereas others reported taking the device off and forgetting to put it back on for one or more days.

MVPA was positively associated with a more favorable cardiovascular risk factor profile (64), less visceral adipose tissue (65), and was inversely related to fatty liver (66). Furthermore, greater PA was associated with lower vascular stiffness but greater left ventricular mass suggesting complex relations of PA with cardiovascular remodeling (67).

Insights From Intervention Studies and Clinical Research in Older Adults

One other new and evolving area of interest in aging research is the use of accelerometers to track changes in PA in intervention research and their potential to track the detection of falls and gait characteristics. Although data are limited as yet, results support the psychometric properties of accelerometers when used with older adults and demonstrate that their use in lifestyle interventions and in clinical research is promising. Data have been generated using accelerometers in many chronic diseases including Parkinson's and other neurological diseases and pulmonary disease, particularly in the areas of clinical trials, where objective measurement of change is important.

Using an earlier model of the ActiGraph accelerometer with older adults in the context of cardiac rehabilitation (the Computer Science and Applications Accelerometer), Focht and colleagues (68) found that CPM during an actual bout of exercise correlated positively with 6-minute walk time (r = 0.62). In addition, randomized controlled trials of exercise among older adults have shown that accelerometers are sensitive to changes in PA behavior. Using the Lifecorder Plus accelerometer, which yields output comparable with the ActiGraph, researchers documented anticipated increases in moderate levels of PA (MVPA) across intervals of 12–18 months when overweight or obese older adults with either knee osteoarthritis (68) or metabolic dysfunction (69) participated in exercise and weight management programs as compared with health education. Finally, in a recent multicenter trial (the Lifestyle Interventions and Independence for Elders, "LIFE" trial), Pahor and colleagues using the ActiGraph GT3X accelerometer across a period of 36 months found that older adults aged 70–89 with compromised physical function randomized to a structured physical activity intervention program (PA) had increases in activity ≥760 CPM as compared with those randomized to a health education comparison group (2). What is also interesting about the accelerometry data collected at 6 months of follow-up are that irrespective of the cutpoint used—tailored, 760 CPM, 1,041 CPM, or 1,952 CPM—the PA group always had higher levels of activity than the health education (47).

Finally, researchers are now applying machine-learning algorithms in conjunction with triaxial accelerometers to classify activities behaviors of older adults into locomotion, lying, sitting, standing, and shuffling, placing the accelerometer on the lower spine at the fifth lumbar vertebrae as opposed to the hip (70). These new developments may well provide information about gait that could be important in understanding health outcomes such as falls and enable clinicians to track activity of older adults across time and develop algorithms for the assessment of fall risk.

Recommendation for Future Directions

The advent of accelerometers for PA research in older populations shows great promise for increasing awareness and understanding

of how PA changes with aging and how these changes contribute to the subsequent development of aging-related chronic conditions. Perhaps most importantly, accelerometers have the potential to capture the low levels of PA that are commonly performed by older adults, which are hard to quantify using questionnaires. These activities, which have been historically difficult to capture and conceptualize, are representative of tasks related to activities of daily living and level of functional independence, two vital criteria for maintaining health and quality of life with aging.

Currently, the considerable lack of uniformity across studies in the areas of device type, placement, and data interpretation (counts, steps, calories, raw data) poses significant challenges to comparing and synthesizing results. For example, data collected at the thigh and hip and interpreted as steps using Actigraph software are not directly comparable with data collected at the chest and interpreted as caloric expenditure by Actiheart software. Moreover, even if data were collected from a uniform placement such as the wrist and stored and analyzed in raw data format (*g*), there is no guarantee that data from different device brands would be directly comparable (20) and the derived metrics may not be clinically meaningful. More methodological research is therefore needed to establish proper guidelines for analyzing and interpreting accelerometry data specific to older populations and translating results into clinically meaningful recommendations, including thresholds to define sedentary time versus active time and differences in measurement properties between younger and older study populations. Improved understanding of these factors will increase the likelihood of eventual harmonization and synthesis of results across studies.

Current public health recommendations for adults aged 65 and older in general good health include 150 minutes of moderate intensity aerobic activity per week and muscle strengthening activities on two or more days (71). Although there are undoubtedly health benefits associated with this recommendation, there are substantial challenges for many older persons in achieving and maintaining moderate—or vigorous—intensity activity in their 70s, 80s, and beyond. The health benefits of light intensity activities, specifically in terms of maintaining active longevity in older populations, have not been defined. Accelerometry research holds the potential to address this gap by providing a more comprehensive assessment of the benefit of the overall amount of time spent ambulatory on a daily basis, and thus help shape future interventions specifically designed for increasing daily PA in older adults and future public health recommendations for maintaining mobility and longevity with aging.

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