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Physical Activity Tracking Wristbands for Use in Research With Older Adults: An Overview and Recommendations

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Traditional physical activity tracking tools, such as self-report questionnaires, are inherently subjective and vulnerable to bias. Physical activity tracking technology, such as activity tracking wristbands, is becoming more reliable and readily available. As such, researchers are employing these objective measurement tools in both observational- and intervention-based studies. There remains a gap in the literature on how to properly select activity tracking wristbands for research, specifically for the older adult population. This paper outlines considerations for choosing the most appropriate wrist-worn wearable device for use in research with older adults. Device features, outcome measures, population, and methodological considerations are explored.

Keywords: data collection, older adults, wearable technology

Over the past decades, researchers and health care professionals have issued a clarion call for increased physical activity (PA) for a growing and predominantly sedentary older adult population (Statistics Canada, 2012; Tedesco, Barton, & O'Flynn, 2017; Vuori, 2018). The World Health Organization recommends 150 min of activity per week (World Health Organization, n.d.). Older adults should strive for approximately 7,000–10,000 steps per day to maintain health (Tudor-Locke et al., 2011). However, the Centers for Disease Control and Prevention (2016) reports that 28% of older adults fail to reach this activity goal. Progressive decreases in PA levels and a corresponding increase in chronic disease have a negative effect on older adults' physical and cognitive wellness (Centers for Disease Control and Prevention, 2016). Investigating the grounds of such physical behavior among this population is critically important for preventing chronic disease, maintaining autonomy, and improving quality of life.

Technological tools, such as wearable sensors, have been used to assess objective wellness and health-related variables. Specifically, current wearable devices are able to assess PA outcomes, such as step count, energy expenditure (EE), and heart rate (HR), and so forth (Appelboom et al., 2014; Bunn, Navalta, Fountaine, & Reece, 2018; Cadmus-Bertram, 2017; de Arriba-Pérez, Caeiro-Rodríguez, & Santos-Gago, 2017; Stewart & Coughlin, 2016). These variables can provide insight into a population's daily behaviors and help define and promote the best PA recommendations for a specific cohort.

There are two primary classifications of wearables in the context of research: research- and consumer-grade devices. Research-grade devices such as the ActiGraph GT3X are highly validated and have a large onboard memory and excellent manufacturer support (Henriksen et al., 2018; Turner-McGrievy et al., 2019); however, they are costly, bulky, and require specific device readers and software (Scott et al., 2019). Consumer wearable devices are considered moderately reliable, are relatively inexpensive, and are practical in everyday life (Bunn et al., 2018; Evenson, Goto, & Furberg, 2015; Straiton et al., 2018). Data collected from these devices can be regularly transferred to a website or mobile application (hereafter, app) and stored for a prolonged time (Wright, Hall Brown, Collier, & Sandberg, 2017). While the model below applies to all wearable technology, this review focuses on consumer grade products.

Smart wristbands or activity tracking wristbands (ATWs) constitute the largest market segment of wearable trackers (Statt, 2015). In general, ATWs are designed to provide useful data for the consumer through a fashionable accessory that challenges the user to meet specific activity goals (Nelson, Verhagen, & Noordzij, 2016; Nelson, Kaminsky, et al., 2016; Sazonov & Neuman, 2014). A major benefit of using consumer ATWs is that data can be seen immediately; in contrast, data from ATWs research-grade counterparts requires postprocessing.

The use of consumer ATWs in research with older adults is becoming a common practice in both observational- and intervention-based studies (Henriksen et al., 2018; Wright et al., 2017). Cadmus-Bertram (2017), Dall et al. (2018), Henriksen et al. (2018), and Turner-McGrievy (2019) published specific guidelines for researchers to consider prior to choosing an ATW. These considerations include the population to be studied, PA outcomes, the type of study (intervention or assessment), budget, accuracy, position of placement, hardware features, metrics, application programming interface (API), and customer service. However, there are several other factors to consider when choosing the proper ATW for research specifically with older adults. The purpose of this paper is to present and discuss relevant literature on the main factors for selecting a wearable device when collecting objective fitness data from older adults based on the population's preferences and usability. Figure 1 breaks down the population characteristics and technical ATW aspects that should be considered in order to develop a successful research design for older adults. In-depth discussion and recommendations regarding older adults' preferences, methodology, and issues of data loss are integrated within the following sections.

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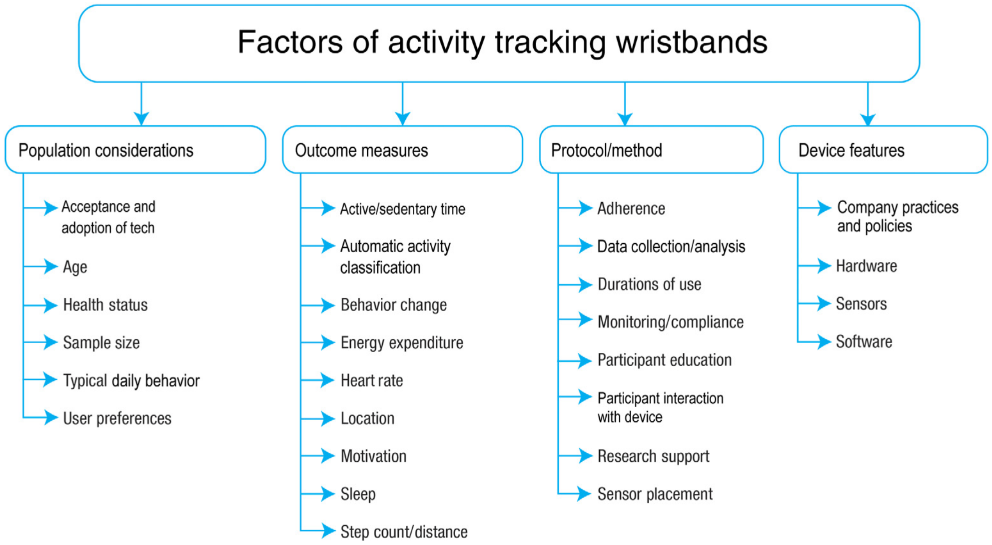

Figure 1 — Factors to consider when choosing an activity tracker in research.

Population Considerations

The older adult population, particularly in developed and emerging countries, has grown progressively in recent decades. It is estimated that worldwide, the number of people over 60 years of age is greater than 962 million, constituting 13% of the global population (United Nations, Department of Economic and Social Affairs: Population Division, 2017). This number is expected to increase to 22% by 2050 (World Health Organization, n.d.).

Most developed countries have accepted a chronological age of 65 years as the definition of an older adult (Milhorn, 2018). However, according to the World Health Organization (2002), chronological age is not a precise marker for the changes that accompany aging, because there are dramatic variations in health status, social participation, and levels of independence among older adults of the same age. In addition, Zenger and Lawrence (1989) suggest that chronological age is associated with a set of attitudes and preferences. In particular, older adult individuals with a positive self-perception about aging show increased longevity and other positive health outcomes (Levy, Slade, & Kasl, 2002).

In general, older adults today are healthier, more diverse, and more educated than in previous generations (Bass, 1995; Garcia & Wong, 2018). Higher levels of education are typically associated with technology adoption. Older adults with disabilities are also less likely to use technology such as wearables (Kaye, Yeager, & Reed, 2008). Despite a trend toward increased use of technology among older adults, technology use is still lower among this group as compared with younger peers.

Research suggests that technology can create opportunities to facilitate everyday tasks, enabling older adults to remain independent longer (Imamura, 2014). Given that older adults represent an increasingly larger proportion of the population and need to be active users of technology, issues surrounding aging and information technologies are of critical importance within the domain of human–computer interaction.

ATW Outcome Measures

The most common method for assessing PA has been through self-report questionnaires (Dowd et al., 2018; Rao, 2019; Shephard, 2016); however, researchers have documented the limitations of self-report bias especially in older adults (e.g., human memory). According to Schaller, Rudolf, Dejonghe, Grieben, and Froboese (2016), self-reported data typically overestimates PA by more than 20 min per day, and it is known that, the longer the period of recall, the less accurate the data (Dowd et al., 2018). Nevertheless, questionnaires are advantageous, because they are versatile in length and easily administered to many people via hard copies, digital formats, or interviews (Shephard, 2016). Questionnaires generally collect data on PA duration and intensity and aspects of exercise, sleep, and sedentary behavior. However, many of these questionnaires do not include information on daily activities that also require EE, such as light-intensity PA (LaMonte et al., 2019; Rao, 2019).

Outcome measures collected by ATWs are dependent on the types of sensors embedded within each device. Generally, ATWs contain an accelerometer and at least one other sensor (Henriksen et al., 2018). The following sections outline outcome measures and sensors commonly used for research with older adults.

Sensors

Accelerometers. Accelerometry is the most widely used method for objective assessment of PA in population studies (Doherty et al., 2017; Henriksen et al., 2018). Modern ATWs contain triaxial accelerometers that measure acceleration in three directions. Variations of accelerometers include uni- and biaxial accelerometers (see Rao, 2019). Accelerometers are widely used to measure step count and classify types and intensity of movement, EE, and sleep (Evenson et al., 2015; Rao, 2019; Sazonov & Neuman, 2014).

Gyroscopes and magnetometers. Often combined with accelerometers to create an inertial measurement unit, gyroscopes and magnetometers correct accelerometer measurements by providing orientation in space (Henriksen et al., 2018; Rao, 2019).

Barometers and altimeters. Barometers and altimeters detect changes in altitude. They can be used to increase the accuracy of some measurements from other sensors, such as the magnetometer and gyroscope. In addition, they provide variables such as stair count and height climbed (Henriksen et al., 2018; Sazonov & Neuman, 2014).

Photoplethysmography. Photoplethysmography is a commonly used method for evaluating peripheral circulation by detecting the rate at which blood pulses at the wrist veins (Allen, 2007; Horton, Stergiou, Fung, & Katz, 2017) using a light-emitting diode (Henriksen et al., 2018).

Company Support and Research Protocol

Researchers should be familiar with companies' customer support solutions and warranty policies, because ATWs may break or malfunction. Providing access to education and support for use increases the chances of success and compliance (Cadmus-Bertram, 2017; Cooper et al., 2018; Rupp, Michaelis, McConnell, & Smither, 2018). Participants should be given training and easy to understand resources in order to interact appropriately with the ATW (e.g., charging, uploading data, wrist placement). Accordingly, researchers may wish to meet face-to-face regularly with participants to troubleshoot and can use such meetings as opportunities to download data from the devices and, if necessary, update software. An alternative solution to collecting and consolidating the data is to employ an API, which assists with data collection visualization and synthesis (Henriksen et al., 2018). It is important, however, to ensure that the API is well documented, public, and supported in case of errors (Turner-McGrievy et al., 2019).

Protocol Considerations

The use of commercial ATWs as research tools has limitations, particularly related to validity and accuracy. Often, companies do not disclose how they validated their devices or which protocols were used to estimate their metrics. Thus, it is difficult for researchers and consumers to compare and generalize the validity and reliability of different devices (O'Brien, Troutman-Jordan, Hathaway, Armstrong, and Moore, 2015).

It is important to note that published validation studies are, in fact, secondary validation. Consumer devices report postprocessed signals rather than raw data. These processed data are being compared against gold standard methods, such as direct observation or research-grade devices (de Zambotti, Cellini, Goldstone, Colrain, & Baker, 2019). This limitation is inevitable when utilizing consumer ATWs in research. The following section outlines three primary factors impacting the accuracy of ATWs: algorithms, sensor placement, and movement patterns of the population.

Algorithms

The measurement algorithms developed for commercial ATWs are usually proprietary. To date, there is no gold standard algorithm-based processing to be followed by ATW producers (Ainsworth, Cahalin, Buman, & Ross, 2015; Kamišalić, Fister, Turkanović, & Karakatič, 2018).

The variability in algorithms is evident when devices with similar sensors and placements are compared. For example, An, Jones, Kang, Welk, and Lee (2017) aimed to assess the accuracy of 10 consumer activity trackers, seven of which were ATWs and four of the ATWs contained only a triaxial accelerometer. The protocol included both in-lab (treadmill and overground) and free-living components (24-hr wear). When comparing the 10 devices, little variation was seen during the treadmill protocol ($r = .9$ to $.7$) compared with the criterion measure. However, variability increased during the overground ($r = -.8$ to $.3$) and 24-hr free-living periods ($r = .9$ to $.6$) when compared with the criterion measure (An et al., 2017). Similar results were evident in Floegel, Florez-Pregonero, Hekler, and Buman (2017) and a review conducted by Evenson et al. (2015).

Activity tracking wristband devices are generally reliable for tracking HR and EE in adults and older adults (Alharbi, Straiton, Smith, Neubeck, & Gallagher, 2019; Straiton et al., 2018). HR measured at the wrist, commonly known as optical HR (OHR), is often assumed to be integrated into the algorithms (Henriksen et al., 2018). A study conducted by Montoye, Vusich, Mitrzyk, and Wiersma (2018) aimed to determine if Fitbit devices containing OHR sensors included an HR calculation when predicting EE and if the Fitbits with OHR were more accurate in reporting EE when compared with models without OHR. Participants were fitted with five Fitbit devices; three measured HR (Blaze, Charge HR, Alta HR), and two did not (Alta, FF2). Criterion measures were also used: Omron HJ-323U pedometer, Polar HR Strap, and ParvoMedics TrueOne 2400 metabolic analyzer. Participants completed a nine-step protocol including stationary, treadmill, and cycling activities. The treadmill protocol was designed so that the number of steps taken during the trial would be similar, but kilocalories and HR would be different (i.e., treadmill walking at 1.1 m/s, 0% incline for one trial and 1.1 m/s, 10% incline for another). Results indicated that OHR influenced the algorithm for EE; however, the mean absolute errors for kilocalorie predictions were similar for both types of ATWs (Montoye et al., 2018). If an ATW is not placed according to the manufacturer's instructions, an increased risk of error occurs, because OHR (or any other sensor) may not be adequately detected.

Movement Patterns

The targeted users of ATWs are healthy adults; therefore, algorithms are generally designed for and tested with this population. Gait changes with age, and older adults may present varied gait patterns compared with healthy adults (Burton et al., 2018; Ko, Hausdorff, & Ferrucci, 2010; Pirker & Katzenschlager, 2017), possibly reducing the accuracy of collected data and its interpretation (Floegel et al., 2017). Accuracy of ATWs has also been shown to be influenced by gait speed, terrain, and mobility (Alinia et al., 2017; An et al., 2017; Bunn et al., 2018; Diaz et al., 2015; Evenson et al., 2015; Fokkema, Kooiman, Krijnen, Van Der Schans, & De Groot, 2017; Hergenroeder et al., 2019; Huang, Xu, Yu, & Shull, 2016). It has been demonstrated that step count is more accurate when participants achieve faster ambulatory speeds (Bunn et al., 2018; Evenson et al., 2015), overestimate time spent in higher-intensity activities, and underestimate step count in controlled settings but overestimate in free-living settings, regardless of placement (Feehan et al., 2018; Straiton et al., 2018).

Floegel et al. (2017) aimed to assess the accuracy of step count using ATWs in older adults with diverse ambulatory abilities. Four consumer devices were placed at the ankle, hip, and nondominant wrist. Four groups of walkers completed the protocol: nonimpaired, impaired, cane users, and walker users. Ankle-placed monitors had the highest agreement in all groups, followed by the hip-based monitor. Wrist-based monitors were only relatively accurate in the nonimpaired walking group (Floegel et al., 2017). Similar results were illustrated by Hergenroeder et al. (2019) who aimed to assess older adults' preferences and device accuracy during a 100-step walking test. For those walking with assistive devices, only the waist pedometer (Accusplit pedometer) was relatively accurate (Hergenroeder et al., 2019). Based on gait speed in both healthy walkers and those with assistive devices, no device was accurate during walking speeds < 0.8 m/s; however, accuracy increased proportionally with gait speed (Hergenroeder et al., 2019).

Placement

Placement of the activity tracker and activity type have been shown to contribute to errors in data collection (Rao, 2019). In a recent study, Edwardson, Davies, Khunti, Yates, and Rowlands (2018) compared the number of steps counted measured by ATWs on both the dominant and nondominant wrist against a waist-worn pedometer. Results indicated there was a difference in agreement between the same tracker worn on the dominant and nondominant wrists, because the dominant side overcounted steps and the nondominant undercounted them. Statistically, there were narrower limits of agreement when comparing nondominant step counts to the pedometer (Edwardson et al., 2018). These results may be explained by the specificity of movement between the dominant and nondominant hands (Clevenger, Molesky, Vusich, & Montoye, 2019). For example, daily tasks such as driving, pushing a shopping cart, or knitting require equal movements of both hands. However, brushing teeth, sweeping, and writing require the use of only one, resulting in more movement of the wrist. Similar errors were shown in wrist-worn monitors worn by those who use assistive devices when walking, because the upper extremities were stationary (Floegel et al., 2017; Hergenroeder et al., 2019).

O'Connell, ÓLaighin, and Quinlan (2017) demonstrated the effect of movement specificity on accuracy. Five activity monitors were placed on different segments of the body: on the chest (Fitbit One), right thigh (activPAL), left hip (NL-2000), right hip (Withings Pulse), and wrist (Jawbone UP). The protocol consisted of nine nonstepping daily activities including desk work, an elevator ride, a bus ride, automobile driving, washing/drying dishes, reaching, indoor and outdoor cycling, and indoor rowing. Results indicated that hip-based devices were, on average, more accurate during the nonstepping activities, because the specific movements required for various activities resulted in different body parts moving. For example, the Jawbone UP recorded an increase in false positives during dishwashing and driving compared to the thigh-placed ActivPAL, which recorded an increase in false positives during cycling (O'Connell et al., 2017).

A similar study conducted by Nelson, Kaminsky, et al. (2016) included validation of EE in addition to step count for three hip-worn activity trackers and two ATWs. The protocol included sedentary daily household tasks and ambulatory activities. ATWs underestimated EE in the sedentary activities; a significant statistical difference was not determined for the hip-placed devices during sedentary activities. All the devices underestimated EE during household activity protocols and overestimated it during the ambulatory activities. A notable result was that the EE estimated by the Fitbit Flex was within 10 of the criterion measure during the household activities and displayed the lowest mean absolute percentage error (Nelson et al., 2016). These results corroborated other studies that indicated that hip-based monitors are less accurate in estimating EE than ATWs (Floegel et al., 2017).

A notable limitation to these validation studies includes placing more than one ATW on each wrist. For example, An et al. (2017) evaluated a total of eight ATWs, placing four on each wrist, and Floegel et al. (2017) had two monitors on the nondominant wrist. Based on the specificity of each algorithm, manufacturers recommend optimal placements of devices. Having multiple devices on a wrist may interfere with data accuracy and contribute to data loss.

ATW Feature Considerations

Usually, commercial activity trackers contain at least an accelerometer to calculate outcome measures (Evans et al., 2018; Yang & Hsu, 2010). Differentiating usability factors are based on interaction with the devices' hardware and software. The literature suggests that the older adult population presents a relatively positive attitude toward the use of technology and is willing to learn how to use it but may not be motivated to access it (Barnard, Bradley, Hodgson, & Lloyd, 2013; Chen & Chan, 2013).

Compliance in wearing ATWs has been pointed out as a limiting factor in using ATWs for research. Compliance can be affected by data utility, user comfort, and user trust in the device (Dall et al., 2018; Godfrey, 2017; Hergenroeder et al., 2019; O'Brien et al., 2015; Steinert, Haesner, & Steinhagen-Thiessen, 2018; Tedesco et al., 2017). In addition, the literature suggests that older adults are more likely to accept and adopt a new wearable technology if its concept is familiar (e.g., a watch or bracelet) and its usage does not negatively impact their daily behaviors (Doherty et al., 2017; Mokhlespour Esfahani & Nussbaum, 2018; Rupp et al., 2018; Tedesco et al., 2017). This section discusses ATW hardware and software features through the lens of older adults' preferences and barriers in order to optimize research protocols and minimize data loss.

Hardware

Successful data collection using ATWs largely relies on participants' interaction time with the device, comfort, and user-friendly features. According to Hergenroeder et al. (2019, p. 11), ". . . the ideal activity monitor is one that is accurate, easy to apply, and allows the individual to access step count without difficulty." Discomfort in using ATWs can result in participants removing their device earlier than is recommended (Tedesco et al., 2017; Turner-McGrievy et al., 2019). To avoid early removal due to discomfort, monitors with hypoallergenic materials, medical grade tubing, and soft corners should be considered (Dall et al., 2018; Turner-McGrievy et al., 2019). Users reported skin irritation after wearing devices for a prolonged time, after sweating, or after getting them wet, primarily due to friction against the skin (Steinert et al., 2018). To mitigate skin irritation, researchers must be mindful of participants' skin sensitivities, recommend that users to take off bands and dry them off after they get wet, and monitor possible discomfort throughout the study.

Physical size and optimal placement of devices may also impact user comfort and compliance (Sazonov & Neuman, 2014). Studies that investigated older adults' preferences indicated that wristband features such as locking mechanisms, button size, and charging mechanisms also influence usability and comfort (Dall et al., 2018; Hergenroeder et al., 2019; Martin, Ramsay, Hughes, Peters, & Edwards, 2015; Steinert et al., 2018). As people age, grip strength and dexterity decline (Martin et al., 2015; Rupp et al., 2018). Rupp et al. (2018) found that older adult participants had the most difficulty using the Fitbit Flex (Fitbit Inc., San Francisco, CA), because the unit contains small components. Specifically, older adults reported that it was difficult to move the device component in and out of the band and the charging base. In addition, both Rupp et al. (2018) and Steinert et al. (2018) found clasp- or button-based locking mechanisms (e.g., Fitbit Flex 2) and rigid bands (e.g., Jawbone [Jawbone, San Francisco, CA]) significantly more difficult than locking mechanisms more similar to watch straps. Ergonomic features of the monitor and comfort were demonstrated to be the most important hardware factors contributing to usability.

A short battery life may impact data monitoring and result in data loss. Moreover, due to age-related vision and memory deficits, older adults may forget to put devices back on, resulting in a lower than optimal wearing times (Dall et al., 2018; Steinert et al., 2018).

Steinert et al. (2018) found that older adults had issues synchronizing devices to external apps, especially when users were required to press small buttons and look at small screens. Because many ATWs have only one button, the number of times the button is pressed or the length of time for which the button is held can initiate different functions. This issue is both a function of hardware and software, because study participants had difficulty in pressing the button and were unsure if the data synced because the notification was too small or because the updated window closed too soon or took too long (Steinert et al., 2018). Due to implications for data quality, onboard memory capability, battery life, reminders to charge, and security to the wrist, coordinated meetings with participants to remove and charge the device should be considered as part of study protocols.

Software

Most commonly, data are transferred from the ATW to the device's server using Bluetooth or Wi-Fi. Consumer ATWs typically export data in specific time epochs or increments; therefore, minute by minute data extraction is impossible without an API in consumer devices (de Arriba-Pérez, Caeiro-Rodríguez, & Santos-Gago, 2016). Daily total data and time epoch can most often be downloaded from the manufacturer's dashboard or website into an Excel file for further analysis. Data processing and cleaning, whether for consumer- or research-grade devices, should include a modeling team of mathematicians and physiologists in order to ensure valid results (Peake, Kerr, & Sullivan, 2018).

Depending on the research questions and the study protocol, studies may require participants to use an ATW, supported apps, and other related software on a daily basis (Cadmus-Bertram, 2017). The use of dynamic websites and mobile apps commonly paired with ATWs might cause confusion for users, resulting in data not being transferred to the appropriate account or data loss. Websites and mobile apps may disorient users with constantly changing interfaces and advertisements (Chen & Chan, 2013; Kuerbis, Mulliken, Muench, Moore, & Gardner, 2017; Preusse, Mitzner, Fausset, & Rogers, 2017; Steinert et al., 2018). Preusse et al. (2017) assessed the usability and acceptance of two activity tracking technologies by older adults: myfitnesspal.com and the Fitbit One+ Fitbit Dashboard. Results indicated similar issues between the two technologies' webpages: misleading hyperlink colors, inconsistent navigation bars, user difficulty, and problems interpreting personalized graphs. A lack of control of these factors may result in unrecorded, inaccurate, or deleted data (Preusse et al., 2017). Steinert et al. (2018) found that older adults had issues when navigating certain apps due to the graphical interface and confusion about how variables such as step count were measured (Steinert et al., 2018). An automatic and consistent data collection process, such as app installation, navigation, and manual syncing would decrease misuse or loss of data through misguided participant efforts (Dall et al., 2018; Turner-McGrievy et al., 2019).

As a result of age-related declines in vision, small device display font sizes are difficult to read (Preusse et al., 2017; Rupp et al., 2018). The font size can be customized on some ATWs. Others (e.g., Fitbit Flex, Jawbone, and Moov Now [Moov Inc., San Mateo, CA]) do not contain a screen and require a secondary device (e.g., a mobile phone or desktop computer with the installed app) to monitor progress (Henriksen et al., 2018). Font size on secondary devices is fully customizable; however, it may require that older adults learn how to use another device.

Recommendations and Limitations

The aim of this review was to provide recommendations for choosing ATWs for use in research with older adults. A summary of key considerations can be found in Table 1.

Researchers are increasingly using ATWs as research tools with older adults. ATWs provide a way of objectively measuring PA, which allows researchers and clinicians to understand the

Table 1 Key Considerations for Choosing an ATW for Research With Older Adults

Factor	Consideration
Outcome measures	• Sensors should be selected based on the primary physiological variable/outcome measure of the research question • Validation and reliability of the device should be assessed or verified for the specific population. If there are no third-party validation studies, one should be performed prior to data collection
Protocol considerations	• Although older adults are becoming more comfortable with technology, ensure proper education on the use of the wearable and the responsibility of the participant with regard to interaction with the device • Accuracy of the device can be impacted by placement based on the health status and daily behavior of the participant • Data downloading and transfer should be completed by researchers to avoid data loss • Device features should be considered based on the research question; for example, not having a screen can provide complete data blindness to participants
Device features	• Older adults experience cognitive and motor deficits; therefore, the device should be user friendly and require minimal interaction by the participants • Hardware should have minimal distraction ○ No screen ○ Lightweight/feels like a watch ○ Large enough buttons ○ Simple clasp • A longer battery life and larger onboard memory is recommended in order to reduce charging time, data loss, and removal of the device • Researchers should be aware of customer support policies and validated API and third-party applications that can assist with data collection and processing

Note. ATW = activity tracking wristbands; API = application programming interface.

relationship between PA, aging, and subsequent health outcomes (Dowd et al., 2018; Schrack, Gresham, & Wanigatunga, 2017; Shephard, 2016). Additionally, a research protocol that requires participants to be blinded to their data during the study could be designed using these devices without an interactive monitor (Turner-McGrievy et al., 2019). However, there remains a large gap in the literature regarding the appropriate selection of this technology for older adults.

Due to the changing landscape of consumer wearable technology and the diverse validation protocols and statistical analyses, providing a definite recommendation is a challenge, because devices cannot be directly compared with one another. Regardless of the device chosen, device measurements should not be taken at face value. Rather, researchers and practitioners should report trends due to the variability of accuracy across populations and activities.

Individual factors such as access to technology, age, education, socioeconomic status, cultural barriers, and physical ability must be considered when developing fitness technologies and research protocols (Gell, Rosenberg, Carlson, Kerr, & Belza, 2015). Facilitators using ATWs with older adults should be mindful of these limitations and provide adequate resources, including relevant education and training. Beyond designing technologies, providing access and support for using wearable devices increases the chances of success and adherence in this population (Cooper et al., 2018).

Previous literature has published guidelines and questions to consider when choosing an ATW for research with any population, including population, outcome measures, study design, budget, device accuracy, placement, hardware features metrics, API, and customer service (Cadmus-Bertram, 2017; Dall et al., 2018; Henriksen et al., 2018; Turner-McGrievy et al., 2019). In addition to these factors, the participants' expected level of interaction with the device, daily behaviors (e.g., the types of activities common in the population of interest), comfort, device onboard memory, battery, and data download methods should also be taken into account with equal weight when working with older adults.

As newer models enter the market, older devices become less expensive but are still supported by manufacturers, making them more desirable for researchers. In selecting such a product, researchers need to be aware of manufacturers' ongoing support timelines. An additional benefit of using older models in research is the potential for peer-reviewed articles to be published, ensuring researchers fully understand the specific device limitations prior to initiating their study.

Future Directions

Multidisciplinary research in health care reveals that health technology is being implemented more frequently within an older adult population. As has been observed in the literature, it is the adoption of new technologies that will have the greatest impact on aging populations (Huston, 2013; Malwade et al., 2018) and the way that practitioners and researchers care for clinical and laboratory outcomes. It is expected that the pace of change will increase as new ATW models are developed (Glasgow, Colbert, Viator, & Cavanagh, 2018; Huston, 2013).

Scientific and technological innovations will have profound effects on the quality and longevity of human life (Lichtenberg, 2015). There is a unique opportunity to use culturally tailored, low-cost, high-impact technological innovations and strategies to promote general health and to advance health equity. Future research should be able to determine whether ATWs are valid when worn by clinical populations. Most of the validation studies conducted have involved young or middle-aged adults; therefore, the results may not be generalizable to older adults and individuals with disabilities. More efforts need to be employed toward developing a standardized measure for all activity trackers in order to allow meaningful comparison across ATWs.

Longitudinal research will face many challenges that are not yet addressed in short-term studies, such as durability, power consumption, comfort, and usability. To advance the use of wearable systems outside of the clinical setting, a systematic and integrated approach is needed to develop user-centric methods for a wide range of applications, such as sleep quality tracking, swallowable sensors, body sensor networks, smart clothing, and wearable cameras.

Finally, wearable technology is moving toward the integration of different devices, automated identification of daily routines, location, and social media interactions. More research is needed on the role of social media platforms, text messaging, and other technological solutions for conducting research with ATW devices, especially in populations that have inadequate education and access to these platforms. Researchers need to be mindful of how data privacy, confidentiality, and security practices affect their studies and subjects. There is an obligation to tell participants what kind of data the researcher or third parties (e.g., developers and data management companies) are collecting and how the data will be used.

Conclusion

Using objective measurement from ATWs involves practical and pragmatic challenges. The considerations presented in this paper will guide researchers regarding how to select a wearable device properly when collecting objective tracked data from older adults. Researchers should pay special attention to the technical abilities of their population and provide adequate resources in order to ensure that participants are comfortable when wearing and manipulating the device. In addition, an ethical protocol should be considered in order to ensure proper use of data and guarantee the privacy and control of collected information. Because each company presents its own algorithm, the comparability of different devices or software versions is limited. In order to facilitate the comparability and consistency of performance information on a component or system obtained from several devices under potentially differing research protocols, a full characterization of the devices and data analysis must be provided.

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