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Validity of a Multi-Sensor Armband for Estimating Energy Expenditure during Eighteen Different Activities

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Abstract

Purpose: To examine the validity of an armband physical activity monitor in estimating energy expenditure (EE) over a wide range of physical activities.

Methods: 68 participants (mean age=39.5 ± 13.0 yrs) performed one of three routines consisting of six activities (approximately 10 min each) while wearing the armband and the Cosmed K4b^2 portable metabolic unit. Routine 1 (n=25) involved indoor home-based activities, routine 2 (n=22) involved miscellaneous activities, and routine 3 (n=21) involved outdoor aerobic activities.

Results: Mean differences between the EE values in METs (criterion minus estimated) are as follows. Routine 1: watching TV (-0.1), reading (-0.1), laundry (0.1), ironing (-1.3), light cleaning (-0.4), and aerobics (0.4). Routine 2: driving (-0.6), Frisbee golf (-0.9), grass trimming (-0.5), gardening (-1.5), moving dirt with a wheelbarrow (-0.1), loading and unloading boxes (0.1); Routine 3: sidewalk walking (-1.0), track walking (-0.8), walking with a bag (-0.6), tennis (1.6), track running (2.2), and road running (2.1). The armband significantly overestimated EE during several light-to-moderate intensity activities such as driving (by 74%), ironing (by 70%), gardening (by 55%), light cleaning (by 15%), Frisbee golf (by 24%), and sidewalk walking (by 26%) ($P<0.05$). The arm band significantly underestimated high intensity activities including tennis (by 20%), and track or road running (by 20%).

Conclusion: Although the armband provided mean EE estimates within 16% of the criterion for nine of the 18 activities, predictions for several activities were significantly different from the criterion. The armband prediction algorithms could be refined to increase the accuracy of EE estimations.

Keywords: Energy expenditure; Indirect calorimetry; SW armband; Accelerometer

Abbreviations: PA: Physical Activity; EE: Energy Expenditure; DLW: Doubly Labeled Water; TDEE: Total Daily Energy Expenditure; PAEE: Physical Activity Energy Expenditure; REE: Resting Energy Expenditure; HR: Heart Rate; SW: Sense Wear; IC: Indirect Calorimetry

Introduction

Physical activity (PA) assessment, including the frequency, intensity, and duration of bouts, as well as the associated energy expenditure (EE), is challenging. Traditionally, survey instruments have been used to assess physical activity, but their accuracy is limited by individuals' ability to recall and report the characteristics of physical activity bouts performed [1]. Doubly labeled water (DLW) is considered by many to be the gold standard of assessing total daily energy expenditure (TDEE). Unfortunately, the DLW method is laboratory-based, cost-prohibitive, cannot give details regarding the frequency, intensity, and duration of bouts. Furthermore, in order to yield information on physical activity EE (PAEE), resting EE (REE) must be measured, or at least estimated.

Objective PA monitors including heart rate (HR) monitors, pedometers, and accelerometers are used in research, but they also have limitations. For example, HR predictions of EE are influenced by non-PA related factors like emotional stimuli, body temperature, fatigue, and caffeine. In addition, HR predictions of EE are less valid for light intensity PA than moderate-to-vigorous PA [2]. Pedometers are small and inexpensive, but provide little information on intensity. Conversely, accelerometers provide information on frequency, intensity, and duration of activity bouts [3-5]. However, neither pedometers nor accelerometers (using single regression equations) are valid for estimating EE across a wide range of activities [6,7].

Recently, devices that use multi-sensor approaches, such as the SenseWear (SW) armband (BodyMedia Inc., Pittsburg, PA), have been developed. The armband contains an accelerometer, in addition to physiological sensors that measure near body and ambient temperature, heat flux, and galvanic skin response to determine EE. Although the SW armband has been tested in several validation studies, newer generations of the armband and software have been released that contain modifications of algorithms to estimate EE. The results of previous validation studies may vary, due to the use of different software versions or armband models. The latest version of the SW armband is the SW Pro 3, which uses "pattern recognition" algorithms to convert the sensor signals to estimates of energy expenditure.

Previous studies of the SW armband validity have focused mainly on laboratory-based activities such as bicycling, treadmill running, or arm ergometry, and only a few have addressed common daily activities such as occupational tasks, housework, or over-ground walking [8-11]. Thus, the purpose of this study was to assess the validity of the SW Pro3 Armband and its software (version 6.1) in estimating EE in adults (18-65 years of age) across a wide range of activities, using indirect calorimetry (IC) as the criterion measure.

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Methods

Participants

68 participants (30 male, 38 female) from the University of Tennessee campus and surrounding Knoxville community volunteered to participate in the study. Informed consent was obtained from all participants and the Institutional Review Board of the University of Tennessee-Knoxville approved the study. Participants completed a brief health history questionnaire to determine their eligibility for inclusion in the study. Potential participants were excluded from the study if they reported any contraindications, such as medications for seizures or heart conditions, chest pain, or cardiovascular events. Participants had their height and weight measured in light clothing without shoes. Testing occurred on campus, at the participant's home, or at the investigator's home. All participant data were stored on a password-protected computer with confidential identification numbers used for all participants' files.

Protocol

Routines: Participants performed 1 of 3 routines, each of which contained six different physical activities.

Indoor Home-Based (Routine 1): Watching Television, Reading a Book, Doing Laundry, Ironing, Light Cleaning, Aerobics.

Miscellaneous (Routine 2): Driving a car, Frisbee Golf, Grass Trimming, Gardening, Moving Dirt with Wheelbarrow, Loading and Unloading 6.8 kg (15 lb) boxes.

Outdoor aerobic (Routine 3): Walking (self-paced on a sidewalk course), Walking (self-paced on a track), Walking with a 6.8 kg (15 lb) bag, Singles Tennis, Running (self-paced on a track), Running (self-paced on a sidewalk course).

For Routine 1, doing laundry included a combination of gathering clothes, loading the washing machine and/or drier, folding clothes, and putting clothes away. Ironing included setting up the ironing board, filling the iron with water, and the actual ironing of clothes. Light cleaning included wiping off countertops or other surfaces, dusting, straightening shelves, putting away small items, and other small tasks. Aerobics was done using the same 10-minute segment from a commercial exercise video, for all participants. The intermediate-level aerobics activities included both upper and lower body movements.

For Routine 2, participants drove their own vehicles through a residential neighborhood. Frisbee golf consisted of aiming for selected targets and then walking to retrieve the Frisbee and continuing this procedure until 10 minutes had elapsed. Grass trimming required the use of an electric string trimmer around gardens, bushes, and trees. Gardening was a combination of planting small bulbs and laying bricks at garden edges with a small spade tool. This activity did not include the carrying of these bricks any distance. Moving dirt with a wheelbarrow included use of a large shovel to load the wheelbarrow, walking with the loaded wheelbarrow, and emptying its contents. For the final activity, participants were asked to walk with a 6.8 kg box in their arms, set it down, pick it up, and carry it to another location.

For Routine 3, both walking and running activities were self-paced. Distance was recorded to determine speed for each subject in these activities. The sidewalk course was the same for all participants during self-paced walking and running. This course included sidewalks, crosswalks, and slightly hilly terrain. The 6.8 kg (15 lb) bag was an over-the-shoulder laptop computer case.

The number of participants varied for routine 1 (n=25), routine 2 (n=22), and routine 3 (n=21). No participant performed more than one routine. For all routines, each activity was performed for 10 minutes with a 3 to 5 minute break between activities. A 10-minute seated rest period was included before the start of each routine, to estimate the resting energy expenditure. During the rest period and each of the six physical activity bouts within a single routine, subjects wore the SW Pro-3 Armband (BodyMedia Inc.), the Cosmed K4b^2 (Cosmed, Rome, Italy), and three other activity monitors as part of a larger study. The weight of all the equipment (2.0 kg) was added to the subject's body mass prior to testing, and this value was used as the subject's total body mass.

Indirect calorimetry

The Cosmed K4b^2 portable metabolic system was used as the criterion measure in the present study. The Cosmed K4b^2 is a breath-by-breath gas analysis system consisting of a facemask, analyzer unit, and battery in a harness system. Before testing each subject, the unit was warmed up for around 30 to 40 minutes and then calibrated according to the manufacturer's instructions. Calibration of instrument included four parts: room air calibration, reference gas calibration (16.03% O_2 and 3.98% CO_2), turbine flow-meter calibration with a 3.0 L syringe (Hans-Rudolph), and CO_2/O_2 analyzer delay calibration with the participant wearing the face mask. The analyzer unit was programmed with each participant's data, the relative humidity, and the barometric pressure. For each participant, a disposable gel-seal was placed on the facemask to prevent air leaks, and the facemask was secured with a headpiece. Before testing began, the facemask was checked to see if it was airtight and devoid of any leaks. To reduce analyzer drift caused by extreme temperatures, the outdoor routines were not performed when the temperature was below 50°F (10°C) [12]. After testing, the Cosmed data were downloaded and analyzed by accompanying software (version 7.5a). After each testing session, the memory of the analyzing unit was cleared and its battery recharged.

SW Pro3 armband

The SW Pro3 Armband is a small (85.3 mm × 53.4 mm × 19.5 mm, wt=0.79 kg) water resistant device; it was worn on the back of the right upper arm secured by an adjustable Velcro strap. An accompanying watch was worn on the right wrist and displayed current measurements. The armband was placed on the arm 10 minutes before testing to allow sensors to adjust to skin temperature. The unit does not require calibration and is battery operated.

Before use, the armband was configured for the participant using a USB port and cable with the accompanying BodyMedia software (version 6.1). The participant's gender, birth date, height, weight, handedness, and smoking status were entered. During the configuration, the armband was synchronized with the computer clock, portable digital clock (used to record real time), and display watch. All start and stop times of activities were recorded both in real time as well as the display time on the Cosmed to allow minute-by-minute data comparison of the two methods. The SW collects data from different sensors on the armband including a biaxial accelerometer and sensors to monitor heat flux, skin temperature, near body temperature, and galvanic skin response and stores them in memory. After the routine was completed, armband data were downloaded and saved to a computer, and the armband's memory was cleared for the next use. Proprietary algorithms were used to analyze the raw data to yield output measures including time spent at different intensities (moderate, vigorous, and very vigorous), number of steps taken, and energy expenditure (in METS and kcal/min).

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Data and Statistical Analysis

The Cosmed K4b² collected breath-by-breath data, but after downloading, data were averaged over 1-minute intervals. The SW collected data in 1-minute periods. For the Cosmed K4b² data, the software converted absolute VO_2 values to relative values (adjusted for body mass) and then to MET values for each activity. For the SW data, proprietary algorithms and specific subject configuration produced average MET level data. All Cosmed and SW data were exported to Excel software. For both instruments, the MET values were averaged over the last five minutes of each activity (excluding the final minute). These averages for each activity were used in all statistical analyses.

Statistical analyses were performed using SPSS (version 15.0) for Windows (SPSS Inc, Chicago, IL, USA). Repeated measures ANOVAs (method x activity) were used to compare the Cosmed MET values and SW predicted MET values for each routine. If significant differences were detected, post-hoc paired samples t-tests were used to locate the differences. Significance was defined as $p<0.05$. To show individual variability in the difference scores (Cosmed minus SW), modified Bland-Altman plots were constructed showing the mean bias and 95% prediction intervals [13].

Results

Participant characteristics are presented in table 1. Complete data were obtained on all participants, with the exception of one participant on whom we did not obtain SW resting EE data, and one participant on whom we did not obtain SW or Cosmed data for singles tennis. Data from these two participants were excluded from the analyses.

For all three routines, analyses showed a significant method x activity interaction ($p<0.001$). *Post-hoc* with an adjusted alpha-level of 0.01 to control for Type I error showed that the SW significantly overestimated EE during ironing and light cleaning in Routine 1 ($p<0.01$) (Table 2). For Routine 2, analyses revealed that the SW significantly overestimated EE during driving, Frisbee golf, and gardening ($p<0.01$) (Table 3). For Routine 3, analyses revealed that the SW significantly underestimated tennis, track run, and road run while and overestimated road walk ($p<0.01$) (Table 4). Figure 1 displays the mean MET values by both methods for all physical activities, in order of increasing intensity.

Modified Bland-Altman plots were constructed to show the difference between the two methods in average EE estimations (Figure 2). Figures 2A-2C show differences for the three routines individually, and figure 2D shows all the data combined. Combining all routines in figure 2D, it was evident that the SW underestimated EE to a greater degree at higher intensities, and there was a significant correlation between the difference scores and activity intensity ($r=0.70$, $p<0.01$).

Discussion

The goal of this study was to examine the validity of the SW Pro3 armband for estimating EE in adults, during field-based activities. This

	Males (n=30) Mean (SD)	Females (n=38) Mean (SD)	Combined (n=68) Mean (SD)
Age (yr)	35.0 (13.2)	42.4 (11.7)	39.5 (13.0)
Weight (kg)	84.9 (18.2)	75.4 (18.1)	79.6 (18.6)
Height (m)	1.79 (0.09)	1.67 (0.07)	1.72 (.10)
Body Mass Index (kg/m²)	26.5 (4.4)	27.0 (6.4)	26.8 (5.6)
Walking Speed (road) (m/min)	87.3 (9.1)	93.8 (12.4)	89.5 (10.5)
Walking Speed (track) (m/min)	89.0 (9.4)	96.4(14.3)	91.5 (11.5)
Walking Speed (with bag) (m/min)	85.8 (10.2)	85.6 (10.3)	85.8 (10.0)
Running Speed (track) (m/min)	178.3 (29.0)	136.1 (37.9)	164.2 (37.3)
Running Speed (road) (m/min)	177.1 (16.3)	132.4 (36.7)	162.2 (32.3)

*N=21 for all walking and running speeds (14 males, 7 females)

Table 1: Characteristics of study participants (n=68).

Activities	Cosmed METs Mean (SD)	SW METS Mean (SD)	Cosmed –SW METs Mean (SD)	95% CI Mean Diff.
Watching TV	0.8 (0.2)	0.9 (0.1)	-0.1 (0.2)	-0.2 to 0
Reading a book	0.8 (0.3)	1.0 (0.3)	-0.1 (0.3)	-0.3 to 0
Doing laundry	2.7 (0.8)	2.6 (0.6)	0.1 (0.7)	-0.2 to 0.4
Ironing	1.9 (0.4)	3.2 (1.0)	-1.3* (0.9)	-1.0 to -1.7
Light cleaning	2.8 (0.6)	3.2 (0.7)	-0.4** (0.6)	-0.7 to -0.2
Aerobics	6.0 (1.3)	5.6 (1.1)	0.4 (1.3)	-0.1 to 1.0
Rest	0.8 (0.3)	1.0 (0.2)	-0.1 (0.4)	-0.3 to 0

*denotes significant difference from zero, p<0.001
**denotes significant difference from zero, p<0.01

Table 2: Cosmed EE measures and Sensewear (SW) EE estimates in Routine 1.

Activities	Cosmed METs Mean (SD)	SW METs Mean (SD)	Cosmed –SW METs Mean (SD)	95% CI Mean Diff.
Driving a car	0.8 (0.2)	1.3 (0.5)	-0.6* (0.5)	-0.8 to -0.3
Frisbee golf	3.8 (0.9)	4.7 (0.7)	-0.9* (1.0)	-1.4 to -0.4
Trimming	2.8 (0.7)	3.3 (1.1)	-0.5 (0.9)	-0.9 to -0.1
Gardening	2.7 (0.7)	4.1 (1.2)	-1.5* (1.1)	-2.0 to -1.0
Moving dirt with a wheelbarrow	4.1 (0.9)	4.3 (0.7)	-0.1 (0.8)	-0.5 to 0.2
Loading and unloading 6.8-kg boxes	4.1 (0.5)	4.0 (0.6)	0.1 (0.8)	-0.2 to 0.5
Rest	0.5 (0.1)	1.0 (0.3)	-0.5* (0.3)	-0.6 to -0.4

*denotes significant difference from zero, p ≤ 0.001

Table 3: Cosmed EE measures and SenseWear (SW) EE estimates for Routine 2.

Activities	Cosmed METs Mean (SD)	SW METs Mean (SD)	Cosmed –SW METs Mean (SD)	95% CI Mean Diff.
Sidewalk walking	4.0 (0.8)	5.1 (0.7)	-1.1* (0.6)	-0.8 to -1.3
Track Walking	4.2 (1.3)	5.0 (0.8)	-0.8 (1.3)	-0.2 to -1.3
Walking with 6.8-kg bag	4.7 (1.1)	5.3 (0.9)	-0.6 (1.1)	-0.1 to -1.1
Singles tennis	8.3 (1.6)	6.7 (1.1)	1.6* (1.4)	0.9 to 2.2
Track Running	10.7 (2.5)	8.6 (1.1)	2.2* (2.4)	1.1 to 3.3
Road Running	10.2 (2.4)	8.1 (0.9)	2.1* (1.8)	1.2 to 2.9
Rest	0.9 (0.3)	1.3 (0.4)	-0.5* (0.4)	-0.3 to -0.7

* denotes significant difference from zero, p<0.001

Table 4: Cosmed EE measures and Sensewear (SW) EE estimates for Routine 3.

is the first study to test this armband model and its accompanying software (version 6.1) with these types of activities, in a group with a wide age range. Of the eighteen activities tested, the SW was found to provide valid estimates of EE in nine activities: watching TV, reading, doing laundry, aerobics, moving dirt with a wheelbarrow, loading and unloading 6.8 kg boxes, walking (track), and walking with a 6.8 kg laptop computer bag. Because the SW is promoted as a useful tool to assess EE in daily life, the errors seen in several other activities are a cause for concern [14]. Though our ability to make comparisons to previous studies is limited due to differences in armband models or software versions, our results are generally consistent with previous studies.

To our knowledge, the only other study to test the same SW armband model and software version is that of Dwyer et al. [15]. Although the primary purpose of their study was to compare the SW EE estimates in cystic fibrosis patients versus healthy controls, the researchers also examined the validity of the SW to estimate EE (compared to IC) during treadmill walking. Using a graded treadmill walking protocol, they found that the SW EE underestimations increased at higher intensities, similar to our results.

The present study was also compared to those that have used previous software versions. The most similar studies to ours in terms of methodology are those by Arvidsson et al. [16,17] that investigated the validity of the SW in children using the SW Pro2 and software version 5.1. The children performed 14 physical activities such as basketball, jumping on a trampoline, playing games on a cell phone, and walking and running at different speeds. Results showed that the SW significantly underestimated EE in most activities, with the degree of underestimation increasing as the intensity increased [16]. Similarly, we noted instances of both over- and under-estimation, and we also observed that the SW underestimated more at higher intensities. For all activities, their study found a positive correlation of r=0.58 (p<0.001) [16] between difference scores of METS and the intensity of the activities, whereas our overall correlation was r=0.70 (p<0.01).

Our study used a sidewalk course for walking and running, and the over- and under-estimations by the SW were seen with intermittent, as well as continuous, walking and running. The sidewalk course included crosswalks, hills, and pedestrian traffic, yet the results showed the same magnitude of over- and under-estimations as on the track. Although previous authors have suggested these inaccuracies were due to the use of adult-specific algorithms in children, our results indicate that the errors persist in an adult population and might be due to the type of activity [16]. In one sense, it is encouraging that the SW remained consistent in its estimates, even if under- and over-estimations exist, because it would seem that adjustments to the algorithms could improve the estimation of EE in walking and running.

The results of our study are also similar to those seen in a study by Galvani [8] that used the SW Pro2 armband. Although their study examined only 8 women, the general categories of activities (occupation, housework, recreation, and conditioning) were similar to our study. For instance, light cleaning could be classified as "housework", and carrying a notebook computer bag to "occupation". As with many of our activities, their study noted significant (p<0.001) differences between the SW and Cosmed for all PA categories [8]. However, no

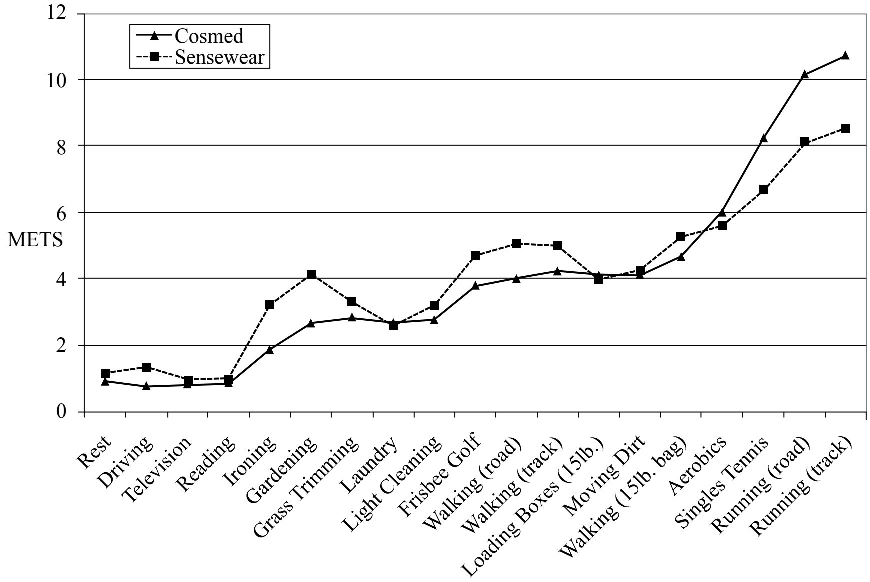

Figure 1: Mean of MET Values by both Methods for all Physical Activities.

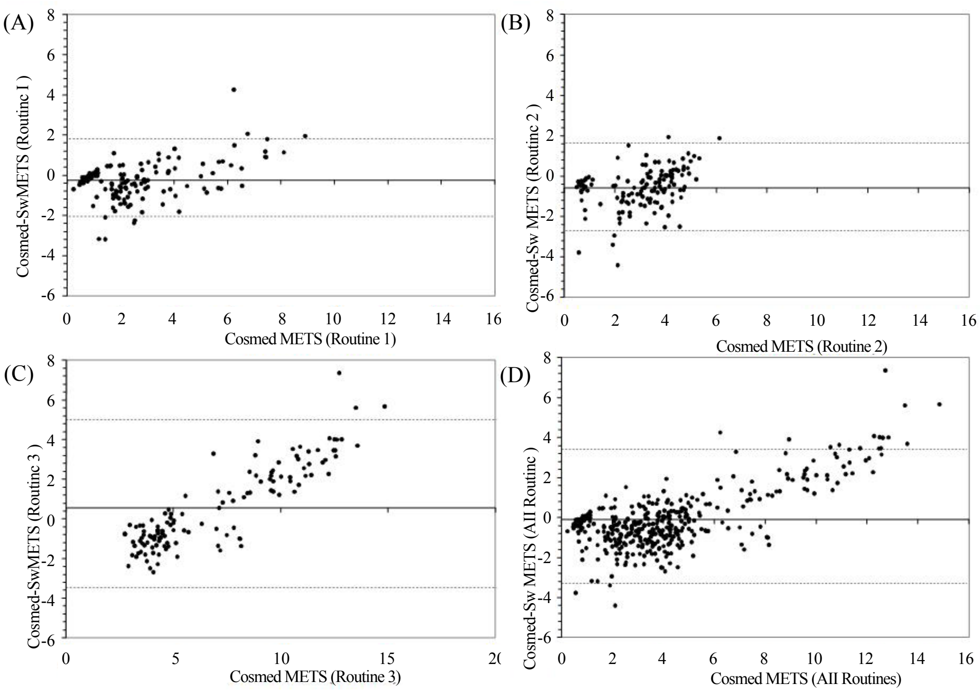

Figure 2: (A-D) Bland-Altman plots displaying differences (Cosmed-SenseWear METs) for rates of energy expenditure. Solid lines represent the mean difference of the observations and dashed lines mark the 95% confidence interval for observations.

statistical details regarding specific activities were provided. A positive correlation between error scores and intensity was noted, with the SW tending to underestimate more at moderate and vigorous intensities. For all activities, the 95% CI of the error scores in their study was -5.07 to 4.85 METS whereas our study showed a smaller 95% CI of -2.8 to 3.0 METS. Overall, our results confirmed findings from previous studies [8,15,17,18] that found a greater underestimation of EE as activity intensity increased.

Continuous updating of the proprietary algorithms has occurred since the introduction of the SW Armband. The development of new algorithms is mentioned in several SW studies including those of Fruin and Walberg-Rankin [19], Jakicic et al. [9] and Cole et al. [18]. Fruin and Walkberg-Rankin tested the first armband model and the accompanying introductory software version. Young adults were required to perform 40-minute of stationary cycling at 60% VO_2 peak, and a 30-minute treadmill test at three intensities: 80.5 m/min (0%

grade), 107.3 m/min (0% grade), and 107.3 m/min (5% grade). After initial analysis with accompanying software and its general algorithms, the data were sent to BodyMedia, Inc. with contextual information about what activities were being performed, for a second analysis. The results indicated no significant differences in EE estimates between SW and IC during cycle ergometry. However, the SW overestimated EE during walking at 0% grade by 14-38% ($p<0.02$), and underestimated EE during walking at 5% grade by 22% EE ($p<0.002$). The SW provided greater EE estimates with increased treadmill speeds, but not with increased percent grades.

In a laboratory-based study by Jakicic et al. [9], young adults performed 20-30 min bouts of increasing intensity on four exercise modes: walking, cycling, stepping, and arm ergometry. The first analysis of data used general algorithms of software version 3.2 and showed the SW significantly ($p<0.001$) underestimated EE in walking, cycling, and stepping and significantly ($p<0.001$) overestimated EE during arm ergometry. After sending data to BodyMedia, Inc. with contextual information such as exercise mode, exercise-specific algorithms were used to perform a second analysis of data. The exercise-specific algorithms showed no significant differences between SW and IC EE estimates in any of the tested activities.

The study of Cole et al. [18] prompted additional software modifications. Unlike the healthy subjects used in prior studies, this study used cardiac patients to test the SW and three software versions. Participants performed 8-min bouts of treadmill walking, recumbent stepping, arm cranking, and rowing with individualized intensities. Using software version 2.2, the SW significantly ($p<0.01$) underestimated EE during treadmill and rowing activities, but did not result in significant between-method differences during the other two activities. Using software version 4.0, no significant differences were found for EE estimates by the SW and IC for any activity. However, significant biases for stepping and arm ergometry persisted in this software version. The SW showed a clear tendency to underestimate EE in these two activities. For rowing and treadmill exercise, between-method variance increased with increasing EE. Given the unique population, BodyMedia developed cardiac-specific algorithms based on a portion of this data, and this software version was tested on the remaining participants' data. Using this software, SW accuracy was further improved with no significant differences for EE estimates in any activity. The between-method variance was reduced compared to previous software versions. These results and those of other studies indicate the improvements made by software modifications [9,18,19]. However, the multiple versions of software highlight the difficulty in directly comparing results among several studies.

The present study has both strengths and limitations. One of its strengths lies in the types of activities selected. Our activities focused on those that are common in daily life as opposed to those that are confined to a laboratory. Our finding that common lifestyle activities like ironing and light cleaning were not accurately measured indicates that more field-based research and software updates are needed. In addition, other studies used clinical populations such as obese individuals or cardiac patients [18,20,21], our study used healthy individuals with a broad age range, so the results should be broadly applicable. The current study also has limitations. The findings are limited to adults only, and we did not obtain data that would allow us to test the accuracy of algorithms used to predict EE in youth. In addition, since none of the subjects performed all 12 activities, our ability to compare results between routines was limited. Future studies might consider using all subjects for all activities to circumvent this problem.

Given future modifications of SW algorithms and improved accuracy, the SW could be useful for a variety of applications. The device is simple to use and unobtrusive, which enhances its feasibility for clinical interventions. For example, a recent study by Polzien et al. [22] highlighted the application of the SW in a weight loss study. In that study, continuous use of the SW armband and software to track EE and record dietary intake, along with standard behavioral counseling, produced significantly greater weight loss ($p<0.05$) than counseling alone. Regardless of any inaccuracies that may have occurred in estimating EE with the SW, weight loss was clearly improved by the SW concept. These results bode well for future weight loss interventions, and suggest that the SW may be useful as a motivational tool.

Although not the focus of our study, the SW can be used to estimate an individual's TDEE. Traditionally, dietitians have calculated TDEE by first estimating resting metabolic rate, then adjusting it by a certain factor based on self-reported physical activity levels [23]. In contrast, the SW uses a multi-sensor approach, individual characteristics, and other information to calculate TDEE. Although our results indicate that the SW is not valid for specific physical activities, the TDEE estimates are still likely to be an improvement over standard prediction equations and self-report. For instance, Johannsen et al. tested two versions of the device: the SW Pro 3 armband and SW Mini against the criterion DLW method over 14 consecutive days [24]. The mean value for the SW Pro 3 armband was within 112 kcal/day of the criterion, and the mean value for the SW Mini was within 22 kcal/day of the criterion. The mean (+ SD) absolute percent errors were similar for the two monitors (SWA: 8.1 + 6.8% error, Mini: 8.3 + 6.5% error).

Conclusion

This study assessed the validity of the SW in estimating energy expenditure over a wide range of activities. Compared to IC, significant differences in average MET levels by the SW were found for several activities. There was a tendency for EE to be significantly overestimated at light-to-moderate intensities, and underestimated at higher intensities. Future studies are needed to confirm our results and to determine whether possible modifications to proprietary algorithms will improve SW accuracy in field-based activities.

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