Current Geriatrics Reports (2019) 8:55–66
https://doi.org/10.1007/s13670-019-0275-3

NEUROLOGY OF AGING (KS MARDER, SECTION EDITOR)

Wearable Sensor Technology to Measure Physical Activity (PA) in the Elderly

Ashwini K. Rao [1]

Published online: 7 February 2019
© Springer Science+Business Media, LLC, part of Springer Nature 2019

Abstract

Purpose of Review The goal of this paper is to provide a review of recent work on the use of wearable devices for measuring physical activity (PA) in the elderly.

Recent Findings In older adults, PA is related to independence in activities of daily living and maintaining a good quality of life. With aging, there is a reduction in PA, which may explain reduced energy expenditure (EE) during rest and PA. In addition, there is also a reduction in the spatial extent of mobility (life-space). Sensors used for measuring PA include pedometers, uni-axial, bi-axial and tri-axial accelerometers, heart rate monitors combined with accelerometers, and complex systems using multiple types of sensors.

Summary Wearable sensors are accurate at measuring step counts, PA intensity, and EE, but need to improve accuracy of measuring type of PA, spatial extent of PA, and measuring non-ambulatory PA. Clear standards for measurement, algorithms used for computing clinically relevant measures, need to be developed.

Keywords Aging · Wearables · Sensors · PA · Energy expenditure · Gait

Introduction

The elderly population (people above the age of 65 years) is steadily growing in the USA. According to the US Census Bureau, the population of people above the age of 65 years is expected to more than double by 2050 [1]. The expansion in the elderly population is expected to increase the number of hospitalizations by 67% [2]. Chronic diseases are increasingly prevalent in the elderly [3]. One of the main risk factors for chronic disease is physical inactivity (in addition to tobacco alcohol use, poor diet) [4]. Since physical inactivity is a modifiable factor, there has been an increasing interest in exploring strategies to increase physical activity (PA) in the elderly, with the aim of reducing the burden of chronic disease.

This article is part of the Topical Collection on *Neurology of Aging*

✉ Ashwini K. Rao
akr7@cumc.columbia.edu

[1] Department of Rehabilitation & Regenerative Medicine (Program in Physical Therapy), G.H. Sergievsky Center, Huntington's Disease Center of Excellence, Center of Excellence in Alzheimer's Disease, Vagelos College of Physicians and Surgeons, Columbia University, Georgian Building, Room 314, Columbia University Irving Medical Center, 617 West 168th Street, New York, NY 10032, USA

Wearable sensor technology has emerged as an important tool that can objectively measure PA and through feedback, increase PA in the elderly [5•, 6•]. The purpose of this review is to provide an overview of the importance of PA in the elderly, examine models of PA, and provide a review of recent studies on the use of wearable devices to measure PA in the elderly.

Importance of PA in the Elderly

There is a wealth of data on the importance of health status as a marker of quality of life in the elderly. PA predicts health status in the elderly in general, and mobility limitations, in particular [7]. This is particularly true for the oldest elderly, in whom reduced levels of PA and mobility is an important predictor of reduced quality of life [8, 9]. Some authors suggest that mobility limitations are part of normal aging [10]. However, others suggest that reduced PA and the resulting reduced overall energy expenditure is associated with progression of brain atrophy, particularly in the frontal lobes, which may explain the basis for impaired mobility [11].

Impaired mobility and reduced PA increases the risk of dependence and disability in activities of daily living [12].

Among elders with impaired mobility, there was an increased risk for inflammatory disease and increased risk for death [12]. These findings have been replicated in population-based studies [13]. Reduced PA increases the risk of falls [14], and risk for institutionalization [15].

Models of Physical Activity in Aging

It is universally accepted that PA and mobility reduce with aging. Several models have been proposed to explain changes in PA and mobility seen with aging. Models of PA describe the ability to perform specific physical activities, the timing and intensity of PA, or the spatial extent of PA. Wearable devices, for the most part, have been designed to measure the timing and intensity of PA, though recently complex systems of wearable devices have begun to measure how well people perform specific physical activities.

The most commonly used model of PA is the WHO model on International Classification of Function, Disability and Health [16]. The WHO model describes the ability to perform PA and its components. This model identifies determinants of mobility disability, including age, sensory, physical, cognitive, or psychosocial impairments, and environmental or financial barriers. PA is seen as an important modifier of mobility disability in the elderly [16]. With aging, several abilities are known to decline, for instance, impairments in motor, cognitive, and sensory systems result in reduction in mobility and overall PA. Environmental barriers may also result in limited mobility [17]. In the past few years, complex systems of wearable devices have been developed to measure an individual's ability to perform PA (see Table 1) [54, 61, 65, 66]. Some of these devices (such as the APDM® and Dynaport McRoberts®) allow assessment of PA included in standardized clinical assessments such as the Timed Up and Go Test and the 6-min walk test.

Changes in PA with aging have been explained using a model of energy expenditure (EE) [67•]. According to this model, total energy expenditure (TEE) is comprised of four major components including resting energy expenditure (REE), thermic effect of feeding (TEF), and physical activity energy expenditure (PAEE, which is further divided into non-exercise activity thermogenesis (NEAT) and volitional exercise thermogenesis (VET)). Total energy expenditure (TEE) describes an inverted U shaped function with age: beginning in late middle age TEE decreases with each decade [68]. Resting energy expenditure constitutes 60–80% of TEE and is responsible for organismal homeostasis. With aging, resting EE (dotted line in Fig. 1) decreases and is closely linked with reduction in whole body fat-free mass and reduction in PA [69]. PAEE is highly variable from one individual to the next, and is much less dependent on whole body fat-free mass. With advanced age, decreases in PAEE (dashed line in Fig. 1) are largely due to reduction in the amount of PA and intensity of movements such as locomotion [70]. Reduction in TEE (solid line in Fig. 1) may explain the fact that older adults, on average, reduce the amount of moderate-to-vigorous PA. Thus, age-related reduction in time and intensity of PA has an influence on reduction in PAEE. The change in EE with age is shown in Fig. 1.

In addition to the ability to perform PA, and the timing and intensity of activity, mobility also consists of the spatial extent of travel within and outside the home environment. One approach to measuring the spatial extent of PA is through the concept of life-space, defined as the area in which a person moved in a given period of time [71•]. In this model, space is conceptualized in expanding concentric zones beginning with the bedroom, and extending to the residence, neighborhood, and town and beyond. Change in life-space in the context of changing energy expenditure with age is shown in Fig. 1. The life-space assessment provides an index of the magnitude of space in which a person habitually lives [71•]. The life-space questionnaire assesses the zone in which a person habitually moved within the past month, the frequency of that movement and whether assistance was required [72]. Given that the life-space assessment is highly correlated with functional independence in the elderly, its inclusion in routine clinical assessment is meaningful. Presently, there are no wearable devices that measure the spatial extent of PA. Devices can be designed to provide a remote assessment of life-space mobility through a combination of GPS and inertial sensors to define the extent of mobility from a defined "home" position such as the bedroom, since it constitutes the innermost zone in the assessment (Fig. 1).

Measurement of Physical Activity in the Elderly

1. Subjective Measurement: The most common method to assess PA in the elderly has been through self-administered or investigator-administered questionnaires [73]. Questionnaires have the obvious advantage of being administered to large numbers of subjects at relatively little cost, which is important for large-scale epidemiological studies [74]. Questionnaires are able to capture the breadth of PA over a period of time (such as a week or a month). Despite these benefits, PA questionnaires have well-documented limitations including recall bias, particularly in older adults. In addition, questionnaires typically assess leisure time PA, which does not include functional activities of daily living. This is particularly important since older adults spend a majority of time in light intensity activities that are likely not captured by questionnaires [74]. Moreover, most self-report questionnaires have not been validated for distinct cultural and ethnic

Table 1 The most commonly reported sensors in each category

Sensor	Optimal location	Measurement	Strengths and limitations
i) Pedometers		Typically spring-loaded, magnetic, or microelectromechanical systems (MEMS)	
Yamax Digiwalker	Waist	Spring-loaded Measures step count [18–20]	Easy to use; under estimates steps; greater error at slow gait speed; error higher for older nursing home residents [18]
Heartline Pedometer	Waist	Step count [21]	Easy to use Less accurate than step activity monitor and Actigraph at step counts
The Step Sensor	Under heel in shoe	Step count [22]	Easy to use; Not accurate for research purpose [22]
Omron Altiva	Hip	Step count [23]	Easy to use; very inexpensive; synchronizes with smartphone application; does not register a number of steps at different speeds; underestimates step counts; higher error at slow walking speeds [23]
ii) Single- and dual-axis accelerometer		Small sensors that record acceleration in one plane (typically the vertical plane) or two planes. Raw acceleration signal is calibrated with known reference standard.	
Actilume uni-axial	Leg [22] Wrist [24]	Step count, PA intensity and frequency, light exposure [22, 24]	Accurate measure of sleep-wake time; prolonged recording possible; not accurate for PA recording
Caltrac uni-axial	Waist	Total activity energy expenditure in METs [25, 26]	Activity EE does not reflect PA [26]; not as good as Actigraph as validated against doubly labeled water [25]
Z80 activity monitor uni-axial	Waist	PA counts per minute [27, 28]	Good for prolonged use; able to detect brisk walking [28]
Kenz Life Corder uni-axial	Waist	Step count, PA intensity [29•]	Good for prolonged use; requires data processing;
Tractivity uni-axial	Ankle	Step count, PA energy expenditure [30, 31]	Application software available for computer and smartphone; reliable step counts; not as accurate as Step Watch
New lifestyles bi-axial	Waist	Step count, distance walked, total calories, minutes in moderate-to-vigorous PA [23]	Easy to use; inexpensive; provides real-time feedback; higher error at slow walking speed [23]
Step Watch Activity Monitor bi-axial	Ankle	Step count, PA intensity [32, 33]	Dual-axis accelerometer; waterproof; does not provide feedback; high accuracy in step count at various speeds
iii) Multi axial accelerometer		Small sensors that record acceleration in three planes. Acceleration data processed as intensity "counts" or available as raw data that can be calibrated against known criteria (such as energy expenditure)	
TriTrac	Waist	Acceleration counts used to compute activity count and PA intensity [22, 34–36]	Larger size than most sensors; poor subject adherence; poor prediction of PA [22]; requires data processing
Actigraph	Waist, Wrist	Step count, PA count, PA intensity, sleep time, PA energy expenditure [21, 37•, 38•, 39•, 40]	Good battery life and memory capacity; Good adherence; access to raw data and processed data using software; does not distinguish postures; used in numerous large-scale studies
Actical	Waist Can be worn on wrist/ankle	Step count, PA energy expenditure [41–43]	Good adherence, waterproof, light sensor; access to raw data and processed data using software; used by Framingham Heart Study [41, 43•]
Activpal	Thigh	PA count, PA intensity, classifies postures (sit, stand, walk), provides subject feedback [44•, 45]	Light, easy to use; accurate and precise for pa count and intensity; thigh location not optimal for adherence; limited capability of software may require additional programming; used in the Maastricht study [44•, 45]
PAMsys	Sternum	PA type, posture type, postural transitions, gait, fall detection, energy expenditure [46]	Raw acceleration signal processed by proprietary software [46]; easy to use; lightweight; capable of long-term monitoring
Geneactiv	Wrist, thigh	Raw acceleration data; signal vector magnitude; temperature [47•, 48, 49]	Waterproof; wear time computed from temperature sensor; requires significant programming to compute PA intensity, postures; used in the Whitehall study [47•]
Logger Technologi	Lower back	Raw acceleration data [50]	Requires significant programming to compute trunk acceleration and variability; Very limited data on elderly
iv) Combined Accelerometer-HR monitor			
Actiheart	Chest	PA counts per minute, PA intensity, heart rate [51•, 52, 53],	Only sensor to measure PA and heart rate; software provides summary data; use of cut points to define PA intensity not optimal; chest placement not best for adherence

Table 1 (continued)

Sensor	Optimal location	Measurement	Strengths and limitations
v) Complex systems		Systems include inertial sensors with accelerometers, magnetometers, and gyroscopes. Systems often use several sensors.	
MTx Inertial Measurement Unit, XSens	Lumbar spine	Raw 3-D acceleration, 3-D rotation, orientation data [54–56, 57•, 58]	Requires significant programming to process raw acceleration and rotation data to compute spatio-temporal measures (step and stride regularity, gait symmetry, variability) [54–56, 57•, 58]
Physiolog BioAGM	Sternum	Raw 3-D acceleration and rotation data	Requires significant programming to process raw acceleration and rotation data to compute angular velocity, sit-to-stand time [59]
iPhone	Sternum	Raw 3-D acceleration, rotation, orientation	Accelerometer, gyroscope and magnetometer; third party software needed for collection, processing of data; requires significant programming to compute acceleration, peak velocity and time to complete the Timed Up and Go Test [60]
Dynaport McRoberts	Lumbar spine	Step count, gait duration, velocity, step time, step symmetry [61, 62•]	Proprietary software and supplier performs analysis; easy to use; gait duration inaccurate at high speeds [61]
Shimmer inertial sensor	Shins bilaterally	Raw 3-D acceleration and rotation data; vector magnitude [63, 64]. Studies used 2–5 inertial sensors to collect data	Requires significant programming to process raw acceleration and rotation data to compute time taken to complete Timed Up and Go Test
Legsys	Shin, thigh, lower back	Gait measures (speed, stride length, stride time, cadence, swing percent, stance percent, double support percent, stride length and stride time variability)	Proprietary software computes gait measures from raw acceleration data from a range of 2–5 sensors [65]
APDM	Lumbar spine, wrist ankle, sternum	Time and frequency domain measures, jerk, spatio-temporal gait measures (speed, stride length, cadence, step symmetry, swing percent, double support percent, turning duration number of steps). 3–6 sensors used to collect data [66]	Easy to use for laboratory settings; provides comprehensive assessment of balance and gait measures; instrumented standardized clinical assessments such as Timed Up and Go, Clinical test of sensory integration and balance, balance error scoring system, sit to stand; limited data with elderly

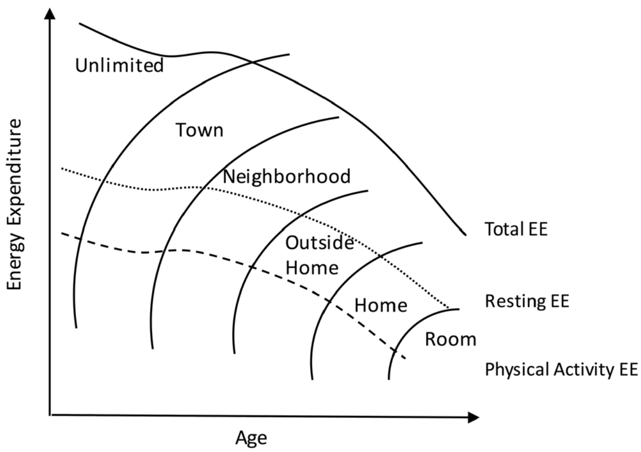

Fig. 1 Change in energy expenditure and spatial extent of physical activity with age

groups [73]. Finally, subjective questionnaires of PA overestimate estimate activity levels. A comprehensive study measured PA levels with a questionnaire and a wearable device: in adults between the ages of 60 and 69 years, time spent in moderate physical activities was 348 min per week and time spent in vigorous activities was 52.9 min per week [75]. However, objectively measured moderate PA was 32.7 min per week and vigorous PA was 1.4 min per week [75]. These limitations underscore the importance of objective measurement of PA.

2. Objective Measurement: Several wearable sensors have been developed to objectively measure PA in free-living conditions. Depending on their type and complexity, sensors are able to provide information on number of steps, PA intensity, duration and type, energy expenditure during PA, heart rate, kinematic measures (joint excursions), and quantitative measurement of gait (speed, step length, cadence, etc.). Some complex systems have been designed to instrument standardized clinical assessments of balance and mobility. The major types of sensors that measure PA are listed in Table 1 (from simple to complex):

a) Pedometers: Pedometers are one of the simplest devices for the measurement of PA. Pedometers are lightweight, portable, and inexpensive devices that are designed to measure the number of steps, though some pedometers also estimate distance traveled and energy expenditure [76]. The recommended placement for most pedometers is on the waist (proximity to center of mass). Pedometers are relatively inexpensive, which enhances their applicability.

The simplest pedometers (Yamax Digiwalker for example) have a spring-loaded lever arm that moves in response to vertical movement of the body center of mass [18–20]. Some pedometers (such as the Omron HJ) use a magnetic switch mechanism to count steps [23]. The third major type of pedometer uses accelerometers with a horizontal beam and a piezoelectric crystal to determine steps based on the number of zero crossings of the acceleration curve over time. New pedometers use microelectromechanical (MEMS) technology and algorithms to process the signal to calculate steps. The number of steps per day is used as a criterion for classifying the amount of PA (sedentary to active). However, these criteria were developed for younger people without disability or chronic illness [77]. Applying these criteria to older individuals may underestimate PA during activities of daily living (which accounts for a larger percentage of PA in the elderly).

The appeal of pedometers is that they are inexpensive, and provide immediate feedback to subjects, which may enhance motivation to engage in PA. However, pedometers have several limitations: they are inaccurate at slow walking speeds. Since most pedometers do not have an internal clock, it is not possible to compute the time spent in each PA. Finally, pedometers do not record the intensity of vertical displacement at each step. Thus the number of steps taken during running and walking the same distance will be the same, despite the differences in energy expenditure between walking and running [78]. Given these limitations, pedometers may not be suitable for use in research studies. They may be appropriate for clinical use to record the number of steps in individuals who walk at a minimum speed of 0.9 m/s.

b) Accelerometers: Accelerometers, like pedometers, are small, non-invasive, lightweight, and portable sensors. They measure acceleration in gravitational units, either along one axis (uni-axial), two axes (bi-axial), or along three axes (tri-axial). Accelerometers are capable of recording data over extended periods of time.

Most accelerometers contain an integrated chip with a mass placed on a piezoelectric crystal. Vertical accelerations compress the crystal, which generates a voltage proportional to the magnitude of acceleration [79•]. The acceleration data are then calibrated against known criterion measures such as energy expenditure, metabolic equivalents (METs), or oxygen consumption [79•]. Given the moderate-to-strong correlation between accelerometer counts and oxygen consumption, acceleration counts have been used to categorize PA as sedentary, moderate, or intense based on published thresholds [80].

b.1) Uni-axial and bi-axial accelerometers: All uni-axial and bi-axial accelerometers measure step count (see Table 1 section ii), and most of them also provide information on either energy expenditure (such as the Caltrac) or intensity of PA (such as the Actillume and Kenz Lifecorder). The Actillume sensor is unique since it provides information on sleep-wake time by measuring ambient light, which may be very useful for older people with sleep difficulty. As seen in Table 1, most uni-axial and bi-axial accelerometers are fairly accurate at step counts but not as accurate for computing intensity of PA and energy expenditure. Accelerometers (such as New Lifestyles and Tractivity) are not accurate at slow walking speeds or as accurate as tri-axial accelerometers. The stepwatch activity monitor is the most accurate at step counts at a variety of speeds [32, 33]. In addition, the Stw?pwatch activity monitor is waterproof which may be important if people forget to take the sensor off while bathing. Most accelerometers are capable of prolonged recording (7 days or more) which is often an important consideration for research studies.

Limitations One challenge is that algorithms for processing accelerometer data are often proprietary so end-users do not have access to the criteria by which PA is classified. In some cases, sensors enable access to the raw acceleration data, but these data requires programming in order to compute magnitude and intensity of PA. Most accelerometers are not accurate at identifying light PA, and none of them is able to measure non-ambulatory activities such as cycling and weight lifting [79•].

b.2) Tri-axial accelerometers: The most common type of accelerometer used to measure PA is the tri-axial accelerometer, listed in Table 1, Section iii. These sensors measure acceleration in three planes, which enable a more accurate computation of movement than sensors with uni-axial accelerometers [81]. While most tri-axial accelerometers are small and lightweight, the TriTac sensor is much larger, resulting in reduced subject adherence [22]. In fact, the TriTac sensor was not rated well by elderly subjects or nursing staff in terms of comfort, ease of application, size, weight, and appearance [22]. None of the accelerometers provide immediate feedback to the subject, which makes them ideal for use in research studies. This may be important in studies that are designed to accurately measure routine PA not contaminated by feedback. In contrast, these sensors may not be suitable for studies that aim to improve PA in older people through the use of feedback.

As seen in Table 1, most accelerometers have accompanying software that process the raw data and provide aggregate measures. The one exception is the Logger Technologi, which only provides raw data that require substantial processing and computation [50]. The most common aggregate data that are provided include step count and PA intensity. A few sensors (Actigraph [37•, 38•], Actical [41, 42, 43•], and PAMsys [46]) provide energy expenditure data as well. While most sensors measure overall magnitude of PA, only two systems (Activpal [44•, 45] and PAMsys [46]) classify type of posture (sit, stand, walk). A few of the tri-axial accelerometers have been extensively used in large-scale epidemiological studies. The Actigraph is a sensor that provides summary data on PA and also provides access to the raw data. The Actigraph sensor has been used in a number of large-scale studies including the Women's Health Study [38•] and the National Health and Nutrition Examination Survey-NHANES [39•]. In the Women's Health Study, accelerometer counts per minute were used to define sedentary behavior (defined as < 100 counts per minute). Based on this criterion, older participants were observed to spend two-thirds of their time in sedentary activity [38•]. In contrast, in the NHANES study, accelerometer counts were used to classify PA intensity (sedentary, light, moderate-to-vigorous). These data showed that non-sedentary activity decreased with age, though men increased sedentary behavior to a greater extent than women [39•]. Most studies attached the Actigraph on the hip, though more recently some studies have begun using the sensor on the wrist.

The Actical sensor is waterproof and can be used for prolonged data collection. This sensor has been used in the Framingham Heart Study (FHS), in which 78% participants ($N = 2672$) wore the sensor on their hip for 8 days. The intensity of PA was defined using accelerometer counts from published data. The Activpal sensor is directly attached to the skin on the thigh and often covered with transparent tape to ensure waterproofing [45]. The Activpal was used in the Maastricht study, a population-based cohort study in which participants wore the sensor for 8 days. The software accompanying the sensor is accurate in step count and calculating PA intensity. In addition, the software is able to classify postures, which enables a more accurate calculation of sedentary versus non-sedentary activity. However, large-scale studies used additional programming to compute PA intensity. An additional limitation was that the thigh location of the sensor was not optimal for adherence [45].

The PAMsys is another sensor with similar capability in terms of classifying postures. The sensor is lightweight, worn on the sternum, and has accompanying software that computes PA with proprietary algorithms [46]. The Geneactiv is a newer sensor that is waterproof and can be worn on the wrist in an attempt to improve adherence. The sensor has been used in the Whitehall study, a longitudinal study of British civil servants. Participants ($N = 3749$) wore the sensor on their wrist for 9 days. Acceleration counts were used to classify activity as sedentary, mild, or moderate-to-vigorous [47•]. The accompanying software uses proprietary algorithms to compute PA intensity, and the raw data are also made available. Tri-axial accelerometers are extremely accurate at step counts and PA intensity, energy expenditure and classification of postures. Since none of the sensors provide immediate feedback, they are optimal for research studies but may not be useful for improving PA.

c. Combined Accelerometer and Heart Rate sensor: A major limitation of accelerometers is that they do not capture non-ambulatory physical activities such as weight lifting, cycling, yoga, etc. Since heart rate is strongly associated with intensity of PA, combined measurement of heart rate and acceleration may provide a more accurate measurement of non-ambulatory activity. The Actiheart is the only sensor that measures heart rate and PA [51•, 52, 53]. The sensor is positioned horizontally on the chest, which may be challenging for continuous wear. However, the Actiheart has been successfully used in large-scale studies such as the Baltimore Longitudinal Study of Aging [51•, 52, 53]. The waterproof sensor can continuously record data for 21 days and provides data on step counts, PA intensity, energy expenditure, heart rate, and inter-beat interval. As with many accelerometers, the Actiheart software uses proprietary algorithms to classify PA.
d. Complex multiple sensor systems: Recent developments in technology has enabled researchers to create complex inertial measurement units (IMU), which contain accelerometers (measure linear acceleration), magnetometers (establish orientation of body in space), and gyroscope (measure rotation) in a single unit. Some of these IMUs, such as the MTx [54, 55], the Physiolog sensor [59], and the iPhone [60] measure raw acceleration data which require significant filtering, processing, and subsequent computational analysis to provide meaningful clinical measures. The only single IMU system that provides clinically relevant measures is the Dynaport [61, 62•], which has been tested for validity and reliability in measuring PA, energy expenditure, body sway, and gait analysis in older adults [82]. Other complex systems use multiple sensors to provide a more accurate measurement of spatio-temporal measures of posture and gait [65, 66]. The major advantages to these complex systems is that they have undergone extensive reliability and validity testing, and have instrumented standardized outcome measures (such as the Timed Up and Go test, the 10-m walk test), which makes them clinically relevant. The disadvantages of these systems are that they are significantly more expensive than single accelerometers and require training in administration and interpretation of the data. In addition, most of the complex systems use proprietary algorithms to compute spatio-temporal measures. Since some of these systems use multiple sensors, they may not be optimally suited to long-term data collection in community settings.

Consumer Grade Wearable Sensors

Within the past decade, the consumer grade wearable industry has grown exponentially. In 2015, the revenue for the consumer wearable industry was $5 billion [83]. The most popular brands of consumer wearable sensors include FitBit, Nike Fuel, Garmin, Polar, Apple iwatch, and Samsung gear fit [84•]. These devices are typically smaller and sleeker, and some of them are less expensive than research grade devices. Consumer grade devices commonly measure step count, distance walked, and energy expenditure [85••]. One feature that distinguishes them from research grade sensors is that they provide immediate feedback to the user, which may be beneficial in providing motivation to older adults for improving PA.

Among commercial trackers, FitBit One, FitBit Charge, FitBit Flex, and the Polar trackers have been tested against research grade sensors [84•]. While these trackers demonstrate a high correlation with research grade sensors for step counts, their accuracy varies with placement [86]. For instance, the FitBit tracker is more accurate at step count when placed at the ankle as compared with the waist, as seen in a recent study in post-surgical patients [87]. Our pilot unpublished work confirmed this finding in older adults walking at slow gait speed (< 1.0 m/s). The major limitations of consumer grade trackers are that they are often released on the market without extensive validity and reliability testing. Moreover, the algorithms used to calculate steps, energy expenditure are proprietary, making it difficult to validate these devices against research grade devices. Most often, these devices do not provide access to raw data, which makes it difficult to conduct validity testing. Perhaps the biggest challenge of consumer grade wearable devices is management of the large amounts of data to ensure security of personal health information, and ensuring adequate processing power to summarize large amounts of data collected from each individual.

While they are fairly accurate at step counts and PA duration for gait speeds above 1.0 m/s, they overestimate step counts and duration of PA for people with slow gait speed and gait impairments [84•]. Since slow gait speed and gait impairments are extremely common in older adults, careful consideration must be used for selecting the most appropriate tracker. Commercial grade trackers also undergo significant changes from 1 year to the next, and sometimes go off the market based on sales rather than utility. These factors are important in choosing the most appropriate tracker. At this time, the most frequently used tracker (FitBit) copyright has been tested for validity and reliability. While the FitBit may overestimate PA when compared with research grade trackers, it may be useful for comparing data within a subject, given its high test-retest reliability [84•]. Other wearable devices such as the Apple iWatch and Samsung Gear are also becoming popular. However, these newer devices have not been validated against research grade sensors.

Conclusions

The past decade has seen an exponential increase in the use of research grade and consumer grade wearable devices in older adults. As discussed in this review, there are numerous sensors ranging from simple pedometers to highly complex multiple sensor systems that use a combination of accelerometers, magnetometers, and gyroscopes. Given the number of sensor options, the choice of sensor depends on addressing the following questions:

What is the purpose of measurement? Is the purpose to monitor PA or is the purpose to use wearable sensors to improve PA? In addition, it is important to consider whether measurement of PA is for research or clinical practice.

What aspect of PA is of interest? Step count, intensity and type of PA intensity, spatio-temporal measures of mobility or gait. If step counts are the primary measure of interest, pedometers or simple accelerometers may be adequate. If PA intensity or type of PA is of interest, tri-axial accelerometers may be the better option, particularly for research studies. If more complex mobility measures or gait is of interest, complex systems may be the best option.

What is the desired length of monitoring?

Are there cost constraints?

Considerations for research: Since there are a wide variety of sensors available and a variety of methods, clear standards for data collection, data processing and computation of PA measures need to be established. If PA is being measured for research, it may be important to consider sensors that do not provide feedback to the user. As discussed earlier, researchers use cut points for acceleration or step count data in order to classify intensity of PA. Recently, the use of cut points has been challenged as these may be inaccurate in predicting energy expenditure [80]. New methods of pattern recognition using machine-learning algorithms need to be explored further [88]. Sensors should be tested for validity against known standards and tested for reliability. This is particularly true for determining type of PA, since there are only a few sensors that currently provide such information.

There is also an important need to establish protocols for non-ambulatory activities such as cycling, swimming, yoga, and weight lifting. Capturing non-ambulatory activity may require integration of accelerometers and heart rate monitor—currently, there is only one sensor (Actiheart) that measures such integrated data. The Actiheart and any newly developed sensors need to be validated for determining intensity of PA during non-ambulatory activity. For research studies, it may be best to use research grade sensors because they have been extensively tested for validity and reliability. For studies aimed at improving PA in older adults, researchers may consider using consumer grade sensors to make use of feedback to provide additional motivation.

Considerations for clinical practice: Reliability, validity, and cost may be important considerations for choosing appropriate wearable sensors. For older adults, it is important to consider sensors that are easy to wear, and require minimal user input for logging data. In addition, clear standards need to be established for minimal wear time in order to capture the desired amount of PA. Clinical practitioners may also consider using consumer grade sensors or using existing sensors in smartphones in order to improve PA in older adults. Data on adherence and unit failures should be carefully recorded.

Considerations for Future: In the future, in addition to development of clear standards for data collection and analysis, sensor developers need to provide access to raw data so that researchers can conduct independent validity testing. Moreover, it is important for hardware and software developers to provide access to algorithms for computation of PA intensity. For sensors that use acceleration data to compute measures related to mobility and gait, clear standards are needed for determining minimum amount of data required for such computations [89•].

An important need in the field is the development of sensors or sensor systems that are capable of measuring the spatial extent of travel within and outside the home environment, in addition to standard measures such as step counts, type and intensity of PA, and energy expenditure. In addition, there is a need for wearable systems to integrate collection of acceleration and heart rate data so that non-ambulatory PA can be captured. Finally, sensitive sensors need to be developed that are able to capture light intensity activity, such as performance of activities of daily living, which constitutes a majority of PA in the elderly. One excellent example of comprehensive measurement of acceleration, heart rate, and GPS data was recently published [90••]. In this study, a system of sensors comprised of tri-axial accelerometers, global positioning system (GPS), and heart rate monitor were wirelessly connected with a smartphone that received and compressed the data and communicated the data to a remote server. The authors noted several challenges including loss of GPS data, high battery consumption, loss of data due to poor wireless communication, and discomfort of the heart rate sensors [90••]. Solutions to these challenges will lead to the development of the next-generation wearable devices that have greater capabilities and provide data that are more comprehensive and clinically meaningful [91•].

Acknowledgements This work was partially supported by the US National Science Foundation under grant SCH-1838725.

Compliance with Ethical Standards

Conflict of Interest Ashwini Rao declares no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

1. Pallin DJ, Allen MB, Espinola JA, Camargo CA Jr, Bohan JS. Population aging and emergency departments: visits will not increase, lengths-of-stay and hospitalizations will. Health Aff (Millwood). 2013;32(7):1306–12. https://doi.org/10.1377/hlthaff.2012.0951.
2. Pallin DJ, Espinola JA, Camargo CA Jr. US population aging and demand for inpatient services. J Hosp Med. 2014;9(3):193–6. https://doi.org/10.1002/jhm.2145.
3. Anderson G, Horvath J. The growing burden of chronic disease in America. Public Health Rep. 2004;119(3):263–70. https://doi.org/10.1016/j.phr.2004.04.005.
4. Bauer UE, Briss PA, Goodman RA, Bowman BA. Prevention of chronic disease in the 21st century: elimination of the leading preventable causes of premature death and disability in the USA. Lancet. 2014;384(9937):45–52. https://doi.org/10.1016/S0140-6736(14)60648-6.
5.• de Bruin ED, Hartmann A, Uebelhart D, Murer K, Zijlstra W. Wearable systems for monitoring mobility-related activities in older people: a systematic review. Clin Rehabil. 2008;22(10–11):878–95. https://doi.org/10.1177/0269215508090675. **Excellent review of wearable sensors to measure PA in older adults.**
6.• Zijlstra W, Aminian K. Mobility assessment in older people: new possibilities and challenges. Eur J Ageing. 2007;4(1):3–12. https://doi.org/10.1007/s10433-007-0041-9. **Excellent review of wearable sensors to measure PA in older adults.**
7. Groessl EJ, Kaplan RM, Rejeski WJ, Katula JA, King AC, Frierson G, et al. Health-related quality of life in older adults at risk for disability. Am J Prev Med. 2007;33(3):214–8. https://doi.org/10.1016/j.amepre.2007.04.031.
8. Stessman J, Hammerman-Rozenberg R, Cohen A, Ein-Mor E, Jacobs JM. Physical activity, function, and longevity among the very old. Arch Intern Med. 2009;169(16):1476–83. https://doi.org/10.1001/archinternmed.2009.248.
9. Yeom HA, Fleury J, Keller C. Risk factors for mobility limitation in community-dwelling older adults: a social ecological perspective. Geriatr Nurs. 2008;29(2):133–40. https://doi.org/10.1016/j.gerinurse.2007.07.002.
10. Mahant PR, Stacy MA. Movement disorders and normal aging. Neurol Clin. 2001;19(3):553–63 vi.
11. Yuki A, Lee S, Kim H, Kozakai R, Ando F, Shimokata H. Relationship between physical activity and brain atrophy progression. Med Sci Sports Exerc. 2012;44(12):2362–8. https://doi.org/10.1249/MSS.0b013e3182667d1d.
12. Hirvensalo M, Rantanen T, Heikkinen E. Mobility difficulties and physical activity as predictors of mortality and loss of independence in the community-living older population. J Am Geriatr Soc. 2000;48(5):493–8.
13. Cabanas-Sanchez V, Guallar-Castillon P, Higueras-Fresnillo S, Garcia-Esquinas E, Rodriguez-Artalejo F, Martinez-Gomez DPA. Sitting time, and mortality from inflammatory diseases in older adults. Front Physiol. 2018;9:898. https://doi.org/10.3389/fphys.2018.00898.
14. Gregg EW, Pereira MA, Caspersen CJ. PA, falls, and fractures among older adults: a review of the epidemiologic evidence. J Am Geriatr Soc. 2000;48(8):883–93.
15. von Bonsdorff M, Rantanen T, Laukkanen P, Suutama T, Heikkinen E. Mobility limitations and cognitive deficits as predictors of institutionalization among community-dwelling older people. Gerontology. 2006;52(6):359–65. https://doi.org/10.1159/000094985.
16. Organization WH. Active ageing: a policy framework. Geneva, Switzerland: World Health Organization2002 Contract No.: WHO/NMH/NPH/02.8; 2002.
17. Webber SC, Porter MM, Menec VH. Mobility in older adults: a comprehensive framework. Gerontologist. 2010;50(4):443–50. https://doi.org/10.1093/geront/gnq013.
18. Cyarto EV, Myers A, Tudor-Locke C. Pedometer accuracy in nursing home and community-dwelling older adults. Med Sci Sports Exerc. 2004;36(2):205–9. https://doi.org/10.1249/01.MSS.0000113476.62469.98.
19. Bennett GG, Wolin KY, Puleo E, Emmons KM. Pedometer-determined physical activity among multiethnic low-income housing residents. Med Sci Sports Exerc. 2006;38(4):768–73. https://doi.org/10.1249/01.mss.0000210200.87328.3f.
20. Farmer BC, Croteau KA, Richeson NE, Jones DB. Using pedometers as a strategy to increase the daily steps of older adults with chronic illness: from research to practice. Home Healthc Nurse. 2006;24(7):449–56.
21. Cohen-Mansfield J, Werner P, Culpepper WJ, Wolfson M, Bickel E. Assessment of ambulatory behavior in nursing home residents who pace or wander: a comparison of four commercially available devices. Dement Geriatr Cogn Disord. 1997;8(6):359–65. https://doi.org/10.1159/000106656.
22. Algase DL, Beattie ER, Leitsch SA, Beel-Bates CA. Biomechanical activity devices to index wandering behavior in dementia. Am J Alzheimers Dis Other Demen. 2003;18(2):85–92. https://doi.org/10.1177/153331750301800202.
23. Martin JB, Krc KM, Mitchell EA, Eng JJ, Noble JW. Pedometer accuracy in slow walking older adults. Int J Ther Rehabil. 2012;19(7):387–93.
24. Ancoli-Israel S, Clopton P, Klauber MR, Fell R, Mason W. Use of wrist activity for monitoring sleep/wake in demented nursing-home patients. Sleep. 1997;20(1):24–7.
25. Plasqui G, Westerterp KR. PA assessment with accelerometers: an evaluation against doubly labeled water. Obesity (Silver Spring). 2007;15(10):2371–9. https://doi.org/10.1038/oby.2007.281.
26. Richardson MT, Leon AS, Jacobs DR Jr, Ainsworth BE, Serfass R. Ability of the Caltrac accelerometer to assess daily PA levels. J Cardpulm Rehabil. 1995;15(2):107–13.
27. Sewell L, Singh SJ, Williams JEA, Collier R, Morgan MDL. Can individualized rehabilitation improve functional independence in elderly patients with COPD? Chest. 2005;128(3):1194–200. https://doi.org/10.1378/chest.128.3.1194.
28. Singh S, Morgan MD. Activity monitors can detect brisk walking in patients with chronic obstructive pulmonary disease. J Cardpulm Rehabil. 2001;21(3):143–8.
29.• Yasunaga A, Togo F, Watanabe E, Park H, Shephard RJ, Aoyagi Y. Yearlong physical activity and health-related quality of life in older Japanese adults: the Nakanojo Study. J Aging PA. 2006;14(3):288–301. **Excellent study of long-term monitoring of PA in older adults in Japan.**
30. Izawa KP, Watanabe S, Oka K, Osada N, Omiya K, Brubaker PH, et al. Differences in daily in-hospital PA and geriatric nutritional risk index in older cardiac inpatients: preliminary results. Aging Clin Exp Res. 2014;26(6):599–605. https://doi.org/10.1007/s40520-014-0233-z.
31. Sallis R, Roddy-Sturm Y, Chijioke E, Litman K, Kanter MH, Huang BZ, et al. Stepping toward discharge: level of ambulation

in hospitalized patients. J Hosp Med. 2015;10(6):384–9. https://doi.org/10.1002/jhm.2343.

32. Fisher SR, Graham JE, Brown CJ, Galloway RV, Ottenbacher KJ, Allman RM, et al. Factors that differentiate level of ambulation in hospitalised older adults. Age Ageing. 2012;41(1):107–11. https://doi.org/10.1093/ageing/afr110.
33. Ostir GV, Berges IM, Kuo YF, Goodwin JS, Fisher SR, Guralnik JM. Mobility activity and its value as a prognostic indicator of survival in hospitalized older adults. J Am Geriatr Soc. 2013;61(4):551–7. https://doi.org/10.1111/jgs.12170.
34. Kochersberger G, McConnell E, Kuchibhatla MN, Pieper C. The reliability, validity, and stability of a measure of physical activity in the elderly. Arch Phys Med Rehabil. 1996;77(8):793–5.
35. Talbot LA, Gaines JM, Huynh TN, Metter EJ. A home-based pedometer-driven walking program to increase physical activity in older adults with osteoarthritis of the knee: a preliminary study. J Am Geriatr Soc. 2003;51(3):387–92.
36. White HK, McConnell ES, Bales CW, Kuchibhatla M. A 6-month observational study of the relationship between weight loss and behavioral symptoms in institutionalized Alzheimer's disease subjects. J Am Med Dir Assoc. 2004;5(2):89–97. https://doi.org/10.1097/01.JAM.0000110646.48753.EF.
37.• Arnardottir NY, Koster A, Van Domelen DR, Brychta RJ, Caserotti P, Eiriksdottir G, et al. Objective measurements of daily physical activity patterns and sedentary behaviour in older adults: Age, Gene/Environment Susceptibility-Reykjavik Study. Age Ageing. 2013;42((1468–2834 (Electronic))):222–9. https://doi.org/10.1093/ageing/afs160. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
38.• Shiroma EJ, Freedson PS, Trost SG, Lee IM. Patterns of accelerometer-assessed sedentary behavior in older women. JAMA. 2013;310(23):2562–3. https://doi.org/10.1001/jama.2013.278896. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
39.• Martin KR, Koster A, Murphy RA, Van Domelen DR, Hung MY, Brychta RJ, et al. Changes in daily activity patterns with age in U.S. men and women: National Health and Nutrition Examination Survey 2003-04 and 2005-06. J Am Geriatr Soc. 2014;62(7):1263–71. https://doi.org/10.1111/jgs.12893. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
40. Harris TJ, Owen CG, Victor CR, Adams R, Ekelund U, Cook DG. A comparison of questionnaire, accelerometer, and pedometer: measures in older people. Med Sci Sports Exerc. 2009;41(7):1392–402. https://doi.org/10.1249/MSS.0b013e31819b3533.
41. Andersson C, Lyass A, Larson MG, Spartano NL, Vita JA, Benjamin EJ, et al. Physical activity measured by accelerometry and its associations with cardiac structure and vascular function in young and middle-aged adults. J Am Heart Assoc. 2015;4(3):e001528. https://doi.org/10.1161/JAHA.114.001528.
42. Benjamin I, Brown N, Burke G, Correa A, Houser SR, Jones DW, et al. American Heart Association Cardiovascular Genome-Phenome Study: foundational basis and program. Circulation. 2015;131(1):100–12. https://doi.org/10.1161/CIRCULATIONAHA.114.014190.
43.• Splansky GL, Corey D, Yang Q, Atwood LD, Cupples LA, Benjamin EJ, et al. The third generation cohort of the National Heart, Lung, and Blood Institute's Framingham Heart Study: design, recruitment, and initial examination. Am J Epidemiol. 2007;165(11):1328–35. https://doi.org/10.1093/aje/kwm021. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
44.• Schram MT, Sep SJ, van der Kallen CJ, Dagnelie PC, Koster A, Schaper N, et al. The Maastricht Study: an extensive phenotyping study on determinants of type 2 diabetes, its complications and its comorbidities. Eur J Epidemiol. 2014;29(6):439–51. https://doi.org/10.1007/s10654-014-9889-0. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
45. van der Berg JD, Stehouwer CD, Bosma H, van der Velde JH, Willems PJ, Savelberg HH, et al. Associations of total amount and patterns of sedentary behaviour with type 2 diabetes and the metabolic syndrome: the Maastricht Study. Diabetologia. 2016;59(4):709–18. https://doi.org/10.1007/s00125-015-3861-8.
46. Parvaneh S, Mohler J, Toosizadeh N, Grewal GS, Najafi B. Postural transitions during activities of daily living could identify frailty status: application of wearable technology to identify frailty during unsupervised condition. Gerontology. 2017;63(5):479–87. https://doi.org/10.1159/000460292.
47.• Menai M, van Hees VT, Elbaz A, Kivimaki M, Singh-Manoux A, Sabia S. Accelerometer assessed moderate-to-vigorous physical activity and successful ageing: results from the Whitehall II study. Sci Rep. 2017;8:45772. https://doi.org/10.1038/srep45772. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
48. Lim SER, Dodds R, Bacon D, Sayer AA, Roberts HC. Physical activity among hospitalised older people: insights from upper and lower limb accelerometry. Aging Clin Exp Res. 2018;30:1363–9. https://doi.org/10.1007/s40520-018-0930-0.
49. Wullems JA, Verschueren SMP, Degens H, Morse CI, Onambele GL. Performance of thigh-mounted triaxial accelerometer algorithms in objective quantification of sedentary behaviour and physical activity in older adults. PLoS One. 2017;12(11):e0188215. https://doi.org/10.1371/journal.pone.0188215.
50. Moe-Nilssen R, Helbostad JL. Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults. Gait & posture. 2005;21(2):164–70. https://doi.org/10.1016/j.gaitpost.2004.01.013.
51.• Nastasi AJ, Ahuja A, Zipunnikov V, Simonsick EM, Ferrucci L, Schrack JA. Objectively measured physical activity and falls in well-functioning older adults: findings from the Baltimore Longitudinal Study of Aging. Am J Phys Med Rehabil. 2018;97(4):255–60. https://doi.org/10.1097/PHM.0000000000000830. **Important large-scale study on the use of wearable sensors to measure PA in older adults.**
52. Schrack JA, Zipunnikov V, Goldsmith J, Bai J, Simonsick EM, Crainiceanu C, et al. Assessing the "physical cliff": detailed quantification of age-related differences in daily patterns of physical activity. J Gerontol. 2014;69(8):973–9. https://doi.org/10.1093/gerona/glt199.
53. Wanigatunga AA, Simonsick EM, Zipunnikov V, Spira AP, Studenski S, Ferrucci L, et al. Perceived fatigability and objective physical activity in mid- to late-life. J Gerontol. 2018;73(5):630–5. https://doi.org/10.1093/gerona/glx181.
54. Martinez-Ramirez A, Martinikorena I, Gomez M, Lecumberri P, Millor N, Rodriguez-Manas L, et al. Frailty assessment based on trunk kinematic parameters during walking. J Neuroeng Rehabil. 2015;12:48. https://doi.org/10.1186/s12984-015-0040-6.
55. Martinez-Ramirez A, Martinikorena I, Lecumberri P, Gomez M, Millor N, Casas-Herrero A, et al. Dual task gait performance in frail individuals with and without mild cognitive impairment. Dement Geriatr Cogn Disord. 2016;42(1–2):7–16. https://doi.org/10.1159/000447451.
56. Millor N, Lecumberri P, Gomez M, Martinez-Ramirez A, Izquierdo M. An evaluation of the 30-s chair stand test in older adults: frailty detection based on kinematic parameters from a single inertial unit. J Neuroeng Rehabil. 2013;10:86. https://doi.org/10.1186/1743-0003-10-86.
57.• Millor N, Lecumberri P, Gomez M, Martinez-Ramirez A, Izquierdo M. Kinematic parameters to evaluate functional performance of sit-to-stand and stand-to-sit transitions using motion sensor devices: a systematic review. IEEE Trans Neural Syst Rehabil Eng. 2014;22(5):926–36. https://doi.org/10.1109/TNSRE.2014.

2331895. **Excellent review of the use of wearable sensors to instrument standardized clinical assessment.**
58. Millor N, Lecumberri P, Gomez M, Martinez-Ramirez A, Rodriguez-Manas L, Garcia-Garcia FJ, et al. Automatic evaluation of the 30-s chair stand test using inertial/magnetic-based technology in an older prefrail population. IEEE J Biomed Health Inform. 2013;17(4):820–7. https://doi.org/10.1109/JBHI.2013.2238243.
59. Ganea R, Paraschiv-Ionescu A, Bula C, Rochat S, Aminian K. Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people. Med Eng Phys. 2011;33(9):1086–93. https://doi.org/10.1016/j.medengphy.2011.04.015.
60. Galan-Mercant A, Cuesta-Vargas AI. Differences in trunk accelerometry between frail and non-frail elderly persons in functional tasks. BMC Res Notes. 2014;7:100. https://doi.org/10.1186/1756-0500-7-100.
61. Dijkstra B, Zijlstra W, Scherder E, Kamsma Y. Detection of walking periods and number of steps in older adults and patients with Parkinson's disease: accuracy of a pedometer and an accelerometry-based method. Age Ageing. 2008;37(4):436–41. https://doi.org/10.1093/ageing/afn097.
62.• Dijkstra B, Kamsma Y, Zijlstra W. Detection of gait and postures using a miniaturised triaxial accelerometer-based system: accuracy in community-dwelling older adults. Age Ageing. 2010;39(2):259–62. https://doi.org/10.1093/ageing/afp249. **Important study in measurement of PA type and gait.**
63. Greene BR, Doheny EP, O'Halloran A, Anne Kenny R. Frailty status can be accurately assessed using inertial sensors and the TUG test. Age Ageing. 2014;43(3):406–11. https://doi.org/10.1093/ageing/aft176.
64. Greene BR, Doheny EP, Kenny RA, Caulfield B. Classification of frailty and falls history using a combination of sensor-based mobility assessments. Physiol Meas. 2014;35(10):2053–66. https://doi.org/10.1088/0967-3334/35/10/2053.
65. Schwenk M, Mohler J, Wendel C, D'Huyvetter K, Fain M, Taylor-Piliae R, et al. Wearable sensor-based in-home assessment of gait, balance, and physical activity for discrimination of frailty status: baseline results of the Arizona frailty cohort study. Gerontology. 2015;61(3):258–67. https://doi.org/10.1159/000369095.
66. Park JH, Mancini M, Carlson-Kuhta P, Nutt JG, Horak FB. Quantifying effects of age on balance and gait with inertial sensors in community-dwelling healthy adults. Exp Gerontol. 2016;85:48–58. https://doi.org/10.1016/j.exger.2016.09.018.
67.• Manini TM. Energy expenditure and aging. Ageing Res Rev. 2010;9(1):1–11. https://doi.org/10.1016/j.arr.2009.08.002. **Excellent review of changes in EE with aging.**
68. Black AE, Coward WA, Cole TJ, Prentice AM. Human energy expenditure in affluent societies: an analysis of 574 doubly-labelled water measurements. Eur J Clin Nutr. 1996;50(2):72–92.
69. Elia M, Ritz P, Stubbs RJ. Total energy expenditure in the elderly. Eur J Clin Nutr. 2000;54(Suppl 3):S92–103.
70. Masse LC, Fulton JE, Watson KL, Mahar MT, Meyers MC, Wong WW. Influence of body composition on physical activity validation studies using doubly labeled water. J Appl Physiol (1985). 2004;96(4):1357–64. https://doi.org/10.1152/japplphysiol.00901.2003.
71.• Stalvey BT, Owsley C, Sloane ME, Ball K. The Life Space Questionnaire: a measure of the extent of mobility of older adults. J Appl Gerontol. 1999;18(4):460–78. https://doi.org/10.1177/073346489901800404. **Interesting framework for examining spatial extent of PA in older adults.**
72. Peel C, Baker PS, Roth DL, Brown CJ, Bodner EV, Allman RM. Assessing mobility in older adults: the UAB Study of Aging Life-Space Assessment. Phys Ther. 2005;85(10):1008–19.
73. Sallis JF, Saelens BE. Assessment of physical activity by self-report: status, limitations, and future directions (vol 71, pg 1, 2000). Res Q Exercise Sport. 2000;71(4):409 -.
74. Matthews CE, Chen KY, Freedson PS, Buchowski MS, Beech BM, Pate RR, et al. Amount of time spent in sedentary behaviors in the United States, 2003-2004. Am J Epidemiol. 2008;167(7):875–81. https://doi.org/10.1093/aje/kwm390.
75. Tucker JM, Welk GJ, Beyler NK. Physical activity in U.S.: adults compliance with the physical activity Guidelines for Americans. Am J Prev Med. 2011;40(4):454–61. https://doi.org/10.1016/j.amepre.2010.12.016.
76. Butte NF, Ekelund U, Westerterp KR. Assessing physical activity using wearable monitors: measures of physical activity. Med Sci Sports Exerc. 2012;44(1 Suppl 1):S5–12. https://doi.org/10.1249/MSS.0b013e3182399c0e.
77. Tudor-Locke C, Bassett DR Jr. How many steps/day are enough? Preliminary pedometer indices for public health. Sports Med. 2004;34(1):1–8. https://doi.org/10.2165/00007256-200434010-00001.
78. Berlin JE, Storti KL, Brach JS. Using activity monitors to measure physical activity in free-living conditions. Phys Ther. 2006;86(8):1137–45.
79.• Ainsworth B, Cahalin L, Buman M, Ross R. The current state of physical activity assessment tools. Prog Cardiovasc Dis. 2015;57(4):387–95. https://doi.org/10.1016/j.pcad.2014.10.005. **Excellent review of wearable sensors to measure PA in older adults.**
80. Freedson P, Bowles HR, Troiano R, Haskell W. Assessment of physical activity using wearable monitors: recommendations for monitor calibration and use in the field. Med Sci Sports Exerc. 2012;44(1 Suppl 1):S1–4. https://doi.org/10.1249/MSS.0b013e3182399b7e.
81. Westerterp KR. Assessment of physical activity: a critical appraisal. Eur J Appl Physiol. 2009;105(6):823–8. https://doi.org/10.1007/s00421-009-1000-2.
82. de Groot S, Nieuwenhuizen MG. Validity and reliability of measuring activities, movement intensity and energy expenditure with the DynaPort MoveMonitor. Med Eng Phys. 2013;35(10):1499–505. https://doi.org/10.1016/j.medengphy.2013.04.004.
83. Erdmier C, Hatcher J, Lee M. Wearable device implications in the healthcare industry. J Med Eng Technol. 2016;40(4):141–8. https://doi.org/10.3109/03091902.2016.1153738.
84.• Straiton N, Alharbi M, Bauman A, Neubeck L, Gullick J, Bhindi R, et al. The validity and reliability of consumer-grade activity trackers in older, community-dwelling adults: a systematic review. Maturitas. 2018;112:85–93. https://doi.org/10.1016/j.maturitas.2018.03.016. **Excellent review of consumer grade sensors and their applications in older adults.**
85.•• Schrack JA, Cooper R, Koster A, Shiroma EJ, Murabito JM, Rejeski WJ, et al. Assessing daily PA in older adults: unraveling the complexity of monitors, measures, and methods. J Gerontol. 2016;71(8):1039–48. https://doi.org/10.1093/gerona/glw026. **Excellent review of wearable sensors in older adults, including details of large-scale studies that have incorporated accelerometers.**
86. Farina N, Lowry RG. The validity of consumer-level activity monitors in healthy older adults in free-living conditions. J Aging PA. 2018;26(1):128–35. https://doi.org/10.1123/japa.2016-0344.
87. Appelboom G, Taylor BE, Bruce E, Bassile CC, Malakidis C, Yang A, et al. Mobile phone-connected wearable motion sensors to assess postoperative mobilization. JMIR Mhealth Uhealth. 2015;3(3):e78. https://doi.org/10.2196/mhealth.3785.
88. Ellis K, Kerr J, Godbole S, Staudenmayer J, Lanckriet G. Hip and wrist accelerometer algorithms for free-living behavior classification. Med Sci Sports Exerc. 2016;48(5):933–40. https://doi.org/10.1249/MSS.0000000000000840.
89.• Caldas R, Mundt M, Potthast W, Buarque de Lima Neto F, Markert B. A systematic review of gait analysis methods based on inertial sensors and adaptive algorithms. Gait Posture. 2017;57:204–10. https://doi.org/10.1016/j.gaitpost.2017.06.019.

Comprehensive review of methods of computing gait measures from inertial sensors.

90.•• Doherty ST, Oh P. A multi-sensor monitoring system of human physiology and daily activities. Telemed J E Health. 2012;18(3):185–92. https://doi.org/10.1089/tmj.2011.0138. **Landmark study that measured many aspects of PA, subject location, and heart rate in order to provide a comprehensive assessment. Despite excellent design and implementation, the study also identifies limitations in technology that need to be addressed.**

91.• Dobkin BH, Dorsch A. The promise of mHealth: daily activity monitoring and outcome assessments by wearable sensors. Neurorehabil Neural Repair. 2011;25(9):788–98. https://doi.org/10.1177/1545968311425908. **Excellent review of the use of wearable sensors in continuous monitoring of PA.**