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I am submitting herewith a thesis written by Paige Dudley entitled “The Validation of the SenseWear Pro Armband to Assess Energy Expenditure During Field-Based Activities.” I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master’s of Science, with a major in Exercise Science.

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The Validation of the SenseWear Pro Armband to Assess Energy Expenditure During Field-Based Activities

A Thesis Presented for
the Master of Science
Degree
The University of Tennessee, Knoxville

Paige Dudley
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Dedication

I would like to dedicate this thesis to my parents. To my mom, thank you for instilling a love of learning at a young age. No parent could give her child a better gift. Without this internal motivation, I would not have made it this far. To my dad, thank you for reminding me that my best is all that is required. May you look down from heaven and smile.

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ABSTRACT

Purpose: To examine the validity of the SenseWear Pro3 armband in estimating energy expenditure during a wide range of field-based activities.

Methods: 41 participants (mean age = 34.5 $\pm$ 11.7 yrs.) performed one of two routines with 6 activities each, Routine 1 (Outdoor Aerobic Activities) or Routine 2 (Indoor Home-based Activities), while wearing the SenseWear Pro3 (SW) and the Cosmed K4b2 portable metabolic unit. Routine 1 (n=16) included road walking, track walking, walking with 6.8 kg (15 lb.) bag, singles tennis, track running, and road running. Routine 2 (n=25) included TV watching, reading, doing laundry, ironing, light cleaning, and aerobics. Each activity was done for approximately 10 min with a 3-5 min break between activities with resting measurements taken for all participants before routines.

Results: The mean differences (Cosmed-SW) in average MET values for Routine 1 were: road walking (-1.0, $p<0.001$), track walking (-0.9, $p<0.001$), walking with bag (-0.7, $p<0.01$), tennis (1.7, $p<0.001$), track running (2.7, $p<0.001$), road running (2.7, $p<0.001$). For Routine 2, mean differences were: watching TV (-0.1, $p>0.05$), reading (-0.1, $p>0.1$), laundry (0.1, $p>0.1$), ironing (-1.3, $p<0.001$), light cleaning (-0.4, $p<0.01$), and aerobics (0.4, $p>0.1$).

Discussion: Compared to indirect calorimetry, significant differences in average MET levels by the SW Pro3 armband were found for several activities with a trend for EE underestimation at higher intensities ($r=0.72$, $p<0.01$). The SW significantly overestimated MET levels of ironing, light cleaning, and all three walking variations, and it significantly underestimated tennis and both running bouts. Algorithms need to be refined for more accurate EE estimations at high intensities and in different field-based activities.

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CHAPTER I

INTRODUCTION

Physical activity has been shown to confer numerous benefits such as decreased risks of cardiovascular disease, type 2 diabetes, obesity, osteoporosis, and premature morbidity and mortality (34, 51, 71, 72). Despite these known benefits, 2005 CDC results from the 1994-2004 Behavioral Risk Factor Surveillance System (BRFSS) indicated that 23.7% of U.S. adults participate in no leisure time physical activity (11). Furthermore, only 49.7% of men and 46.7% of women reported engaging in regular physical activity, defined as meeting the American College of Sports Medicine, American Heart Association and Healthy People 2010 recommendations (12). These current recommendations suggest that healthy adults aged 18 to 65 years should perform “moderate intensity aerobic (endurance) physical activity for a minimum of 30 min on five days each week or vigorous intensity aerobic physical activity for a minimum of 20 min on three days each week” (28). In order to be counted towards the daily recommendation, activities should be performed in bouts of ten minutes or longer. Light intensity activities of daily living such as grocery shopping do not fulfill the daily recommendation but are encouraged. However, normal daily activities of moderate or vigorous intensity which are at least 10 min in duration may be included as part of the recommended amount.

In order to determine the efficacy of these recommendations, objective measures of daily physical activity, including the intensity of such activity, and the associated energy expenditure (EE) are needed. One method, doubly labeled water (DLW), is considered by many to be the gold standard of EE assessment (57, 58, 60). This method is based on the principle that the labeled hydrogen will leave the body as water and labeled oxygen will be eliminated as water and carbon dioxide. By determining the amount of carbon dioxide produced, the researcher may calculate the amount of oxygen consumed and thus the total EE over a certain time period – generally a few days or a week. Unfortunately, this method is lab-based, cost-prohibitive, and cannot give details regarding activity intensity, duration, or activity-specific energy expenditure. When using DLW, physical activity energy expenditure (PAEE) must be calculated, rather than directly measured, by taking the difference between total energy expenditure and resting metabolic rate (60).

In an attempt to overcome these limitations, indirect calorimetry (IC) instruments such as metabolic carts or portable metabolic units are frequently used to measure EE. IC determines energy expenditure based on a specific volume of oxygen being consumed for every kilocalorie burned. Some IC instruments such as the SensorMedics Vmax or Parvomedics system are confined to the lab, while others such as the Oxycon Mobile or Cosmed K4b^2 are conducive to field-based research. Several studies have validated the Cosmed K4b^2 and its ability to accurately assess the energy expenditure of activities both in the lab and during lifestyle activities (22, 36, 44, 50). These IC methods are

capable of measuring both duration and intensity of PA as well as overall PAEE. However, in general, these instruments are bulky, require extensive calibration, and are best suited for research on EE of various activities but not for prolonged use in the field. For these reasons, other more portable and user-friendly instruments are frequently tested against criterion methods (e.g. DLW or IC) to validate their estimations of EE in different contexts.

Abundant research has been conducted on objective PA monitors including heart rate (HR) monitors, pedometers, accelerometers, and multi-sensor models but, as of yet, no single instrument has been determined valid in all activities or with all populations. Each instrument has limitations and circumstances where its validity is compromised. For instance, HR monitors determine energy expenditure given that increased heart rate is linearly related to activity EE (25, 41, 65, 66). Yet EE predictions may be skewed when HR is elevated due to emotional stimuli, body temperature, fatigue, caffeine, and other substances rather than by PA (13). HR response is also largely influenced by age and fitness level. In addition, HR predictions of EE are less valid at lower levels of PA, as are common in daily activities like light cleaning or watching television (41). To acknowledge these limitations, researchers often use pedometers or accelerometers. Pedometers are small and inexpensive, but data collection is generally limited to step counts and gives little information regarding intensity of PA. Also, previous studies have shown pedometers are less valid at lower walking speeds and in obese individuals (6, 20, 21, 37, 70). In contrast, accelerometers can give information on frequency, intensity, and duration of

activity. Accelerometers rely on regression equations to convert raw activity counts into estimations of metabolic equivalents (METS) or kilocalories used. These equations are developed using a grouping of activities and must be validated when other activities are used (13, 19, 43). Neither pedometers nor accelerometers have proven valid in certain activities such as cycling, weightlifting, and primarily upper-body activities, and they may not be used in water-based activities such as swimming.

Because both pedometers and accelerometers rely on a single sensor to collect data for EE estimation, recent research has focused on new methods with a multi-sensor approach, such as the IDEEA (Intelligent Device for Estimating Energy Expenditure and Activity) monitor and SenseWear Armband. The IDEEA monitor uses accelerometry sensors at five different body sites to determine the type of activity as well as speed, distance, and power output, and it has been validated against IC (76, 80, 81). The SenseWear Armband uses an accelerometry sensor in addition to physiological sensors to measure near body and ambient temperature, heat flux, and galvanic skin response to determine EE. Though the SenseWear has been tested in several validation studies, a new generation of armband and software has recently been released with modifications to algorithms used for EE estimation. Results from previous studies are varied and may be attributed to different software versions or armband models. Prior studies have also concentrated mainly on lab-based activities such as cycling, treadmill running, or arm ergometry, and few have addressed common daily activities such as reading a book, housework, or overground

walking (27, 33, 35, 74). In a lab-based study by Jakicic et al. (33), no significant differences were observed in EE estimates by the SenseWear for treadmill, cycle ergometry, and arm ergometry exercises. In contrast, only one known study has compared SenseWear EE estimates to the Cosmed K4b^2 in daily lifestyle activities (27). Results of this small study showed significant ($p<0.001$) differences in PAEE estimates between methods. A recent and thorough study of children by Arvidsson et al. (4) addressed a broad range of 14 common activities, such as walking or playing cell phone games. Authors found that, compared to IC, the SenseWear significantly underestimated EE in most activities. This underestimation became greater as PA intensity increased (4). In addition to the equivocal nature of existing SenseWear studies, validation of the SenseWear is further limited as previous studies have used small, narrow samples such as college students (33), obese individuals (16, 49), COPD patients (53, 69), and children (3, 4). Consequently, the purpose of this study is to assess the validity of the SenseWear Pro3 Armband and accompanying software (version 6.1) in estimating EE of a heterogeneous group across a wide range of activities using indirect calorimetry as the criterion measure.

CHAPTER II

LITERATURE REVIEW

Given the known benefits of physical activity, it is important that researchers are able to quantify frequency, intensity, and duration of daily activities. From the 1982 study by Schoeller validating the doubly labeled water method to current studies of the SenseWear Pro Armband, there has been an overwhelming amount of research investigating energy expenditure during rest and activity (4, 60). The breadth of this research continues to expand from strict laboratory studies to novel field-based approaches. The validation of instruments which monitor physical activity and associated energy expenditure is paramount in many studies. In order to refine physical activity recommendations, such as those published by the Centers for Disease Control and American Heart Association or the Surgeon's General, accurate instruments must be available for research. Abundant studies exist on the most common methods for energy expenditure assessment such as doubly labeled water, indirect calorimetry, heart rate monitors, pedometers, and accelerometers but research is limited on newer devices such as the SenseWear Pro Armband.

Doubly Labeled Water

The method often referred to as the "gold standard" for measuring energy expenditure is the doubly labeled water (DLW) method developed by Nathan

Lifson (57, 58, 60, 61). First validated in humans in 1982, DLW has since been used in almost 600 studies. To use this method, subjects ingest isotope labeled water containing deuterium (H2) and oxygen-18 molecules. As this labeled water disperses throughout the body, the deuterium molecules will leave the body as water in urine, feces, and sweat whereas the oxygen will be eliminated as water and in carbon dioxide. After a subject ingests the DLW, he/she resumes normal activities and returns to the lab 3 days to 3 weeks later to provide a urine sample to determine the amount of isotope remaining in the body (59). By measuring the difference in elimination rates of the hydrogen and oxygen, the carbon dioxide production is determined with a mathematical model. A variety of equations have been tested but the equation which accounts for dilution space is the most frequently used (57). However, no consensus has been reached on the best mathematical model to use. Carbon dioxide production is then converted to energy expenditure by using heat production which is determined by reported energy intake and the calculation of the food quotient. Because of this calculation, an accurate dietary record is needed during DLW measurement (62). Only a measure of Total Energy Expenditure (TEE) is directly obtained from the DLW method. A review of validation studies by Schoeller found that the DLW method is accurate for estimating TEE between 2-8% with the range of variability due to loading dose, length of monitoring period, and the number of urine samples taken (57). These studies included a wide variety of study populations with respect to age, diet, ethnicity, health status and daily physical activity patterns. DLW is most accurate for TEE but is limited for prediction of physical

activity energy expenditure (PAEE). Rather than being directly measured during activity, PAEE is determined by taking the difference between total energy expenditure (TEE) and resting metabolic rate, with or without inclusion of the thermic effect of meals (58). If an estimation error exists in TEE or RMR, it is transferred to the PAEE estimate (58). In addition, DLW does not produce information on duration, patterns, or intensity of activities throughout the monitoring period. Though daily urine samples can be made, these do not allow EE estimations for specific activities or time periods within the day. Overall, the DLW method is well accepted for TEE estimations. However, due to the high cost of O-18 labeled water, the lab-based nature of this method, and the limitations of its measurements, it is not practical for large studies or those focused on physical activity energy expenditure. Consequently, researchers have validated other methods for these uses such as indirect calorimetry.

Indirect Calorimetry

In order to more accurately assess PAEE, indirect calorimetry (IC) has been validated whereby oxygen consumption and carbon dioxide production are directly measured to calculate energy expenditure (EE). Common IC methods include metabolic carts such as the SensorMedics, and portable metabolic units such as the Cosmed K4b^2 unit (Rome, Italy). Portable metabolic units are particularly useful for EE estimations in field-based studies as they place little restriction on movement and can quantify intensity, duration, and frequency of

activities. One reliable method that provides accurate EE predictions against different criterion methods is the Cosmed K4b^2 (23). The Cosmed K4b^2 is an updated model from the previously validated Cosmed K2 and Cosmed K4 (29). The Cosmed K4b^2 system consists of a face mask secured by a headpiece, an analyzer unit, and a rechargeable battery placed in a harness. Once calibrated, the Cosmed analyzer unit measures expired gases breath-by-breath via a Permapure tube connected to the facemask turbine flowmeter. The oxygen analyzer has a reported range of 7-24% with an accuracy to 0.02%, and the infra-red carbon dioxide analyzer, not present in previous models, has a range of 0-8% with an accuracy of 0.01% (52). The bidirectional digital turbine and opto-electric reader of the flowmeter have a linear response in the ventilation range of 0-300L/min with an accuracy of $\pm$ 2% (52). Measured values include minute ventilation (VE), FEO_2, and $FECO_2$. Oxygen consumption (VO_2), Carbon dioxide production (VCO_2), and respiratory exchange ratio (RER) are calculated values based on Haldane transformation using FIO_2 (20.93%), $FICO_2$ (0.03%), FEO_2, $FECO_2$, Vi (volume of inspired air), and VE. The analyzer unit stores data during testing which is then downloaded to a computer for analysis with proprietary Cosmed software including algorithms to calculate energy expenditure.

In a study by McLaughlin et al. (44), the Cosmed K4b^2 was validated against the Douglas Bag (DB) as a criterion method during cycle ergometry tests of varying intensities (50, 100, 150, 200, 250W) performed by young male subjects. In these 5 minute stages, minute averages of the Cosmed values were used. No significant differences were found for VO_2 measures between

methods at rest or at 250W. However, Cosmed values were significantly higher than DB at 50, 100, 150, and 200W ($p<0.05$). Yet, authors emphasized that the magnitudes of the differences were small, all less than 0.1L/min, and would be physiologically insignificant. For VCO_2, no significant differences were found between methods from rest to 150W, but the Cosmed was significantly ($p<0.05$) lower than the DB at 200W and 250W. Because of the inaccuracies in VO_2 and VCO_2, R values were significantly different at every workload. Most importantly, despite the aforementioned differences, the mean exercise energy expenditures calculated by both methods were not significantly different (11.0kcal/min for Cosmed versus 10.8kcal/min for DB). A separate study by Parr et al. (50), also found the Cosmed accurately measured VO_2, VCO_2, and RER at lower intensities, up to 200W when compared to the DB method. Both studies concluded that the Cosmed was accurate for EE estimation in separate bouts of varying intensities of physical activity, where the total EE as given by DLW would not be meaningful and where the DB technique would impair bodily movement due to its bulk (44, 50).

Similar to the previous study, a study by McNaughton et al. (45) also supports the validity of the Cosmed to assess energy expenditure. Using a mass spectrometer to measure the molecular composition of expired air, subjects completed submaximal and maximal cycle ergometry tests. VO_2 and VCO_2 values by the Cosmed were significantly higher than mass spectrometer values at 250W ($p<0.05$ and $p<0.002$, respectively) and at 300W ($p<0.002$; $p<0.005$) but did not differ significantly at lower workloads. Despite the tendency throughout

all workloads for the Cosmed to overestimate, the differences between VO_2 and VCO_2 levels remained relatively constant to create Cosmed RER values that did not differ from those of the mass spectrometer. Despite some variation in methods' estimations, authors concluded that either system is appropriate to use for EE estimations across a wide range of exercise intensities (45). Two additional studies support the use of the Cosmed in maximal cycle ergometry (22, 36). In both studies, the Cosmed was compared to laboratory metabolic carts and no significant differences ($p<0.05$) were found between VO_2 estimations by the two methods.

Unlike the previous cycling studies, one study examined the Cosmed during treadmill running at various speeds (8, 11, and 14 km/hr) (52). Estimations by the Cosmed of FEO_2, $FECO_2$, VO_2, VCO_2, and VE were compared to measurements by a Servomex oxygen analyzer, Datex CO_2 monitor, and Morgan ventilation monitor. Primary findings indicated significant differences between the two methods for FEO_2, $FECO_2$, and VE ($p<0.05$). However, strong correlation ($r = 0.925$-0.982) of these measures showed a consistency of Cosmed error. The Cosmed overestimated VO_2 by 8% and underestimated VCO_2 by 3.2%, resulting in an underestimation of RER by 0.10 (12.0%) (52). Due to the pattern of estimation errors by the Cosmed, it was suggested that an adequate regression analysis could be used to improve the accuracy of VO_2 calculations and resulting EE estimations.

The difficulty in comparing Cosmed validation studies is their use of varied criterion methods (metabolic cart, Douglas bag, and mass spectrometer).

Despite some inconsistencies, the Cosmed K4b^2 is one of the most well-validated, portable IC methods. Validation of this portable IC method allows its use as a criterion method against activity monitors. Objective activity monitors such as heart rate monitors, pedometers, accelerometers, and, more recently, multi-sensor models are frequently used to estimate energy expenditure and other variables of physical activity given their lack of interference to normal movement. Validation studies cover an expansive range of activities both in laboratory and in real-world settings.

Heart Rate Monitors

One of the most common methods to assess EE is heart rate (HR) monitoring. HR monitors are inexpensive, non-invasive, easy to use, and more conducive to testing lifestyle activities than IC, and they give information about activity patterns that DLW does not. HR monitors have been repeatedly validated against ECG monitors to assess HR. For example, one study by Treiber et al. (68), validated HR monitors against ECG for simple HR values in lab and field tests of children. Cycle, treadmill and various outdoor tests showed a very high correlation between methods (r = 0.94-0.99, SEE: 1.1-3.7 bpm) which is supported by additional studies in adults (8, 13, 40). Although originally validated against ECG monitors, HR monitors have since been used for EE estimates against indirect calorimetry (40, 68). EE estimates are based on the positive linear HR-VO2 relationship (R^2 = 0.5) during aerobic exercise, or at levels above basal EE and

below maximal output (41, 63, 65, 66). Once the VO_2 corresponding to a HR is determined, heat production and consequently EE can be calculated through indirect calorimetry calculations. However, this relationship varies by individual with fluctuations due to age, fitness level, activity mode, emotional stimuli, posture, fatigue, and stimulants like caffeine and ephedrine (31, 41, 66). Also, deviation from this linear relationship has been shown at low levels of activity (47, 63, 78).

In order to increase accuracy of EE predictions, regression equations are developed for individuals. One such regression equation is with the FLEX-HR method. For this method, a HR-VO_2 calibration curve is developed for the individual and then a certain HR (FLEX-HR) is identified which discriminates between resting and exercise HR (41). The calibration curve is based on the individual's HR-VO_2 responses when lying down, sitting, standing, and during cycling and stepping exercises. FLEX-HR is defined as the mean of the maximum HR when standing and the minimum HR when exercising. Calibration curves allow a certain energy expenditure to be assigned for heart rates above FLEX-HR. Below FLEX-HR is considered resting metabolic rate (RMR), and, during sleep, basal metabolic rate (BMR) is used to estimate EE. Calibration curves and their regression equations typically account for age, gender, and fitness level of the individual (5, 25, 65). A validation study by Livingstone et al. (41), assessed free-living EE using the FLEX-HR method against DLW. Average FLEX-HR was 97 $\pm$ 8 bpm. EE above and below FLEX-HR was summed for 24-hours to give TEE estimates. Results showed mean HR-TEE gave similar

estimates to DLW-TEE over several days, overestimating 2.0 ± 17.9% but not significantly. However, individual errors were high and ranged from -22.2% to +52.1% showing this method was more accurate for group, rather than for individual estimates. Individual errors in TEE prediction may be due to estimation, rather than direct measurement, of BMR during sleep. Also, any errors in RMR measurement explain the imprecision of the FLEX-HR method at low activity levels, as in sedentary individuals, or in resting conditions (41, 63). At very high levels of activity, where HR is not close to or below FLEX-HR, the prediction of EE is more dependent on the accuracy of the FLEX-HR or particular regression equation used. Using whole body indirect calorimetry as the criterion method, another study also assessed the validity of the HR monitor and the FLEX-HR method to measure TDEE and PAEE (63). During a 22-hour monitoring period with four 30-minute cycling protocols of varying intensity, no significant differences were found between HR and IC estimations of TDEE and PAEE in any of the sex or exercise protocols. The maximum error of TDEE was -15% to +20% (63).

Whereas the FLEX-HR method develops calibration curves for individuals, other methods such as the Polar Heart Rate monitor use raw HR data and proprietary algorithms to determine exercise EE (17). Stored data from the HR monitor may be analyzed by accompanying software to calculate HR 1-minute fluctuations and then EE (40, 68). This technique may be more useful in large studies where the determination of individual HR-VO_2 curves is not feasible (62). Validation of this HR method in lifestyle activities has demonstrated moderate

correlation and some significant overestimations of EE by HR compared to indirect calorimetry. For example, one study by Strath et al. (66) tested the Polar HR monitor against the Cosmed K4b^2 during common activities of varying intensity such as vacuuming, gardening, tennis, and grocery shopping. Results showed moderate correlation ($r = 0.68$) between HR (bpm) and VO_2 (ml/kg/min) during moderate intensity activities, with HR accounting for 47% of the variability in VO_2 (66). Furthermore, measured EE by the Cosmed against estimated EE by HR showed a correlation of $r = 0.87$, SEE = 0.76 METS after adjustments for age and fitness level. In a separate lifestyle activity study, the HR method significantly overestimated EE (mean difference = 0.4 METS, $p<0.001$) during various intensity activities (range = 2.1 to 6.1 METS). Part of this error may be due to the observed inability of the Polar monitor to record EE at rest and with light intensity activity; EE estimates may only be made when HR is $\geq$ 90 bpm or $\geq$ 60% HR max (17). In contrast, in a lab-based study comparing the Polar S410 HR monitor to IC during cycling, rowing, and treadmill submaximal tests, the HR method gave reasonable predictions of EE. Importantly, these are the activities for which motion sensors often fail to estimate EE accurately (17). Other than EE prediction inaccuracies mentioned previously, the HR monitor also is limited because it takes 2-3 minutes for the HR to increase to a level representative of a particular activity unlike the immediate response of the motion sensors (66). In addition, a significant ($p<0.001$) difference has been observed in EE estimates immediately following exercise due to the slower return of HR to baseline levels than IC (62). EE prediction errors also occur during arm activity; the HR will be

higher for any given VO_2 during arm activity compared to lower-body activity or full body activity (65). Overall, assessment of EE by HR monitoring has been validated with a wide range of subjects in both lab and field-based activities. Limitations of these predictions have been acknowledged such as reduced accuracy with low-intensity activities, differing age and fitness levels, improper PAEE and TEE estimates, and emotional influences, and they have often lead to the alternative use of motion sensors.

Pedometers

The pedometer is a commonly used motion sensor for monitoring PA. In general, pedometers were designed to measure the number of steps and time spent in physical activity but not to describe intensity, type, or patterns of PA (16). For example, in multiple studies, pedometers' step counts have shown a strong correlation with time in observed activity (median r = 0.82, range = 0.42-0.97) (16). Measurement of the number of steps primarily is achieved by either a spring-levered or piezo-electric mechanism. Spring-levered pedometers have a suspended lever arm that moves with vertical acceleration when walking. Each time the spring-levered arm moves, a step is recorded because of electrical contact between two metal pieces. In order to function properly, the monitor must be perpendicular to the ground (20). In contrast, the piezo-electric pedometer has a weighted beam which, upon detection of acceleration, compresses a piezo-electric crystal which generates an electric current and

subsequent recording of a step based on the acceleration-versus-time curve (20, 56). Different pedometer models utilize different sensitivities and thus the amount of acceleration necessary to trigger a step varies. Unfortunately, this contributes to the wide variability between models as evident in comparison studies of different pedometer brands (21, 55). The validity of the Yamax DW-500 was established as accurate within $\pm$ 1% of observed step counts on a treadmill (6). Because of this, one comparison study used the Yamax as the criterion model (55). In this study of free-living activity, a significant ($p<0.05$) difference was found between 13 pedometer models with instances of both under and overestimation (55). Those models which were highly sensitive had a tendency to overestimate number of steps, while those which were less sensitive were more likely to underestimate (55). Authors suggested more underestimation with models that begin counting steps only after 4 consecutive steps. Other general limitations of pedometers include inaccuracies resulting from variations in stride length, walking speed, and adiposity. Although total distance walked may be a desired outcome measure, it relies on a calculation based on stride length. The difficulty encountered with distance estimations is the variance of stride length over walking speeds. If the walking speed is slower than average walking speeds, error is more likely in pedometer measures (6, 7, 20, 21, 37, 55, 70). The cause of this error has been suggested as decreased vertical acceleration at the waist during slow walking speeds (21). For example, at 54 m/min, many pedometers underestimate steps and overestimate distance due to the shorter stride length with slower speed (5, 6, 21, 37). This trend is

also evident in the tendency of several models to overestimate distance at slower speeds (<80 m/min) and underestimate distance at faster speeds (21). Pedometers are fairly accurate both in step count (some models within ± 1% of observed) and distance (within ± 10% of observed) at an average speed of 80 m/min (5, 21). Additional error is seen in persons who have a shuffling gait, such as the elderly. In these individuals, the shuffling is not likely to be detected as true steps, thus underestimating step count and distance (70). Pedometer inaccuracies also occur in overweight and obese individuals; abdominal adiposity is thought to cause monitor tilt and consequent disruption of pedometer mechanisms (20, 70). For spring-levered pedometers, significant ($p<0.05$) underestimation of step counts versus observed steps was seen for overweight and obese individuals performing various speeds of treadmill exercise. In contrast, the piezo-electric models were not affected by tilt, and showed only the underestimation typical at slow speeds (20, 25, 38).

Calculation of EE may be accomplished by assigning a certain kcal/step conversion based on individual characteristics such as gender, age, weight, and fitness level (5, 20, 70). Whereas measures of steps and time in activity are often validated against direct observation, EE is generally validated with indirect calorimetry. A large, multi-study review by Tudor-Locke (16) examined this weakness of pedometers. Depending on the population and criterion method of EE assessment, only a moderate correlation was found between step counts and EE (median $r = 0.68$, range = 0.46-0.88). For pedometers versus indirect calorimetry specifically, the correlation ranged from $r = 0.49$-0.81 (70). For

example, one validity study using lifestyle activities showed overestimation of net kcal EE in walking at speeds of 78-100 m/min but underestimation during other lifestyle activities. Underestimations were especially common in activities with frequent arm use, pushing of objects, going up an incline, or using stairs (7).

The most validated use of pedometers is in ambulatory activities with the number of steps or steps/day as the most useful output variables to eliminate opportunities for error through additional conversions as for energy expenditure (21, 25, 70). Therefore, pedometers may be useful to compare step count levels and to show progression of a PA intervention between individuals and different populations but they are not ideal for determining PAEE (25, 39, 55).

Accelerometers

Like pedometers, accelerometers allow PA monitoring over longer time periods than can be afforded by indirect calorimetry, making them quite popular for research. Although pedometers are generally less expensive, accelerometers can provide additional information about exercise intensity, duration, and energy expenditure. As with pedometers, there are various models often with accompanying software for data analysis; common models include the Caltrac, Actigraph (formerly Computer Science and Applications (CSA) and Manufacturing Technology Inc. (MTI)), Actical, TriTrac-R3D, and Tracmor. In general, accelerometers measure the acceleration of the body during activity which is proportional to the amount of muscular force generated (48). The two

basic types are uniaxial and triaxial accelerometers, with references to the anatomical planes in which acceleration is measured. Based on voltage changes detected, the sum of these accelerations in a certain time period or epoch (ranging from 1 sec to 15 min depending on the model) gives the primary accelerometer output measure of “activity counts” (13). The frequency detected depends on the model and may range from 1-64 Hz; higher frequency of movement necessitates a model capable of detecting higher frequencies (13). The activity counts generated may then be used to determine duration of PA at different intensities based on absolute cut-points or certain intervals of counts corresponding with light, moderate, and vigorous activities. Several studies have investigated cut-points for different intensities with various accelerometers but no consensus has been reached (30, 67). It is exceedingly difficult to identify cut-points which will apply to all activity types, especially in distinguishing light and moderate activity (43). Some research has focused on the linear relationship of accelerometer counts to oxygen consumption or EE. In a review of ten studies, the correlation found between accelerometer counts and IC in assessing EE ranged from r = 0.58- 0.92 (13). In another review, similar correlations (r=0.62-0.93) were reported between accelerometers and oxygen consumption in children and adolescents (62). For both populations, the wide range of correlations is likely dependent on activities monitored, placement of accelerometer, and the monitor brand (75, 76).

Activity counts are commonly analyzed using a variety of published regression equations to estimate EE based on age, body weight, movement type,

and other variables. The conversion of raw counts to more meaningful units such as MET values or kilocalories expended is made possible by metabolic calibration (75). For the Actigraph model alone, there are 15 different calibration equations available (18). There has been extensive research validating the use of accelerometers and their calibration in a broad range of activities and populations, and a complete analysis of all models' validities exceeds the scope of this review. However, there are general trends which pervade across several of the most common accelerometers. For example, it is well accepted that hip-mounted accelerometers do not adequately measure EE of arm activity, differences in postures, walking on an incline or up stairs, carrying heavy loads or weightlifting, bicycling, or water activities (10, 13, 38, 39, 48). Yet, considerably less agreement exists as to which regression equation is most accurate. The first calibration equation was developed by Freedson et al. (24) using the CSA monitor (now Actigraph) and data for level treadmill walking and running. Using this equation, rather than that provided by the manufacturer, results showed a high correlation ($r = 0.91$) between CSA counts and VO_2 at intensities of 3.7-9.7 METS. However, later research using the Freedson equation showed that neither the CSA nor Caltrac was sensitive to grade changes with significant underestimations ($p<0.01$) at 3% and 6% regardless of treadmill speed (48). Furthermore, when this equation was applied to lifestyle activities, as in several studies, correlations between methods in measuring EE were much lower (18, 39, 76). For example, in a study by Welk et al. (76), predicted MET values from the CSA-Freedson equation strongly correlated with VO_2 in treadmill activity (r

=0.85-0.92) but this correlation decreased considerably with lifestyle activities, such as vacuuming, sweeping, and stacking groceries (r = 0.48-0.59). In these lifestyle activities, the CSA, as well as two other accelerometers, significantly underestimated EE by 42-67% ($p<0.001$) (76). Likewise, in a 7-day study of free-living EE by Leenders et al. (38), PAEE estimated by the CSA-Freedson equation significantly underestimated PAEE compared to DLW (-59%, $p\leq0.05$). Similar underestimations were observed with the Tritrac accelerometer and its manufacturer's regression equation; PAEE estimates were significantly underestimated (-35%, $p\leq0.05$) (38).

Attempting to remedy the shortcomings of the Freedson equation, Hendelman et al. developed new regression equations based on walking and applied them to moderate intensity recreational and household activities (30). Using IC as the criterion, correlations between CSA counts and MET values were stronger for walking (r = 0.77, explaining 58.9% variance in EE) than for all activities together (r = 0.59, explaining 35.2% variance in EE). Predicted MET values for golf and household activities were underestimated 30-60% ($p<0.001$) by using the regression equations developed (30). Similar findings applied to another accelerometer, the Tritrac, that was also evaluated in this study (30).

Rather than developing equations based on walking or running, Swartz et al. took a unique approach and used data from 28 different lifestyle activities to formulate new regression equations for use with the CSA monitor (67). This study evaluated prediction equations from data of CSA devices at the hip, wrist, and the combined data. Compared to IC, significant correlations were found

between EE (METS) and CSA hip counts ($r = 0.563$, $p<0.001$). The CSA hip regression equation explained 31.7% of the variance in EE whereas the combined hip-wrist model explained slightly more with 34.3% (67). However, significant ($p\leq0.001$) underestimation was found for push-mowing EE and the energy cost of ironing, caring for children, and slow walking was significantly overestimated by the CSA (67). Importantly, MET predictions by the Swartz regression equations for all other activities resulted in no significant differences between methods.

In efforts to determine the most accurate regression equation, several studies compared the accuracy of various equations over a wide range of physical activities (7, 18). In a study comparing four activity monitors (3 accelerometers and 1 pedometer), three different regression equations were used to analyze CSA data including the one provided by the manufacturer, the Freedson equation, and the Hendelman equation (7). In predicting EE (METS) across 28 different moderate intensity activities, mean error scores against IC ranged from 0.05 METS (Hendelman equation) to 0.97 METS (manufacturer's equation) for all accelerometers. All error scores were significantly ($p<0.001$) different from zero, except the Hendelman equation whose error scores did not differ from zero for any of the activities. In contrast, the Freedson equation underestimated EE in all 28 activities. Overall, correlation coefficients ranged from $r = 0.32$-0.62 for EE predictions versus IC, and, depending on the activity type, both under and over-estimation by monitors were observed. In general, the monitors overpredicted the EE of walking but underpredicted common activities

such as raking leaves, cooking, and housework. Such lifestyle activities tend to incorporate more of the activities which are notoriously underestimated by accelerometers due to the predominance of upper body motion and little vertical acceleration (7, 24, 30, 76). In a similar study, Crouter et al. (18) examined EE estimations (METS) by three accelerometers and a total of 18 available regression equations versus IC. Activities ranged in intensity from rest to vigorous and included many daily activities such as computer work and filing papers. As in the previous study, monitors were found to overestimate EE during walking and sedentary activities but underestimate many other lifestyle activities, including significant ($p<0.05$) underestimations of vigorous activity (18). For the activities considered, authors concluded that certain prediction equations were the most accurate: for the Actical- the double regression model, for Actigraph MET prediction – the Swartz lifestyle equation, and for Actigraph kcal/min – Freedson kcal equation (18). As concluded by previous research, no model could accurately predict EE in all circumstances. Based on this data, the authors developed a new approach to accelerometer data analysis whereby two regression equations are used instead of the previous studies' single regression models (19). In this new method, either a walk/run regression or a lifestyle/leisure time regression was used depending on the calculated coefficient of variation (CV) for accelerometer counts per 10 seconds. The Crouter model was tested on the previous activity data and found to be more accurate in EE predictions and duration of PA at various intensities than any of the prior equations (18, 19). Compared to IC, the Crouter method resulted in no

significant differences in any of the activities for EE estimation (METS) or overall time spent in light, moderate, or vigorous activity (19). In conclusion, the use of equations developed in the lab on locomotor activities such as walking or running tends to underestimate the PAEE when applied to more complex movements as in lifestyle activities whereas equations developed from data of field-based activities tend to overestimate PAEE of locomotor activities (18, 43, 76). Because individual regression models best predict EE for the activities on which they were developed, as of yet, no single calibration equation appears sufficient to assess all types of activities whereas using multiple models has yielded more accurate predictions (5, 7, 19, 43).

Multi-Sensor Monitors

To overcome the limitations of other activity monitors, multi-sensor models such as the IDEEA (Intelligent Device for Estimating Energy Expenditure and Activity) monitor and SenseWear (SW) Pro Armband (BodyMedia, Inc., Pittsburgh,PA) were developed. For example, unlike most accelerometers' use of a single regression equation to estimate EE, multi-sensor models often use activity-specific regression equations based on the activity detected by the instrument. The IDEEA monitor uses electrodes at various body positions to classify postures and activities done by a subject based on accelerations in two orthogonal directions. Processing software gives the following output measures: EE in kcal/min, speed, distance, power output, and an activity movement code (80, 81).

In contrast to the accelerometry basis of the IDEEA, the SenseWear Pro3 Armband takes a broader approach by including both an accelerometer and physiological sensors. The SW uses a biaxial micro-electric accelerometer and also has sensors to detect heat flux, near-body ambient and skin temperatures, and galvanic skin response. The bi-axial accelerometer detects acceleration in the transverse and longitudinal planes. The proprietary heat flux sensor gives the change in skin temperature versus near-body temperature in order to calculate heat loss. Galvanic skin response measures the conductivity of the skin, corresponding with evaporative heat loss and constriction or dilation of the vascular periphery. In order to estimate total energy expenditure, the SW records 21 measurement parameters (35). By combining the input from all sensors with programmed subject data (i.e. birthdate, gender, height, and weight), the SW distinguishes between periods of inactivity and activity, including sleep duration estimation, and applies activity-specific algorithms. No information is available as to how raw data is weighted in these equations, since they are proprietary. Output measures include duration and intensity of physical activity, number of steps taken, TDEE, and PAEE. Because the SW is small, portable, and easy to use, it is an appealing alternative to the criterion methods of DLW and IC to measure energy expenditure both at rest and during physical activity; consequently, validation studies have been conducted using the SW against these methods. Given the different generations of the SW armband and versions of the software and compounding this with the specific populations

addressed, a substantial hurdle exists in comparing the results of all validation studies.

Total Daily Energy Expenditure and Resting Energy Expenditure

Several studies have focused specifically on the ability of the SW to assess Total Daily Energy Expenditure (TDEE) and Resting Energy Expenditure (REE). In the only study to compare the SW to DLW, St. Onge et al. found a significant ($p<0.01$) underestimation of mean TDEE in free-living adults over a ten day period by the SW over DLW (2375 $\pm$ 366 kcal/day vs. 2492 $\pm$ 444 kcal/day, respectively) (64). However, there was a significant intraclass correlation (ICC) of 0.81 ($p<0.01$) indicating that individual estimates by the SW were good. A moderate and significant correlation ($r = 0.86$, $p<0.01$) was observed between the two methods. No conclusions may be made about day-to-day estimations because DLW data was given only for the 10-day period. Though not the primary purpose, PAEE estimations were also compared. As with TDEE estimates, the SW significantly underestimated PAEE with a mean difference of -225 kcal/day ($p<0.01$) and an ICC of $r = 0.46$ (95% CI 0.19-0.67, $p<0.01$) (64). Lower correlation ($r = 0.70$, $p<0.01$) was observed for PAEE than for TDEE estimations by SW against IC. As mentioned previously, DLW can only estimate PAEE by subtracting resting metabolic rate and thermic effect of a meal from TDEE. As such, it is uncertain whether the PAEE estimation error was due to DLW equations or the SW armband estimates.

More common than the use of DLW is the use of indirect calorimetry to validate the SW. Two separate studies have validated the use of the SW to measure REE against metabolic cart (SensorMedicsVmax 29N) estimations during simultaneous measurement (26, 42). Both studies used healthy, normal weight adults and, despite using two different versions of the SW software (v. 1.0 and v. 4.0), found no significant differences between methods in REE estimations. Both studies reported significant strong correlations ($r = 0.76$, $p<0.004$ and $r = 0.86$, $p<0.0001$) between SW and IC. In unique populations such as the morbidly obese, the validity of the SW to assess TEE may be altered as demonstrated by Cristofaro et al. (16). In comparing the SW to a metabolic cart (SensormedicsVmax 29N), there was significant ($p = 0.009$) overestimation of TEE by the SW (2002 $\pm$ 433kcal/day) versus IC (1742 $\pm$ 403kcal/day) (16). Conversely, in a large study of obese individuals there was a significant underestimation of REE by the SW (mean difference of 8.8%) compared to the SensorMedics, despite a significant correlation of REE estimates ($r = 0.85$, $p<0.001$) (49). As noted in several studies, as EE increased, so did the difference between methods (33, 49). As suggested in another validation study, the tendency for fat accumulation in the upper arm region of SW placement may be a contributing factor to these inaccuracies (14).

Physical Activity Energy Expenditure

Lab-based Studies

Although it is encouraging that the SW has been validated for TDEE and REE assessment in some populations, the validation of PAEE estimation has been more intensely examined. Several studies have investigated the SW validity in lab-based settings using treadmills, cycle ergometers, arm ergometers, and stair-stepping while a few have assessed validity in field-based settings. Lab-based studies are often useful due to the level of test control such as for the intensity or duration of exercise. The results are equivocal perhaps because of the variety of criterion methods, SW models, and software versions used in the research. One of the earliest studies to test SW validity was that of Fruin and Rankin using the first armband model and first software version (which lacked exercise-specific algorithms) (26). After initial EE estimates by the accompanying software, raw data was sent to BodyMedia, Inc. for analysis with contextual information including time and type of activities; EE estimates were then returned to the authors. As might have been expected with novel exercise-specific algorithms, SW results showed significant differences from IC estimates. Using young adult participants for 30-minute treadmill tests at three intensities (80.5 m/min, 0% grade; 107.3 m/min, 0% grade; 107.3 m/min, 5% grade), moderate correlations were found between methods ($r = 0.47$-0.69). However, the SW was found to significantly overestimate EE of walking with no grade (13-27%, $p<0.02$) and significantly underestimate walking with 5% grade (22%, $p<0.02$) (26). According to the authors, similar magnitudes of over- and under-estimation for treadmill

exercise have been reported in triaxial accelerometer studies, suggesting the possible importance of the armband's accelerometer data in the EE algorithm used. However, no significant differences between the SW and IC estimates of EE were found for a 40-minute cycle test of 60 rpm at 60% VO_2peak but poor correlations (r = 0.03-0.12) were found between measures (26). Shortly after this study both the armband and software were updated in attempts to increase the accuracy of the SW in measuring EE during exercise.

A lab-based study to develop and test new software was that of Jakicic et al. (33). This study used two sets of algorithms (software version 3.2) to evaluate SW accuracy in healthy young adults. Subjects completed 20-30 min bouts of increasing intensity on 4 exercise modes: walking, cycling, stepping, and arm ergometry, while simultaneously being monitored by both the SW and IC (SensorMedicsVmax or Parvomedics). Energy expenditure (kcal/min) per 10-minute bout and total kilocalories burned during exercise were the values used for analysis. Results using the first general set of algorithms indicated significant ($p<0.001$) SW underestimation of total EE during walking, cycling, and stepping (mean difference 14.9 kcal to 32.0 kcal) and significant ($p<0.001$) overestimation during arm ergometry. The overall bias for EE estimates showed that increased EE yielded a larger difference between SW and IC. Intraclass correlations ranged from a low r = 0.28 (cycle) to a high r = 0.77 (walking). Because of these profound inadequacies of the SW, BodyMedia used this data to create new exercise-specific algorithms which were used for a second analysis. Because the type of exercise was known to those developing the algorithms, it is logical

that large improvements would be seen in EE estimates compared to the general algorithms used previously. Using the new set of algorithms, no significant differences were found in any of the exercise modes for total EE during exercise. Unlike with the original analysis, no systematic bias was observed for EE predictions. In addition, intraclass correlations were also increased for most exercise modes, but most profoundly for cycle ergometry (from $r = 0.28$ in first analysis to $r = 0.89$ in second analysis). Based on the second set of algorithms, the preliminary accuracy of the SW during four particular exercises was established but needed further validation given the circumstances under which the algorithms were developed and data analyzed.

A study by Cole et al. (14) prompted additional software modifications to improve SW validity. Unlike the healthy populations of prior studies, this study focused on a more narrow population of cardiac patients and total EE estimates during arm ergometry, treadmill, recumbent stepping, and rowing ergometry exercise in 8-minute bouts. Intensity of the exercise was dependent on the individual and his/her rehabilitation. For version 2.2, the SW significantly ($p<0.01$) underestimated EE during treadmill and rowing activities. However, when version 4.0 with updated algorithms was used, no significant differences were found for any activities ($p>0.2$) although a tendency for the SW to overestimate EE with high intensity treadmill activity and to underestimate step and arm ergometry was noted. Significant correlations between methods were observed with both software versions ($p<0.05$). Further improvements in SW estimations were seen once BodyMedia created algorithms for this specific

cardiac population. Interestingly, in another study of obese individuals using similar activities (cycle ergometry, stair stepping, and treadmill walking), the same version 4.0 software did not yield similarly accurate estimates (49). For 5-minute exercise bouts, the SW significantly ($p<0.05$) overestimated all activities' EE compared to IC and had poor intraclass correlation ($r = 0.03$-0.18). Overall, based on these results and that of other studies, it appears the SW algorithms need further refinement to be valid in narrow populations such as obese individuals or cardiac patients (16, 49).

Using the same software version 3.0 as Jakicic et al. (33), a similar lab-based study analyzed SW accuracy using various speeds of treadmill walking and running as the focus activities (35). In addition to IC as the criterion compared to the SW, several accelerometer models (Computer Science Applications – CSA, Tritrac R3D, RT3, and Biotrainer Pro) were also used to estimate EE (kcal/min) during activity. Given the frequency of accelerometer use, it is important to compare the differences in EE estimates obtained with the SW and the accelerometers. The validity of the SW compared to accelerometers was confirmed in this study. No significant differences ($p>0.05$) were found between any monitors' EE estimates, at any speed. Despite the previous study finding no significant differences between IC and SW (33), this study found significant ($p<0.001$) overestimation of EE for all monitors against IC, except for the CSA's underestimation at two speeds (35). Of all the monitors, the SW displayed the highest correlations to IC at all but the lowest speeds ($r = 0.65$ at 54 m/min to $r = 0.82$ at 214 m/min). These results indicated that the SW was

more accurate for measuring total exercise EE than both uniaxial and multiaxial accelerometers for most walking and running speeds. Yet, SW errors in estimation remain when compared to IC.

In contrast to the inaccuracies previously reported, several recent, small lab-based studies have supported the results of Jakicic et al. (33). For example, one study had subjects perform a 60-minute routine combining short bouts of sitting, standing, and walking, and determined EE with SW and IC (46). No significant differences ($p>0.05$) between methods were found in EE estimates for the entire session though estimates for specific activities were not given. Also, significant correlations were found between methods ($r = 0.71$, $p<0.05$). Likewise, another study with alternating periods of rest, treadmill walking, and supine rest in 15-min increments showed significant correlations between SW and IC estimates of EE both for activities individually and overall ($r = 0.79$-0.95, $p<0.05$) with no differences reported between methods (74).

Field-Based Studies

Though not afforded the stringent conditions of lab-based studies, the results of field-based studies offer more applicability to everyday living and activity. For an instrument assessing EE, its validity is equally important in both lab and real world settings. Unfortunately, field-based studies or those with activities resembling daily life are underrepresented in SW validation studies. However, several studies have provided good preliminary information on SW validity during

lifestyle activity. Only two SW validation studies with daily lifestyle activities have used IC as the criterion measure. In the first SW study of children, by Arvidsson et al. (4), the PAEE of 20 children was measured by the SW and IC during rest (30 min) and a wide variety of activities (5 min each of playing cell phone games, using a stepboard, stationary cycling, trampoline, basketball, and walking and running at 8 different speeds on a treadmill). Such activities are a clear departure from those in most of the previous SW studies but are indeed particularly common for the population of interest. Using software version 5.1 for analysis, results indicated significant SW underestimation of all 14 activities, including rest, except for trampoline jumping and walking 2 and 3 km/hr (all $p<0.001$ except walking 4-6 km/h, $p<0.05$). The most profound difference was noted in cycling with a 51% underestimation by the SW. For all activities, the correlation between intensity of activity and difference between methods was -0.58 ($p<0.001$); in other words, underestimation by the SW increased with increasing intensity. As suggested by the authors, the inaccuracies of the SW may be due to the adult-specific nature of some algorithms (4). Underestimation seen at increasing treadmill speeds is in contrast to the overestimation observed in a similar activity within an adult study (35) as well as in another study of children performing only treadmill exercise (3). In the only other SW validation study of children, Andreacci et al. (3) found no significant differences between SW and IC estimates of EE during treadmill exercise at 1.7 mph, 2.5 mph, and 3.4 mph in 8-min sessions. The mean absolute % error for EE estimation during the tests was 13.1%, 10.4%, and 9.6% for the increasing treadmill speeds,

respectively. However, this study used some of the subjects to develop new algorithms while the remaining children were used to validate the algorithms. Because the algorithms were formulated on this study, it is likely that estimations would be more accurate than in altered testing conditions or with different activities as in the Arvidsson et al. study (4).

Only one other SW study using IC closely replicates daily living activities. In addition, this is the only previous study to use the Cosmed K4b^2 as the criterion measure. In this small study of eight women, Galvani et al. (27) used the SW, Actiheart (AH), and Cosmed K4b^2 to estimate EE during resting, occupation, housework, conditioning, and recreation activities. Significant differences ($p<0.001$) were found between PAEE estimates by the SW and IC with a trend for the SW to underestimate PAEE at moderate and vigorous intensities (27). However, strong correlations were observed between methods (SW and IC, $r = 0.795$, $p<0.001$; AH and IC, $r = 0.785$, $p<0.001$). Compared to the AH, the SW produced lower systematic error in PAEE estimates of moderate and vigorous activities, indicating that for this study, the SW was more accurate than a heart rate monitor in EE prediction.

Given the challenges of using indirect calorimetry outside of the lab, several studies have opted to compare the SW to either a different activity monitor (IDEEA) or a subjective method of PA assessment (24-hour Physical Activity Recall (24PAR) and International Physical Activity Questionnaire (IPAQ)). Because the IDEEA also utilizes a multi-sensor approach, two studies have used it as the criterion method against which the SW was compared (9, 79). In

contrast to many previous studies, both studies assessed activity under free-living conditions. Because of this, PA duration (min), intensity (METS), and EE (kcal) could be determined. In the first study by Calabro et al. (9), strong correlations ($r = 0.81$-0.89, $p<0.05$) and no significant differences were reported between IDEEA and SW for total EE estimates. However, low correlations ($r = 0.38$ to $r = 0.60$, $p<0.05$) were noted for estimates of moderate and vigorous PA duration (IDEEA: 149.9 $\pm$ 78.5 min versus SW: 170.3 $\pm$ 74.8 min). In addition to duration estimates for moderate and vigorous activity, a second study of free-living individuals by Welk et al. (79) used slightly different measures including MET averages for activities and total EE in kcal/kg/day. Before analysis, activities throughout a normal day were grouped according to IDEEA classifications (lie, lie variations, sit, sit variations, stand, stand variations, and walk). For PA duration, both SW software versions (version 3.9 and version 4.1) resulted in estimates which were significantly different ($p<0.05$) from the IDEEA though high correlations existed between measures ($r = 0.84$-0.90). MET estimates by the SW with software version 3.9 were significantly different ($p<0.05$) from the IDEEA but these differences were mostly resolved when version 4.1 was used. With version 4.1, across the 7 activities, the EE estimates were within 0.01 METS with a mean bias of 0.15 METS. For mean METS (kcal/kg/hr) in individual categories of activity, significant differences were only seen for sit variations, regardless of the software version used ($p<0.05$). Without separating by activity group, the overall correlation for EE was better for version 4.1 versus IDEEA ($r = 0.82$) than version 3.9 versus IDEEA ($r = 0.71$) indicating

that useful adjustments had been made to the algorithms. Based on the conflicting results of these studies, it appears that more investigations are needed with a variety of activities to determine if the SW and IDEEA are equally valid and if they may be used interchangeably.

Despite the paucity of data to support the SW as a valid measure in many diverse activities or in all populations, some studies have used it as the criterion objective measure against which subjective measures including the IPAQ and 24PAR have been validated. The computer-based 24PAR was found to significantly ($p<0.05$) overestimate EE (kcal/day) by a mean difference of 164 kcal/day compared to the SW (77). Correlation was high ($r = 0.88$) between measures for overall EE but lower when only moderate and vigorous PA were considered ($r = 0.60$). Interestingly, overestimation of the 24PAR was similar when compared to the IDEEA in the same study with a mean difference of 102kcal/day ($p<0.05$). Although not addressed, this suggests that the IDEEA and SW are more similar to each other than to the subjective measures in EE estimations. In a study by Wadsworth et al., validation of a 7-day questionnaire, the IPAQ, against the SW was even less successful than that of the 24PAR (73). Significant differences between methods were found for estimations of total days, minutes, and METmin/wk of moderate and vigorous PA ($p<0.001$). Furthermore, no significant correlations were found for any variable ($p>0.05$). Self report via the IPAQ was found to underestimate moderate activity and overestimate vigorous activity. However, the results of these studies should be interpreted with caution until the SW is validated in more studies or until a more accepted

measure of EE such as DLW or IC is incorporated into similar study designs as those previously outlined.

In conclusion, based on available studies, it appears the validity of the SW hinges on the ability of the software to apply appropriate algorithms to the raw data collected by the armband. Because these are proprietary algorithms, the exact cause of these inadequacies is unknown. One may postulate that less common and previously untested activities such as occupational or leisure activities would yield less accurate SW estimates of EE until new algorithms could be developed. Such refinements could be based on new data as has been done previously. Considerable holes still exist in current validation studies and necessitate future studies. Problematic areas requiring further investigation include a wider variety of lifestyle activities (such as watching television or gardening), more frequent use of criterion methods outside of the lab, and the inclusion of more diverse populations.

CHAPTER III

MATERIALS AND METHODS

Participants

41 participants (23 male, 18 female) from the University of Tennessee campus and surrounding Knoxville community volunteered to participate in 1 of 2 physical activity routines. Informed consent (Appendix A) was obtained from all participants and all methods were approved by the Institutional Review Board of the University of Tennessee-Knoxville. Participants completed a brief health history questionnaire to determine their eligibility for inclusion in the study (Appendix B). Potential participants were excluded from the study if they reported any contraindicating medications such as for seizures or heart conditions or if they indicated medical history that would preclude full participation, such as chest pain or cardiovascular events. Participants were weighed and height was measured before instrument initialization. Testing occurred either on campus, at the participant's home, or at the investigator's home. Participants received $80 for their involvement. All participant data were stored on a password-protected computer with confidential identification numbers used for all participants' files.

Procedures

Routines

Participants performed 1 of 2 routines, each with 6 activities in the following sequences:

Routine 1 (Outdoor Aerobic Activities): Walking (self-paced on a road 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 road course)

Routine 2 (Indoor Home-based Activities): Watching Television
Reading a Book
Doing Laundry
Ironing
Light Cleaning
Aerobics

For Routine 1 (Outdoor Aerobic Activities), both walking and running activities were self-paced. Distance was recorded to determine speed for each subject in these activities. The road course was the same for all participants and

for both walking and running. This course included sidewalks, cross-walks, slightly hilly terrain, and normal pedestrian traffic. The 6.8 kg (15 lb) bag was an over-the shoulder bag with textbooks to meet the weight requirement. Track and road course activities were selected as to examine both continuous and intermittent walking and running conditions.

For Routine 2 (Indoor Home-based Activities), 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 actual ironing of clothes. Light cleaning included wiping off countertops or surfaces, dusting, straightening shelves, putting away small items, and other small tasks. All participants performed the same aerobics routine using a 10-min segment from a commercial exercise video. The intermediate-level aerobics' activities included both upper and lower body movements while standing.

Routine 1(Outdoor Aerobic Activities) included 16 participants and Routine 2 (Indoor Home-based Activities) included 25 participants. No participant performed both routines. If participants did not regularly exercise, they were included in Routine 2 rather than Routine 1 due to the nature of the activities. For both routines, each activity was performed for approximately 10 minutes with a 3-5 minute break between activities. A 10-minute seated resting measurement was obtained before the start of each routine. For rest and the six routine-specific activities, subjects wore the SenseWear Pro3 Armband (BodyMedia Inc., Pittsburgh, PA), the Cosmed K4b^2 (Rome, Italy), and 3 other activity monitors as

part of a larger study to be discussed elsewhere. The weight of all monitors (2 kg) was added to subject data prior to testing and statistical analyses.

Indirect Calorimetry

The Cosmed K4b^2 (Rome, Italy) portable metabolic system was used as the criterion measure of indirect calorimetry throughout all routines. The Cosmed K4b^2 is a breath-by-breath gas analysis system consisting of a face-mask, analyzer unit, and battery in a harness system. Before testing each subject, the Cosmed analyzer was turned on for 45-60 minutes and then calibrated according to the manufacturer's instructions. Calibration of the analyzer included 4 parts: room air calibration, reference gas calibration (16.03% O_2 and 3.98% CO_2), turbine flowmeter calibration with a 3.0 L syringe (Hans-Rudolph), and CO_2/O_2 delay calibration with the face-mask. The analyzer unit was programmed with the participant's data and the measured relative humidity of the testing location (to adjust for barometric pressure differences). For each participant, a disposable gel-seal was used with the face-mask to prevent air leaks, and the facemask was secured with a mesh-cloth headpiece. Before testing began, one exhalation by the participant allowed a final check for an airtight seal. To eliminate possible complications of O_2 analysis in extreme temperatures, the aerobic routine was not performed when the temperature was below 50°F (10°C) (15). After testing, data were downloaded and analyzed by accompanying software (version 7.5a). After each subject, the memory of the analyzing unit

was cleared and its battery recharged. All facemask and flowmeter parts were sanitized between uses. To ensure reliability of Cosmed VO_2 measures, calibration testing was conducted every ten subjects. The same subject rode a calibrated Monark cycle ergometer at 1, 2, 3, and 4kp at 50 rpm for 6 min stages. Predicted VO_2 values of 0.9, 1.5, 2.1, and 2.7 L/min were compared to measured values to confirm reliability of gas analyzers within $\pm$ 100 ml/min (1).

SenseWear Pro3 Armband

The SenseWear Pro3 Armband is a small ((l) 85.3 mm x (w) 53.4 mm x (h) 19.5 mm, wt = 79 g) body monitoring system by BodyMedia Inc. designed to measure energy expenditure throughout daily living. The water resistant armband was worn on the back of the right arm midway between the acromion and olecranon processes and was secured by an adjustable Velcro strap. A display watch was worn on the right wrist and was synchronized with the armband when testing began to display 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 (1-AAA battery allows 14 days of continuous data collection according to the manufacturer). Before use, the armband was configured for the participant using a USB port and cable with the accompanying BodyMedia software (version 6.1) Configuration uses the subject's gender, birth date, height, weight, handedness, and smoking status. During the configuration, the armband was synchronized

with the computer clock and the portable digital clock (stopwatch) used during testing to time activities. All start and stop times of activities were recorded both in real time as used by the SenseWear as well as the display time on the Cosmed to allow minute-by-minute data comparison of the two methods. Raw data collection by the SenseWear occurs in 1-minute periods by five different sensors on the armband including a biaxial accelerometer (transverse and longitudinal planes) and sensors to monitor heat flux, skin temperature, near body temperature, and galvanic skin response. After routine completion, armband data were downloaded and saved to a computer via BodyMedia software and the armband's memory was cleared for the next use. Raw data were analyzed by proprietary algorithms to yield output measures including PA duration (min) and intensity (moderate ($\geq$ 3 METS), vigorous (>6 METS), and very vigorous (>9 METS)), number of steps taken, and energy expenditure (METS and kcal/min). The armband and display watch surfaces and Velcro strap were cleaned with soap and water between uses.

Data and Statistical Analysis

The Cosmed K4b^2 collected breath-by-breath data, but after downloading, data were filtered into 1-minute averages. The SenseWear collected data in 1-minute periods. For the Cosmed K4b^2 data, software converted absolute VO2 values to relative values (adjusted for body mass) and then to MET values for each activity. For the SenseWear data, proprietary algorithms and specific subject

configuration produced average MET level data. All Cosmed and SenseWear 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 for differences between methods.

Statistical analyses were performed using SPSS (version 15.0) for Windows (SPSS Inc, Chicago, IL, USA). A repeated measures ANOVA (method x activity) allowed comparison of Cosmed MET values and SenseWear predicted MET values for each activity. Significance was defined as $p<0.05$. *Post-hoc* testing with paired samples t-tests examined differences within each activity and used an adjusted alpha-level of 0.01 to control for Type I error. To show individual data variability (Cosmed METS to SenseWear METS), a modified Bland-Altman plot was constructed including mean-error score and 95% confidence interval (8). Data points above zero are considered an underestimation and those below zero are an overestimation. Ideally, the mean differences between methods (Cosmed-SW METS) will have a small interval around zero, indicating good agreement with Cosmed actual METS.

CHAPTER IV

Results

The participants' characteristics are presented in Table 1. Complete data were obtained for all participants with the exception of one missing SenseWear resting EE value and, for one participant, missing SenseWear and Cosmed values for singles tennis. Wide ranges of age (21-60 years) and body mass index (17.7-38.9 kg/m^2) were represented. Walking and running speeds for Routine 1 participants are displayed in Table 2.

For Routine 1(Outdoor Aerobic Activities), a significant interaction ($p<0.001$) was observed for method x physical activity. Results of the t-tests showed significant differences in each activity of Routine 1 for SW versus Cosmed EE estimates ($p<0.01$). The SW armband underestimated EE of singles tennis, running (track), and running (road course), and it overestimated EE of walking (road course), walking (track), walking with a 6.8 kg (15 lb) bag, and rest (Table 3).

For Routine 2 (Home-based Activities), analyses showed a significant method x physical activity interaction ($p<0.001$). *Post-hoc* analysis revealed significant differences ($p<0.01$) only for ironing and light cleaning. On average, the SW overestimated the EE of ironing by 1.3 METS and light cleaning by 0.4 METS (Table 4).

Table 1. Participant Characteristics

	Males (n=23)	Females (n=18)	Combined (n=41)
	Mean (SD)	Mean (SD)	Mean (SD)
Age (yr)	32.4 (11.6)	37.3 (11.7)	34.5 (11.7)
Weight (kg)	80.0 (14.7)	69.2 (15.3)	75.2 (15.7)
Height (m)	1.77 (.09)	1.68 (.07)	1.73 (.09)
Body Mass Index (kg/m^2)	25.5 (4.1)	24.6 (4.9)	25.1 (4.4)

Table 2. Walking and Running Speeds During Routine 1 (Outdoor Aerobic Activities)

	Males (n=13)	Females (n=3)	Combined (n=16)
	Mean (SD)	Mean (SD)	Mean (SD)
Walking Speed (road) (m/min)	86.8 (9.3)	89.6 (12.1)	87.3 (9.5)
Walking Speed (track) (m/min)	88.9 (9.8)	89.5 (8.8)	89.0 (9.3)
Walking Speed (with bag) (m/min)	85.8 (10.6)	82.2 (11.3)	85.1 (10.5)
Running Speed (track) (m/min)	175.3 (27.9)	159.9 (43.8)	172.5 (30.3)
Running Speed (road) (m/min)	176.3 (16.6)	161.3 (33.8)	173.5 (20.2)

Table 3. Comparison of SenseWear to Cosmed EE estimates in Routine 1 (Outdoor Aerobic Activities)

Activities	Cosmed METS Mean (SD)	SenseWear METS Mean (SD)	Mean Difference (Cosmed METS-SenseWear METS) (SD)	95% Confidence Interval of the Mean Difference
Walking (Road)	4.0 (0.6)	4.9 (0.8)	-0.9* (0.6)	0.7 to 1.3
Walking (Track)	4.0 (0.6)	4.9 (0.9)	-0.9* (0.8)	0.5 to 1.3
Walking with 15lb. bag	4.6 (0.7)	5.3 (1.0)	-0.7** (1.0)	0.2 to 1.3
Singles Tennis	8.5 (1.5)	6.8 (1.2)	1.7* (1.3)	-2.5 to -1.0
Running (Track)	11.4 (2.0)	8.7 (1.0)	2.7* (2.2)	-3.9 to -1.5
Running (Road)	11.0 (1.5)	8.3 (0.7)	2.7* (1.4)	-3.4 to -1.9
Rest	0.9 (0.2)	1.4 (0.4)	-0.5* (0.4)	0.3 to 0.7

* denotes statistical significance, $p<0.001$
** denotes statistical significance, $p<0.01$

Table 4. Comparison of SenseWear to Cosmed EE estimates in Routine 2 (Indoor Home-based Activities)

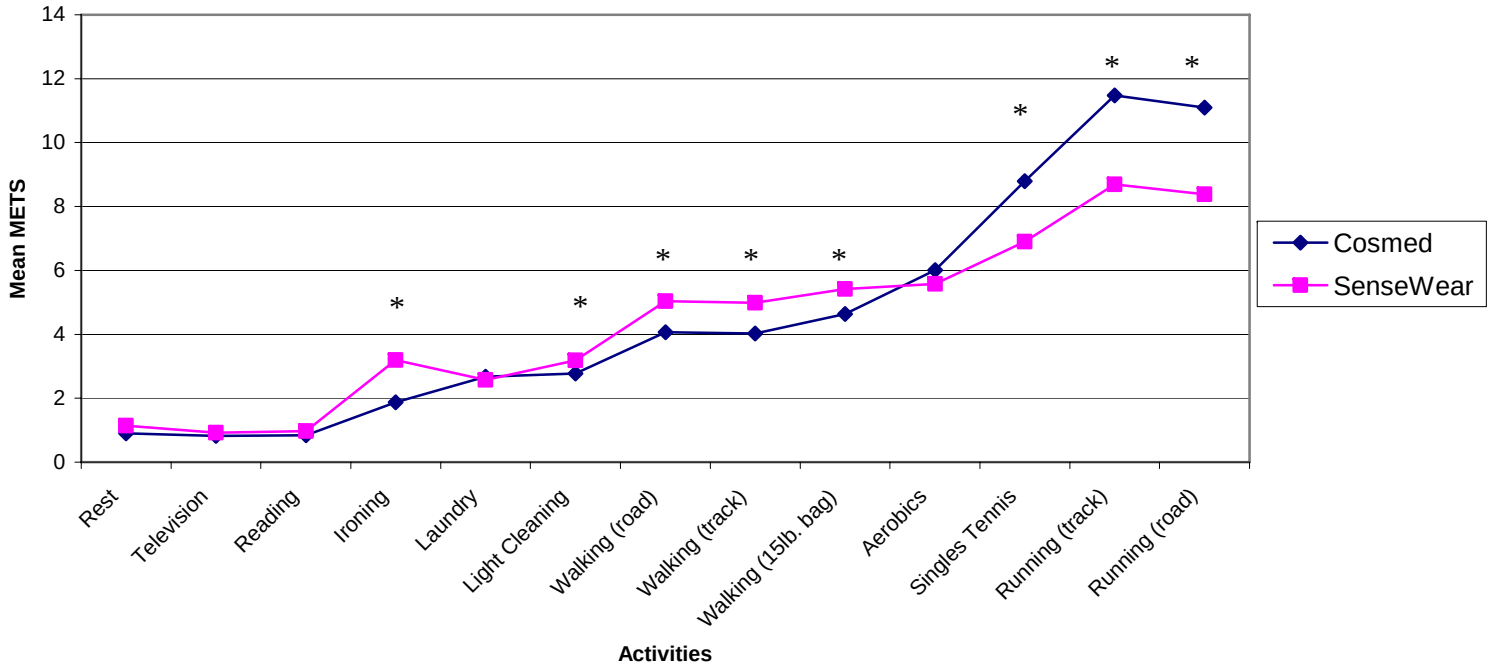
Activities	Cosmed METS Mean (SD)	SenseWear METS Mean (SD)	Mean Difference (Cosmed METS-SenseWear METS) (SD)	95% Confidence Interval of the Mean Difference
Watching TV	0.8 (0.2)	0.9 (0.1)	-0.1 (0.2)	0 to 0.2
Reading a book	0.8 (0.3)	1.0 (0.3)	-0.1 (0.3)	0 to .3
Doing laundry	2.7 (0.8)	2.6 (0.6)	0.1 (0.7)	-0.4 to 0.2
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)	0.2 to 0.7
Aerobics	6.0 (1.3)	5.6 (1.1)	0.4 (1.3)	-1.0 to 0.1
Rest	0.8 (0.3)	1.0 (0.2)	-0.1 (0.4)	0 to 0.3

*denotes statistical significance with p<0.001
**denotes statistical significance with p<0.01

As measured by the Cosmed, the highest mean intensity was 11.4 METS during running (track) whereas the lowest mean intensity was 0.8 METS while watching TV. Figure 1 displays mean MET estimations by both methods for all activities, in order of increasing values not necessarily routine order.

Modified Bland-Altman plots were conducted to show the difference between the two methods in average EE estimations. Figures 2A-C show differences for routines individually and then for all data combined. As seen in Figure 2-A, the correlation between activity intensity and the difference between methods for Routine 1(Outdoor Aerobic Activities) was $r = 0.84$ ($p<0.01$) indicating increasing underestimation of the SW with increasing activity intensity. In contrast, as seen in Figure 2-B, the mean difference values in Routine 2 (Indoor Home-based Activities) were clustered more tightly around zero and did not exhibit a strong linear relationship ($r = 0.37$, $p<0.01$). The smaller 95% confidence interval of the observations indicates a better agreement between methods through the range of intensities measured in Routine 2. Combining the two routines in Figure 2-C, the trend for the SW to underestimate activities of higher intensity remained, though somewhat attenuated ($r = 0.72$, $p<0.01$).

Figure 3 displays the percent differences between methods for all observations in both routines. There appears a greater variance in under- and over-estimations at lower intensities, including several instances of 300-400% overestimation, than at higher intensities.



Rest (n=41), Routine 1 activities (n=16), Routine 2 activities (n=25); statistical significance ($p < 0.01$) denoted by asterisk (*)

Figure 1. Energy Expenditure (METS) Estimations by Cosmed K4b^2 and SenseWear Pro3 During a Wide Range of Activities

A)

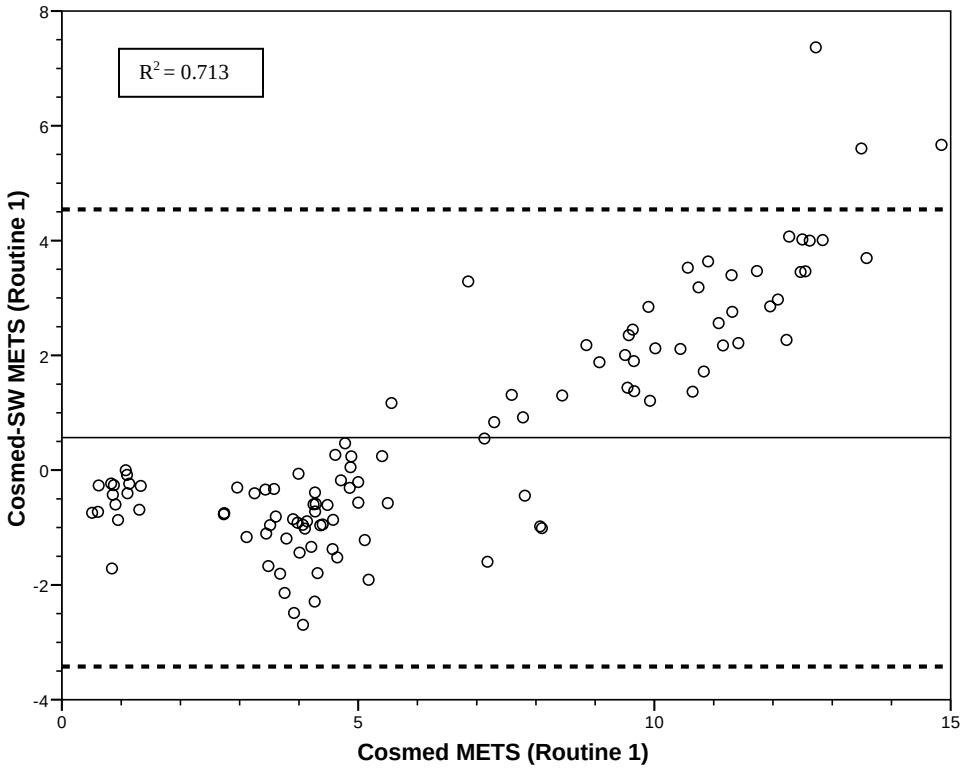
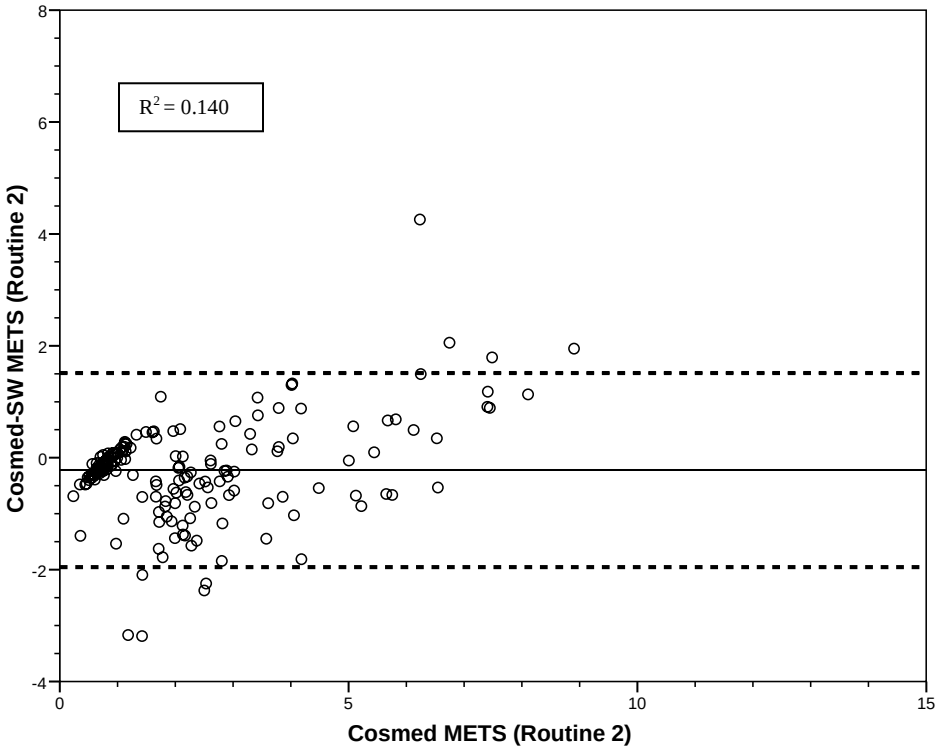


Figure 2. (A-C) Bland-Altman plots displaying differences (Cosmed-SW METS) for energy expenditure estimations. Solid lines represent the mean difference of the observations and dashed lines mark the 95% confidence interval for observations.

(A) Routine 1 (Outdoor Aerobic Activities)

Figure 2, continued.

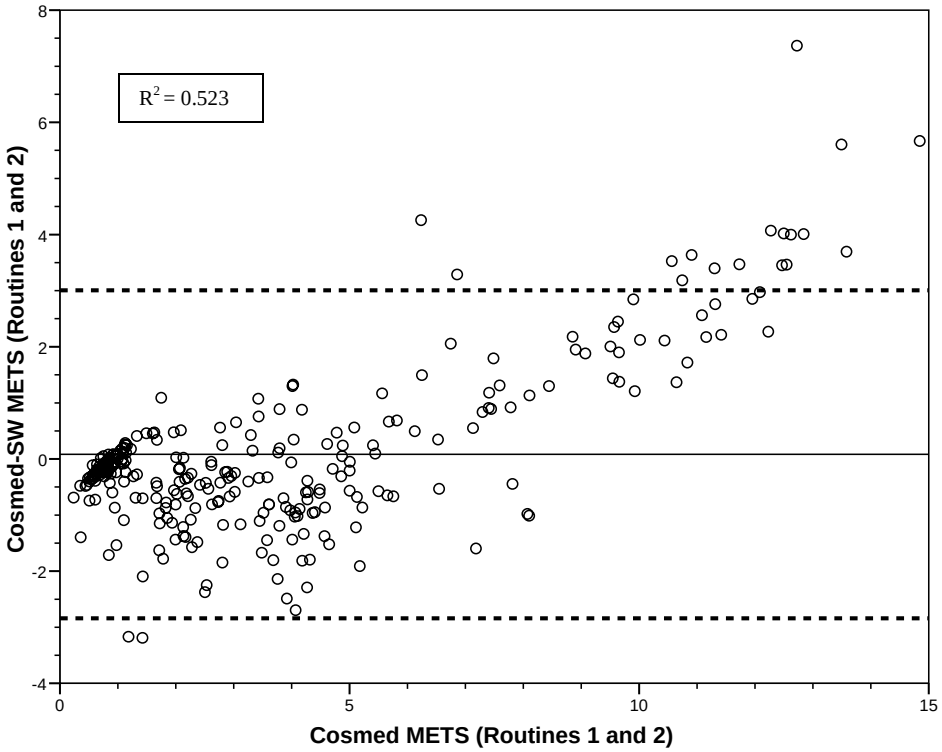
B)



(B) Routine 2 (Indoor Home-based Activities)

Figure 2, continued.

C)



(C) Routines 1 and 2 Activities

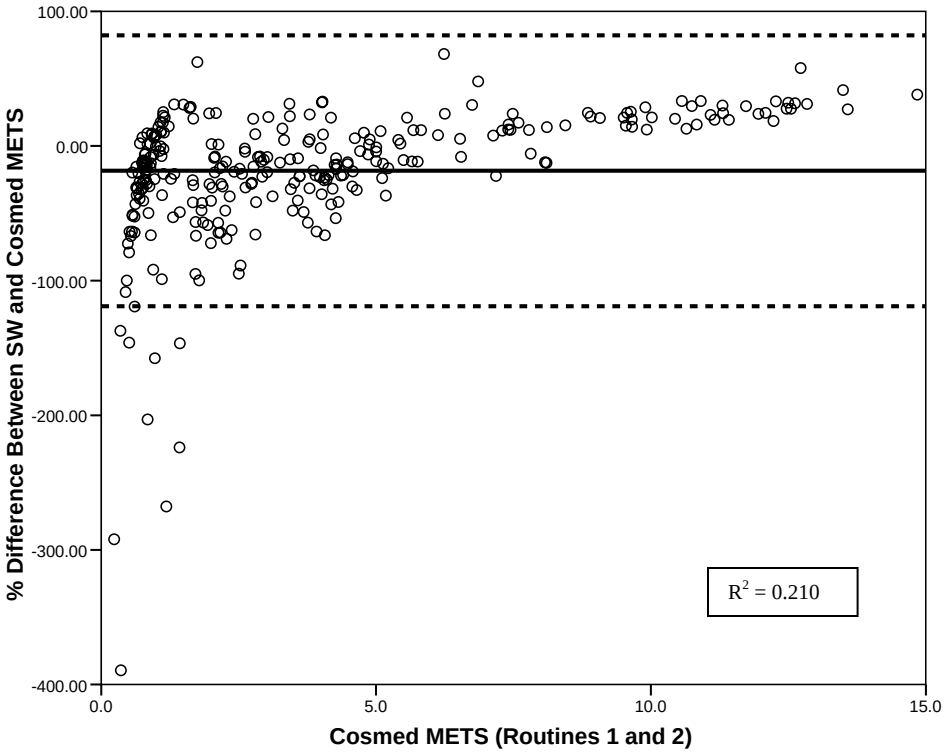


Figure 3. Bland-Altman plot displaying percent differences between Cosmed and SW energy expenditure estimations. Solid lines represent the mean percent difference of the observations and dashed lines mark the 95% confidence interval for observations. Below zero indicates a percent overestimation whereas above zero indicates a percent underestimation.

CHAPTER V

DISCUSSION AND CONCLUSION

The goal of this study was to examine the validity of the SenseWear Pro3 armband for estimating EE in field-based activities. This is the first study to test this armband model and its accompanying software (version 6.1) with these types of activities. Of the twelve activities tested, the SW was found to accurately measure EE in four home-based activities: watching TV, reading, doing laundry, and aerobics. Because the SW is promoted as a useful tool to assess EE in daily life, the errors seen in the other eight activities are a cause for concern (2). Though comparisons to previous studies are difficult due to differences in armband models or software versions, our results support several previous studies but conflict with others.

The most similar study to our methodology is that of Arvidsson et al. (4) which investigated the validity of the SW (software version 5.1) in children. They examined 14 various common activities such as basketball, jumping on a trampoline, playing games on a cell phone, and walking and running at different speeds. Compared to the Oxycon Mobile portable metabolic system, the SW underestimated EE in most activities, with the degree of underestimation increasing as the intensity increased (4). Although we noted cases of both over- and under-estimation, we found a trend for the SW to underestimate at higher intensities (Figure 1). During treadmill walking and running, Arvidsson et al. (4)

found a correlation of -0.71 ($p<0.001$) for the intensity of activity versus the difference between methods (SW-IC). Likewise, in our Routine 1, which consisted mostly of walking and running activities, we found a correlation of $r = 0.84$ using the mean difference between methods (IC-SW). For all activities, their study found a correlation of -0.58 ($p<0.001$) whereas our overall correlation was $r = 0.72$ ($p<0.01$). Depending on the activity, their mean error scores ranged from -3.5kcal/min (basketball, $p<0.001$) to 0.3kcal/min (walking 2.0km/h, $p = 0.08$). Overall, our results confirmed this study (4) and others (14, 27) who noted a greater underestimation of EE by the SW as activity intensity increased. In addition, our study noted an overestimation by the SW during low intensity activities like walking. Because our study used a road course for the walking and running activities, we conclude that the over- and under-estimations by the SW persist with intermittent as well as continuous walking and running. Our road course included cross walks, hills, and normal pedestrian traffic yet results showed the same over- and under-estimations (SW walking = +1.0 METS, SW running = -2.7 METS versus IC) as continuous track activities (SW walking = +0.9 METS and SW running = -2.7 METS). Although previous authors suggested these inaccuracies were due to the use of adult-specific algorithms in children, our results indicate that these errors persist in an adult population and might be due instead to the unique activity types (4). In one sense, it is encouraging that the SW remained consistent in its measures, even if under- and over-estimations exist. This result suggests that adjustments to algorithms would

improve the estimation of EE in both lab and field-based walking and running activities.

The results of our study are also similar to those seen in the small study of Galvani et al. (27). Although their study examined only 8 women, it is the only SW validation study to have also used the Cosmed K4b^2 as the criterion measure to assess EE. In addition, the categories of activities (occupation, housework, recreation, and conditioning) were similar to our study. Although specific activities of this study are unknown, our activities could readily be assigned to one of these categories such as light cleaning to "housework" or carrying a weighted bag to "occupation." As with many of our activities, Galvani et al. (27) observed significant ($p<0.001$) differences between the SW and Cosmed for all PA categories. (However, no statistical details regarding specific activities were provided.) Their study found that the SW tended to underestimate EE at moderate and vigorous intensities. Across all activity categories, the 95% CI of the errors was -5.07 to 4.85 METS whereas our study showed a smaller 95% CI of -2.8 to 3.0 METS.

Our results contrast with a preliminary study on children by Andreacci et al. (3) which used treadmill walking (1.7, 2.5, and 3.4 mph). These authors collected SW and EE data for the purpose of helping to update the SW algorithms. Thirteen of their subjects were used to develop new algorithms while twenty-one subjects were used to test these algorithms and their accuracy to predict EE during sub-maximal exercise. Although their results showed no significant differences in SW and IC EE estimates, our results for walking were

not as encouraging. For all three walking bouts (road, track, and with a 6.8 kg bag), we found significant overestimations, despite using similar speeds. Our three walking activities showed average speeds of 3.2 to 3.3 mph. Based on our results, it appears that the algorithms, in their current form, are not applicable to populations outside of the sample on which they were developed. However, the proprietary nature of the algorithms prohibits conclusions regarding what has been modified and what has remained constant across software versions. The software version used in the Andreacci et al. study (a version released in 2005) was different from the version used currently (version 6.1, released in 2007), so further comparisons are limited (3).

Continuous refinement and updating of the SW proprietary algorithms has taken place since the inception of the BodyMedia company. The frequent modification of manufacturer algorithms is unique, but it limits accuracy comparisons between studies. The use of study data to develop new algorithms is characteristic of several SW studies including those of Fruin and Rankin (26), Jakicic et al. (33), and Cole et al. (14). As the first study to examine SW validity, Fruin and Rankin tested the first armband model and accompanying first software version. This study used young adult participants for both 40-minute cycling tests at 60% VO_2 peak and 30-minute treadmill tests at three intensities (80.5 m/min, 0% grade; 107.3 m/min, 0% grade, 107.3 m/min, 5% grade). After initial analysis with accompanying software and its general algorithms, data were sent to BodyMedia with contextual information about exercise for a second analysis. After using exercise-specific algorithms, results indicated that the SW

accurately estimated EE during cycle ergometry. In contrast, the SW significantly ($p<0.02$) overestimated (14-38%) EE of walking at 0% grade at both speeds and significantly ($p<0.002$) underestimated (22%) EE at a 5% grade. The SW appropriately increased EE estimates with increased treadmill speed, but did not do so with increases in % grade. This can be interpreted as evidence that the SW is using the accelerometer data to predict EE during walking/running, but during cycle ergometry (when no vertical accelerations are detected) it relies on the heat flux measurements to predict EE.

In the lab-based study by Jakicic et al. (33), 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 and showed the SW (software version 3.2) 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 with contextual information such as exercise time and mode, exercise-specific algorithms were used to perform a second analysis of data. Exercise-specific algorithms showed no significant differences between SW and IC EE estimates in any of the tested activities. In addition, the increased error of the SW to estimate EE at higher intensities as present with the general algorithms was eliminated with the exercise-specific algorithms.

The study of Cole et al. (14) prompted additional software modifications based on their specific sample. Unlike the healthy populations of prior studies, this study used cardiac patients to test the SW and three software versions

(version 2.2, version 4.0, and preliminary cardiac software). Participants performed 8-minute bouts of arm ergometry, treadmill walking, recumbent stepping, and rowing ergometry with individualized intensities. Using version 2.2 for EE estimates, the SW significantly ($p<0.01$) underestimated EE during treadmill and rowing activities but accurately predicted the other two activities. Using 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, the errors in estimated EE increased with increasing exercise intensity. Given the unique population, BodyMedia developed cardiac specific algorithms based on some of the participants, and this preliminary cardiac software was then tested on the remaining participants. Using this software, SW accuracy was further improved, resulting in no significant differences for EE estimates in any activity. The errors in estimated EE were reduced compared to previous software versions. The results of Cole et al. (14) and those of other studies (26, 33) indicate the improvements made by software modifications. However, the multiple versions of SW software highlight the difficulty in comparing results among several studies.

One of the strengths of our study was the types of activities selected. Our activities focused on those which are common in daily life, as opposed to many previous studies which were confined to the laboratory. If a device is to be used in a weight loss program or to measure and improve daily physical activity, it

must be valid under a variety of conditions. 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. A second strength was that while other studies have used clinical populations such as obese individuals or cardiac patients, our study used healthy participants with a wide age range (14, 16, 49).

However, the current study also has several limitations. First, although the sample size is similar to previous studies, a larger, more diverse sample (i.e. more females in Routine 1) would have increased the generalizability of our results. Also, because all subjects did not perform all 12 activities, our ability to compare results between routines was limited. For example, based on significant differences versus IC, it appears that the SW was more accurate at EE estimation for aerobics than walking despite the higher intensity of aerobics. Yet, because of distinct routine groups, the relative degree of error of two activities both showing significant overestimations (i.e. walking and ironing) cannot be easily established. Future studies should 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 in a variety of clinical applications, because it is unobtrusive and easy to use. For example, a recent study by Polzien et al. (54) highlighted the application of the SW in a weight loss intervention. Continuous use of the SW and SW software with standard behavioral counseling produced significantly greater weight loss ($p<0.05$) than counseling alone. Regardless of any

inaccuracies which may or may not have occurred in estimating EE, weight loss was clearly improved by the SW concept. These results bode well for future clinical and individual applications of the SW in weight loss programs. Although not the focus of our study, the SW may be useful due to its ability to estimate TDEE (54). Traditionally, clinicians have predicted TDEE by using equations to estimate resting metabolic rate (RMR) and multiplying by a certain factor that represents the individual's self-reported physical activity status (32). In contrast, the SW uses the multi-sensor approach, individual participant characteristics, and specific PAEE information to calculate TDEE. Though our results do not validate the SW in all activities, its EE estimates are likely to be an improvement over the standard method of estimating TDEE. Several past studies have tested the accuracy of the SW in TDEE and REE, but results are conflicting, in part due to different models and software used. Given the amount of raw data provided by the SW software, there are many additional measures which could be examined from a clinical, rather than a research, perspective. Based on the positive conclusions of Polzien et al. (54), future investigations are warranted for other SW clinical applications such as in weight management, nutritional counseling, and behavior modification.

Based on the current results, we can only recommend the use of the SW for accurate EE estimation in low-intensity activities (such as reading or doing the laundry). However, given the inconsistency of SW accuracy across similar low intensity activities (such as light cleaning and doing the laundry), measurement of these activities should be approached with caution until similar studies are

conducted to confirm or refute the results reported in this study. EE estimations in other common activities such as walking and running at various speeds showed clear inaccuracies and necessitate future study. In addition to accepted criterion methods, other future studies should investigate whether the accuracy of the SW exceeds that of other more common objective monitors such as pedometers and accelerometers. Although not the purpose of this study, a preliminary comparison of the SW validity to the more commonly used accelerometers should be made. One previous study by King et al. compared the SW to four accelerometers (CSA, TriTrac-R3D, RT3, and BioTrainer Pro) for estimating EE (35). Healthy adult participants performed 10 minutes of treadmill walking (54, 80, and 107 m/min) and treadmill running (134, 161, 188, and 214 m/min). The SW, TriTrac-R3D, and RT3 showed significant ($p<0.05$) increases in EE estimations with increasing speeds whereas the CSA and BioTrainer Pro failed to detect EE differences above 161 m/min. Compared to IC, all monitors significantly ($p<0.001$) overestimated EE across all speeds, except for underestimation by the CSA at 54 and 214 m/min and no significant difference for TriTrac-R3D estimates at 214 m/min. This study concluded that, for treadmill activity, the SW provides the most accurate EE estimates across a wide range of speeds when compared to both uniaxial and triaxial accelerometers. However, our results did not support this study. Our results showed the SW overestimated EE during walking but underestimated EE during running. Differences in results may be due to the earlier software version (version 3.0) or the controlled conditions of walking and running used by King et al. (35). No similar study has

been conducted using different activities, either lab-based or field-based, so further conclusions are limited.

Conclusion

This study assessed the validity of the SenseWear in energy expenditure estimation during a wide range of activities. Compared to indirect calorimetry, significant differences in average MET levels by the SW were found for several activities with a trend for EE underestimation at higher intensities. To our knowledge, this was the first study to investigate the SenseWear Pro3 and its use in common activities such as ironing, walking with a weighted bag, watching television, and aerobics. Future studies are needed to confirm our results with possible modifications to proprietary algorithms to improve SW accuracy in field based activities.

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APPENDICES

APPENDIX A

INFORMED CONSENT FORM

Physical Activity Assessment Using Variability in Accelerometer Counts

Researchers:

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Purpose

The purpose of this study is to develop a new method of analyzing human movement data, using a small device worn at the waist that measures vertical acceleration (an accelerometer).

Procedures

The testing will take place at one of three locations: the University of Tennessee (UT) in Knoxville, in a community setting such as your work place or home, or outside the UT Applied Physiology Lab.

Testing Protocol

We have already asked you to fill out a health history questionnaire, and determined that you are eligible for the study. If you choose to participate, we will record your age, height, weight, and gender. You will then be asked to wear an accelerometer and a portable metabolic system (described below).

While wearing these devices, you will be asked to complete one of the following protocols (the one that is checked):

___ Perform two bouts of predetermined activities (Either playing basketball, tennis, or raking leaves and walking at a moderate pace). Before the activity, you will sit for 15 minutes. You will then perform activity 1 for 8 minutes, followed by 8 minutes of seated rest; then you will perform activity 2 followed by 8 minutes of seated rest. The total time commitment is 1 hour and 45 minutes.

___ Perform six tasks from the following list:
Watching television, driving a car, reading a book, self-paced track walking, self-paced walking (road course), self-paced track running, self-paced running (road course), singles tennis, Frisbee golf, aerobics, doing laundry, ironing, light cleaning, using a string trimmer, gardening, moving dirt with wheel barrow, loading/unloading 15 lb boxes, walking a track course with a 15 lb computer bag. Each task will last 10 minutes and you will have 3 minutes rest between tasks. The total time commitment is 3 hours.

Physical Activity Monitors
You will be asked to wear several small, electronic devices that are thought to provide accurate estimates of calorie burning. Two of these are matchbox-sized devices worn on your belt or waistband. Two other devices will be positioned on your upper arm and the ankle, respectively, using elastic bands. These devices respond to body movements and they store this information, which will later be transferred to a computer. The activity meter enables us to predict the intensity of physical activity bouts, and classify them as light, moderate, or strenuous. It must be returned at the end of the study.

Portable Metabolic System
You will also be asked to wear a portable device called a Cosmed K4b^2 metabolic measurement system. This is a little bit larger than a Walkman cassette player and it is worn on a harness strapped to your torso. It is attached to a facemask that you will wear over your mouth and nose. You can breathe normally, and even talk, when the facemask is in place.

Risks and Benefits
The risks of being in this study include injury to muscles and/or joints, dizziness, headache, abnormal heart rhythms, abnormal blood pressure responses, and in very rare instances heart attack and/or sudden death. However, we will try to minimize these risks by using a health history questionnaire, and by selecting participants who are accustomed to regular, vigorous physical activity to perform the vigorous bouts in Part 2 (structured 10-minute bouts). The benefits to being in the study include the receipt of a report showing your test results, and payment ($30 for part 1, or $80 for part 2).

Confidentiality
The information from these tests will be treated as private and will not be shown to any person without your consent. The numbers may be used in research reports but your name or other identity will not be used.

Contact Information
If you have questions at any time concerning the study or the procedures, (or you experience adverse effects as a result of participating in this study,) you may contact David Bassett at (865) 974-8766. If you have questions about your rights as a participant, contact the Research Compliance Services of the University of Tennessee Office of Research at (865) 974-3466.

Right to Ask Questions and to Withdraw
You are free to decide whether or not to be in this study and you may withdraw from the study at any time without penalty or loss of benefits. Before you sign this form, please ask questions about anything that is unclear to you.

Consent
By signing this paper, I am indicating that I understand and agree to take part in this study.

Your signature	Date
Researcher's signature	Date

APPENDIX B

(Staff Use) ID#	HEALTH HISTORY QUESTIONNAIRE	(Staff Use) DATE

Name: _____

Address: _____

City/State: _____ **Zip Code:** _____
Phone: _____ **Date of Birth:** _____
Age: _____

Gender: ___ M ___ F **UT Faculty/Staff:** _ Y ____ N
Do You Live Alone? _____ Y ____ N

Occupation: _____
Full Time? _____ Y ____ N

Marital Status: (circle one) Single Married Divorced Widowed

Education: (check highest level completed)

Elementary _____ High School _____ College _____ Graduate School____

Race: White _____ American Indian/Alaska Native ____ Asian _____

Black / African American _____ Native Hawaiian / Pacific Islander _____

Other _____

Ethnicity: Hispanic or Latino_____ Not Hispanic or Latino _____

Personal Physician: _____ **Location:** _____

Are you taking any prescription or over-the counter medication?
YES _____ NO _____

Name of Medication	Reason for Taking, For How Long?

Emergency Contact
Name: _____

Relationship: _____ Phone: Work: _____
Home: _____

PAST HISTORY

Have you ever had? (please check all that apply)

_____ Heart attack
_____ Stroke
_____ Any heart problems
_____ Blood Clots
_____ Arthritis
_____ Cancer
_____ Recurring leg pain (not related to arthritis)
_____ Liver or Kidney Disease
_____ Any breathing or lung problems
_____ Ankle swelling (not related to twisting)
_____ Low back or joint problems
_____ Diabetes

PRESENT SYMPTOMS

Do you currently have? (please check all that apply)

_____ Chest pain / discomfort
_____ Cough on exertion
_____ Shortness of breath
_____ Coughing of blood
_____ Heart palpitations
_____ Dizzy spells
_____ Skipped heart beats
_____ Frequent headaches
_____ Chronic Fatigue Syndrome
_____ Orthopedic / joint problems
_____ Diabetes
_____ Back Pain

VITA

Paige was born and raised in Knoxville, Tennessee. She graduated with honors from West High School in 2001. She attended Furman University in Greenville, South Carolina where she graduated *Summa Cum Laude* with a Bachelor's of Science in Health and Exercise Science in 2005. While at Furman, she was a teaching assistant for Anatomy and a teaching fellow for Health Promotion. She had leadership roles in the community health initiatives Greenville Shrinkdown and Greenville Walks. Returning home to the University of Tennessee for graduate school, Paige was a graduate research assistant for exercise physiology and an adjunct faculty member for the dance department. She received a Chancellor's Honors Award for Extraordinary Professional Promise in 2008. Paige will graduate in May 2008 with a Master's of Science in Exercise Science with a concentration in Exercise Physiology. She is a member of both Phi Beta Kappa and Phi Kappa Phi honor societies. She will continue her education as she begins medical school in the summer of 2008.