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Accuracy of SenseWear Armband Mini-Fly for Estimating Energy Expenditure in Normal Weight, Overweight, and Obese Individuals

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I am submitting herewith a thesis written by Bethany MaryAlice Forseth entitled "Accuracy of SenseWear Armband Mini-Fly for Estimating Energy Expenditure in Normal Weight, Overweight, and Obese Individuals." 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 of Science, with a major in Kinesiology.

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Accuracy of SenseWear Armband Mini-Fly for Estimating Energy Expenditure in Normal Weight, Overweight, and Obese Individuals

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ABSTRACT

Obesity has become one of the greatest public health issues in America. BodyMedia promotes their SenseWear Armband physical activity monitor as a way to help with weight management. **Purpose:** to assess the accuracy of the SenseWear Armband Mini-Fly (SWA-MF) in adults of different BMI categories during rest, recovery, and two walking speeds. **Methods:** Forty-six participants were assigned to one of three BMI classifications: normal weight (n =15; 18.5-24.9 $kg \cdot m^{-2}$ [kilograms per meter squared]), overweight (n=17; 25-29.9 $kg \cdot m^{-2}$), or obese (n= 14; ≥30 $kg \cdot m^{-2}$). Height and weight were measured. Participants began the test with15 minutes of seated rest, then walked on a treadmill for 8 minutes at 50 $m \cdot min^{-1}$ [meters per minute], engaged in a seated recovery for a second 15 minute period, and then walked on a treadmill for 8 minutes at 75 $m \cdot min^{-1}$. During the test, participants wore the SWA-MF over their left triceps, and the ParvoMedics metabolic system was used to measure oxygen consumption. Calories per minute ($kcal \cdot min^{-1}$) [calories per minute] were used to quantify energy expenditure in both systems. **Results:** The SWA-MF error score was not affected by the participants' BMI (p = 0.543.). The SWA-MF significantly underestimated measured energy expenditure during the resting condition by 0.21 $kcal \cdot min^{-1}$ ($p < 0.001$) and during the recovery by 0.27 $kcal \cdot min^{-1}$ ($p < 0.001$), but significantly overestimated measured energy expenditure during walking at 50 $m \cdot min^{-1}$ by 0.70 $kcal \cdot min^{-1}$ ($p < 0.001$). The SWA-MF was not significantly different from measured energy expenditure during walking at 75 $m \cdot min^{-1}$ ($p = 0.672$) or over the duration of the total testing session ($p = 0.913$). Bland-Altman plots for energy expended during the total testing session showed mean biases between -0.09 and 0.09 $kcal \cdot min^{-1}$, and 95% prediction intervals between -1.16 and 1.20 $kcal \cdot min^{-1}$.**Conclusion:** The primary finding from this study is that the validity of the SWA-MF does not differ among BMI groups. Secondary findings support that the SWA-MF underestimates measured energy expenditure during seated resting and recovery periods and overestimates measured energy expenditure during brief periods of slow walking at 50 $m \cdot min^{-1}$.

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CHAPTER I: INTRODUCTION

Obesity has become one of the biggest health issues facing Americans (1, 2). In recent decades the prevalence of overweight/obesity has risen, according to data from the National Health and Nutrition Examination Survey (NHANES) that assesses the weight status of the population based on body mass index (BMI). Currently, 34.2% of the adult population are classified as overweight (BMI of 25-29.9 $kg \cdot m^{-2}$), and 33.8% of the population are classified as obese (BMI ≥ 30.0 $kg \cdot m^{-2}$) (3, 4). Obesity is often associated with co-morbidities including, but not limited to: hypertension, heart disease, type II diabetes, and dyslipidemia (5-7).

Physical activity is a key component to maintaining a healthy weight status and helps to prevent weight gain (6, 8-10). Research has also shown that an increase in physical activity, in conjunction with dietary restrictions, is effective for inducing weight loss (9-13). Walking is the most commonly performed method of structured physical activity in adult populations (14). Walking is an easy, low-cost, and accessible activity that has been shown to be effective in health promotion and weight management. As a result, walking is commonly prescribed for physical activity (11, 14).

There are many different subjective and objective methods to quantify physical activity. Subjective measures are less costly, but are limited in accurate physical activity measurements due to problems with individual recall (13, 15-17). Objective monitors provide a more accurate measure of physical activity performed (16, 18). Pedometers and accelerometers are objective monitors that help to quantify physical activity (19).

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Objective monitors have been shown to be effective at increasing compliance and adherence to exercise prescriptions (13).

The SenseWear Armband Mini-Fly (SWA-MF) (Body Media, Pittsburg, PA) is an objective physical activity monitor that uses a variety of different inputs to estimate energy expenditure of an individual. The SWA-MF uses acceleration, heat flux, galvanic skin response, and skin temperature to estimate total energy expenditure, physical activity energy expenditure, steps, and sleep variables (20). BodyMedia promotes their product as a tool for self-monitoring physical activity that is helpful for increasing compliance to physical activity recommendations, especially in obese populations (20). The first SenseWear Armband model came onto the market in the year 2000 and utilized software created by BodyMedia to analyze data collected. Changes from the first SenseWear Armband to the current SWA-MF include: taking out the heart rate sensor, adding in a third accelerometer, and allowing the monitor to be charged via USB cable rather than AAA battery (20). In addition, the current software version 7.0, uses propriety algorithms. The software uses propriety algorithms to analyze the data, and only the results from the analysis are seen by the user, but the specific algorithms used by the software have yet to be released to the public. Each advancement in the software indicates that there has also been a modification to some part of the algorithms that are used to assess raw data from the monitor. A change in the SenseWear monitor model or software version used could mean a change in the output given. Therefore both the SenseWear monitor model and the software version used in research should be reported. The SWA-MF is worn over the triceps on the left arm, a location that has

been shown to be feasible for intervention studies (21, 22). The SWA-MF has potential

to give more accurate energy expenditure estimation based on their integrated methods

of sensors and wear location, compared to other objective monitors.

Several validation studies have indicated that the SenseWear Armband Pro2 has

reasonably good validity for estimating energy expenditure (EE) in normal weight

participants (23-25). However, results of studies conducted in overweight and obese

populations have shown poor accuracy at assessing EE. Papazoglou, et al. (26)

assessed the accuracy of the SenseWear Armband Pro2 with software 4.0 against

indirect calorimetry and through the use of Bland-Altman plots and interclass

correlations. They found that the SenseWear Pro2 overestimated measured energy

expenditure in obese populations during treadmill walking (7.62 ± 2.0 vs. 5.8± 0.66

kcal/min; $p < 0.001$), cycle ergometer (5.78 ± 1.66 vs. 4.85±0.5 kcal/min; $p < 0.001$),

and stair stepping (7.26 ± 1.76 vs. 5.56 ±0.58 kcal/min; $p < 0.001$), but underestimated

resting energy expenditure (1811± 346 compared to 1880 ±382 kcal/day; $p < 0.001$)

(26). Similarly, Browning, et al. (27) reported that the SenseWear Armband Pro2,

software version 7.0, significantly overestimated EE by 71.6 ± 46.7% ($p = 0.003$) during

walking in an obese population (27).

To our knowledge, no single study has compared the accuracy of the SWA-MF in

normal weight, overweight, and obese populations, nor has any study examined the

criterion-referenced validity of the latest software model in these populations. The latter

point is important since the device uses proprietary algorithms that may change, as new

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research becomes available. With BodyMedia specifically marketing their product for use in overweight and obese populations, its accuracy needs to be assessed before clinicians promote it to their patients. If the SenseWear Armbands overestimates energy expenditure in obese patients, this may lead them to believe they have expended more calories than they actually have, resulting in a positive energy balance. By evaluating the accuracy of the SWA-MF for estimating energy expenditure in different BMI categories, both researchers and the general population will have more information when selecting a device for their designated purpose. Therefore, the purpose of this study was to determine the validity and accuracy of the SWA-MF in normal weight, overweight, and obese individuals during seated rest, two walking speeds, recovery from the first walking bout and the total testing session.

RESEARCH QUESTION 1: How accurate is the SenseWear Armband – Mini Fly for estimating resting energy expenditure (kcal/min) in normal weight (BMI 18.5-24.9 $kg\cdot m^2$), overweight (25.0-29.9 $kg\cdot m^{-2}$), and obese (BMI ≥30.0 $kg\cdot m^{-2}$) adults?

RESEARCH HYPOTHESIS 1: The SenseWear Armband – Mini Fly will be accurate at estimating resting energy expenditure, in all BMI classifications.

RESEARCH QUESTION 2: How accurate is the SenseWear Armband – Mini Fly at estimating EE ($kcal\cdot m^{-1}$) during structured treadmill walking at 50 $m\cdot min^{-1}$ and 75 $m\cdot min^{-1}$, in normal weight (BMI 18.5-24.9 $kg\cdot m^{-2}$), overweight (25.0-29.9 $kg\cdot m^{-2}$), and obese (BMI ≥30.0 $kg\cdot m^{-2}$).

RESEARCH HYPOTHESIS 2: The SenseWear Armband –Mini Fly, will be accurate at estimating EE of treadmill walking at 50 m·min^{-1} and 75 m·min^{-1} in the normal weight population, and will significantly underestimate EE in the overweight and obese populations.

RESEARCH QUESTION 3: How accurate is the SenseWear Armband – Mini Fly for estimating EE (kcal·m^{-1}) during the entire testing session in normal weight (BMI 18.5-24.9 kg·m^{-2}), overweight (25.0-29.9 kg·m^{-2}), and obese (BMI ≥ 30.0 kg·m^{-2}) adults?

RESEARCH HYPOTHESIS 3: The SenseWear Armband –Mini Fly, will provide accurate estimates of EE during the entire testing session in the in the normal weight population, and will significantly underestimate EE in the overweight and obese populations.

DEFINITION OF TERMS

Normal weight: Individuals with a BMI between 18.5-24.9 kg·m^{-2}

Overweight: Individuals with a BMI between 25-29.9 kg·m^{-2}

Obesity: Individuals having a BMI ≥ 30 kg·m^{-2}

CHAPTER II: REVIEW OF LITERATURE

1.0 Introduction

In the United States (U.S.), rates of overweight and obesity along with obesity-related co-morbidities have increased in recent decades (7, 9, 28, 29). Physical activity is a key component to reducing body weight in overweight and obese individuals, and is important for maintaining a healthy weight (6, 9, 10, 30). Methods of accurately assessing physical activity are needed to better define the relationship between physical activity and weight loss.

Advances in technology allow a single monitor to take data from multiple inputs, including body acceleration and physiological signals (e.g. heat flux and skin galvanic response), allowing for more accurate estimation of an individual's energy expenditure during physical activity. The SenseWear Armband is an example of such a monitor. BodyMedia promotes their SenseWear Armbands to overweight and obese individuals and medical health professionals to encourage adherence to physical activity recommendations by providing information on total daily energy expenditure (TDEE) and energy expenditure during physical activity (20). Even though the SenseWear Armband is promoted to obese and overweight individuals, results on how accurate this monitor is in this population are inconclusive (26, 27). This review of literature will discuss the need for monitors to accurately assess energy expenditure during physical activity and describe how different versions of the SenseWear Armband have progressed in technology in an attempt to meet this need.

2.0 Obesity

2.1 Definitions & Prevalence

Many organizations including the American College of Sports Medicine (ACSM), the World Health Organization (WHO), and the National Heart Lung and Blood Institute (NHLBI) use the body mass index (BMI) to define overweight and obesity (9-11). BMI is a rough index of adiposity, and may be used as an index of adiposity at the population level, although due to its failure to account for lean vs. fat tissue its use can lead to misclassification of individuals (31). The BMI scale classifies individuals according to their height and weight, and BMI = body weight (kg) / (height^2) (m). Classifications range from underweight to obese class III (**Table 1)** (11).

Table 1.1. Body Mass Index (BMI) Classifications

BMI (kg·m^{-2})	Classification
Less than 18.5	Underweight
18.5-24.9	Normal weight
25-29.9	Overweight
30-34.9	Obese Class I
35-39.9	Obese Class II
≥ 40	Obese Class III

The overweight classification ranges from 25-29.9 kg·m^{-2} and accounts for 34.2% of the population and those with a BMI greater than or equal to 30.0 kg·m^{-2}, obese classification, account for 33.8% of the population (4, 29, 32, 33).

The prevalence of severe obesity (BMI $\geq$ 40 kg·m^{-2}) has increased as well; between 1986 and 1990 this group quadrupled and continued to increase by three fold from 1990 to 2000 (28, 34). Some evidence is suggesting that the classification of obese class III is increasing twice as fast as the obese class I classification (28).

2.2 Causes of Obesity

Obesity is a multifaceted condition that involves many potential causes for the rapidly increasing rates (5). While there is a genetic component to obesity, there are also many environmental factors contributing to the world-wide secular trend towards increased obesity rates (9). Environments help to shape behaviors and choices made within them. Some of the current environmental factors contributing to obesity include: the promotion of non-active transport methods (e.g. personal automobiles, city transportation systems), sedentary jobs over manual labor, sedentary leisure activities, and calorie-dense foods that are both cheap and highly palatable over healthier options (9, 28, 32). The combination of genetic and environmental factors has led to energy imbalances and weight gain (32).

2.3 Comorbidities of Obesity

Physical activity is strongly correlated to body weight classification. By not being physically active, caloric balance becomes more difficult to achieve. Physical inactivity, or insufficient participation in physical activity, is associated not only with weight gain, but also with hypertension, coronary heart disease, type II diabetes, dyslipidemia, some cancers, osteoarthritis, metabolic syndrome, lower quality of life, and higher mortality

rates (5-7). It is important to note that while many of these conditions have been

associated with inactivity, there have also been some studies performed that have

linked some of these conditions to being overweight/obese, independent of activity level

(7, 9, 35).

2.4 Economic Cost of Obesity

The association of overweight/obesity and many chronic medical conditions,

means that those who are overweight or obese have higher health care costs (9). The

health care costs of obesity can be accumulated directly from the obesity link or

indirectly through comorbidities of obesity. In 1995 the direct cost of obesity was

estimated to be 5.7% of the U.S. health expenditure and indirect costs were roughly

$47.6 billion (9). It has been suggested that those with even higher BMIs accumulate

even higher costs (12, 32, 36). Andreyeva, et al. (36) estimated that, in 2004 an

individual who has a BMI greater than 30 kg$\cdot$m^{-2}is likely to spend 33% more on health

care than someone with a BMI less than or equal to 25 kg$\cdot$m^{-2}. The analysis continued

by showing individuals with a BMI greater than 35 kg$\cdot$m^{-2} will have medical expenditures

more than twice that of normal weight individuals (36). More recently, Sturm (37)

suggested that in 2005 individuals who are severely obese, having a BMI greater than

or equal to 40 kg$\cdot$m^{-2}; pay between two and four times more in health care costs

compared to someone who is of a normal weight (37).

It is estimated that obesity comorbidities cost more than health conditions caused

by both smoking and alcohol consumption (32). Obesity is associated with an increase

in medical costs of $395/year while smoking is associated with an increase of $230/year

and health conditions caused by alcohol consumption account for roughly a $150/year increase (32). In the early 2000s, cancer, diabetes, and coronary heart disease, all of which are associated with higher BMI status, accounted for the largest costs in health care spending (32). Hypertension, which is the most common comorbidity of obesity, has contributed to increased health costs over recent years, with direct costs equating to roughly $131 billion/year (7, 35). In 2002, Sturm (32) estimated that there was an increase of 36% in health care costs (i.e. doctor visits and medical stays) and an increase of 77% in medications in individuals who were overweight and obese compared to normal weight individuals (32).

2.5 Solutions for Obesity

As seen from the large increases in obesity prevalence, obesity comorbidities, and medical expenditures associated with these conditions, obesity is a threat to the health and well-being of society. Many organizations and individuals advocate that there should be a focus/emphasis on preventing obesity (9, 29, 34). There are many different ideas on how to combat obesity ranging from creating environmental strategies to community or individual based interventions. A key concept in all obesity treatment involves negating the positive energy balance by either increasing physical activity or decreasing the amount of calories consumed (9). Weight reduction is achieved through creating a negative energy balance (i.e. through increasing physical activity, dietary restriction, surgery, or weight loss drugs). The reduction of weight (≥5% of current body weight) may help to reduce medical expenditures by an estimated 8 to 20% (12).

Physical activity is beneficial because it can cause weight loss, as well as decrease the risk of many comorbidities of obesity. Moreover, physical activity has benefits on cardiovascular risk factors, independent of weight reduction. Blair (6) has conducted research on the 'fit versus fat' debate. His research supports the notion that physical fitness and body fatness are independently related to risk of mortality. Those who are "fit and fat" have a 50% reduced risk of mortality compared to those who are normal weight but unfit (6). Physical activity needs to be performed to counteract the trends of the rising obesity rates and rising medical expenditures (8).

3.0 Energy Balance and Imbalances

3.1 Components of Total Daily Energy Expenditure

Overweight and obesity result from a person being in positive energy balance for extended periods of time. A positive energy imbalance results when more calories are consumed than expended in an individual's TDEE. TDEE has three components: resting metabolic rate (RMR), thermic effect of food (TEF), and physical activity energy expenditure (PAEE) (39). Other factors such as climate and pregnancy may also affect an individual's TDEE (39).

RMR accounts for the largest portion of TDEE (about 60-75%) and includes the energy needed to fuel metabolic reactions and rest periods. Individual differences in RMR arise from that amount of fat-free mass an individual has, and their sex (39, 40). TEF usually is the smallest component, accounting for up to 10%, of TDEE. This component of TDEE accounts for energy expended during the digestion process of food

and stimulating the metabolic rate (39). The final component of TDEE, accounting for 15-30%, is PAEE (39). PAEE is the most modifiable component of TDEE and it depends on the activity level of an individual (both planned and spontaneous) (40). The frequency, duration, and intensity of activity bouts all affect PAEE (39, 40). Other influences on PAEE include one's fitness level, and the muscular efficiency of the activities performed (40, 41).

Body mass is considered to be one of the most important factors when estimating TDEE, therefore individuals who are overweight or obese will have a higher TDEE. Having a higher body mass, especially more fat free mass, will require more internal work, which will be reflected in the RMR (39, 42, 43). It is estimated that obese individuals have a RMR that is about 13% higher than normal weight individuals (40).

Energy expenditure during physical activity will also be increased in an overweight individual because more work must be performed during weight-bearing activities, such as walking or running (39, 40, 42, 44, 45). Browning, and colleagues, have extensively studied the effects of body mass on walking in females. In 2005, Browning, et al. (44) compared walking speeds and energy expenditure in normal weight and overweight women. Five walking speeds were evaluated; those who were overweight expended 11% more energy than normal weight participants (1.40 vs. 1.47m/s, $p = 0.07$). This study associated the 11% higher energy expenditure to the greater oxygen consumption in the overweight women, meaning that at the same speed they would require more aerobic effort to continue the activity (44). A few years later,

Browning and Kram (45), reviewed the relationship between obesity and walking energetics. Their review showed that obese adults have a greater metabolic cost by 10-12% during walking, compared to normal weight adults, and 25% increased metabolic weight in obese adolescents. The results of this study pointed to total body mass being one of the biggest factors in metabolic cost of weight-bearing activity (45).

3.2 Measuring Energy Expenditure

The most accurate way to measure TDEE is through the use of doubly labeled water (46). In this collection method, participants consume water with a known amount of specific isotopes (i.e. Deuterium and oxygen-18) and a few days to two weeks later will give a urine sample to test how much of the isotopes are left. This measure allows researchers to accurately assess energy expenditure in the free-living environment. While this methodology is considered to be the gold standard for measuring TDEE, information regarding the pattern of physical activity (i.e. frequency, intensity, and duration of bouts) and the "context" of the activity (location and social setting) cannot be determined. For this reason and due to the costly procedure, doubly labeled water is not commonly used in research (15, 39, 46)

Direct calorimetry includes the use of a room calorimeter and is another technique to assess energy expenditure. This method of data collection is often not feasible, due to expensive equipment, and the inability for data collection outside of the lab (39). Indirect calorimetry is another valid standard for collecting energy expenditure

data, and is a more realistic method to use in most studies (compared to DLW or direct calorimetry). A participant wears a mouth piece, allowing inspired and expired gas to be analyzed, which ultimately allows for assessment of energy expenditure and substrate utilization (47).

4.0 Subjective Measures of Physical Activity

Subjective instruments are one option to measuring physical activity behaviors and roughly estimate PAEE. Subjective measurements are one of the most cost effective forms of physical activity measurements, and are easy to administer. There are many types of subjective instruments including: physical activity diaries or logs, questionnaires, interviews, and surveys (15, 18, 48). Subjective measures can be used to collect population level information, as a way to self-monitor or to obtain a more in-depth look at physical activity behaviors (13, 17, 18). Subjective measures can be more accurate when more detail is included in the data collection. For example, specifying the type, duration, intensity, and frequency will help to create a better picture of the activity behaviors and will usually result in greater validity (17, 46). Many subjective methods, including questionnaires, have been validated as a way to assess physical activity (17).

While subjective methods are considered to be valid means of assessing physical activity, there are many limitations to their use. Their greatest weakness is that they are based on self-reported data (15). Self-reported data has a recall bias and often overestimates physical activity (13, 15, 18). While most activities are overestimated,

some spontaneous activities and activities of daily living, such as walking, may be underestimated (15-17). Subjective measures can be a useful tool to assess physical activity, but depending on the research purpose, they may not be as accurate as objective monitors.

5.0 Objective Monitors

With the increase in obesity rates, there is a need for accurate, reliable assessment of physical activity, and objective monitors can provide a solution. Objective monitors use either physiological markers or body movement to assess how much activity is being performed (15). Two common types of objective monitors include pedometers and accelerometers. Benefits of these monitors include low cost and feasibility, in addition to the fact that they are considered to be accurate and valid tools for assessing physical activity.

5.1 Pedometers

Pedometers collect data on the number of steps an individual takes. The early versions of pedometers were created with the use of spring levers and were often worn on the hip. As technology has progressed pedometer accuracy has improved with the piezoelectric pedometers, which are now preferred over the spring levered pedometers. With the advent of piezoelectric pedometers, the potential wear sites of pedometers have increased (19, 49). While some pedometers are still worn on the hip, some have

been designed to be worn on the foot (e.g., Step Watch 3), in pockets (e.g. Omron pedometer and Fitbit Zip), or on a wrist (e.g. Nike Fuelband) (19). Most recent pedometers have been studied to show accuracy and validity in a variety of populations (19).

Early spring-levered pedometers, and some piezoelectric pedometers may not count steps accurately at slower walking speeds (19, 49). This presents a possible issue in the accuracy of obese and elderly populations because individuals within these populations may have slower self-selected walking speeds (19, 50). Despite this concern, many piezoelectric pedometers have shown good accuracy in obese populations, with step counting errors not being significantly correlated to BMI status (19, 49-51). Recent studies have also shown that newer versions of pedometers do a much better job of counting steps at slower walking speeds.

In 2003, Swartz, et al. (51) investigated the relationship between BMI and the accuracy of Yamax SW-200, an electric pedometer (51). The study included three BMI classifications of normal weight, overweight, and obese. Pedometers were placed at the waistline/belt level in three different places: on the anterior midline of the thigh (according to manufacturer protocol), on the individual's side, and along their back. Subjects walked on a treadmill at five different walking speeds and all pedometer outputs were compared to direct observation and counting of steps. Results of this study did not find significant differences in the accuracy of pedometer output between the different BMI classifications or waist circumference measurements (51).

The following year, Melanson, et al. (50) looked at the accuracy of pedometers in older (46-85 years) obese patients, which created a focus of the study on the accuracy during slow walking. The pedometers used in this study included three spring levered pedometers, Yamax SW-200-024, Walk-4-Life LS 2500, and the Step Keeper HSB-SKM, and one piezoelectric pedometer, Omron HF-100. Each pedometer was placed on the body according to manufacturer recommendations. This study concluded that the older, spring levered monitors were not as accurate for assessing the number of steps taken at slower speeds when compared to the piezoelectric pedometers. This study also supported the concept that BMI was not a determinant in the step count error (50).

Crouter, et al. (49), in 2005, examined the difference in accuracy between a spring levered and piezoelectric pedometer in overweight and obese individuals based on their BMI, waist circumference, and the tilt of the pedometer. The study compared outcomes from the Yamax Digiwalker SW-200 and the New Lifestyles NL-2000 to the actual steps taken (counted by the investigators). The piezoelectric pedometer was more accurate than the spring levered pedometer in overweight and obese populations in both lab and free-living conditions. The error observed in the spring levered pedometer was correlated with the pedometer tilt ($p < 0.05$), more than waist circumference and BMI (49).

Finally, the StepWatch 3 is a pedometer that is worn on the ankle. This pedometer is one of the most accurate and records steps within 3% of actual steps taken during a wide range of walking speeds (19). Previous studies have shown that

pedometer accuracy may be affected by slower walking speeds or pedometer tilt when worn at the waist, but the StepWatch 3 accuracy is not affected by adiposity or slow walking speeds (52, 53). Studies have shown that piezoelectric pedometers can be accurate at a variety of speeds and are not influenced by BMI status.

5.2 Accelerometers

Accelerometers are objective monitors that measure the acceleration of body movements in one to three planes (54, 55). Accelerometers have been shown to be valid in a variety of lab and free-living situations (55, 56). As technology progresses, equations to analyze accelerometer data have become more accurate (e.g., pattern recognition) and this has allowed researchers to achieve improved accuracy for TDEE, energy expenditure during physical activity, and classify different modes of activity (55, 57, 58).

One drawback to using accelerometers is that outcomes or activity counts, cannot be directly compared between monitors. While outcome measures are all related to acceleration and frequency, different brands may incorporate different outcome variables or use equations based on different cutpoints, which does not allow for direct comparison between research studies (55, 59). While raw data outcomes may be hard to directly compare, researchers are able to compare duration and intensity of physical activity bouts (55, 59).

Bassett and John (19), in a review article, considered a variety of pedometers and accelerometers that are commonly utilized. The article pointed out many limitations and inaccuracies of accelerometers and the equations used to analyze the accelerometer data to estimate energy expenditure. Equations work best for predicting the energy expenditure of activities that they are developed on but are less accurate for predicting energy expenditure of other activities. Another limitation of using accelerometers is that different brands cannot necessarily be compared. The article pointed out a study in which the Actical monitor recorded less counts per day of daily physical activity than the ActiGraph during free-living environments. The RT3 activity monitor does not provide raw data, but converts the data into outcomes (kcals, duration, and intensity of activity). The RT3 commonly overestimates moderate and vigorous PAEE and underestimates free-living energy expenditure. Finally, the SenseWear armband and software was found to underestimate energy expenditure of many activities (19).

Accelerometers have been shown to be accurate and valid in a variety of conditions and are a good choice for many research applications (61). Many inaccuracies in estimating energy expenditure arise during free-living situations, rather than lab based research, because the body movements may come from smaller upper body muscle groups or if activities are intermittent in nature (56). With advances in technology and in the methods used to assess accelerometer data the trend for inaccurately assessing free-living activities is now becoming a trend for accuracy (57, 60). With the growing trend for accelerometer use, further research is needed to

improve the technology, and to test the accuracy and validity of each new

accelerometer (55).

5.3 Monitors using a combination of methods

Heart rate and oxygen consumption have a linear relationship for most physical

activities. This linear relationship can provide a way to estimate energy expenditure by

using heart rate on a physical activity monitor. While this method is often used in

commercial physical activity monitoring devices, such as polar heart monitors and

watches, there are some issues with using heart rate. Heart rate can be influenced by

factors besides exercise, including stress, caffeine, fatigue, and fitness; thus, increases

or decreases in heart rate may not always be relatable to energy expenditure (39, 62).

Because heart rate is influence by a variety of factors, it has been shown to be poor

indicator for assessing physical activity during sedentary behaviors and light intensity

activities (80).

The SenseWear Armband is one product that uses a combination of methods to

estimate energy expenditure. This monitor quantifies physical activity by using a tri-axial

accelerometer, galvanic skin response (GSR), a heat flux sensor, and near body

temperature monitors (20). GSR, through the use of electrodes on the skin, senses

physiological responses of the secretary activity of sweat glands (63). In the SenseWear

monitors, the GSR records information on the amount of sweat lost by an individual and

attributes it to the intensity of the activity, or to the surrounding environmental conditions

(20). The heat flux sensor measures the heat lost during physical activity, with more

heat lost being attributed to more work being done by the body. This sensor uses the difference between skin temperature and near body temperature to assess the heat loss (20). The SenseWear Armband's ability to combine data from multiple sensors should improve the accuracy to estimate energy expenditure during physical activity.

5.4 Wear Location

Wear location of objective monitors can impact how much activity is, or is not recorded. In pedometers, if the wear location is on the hip of an obese or pregnant person, the monitor may be tilted farther away from the vertical axis, therefore not registering steps and giving lower step counts (19, 49, 51, 64, 79). In contrast, wearing a pedometer on the hip of a normal weight individual or on an ankle may result in increased accuracy in step counts (1)

Wear location of accelerometers has moved from the hip to include wear sites over the triceps, wrist, and leg (65, 66). The Genea accelerometer is a wrist worn monitor that was reported to have good validity. Esliger, et al (65) placed the Genea monitors on the waist, left and right wrist while subjects completed 12 different activities. The waist mounted GENEA was most highly correlated to energy expenditure (r = 0.87), followed closely by the left wrist worn monitor (r = 0.86) and then the right wrist worn monitor (r = 0.83). While the wrist worn monitors were less correlated with energy expenditure than the monitor worn at the waist, they were found to be accurate at estimating energy expenditure (65). In a different study validating Esliger's cutpoints for the left wrist, during light, moderate, and vigorous physical activity against indirect

calorimetry were found to have lower accuracy when subjects performed a different group of activities (including treadmill-based, home and office activities, and sport activities). The GENEA was placed on left wrists, in individuals who were right-hand dominant. Only 41.4% of the energy expenditure from all activities explained by the GENEA, and only 52.8% of activities performed were correctly classified by intensity level. This study concluded that when the GENEA was worn on the left wrist, it did not meet accuracy standards for classifying activity intensity or energy expenditure (67).

The SenseWear Armband was designed to be worn on the upper arm, over the triceps (20, 68). While this device has been validated in a variety of populations and situations, there have been studies that report over estimation of energy expenditure for activities that involve large arm movements (69, 70). Davis, et al. (71) in 2007, looked at the effect of wearing long and short sleeves on the SenseWear Armband Pro2 energy expenditure estimates. Results showed that the monitor was accurate at quantifying energy expenditure against indirect calorimetry, regardless of the clothing's sleeve length (71).

6.0 SenseWear Armband

6.1 Creation and Progression of the SenseWear

The SenseWear Armband is an objective physical activity monitor that uses a variety of integrated sensors to estimate and quantify energy expenditure. BodyMedia describes their product as,

"easy-to-use, reliable, and accurate way…to assess metabolic physical activity and energy expenditure outside the lab (20, 68)."

While this product is often used in laboratory settings, it has been marketed to the general population and to health care providers as a method of accurately recording energy expenditure, with applications for obese and diabetic populations (20, 68).

The SenseWear Pro1 monitor included a biaxial accelerometer, a heart rate monitor, a skin temperature sensor, two galvanic skin response (GSR) sensors, a heat flux sensor, and finally a near-body ambient temperature sensor (48, 68). The SenseWear Armband has improved with technological progress so that the latest version, the SenseWear Armband Mini-Fly (SWA-MF) includes a triaxial accelerometer, charges via a USB cable, does not contain the heart rate monitor (which was included in the SenseWear Armband Pro1) (68). Throughout the process of changing the physical monitor, the software has also progressed to incorporate new algorithms (e.g., pattern recognition). According to BodyMedia, the SenseWear Armband uses pattern recognition to classify several activities such as walking, cycling, biking, and stair climbing, along with other modes of activity (68). BodyMedia uses proprietary algorithms, which are not released to the public. The resting algorithms use RMR prediction equations that take into account and individual's height, weight, age, and sex (72). The latest version of the software is Version 7.0 (20). This software gives raw data counts, in addition to data that is converted to output measurements of energy expenditure (joules and METs), steps taken, and activity duration (27, 68).

6.2 SenseWear Pro1 Validation Studies

Validation studies have been completed with each new version of the SenseWear Armband. Liden et al, (69) was the first to validate the SenseWear Armband Pro 1 monitor through a series of studies. The studies examined the relationship between the accelerometer and the heat flux compared to indirect calorimetry in 40 participants in three BMI ranges (underweight, normal weight, and overweight) who were monitored during walking and biking at different speeds, and at rest. This study found that BodyMedia's algorithms were within ±9.4% of the measured total energy expenditure across all activities (69).

Jakicic, et al. (25) performed a validation on the SenseWear Armband Pro 1 monitor and used software version 3.0. The validation consisted of 40, healthy weight subjects, who performed: walking, stair climbing, cycle ergometer, and arm ergometer. Results were compared against indirect calorimetry. The SenseWear Armband Pro1 significantly underestimated the energy expenditure during walking (14.9 ±17.5 kcals; $6.9 \pm 8.5\%$; $p < 0.001$), stair climbing (28.2 ± 20.3 kcals; $17.7 \pm 11.8\%$; $p < 0.001$), and the cycle ergometer (32.4 ±18.8 kcals; $28.9 \pm 13.5\%$; $p < 0.001$). In contrast, during arm ergometry, the SenseWear Armband Pro1 over-estimated energy expenditure (21.7 ± 8.7 kcals; $29.3 \pm 13.8\%$; $p < 0.001$). Based on results from this study, it was recommended that BodyMedia created activity specific algorithms to increase the accuracy of the energy estimates (25). Overall, the SenseWear Armband Pro1 tended to under estimate energy expenditure of most activities.

6.3 SenseWear Pro2 Validation Studies

BodyMedia took the results and recommendations of these studies to create more accurate software and monitoring devices, resulting in the SenseWear Armband Pro 2. Along with the new monitor came new software versions, 4.0 and 4.1, which began to use pattern recognition technology (20, 73). In 2004, Fruin, et al. (74) investigated the new generation of SenseWear Armband monitors in cycling, walking, and resting conditions. Thirteen healthy, young adults participated in the validation (74). Data from the SenseWear Armband Pro 2 was validated against indirect calorimetry. Reliability of the monitor was established in this study through comparing two separate resting measurements. The SenseWear Armband Pro2 showed the largest errors in estimating energy expenditure during treadmill walking. The SenseWear Armband Pro2 overestimated energy expenditure of walking on a flat surface by 13-27% ($p < 0.02$), and underestimated energy expenditure by 22% when walking at an incline set at 5 ($p < 0.002$). Cycling and resting had no significant differences from the criterion. Resting was not significantly different than indirect calorimetry and was highly correlated with indirect calorimetry (r = 0.93; $p < 0.001$). While no significant differences were found among the total energy expenditure, the SenseWear Pro 2 was only moderately correlated to the measured values from indirect calorimetry (r = 0.47-0.69). The authors concluded that the SenseWear Armband Pro2 error was not impacted by gender, and they recommended that future studies look at more diverse populations and at light activity levels (74).

King et al. (48) chose to examine the validity of the SenseWear Armband Pro2, along with four other activity monitors at different walking and running intensities compared to indirect calorimetry. Twenty-one subjects were tested with five physical activity monitors, including the SenseWear Armband Pro 2, RT3, TriTrac-R3D, the Computer Science Applications (CSA; commonly known as the ActiGraph), and the Bio Trainer – Pro. The findings of this study showed the SenseWear Armband Pro2 slightly overestimated the energy expenditure of walking at different speeds. At 54 m/min the SenseWear Armband Pro2 over estimated accelerometer counts by 4.34 ± 0.49 counts ($r = 0.65$, $p < 0.01$) and at 214 m/min overestimated by 13.44 ± 1.70 counts ($r = 0.82$; $p < 0.001$). Despite this, the SenseWear Armband Pro2 had the highest correlations with indirect calorimetry (54 m/min, $r = 0.65$; 80 m/min, $r = 0.82$; 214 m/min, $r = 0.82$) and the least error at most speeds compared to the other monitors (48). Wadsworth, et al. (75) also found the SenseWear Armband Pro2 had significant correlations with resting energy expenditure ($r = 0.79$; $p < 0.001$) and good accuracy compared to indirect calorimetry in predicting the energy expenditure of rest and walking at a speed of 3.5mph ($r = 0.94$; $p < 0.001$) among healthy adults (75).

The technology used to assess activity patterns in the SenseWear Armband Pro2 was tested in 2007 by Welk, et al. (73). They had 30 subjects perform a variety of daily living activities while wearing the SenseWear Armband Pro2, the ActiGraph and IDEEA monitors, with IDEEA being used as the criterion. Welk and colleagues were able to compare the 3.9 and 4.1 software versions during their research. Mean SenseWear Armband Pro2 estimates of energy expenditure were within 0.10 METs of the mean

IDEEA criterion, but were only moderately correlated (range: r = 0.61 to r = 0.66). Other correlations from the ActiGraph exceeded r = 0.76. Results also supported that the 4.1 version of the software was better at estimating total energy expenditure and physical activity intensity compared to the 3.9 software (within .10 METs; and 0.12 METs, respectively), based on having smaller error scores. This shows that the software is progressing and becoming more accurate (73). This study assessed only light and moderate-intensity activities, and did not examine vigorous activities. In the same lab, McClain, et al. (70) looked at the accuracy of the SenseWear Armband Pro2 energy expenditure estimates during steady state exercises compared to indirect calorimetry. Significant differences and poor correlations were found while standing still and walking with swinging arms (r = 0.44). Besides these limited conditions, the study found moderate to high correlations between the SWA and measured energy expenditure (r = 0.77 to 0.88) (70).

Malavolti, et al. (76) re-assessed the validity and accuracy of the SenseWear Armband Pro2 for measuring resting energy expenditure. Resting energy expenditure was tested in 99 healthy subjects, with indirect calorimetry being used as the criterion method. This study found that the SenseWear Armband Pro2 high correlations with the measured values in this population (r = 0.86, *p* <0.001), with the SenseWear Armband Pro 2 recording 1540 ± 280 kcal/day, which was not significantly different from the measured values. Researchers suggested further research using the SenseWear Armband Pro2 in overweight and underweight populations (76).

St-Onge, et al. (77) validated the SenseWear Armband Pro2 using the software version 4.02. While many of the previous studies had used a criterion method of indirect calorimetry, St-Onge used doubly labeled water (DLW). The study was designed to validate the SenseWear Armband Pro2 against TDEE and also tried to measure PAEE in free-living adults. Subjects were given DLW and asked to wear the SenseWear Armband Pro2 for a total of 10 days. TDEE was given as an output from both measures. PAEE was estimated from the DLW by subtracting each individual's recorded RMR from the collected TDEE; 10% of the TDEE was also subtracted to account for TEF. The study concluded that the SenseWear Armband Pro2 was correlated to assess TDEE in individuals ($r^2 = 0.81$, $p < 0.01$), and only slightly underestimated TDEE by a mean of 117 kcal/day lower than DLW ($p < 0.01$). The SenseWear Armband Pro2 was less correlated to DLW when evaluating PAEE ($r^2 = 0.46$, $p < 0.01$), with 46% of this variation being explained by inter-individual differences (77).

Bernsten, et al. (24) used the SenseWear Armband Pro2 software version 5.1. This study tested the SenseWear Armband Pro2 accuracy during free-living activities that were structured in bouts, a concept similar to Welk's research conducted three years earlier (73). The activities tested were: sport related activities, strength training, common occupation and home activities, and home repair. Bernsten looked at the accuracy of energy expenditure compared to indirect calorimetry. The SenseWear Armband Pro2 tended to overestimate the time spent in moderate to vigorous physical activity by 2.9%, which led to overestimates of energy expenditure at these intensity levels. Overall the SenseWear Armband Pro2 underestimated total energy expenditure

during free-living activities by 9%, and was moderately correlated (r = 0.73; p <0.001)

when compared to indirect calorimetry. Much of the variance seen between the

SenseWear Armband Pro2 and indirect calorimeter was due to individual differences of

the subjects. This finding shows that this device may not be accurate at an individual

level, but when individual inaccuracies are grouped together and analyzed, the

inaccuracies become less because across the group. Bernsten pointed out that since

BodyMedia algorithms are not shared, criterion for different intensity levels cannot be

evaluated, and this may be the reason why time and energy expenditure in moderate to

vigorous activity was overestimated (24).

The final validation of the SenseWear Armband Pro2 in a general adult

population was completed by Drenowatz, et al. (72) and looked at the validation of the

SenseWear Armband Pro2 during treadmill running at levels of high intensity (greater

than 65% of VO_{2max}). No previous research had looked into SenseWear Armband Pro2

during vigorous activities. Twenty endurance trained athletes were tested at 65, 75, and

85% of their maximal oxygen consumption. This study used the Oxycon Mobile portable

indirect calorimeter to collect actual energy expenditure and analyzed the information

with software version 6.1. Results showed that the SenseWear Armband Pro2

correlation to the Oxycon was r = 0.66 ± 0.25 for the entire sample during vigorous

exercise. MET values obtained at all intensities showed that the SenseWear Armband

Pro2 was inaccurate at estimating PAEE above 10 METs, which was equivalent to 6

mph during treadmill running (p < 0.05) (72).

6.4 SenseWear Armband Pro3 and Mini-Fly Validation Studies

In 2005, BodyMedia released the third generation of the SenseWear Armband, the SenseWear Armband Pro 3, along with the SWA-MF. These monitors, while still collecting data from multiple sensors, also collected data on sleep duration, sleep efficiency, and duration of laying down (20). With a new version of the monitor, came a new round of validation testing. Johannsen, et al. (61) were the first to test the new versions of the monitor, both the SenseWear Armband Pro3 and the SWA-MF; with software version 6.1 to estimate TEE. Participants in this study had a wide range of BMI to help in creating generalizable results. Like St-Onge (77), Johannsen, et al. (61) used DLW as their criterion measure, and found that the SenseWear Armband Pro3 underestimated TEE by 112 kcal/day, (error rate = 8.1% ±6.8%, p = 0.07) a 4% underestimation when compared to DLW, but this was not significant. The SWA-MF also underestimated TEE by 22 kcal/day (error rate = 8.3% ±6.5%, (p = 0.69)), which was an underestimation by less than 0.1% when compared to DLW. The SWA-MF seemed to be more accurate than the SenseWear Pro 3, but research supports the use of both these tools in research (61).

Dudley, et al. (23) also examined the accuracy of the SenseWear Armband Pro3, using software 6.1, in normal weight, healthy adults during 18 different activities. This study compared SenseWear Armband Pro3 results against indirect calorimetry, and quantified physical activity in METs. Results showed that the SenseWear Armband Pro3 had a tendency to overestimate METs during light to moderate activities by 15-70% (e.g. ironing, sidewalk walking, and light cleaning) (p < 0.05). The SenseWear Pro3

underestimated METs during high intensity activities by 20% (e.g. tennis, and track running) ($p < 0.01$), and a significant correlation was found between the error score of the devices and the intensity of activities (r = 0.70, $p < 0.01$) (23).

6.5 Validation Studies with Special Populations

The SenseWear Armband monitors have been found to be valid across many studies in adult populations, with the newer generations of the monitor and software, together, becoming more accurate at estimating energy expenditure. While it is important to validate physical activity monitors in healthy populations, it is also important to expand the validation studies to include special populations. The SenseWear Armband models have also been used in validation studies with such special populations including: in persons with a stroke, pregnant women, older populations, and in children. Manns et al. (78) assessed validity of the SenseWear Armband Pro3 in estimating energy expenditure and step counts in persons who suffered from a stroke. Data from the SenseWear Armband Pro3 was assessed using the software version 6.1 and was compared against the Oxycon, a portable indirect calorimeter. This population was of special interest because of the effects that a stroke may have on an individual's motor behavior and abilities. The SenseWear Armband Pro3 was tested both on the hemiplegic arm and non-hemiplegic arm of each participant. In patients who had a stroke, the hemiplegic arm may lose some of its function including minimizing or losing movement functions; it may also become less vascular, resulting in a cooler temperature along this body part. The study used interclass correlations to concluded that the SenseWear Armband Pro3 was most accurate on the non-affected side

compared to the hemiplegic arm (ICC = 0.702, ICC = 0.586, respectively) and steps poorly correlated in individuals who walked at a speed slower than 50 m/min (ICC <0.352). Because of the inaccuracy at slower walking speeds, Manns, et al, suggest a lower threshold for gait speed of 50 m/min (78).

Another special population that was used in testing the accuracy and validity of the SenseWear Armbands was pregnant women. Pregnancy increases RMR and TDEE in woman, which potentially creates a challenge for the SenseWear Armband to accurately detect energy expenditure. Bernsten, et al. (79) used the SenseWear Armband Pro2 software version 6.1, in 20 pregnant women during different activities and compared it to indirect calorimetry. Activities included: seated rest, stretching, brisk road walking, cycling and calisthenics, totaling 90 minutes. Regardless of the pregnancy trimester, the SenseWear Armband Pro2 underestimated energy expenditure by 9%, for the total bout of activity. Interclass correlation showed a strong correlation between the SenseWear Armband Pro2 and indirect calorimetry (ICC = 0.85; 95% CI 0.71- 0.93; $p <$ 0.001) (79).

Some researchers have examined the validity of the SenseWear Armbands in different populations based on age, including: older adults, children and adolescents. In 2011, Mackey, et al, (21) validated the SenseWear Armband Pro3, software versions 5.1 and 6.1, energy expenditure estimation in older adults. SenseWear Armband Pro3 data was compared against DLW, and outputs from both software versions were compared to each other. Results showed strong correlations for total energy

expenditure between DLW and software versions 5.1 and 6.1 (r = 0.901, $p < 0.001$; r = 0.893, $p < 0.001$, respectively) (21).

In 2010, Backland, et al. (81) expanded the validity research in children by assessing the accuracy of the SenseWear Armband Pro 2 in overweight and obese children. This study looked at energy expenditure in a free-living environment and compared the SenseWear Pro2 to DLW. Software versions 5.12 and 6.0 were also compared. Results showed that version 5.12 was accurate than version 6.0 when assessing energy expenditure in obese and overweight children. Software version 5.12 was not significantly different than DLW ($p = 0.95$); in contrast software version 6.0 significantly underestimated energy expenditure by 18% ($p < 0.001$). A possible explanation for the underestimation by software version 6.0 is that the output given showed less time in physical activity being recorded compared to software version 5.12. This study supports that each new version of the software should be validated to evaluate if BodyMedia algorithms used are accurately estimating energy expenditure.

Previous studies have shown validation of the SenseWear Armband Pro2, SenseWear Armband Pro3, and SWA-MF in a variety of populations and situations, however there is still concern regarding validity in obese individuals. It is imperative that the SenseWear Armband monitors are able to accurately estimate energy expenditure during physical activity and TDEE in this population because their marketing strategy targets this population (20). Research in this area has resulted in conflicting results of the validity in adult populations.

Papazoglou, et al. (26) examined the accuracy of the SenseWear Armband Pro2 in obese individuals (BMI ≥ 30 kg·m^{-2}) during rest and three different modes of activity, compared to indirect calorimetry. Activities included the cycle ergometer (at 60 watts and 60 RPM), stair stepping (with 16 cm step height), and walking (at 3 km/hr). Results showed that the SenseWear Armband Pro2 overestimated measured energy expenditure in obese participants during treadmill walking (7.62 ± 2.0 vs. 5.8± 0.66 kcal/min; r = 0.03), cycle ergometer (5.78 ± 1.66 vs. 4.85±0.5 kcal/min; r = 0.18), and stair stepping (7.26 ± 1.76 vs. 5.56 ±0.58 kcal/min; r = 0.06), but underestimated resting energy expenditure (1811± 346 compared to 1880 ±382 kcal/day; r = 0.88, p < 0.001 compared to r = 0.96, p < 0.001) (26).

In 2012, Browning, et al. (27) investigated the accuracy of different monitors, including the SenseWear Armband Pro2, compared to indirect calorimetry, in obese class III (BMI ≥ 40 kg·m^{-2}) bariatric patients. The SenseWear Armband Pro2 non-significantly underestimated steps taken, by 12% (p = 0.086), but significantly over estimated physical activity energy expenditure by 71.6 ± 46.7% (p < 0.001) compared to indirect calorimetry (27).

The SenseWear Armband monitors have been validated in a variety of populations over the last decade, but research results have been inconsistent with regard to the accuracy of the SenseWear Armband in overweight and obese individuals. Another common trend among studies is that there is a lot of variance in accuracy at an individual level, but when the estimated energy expenditure is averaged across a group

is statistically accurate. Further research is needed to assess the validity of the

SenseWear Armbands in overweight and obese populations, across different exercise

intensities.

CHAPTER III: MANUSCRIPT

Accuracy of SenseWear Armband Mini-Fly for Estimating Energy Expenditure in Normal Weight, Overweight, and Obese individuals

Introduction

Rates of overweight and obesity have increased in most countries over the past four decades (7, 9, 28, 29). Physical activity is a key component for reducing body weight in overweight and obese individuals and is important for maintaining a healthy weight (6, 9, 10, 30). There is a need for the general population to be able to quantify their level of activity to assist in improving or maintaining their weight status. The ability to quantify physical activity allows for a better understanding of how many calories have been expended throughout the day. Many physical activity monitors have been developed to aid consumers in tracking their caloric expenditure, which can help them to achieve negative caloric balance.

The SenseWear Armband Mini-Fly (SWA-MF) is marketed as a device to assess physical activity and sleep (20). The SenseWear Armband combines input from several different sensors in order to estimate energy expenditure. These sensors include: a tri-axial accelerometer, galvanic skin response monitor, a heat flux sensor, and a near body temperature monitor (20). The combination of sensors may be beneficial over a single sensor because it collects more data on the environment (surrounding temperature and humidity) and movement (including intensity level and planes of movement), which may allow for more accurate energy expenditure estimates. The

SenseWear Armband is promoted to consumers, and specifically targets overweight and obese individuals.

Previous research validating different models of the SenseWear Armband and the software in normal weight populations have shown the monitor to be reasonably accurate for activities including: cycling, stair stepping, and rest (48, 70, 73, 76). In contrast, other studies that include participants who are overweight or obese have seen an overestimation of energy expenditure in previous SenseWear Armband monitors and software versions (26, 27). Thus, the purpose of this study was to assess the accuracy and validity of the SWA-MF at rest, during two treadmill walking speeds, recovery, and during the total testing session, in adults with normal, overweight, and obese body mass index (BMI) classifications.

Methods

Participants

Forty-six participants, (15 men, 31 women) volunteered for the study. Participants had to be 18-45 years of age, apparently healthy, not pregnant, and able to walk without assistive devices. Individuals were recruited from The University of Tennessee, Knoxville and the surrounding community by paper flyers, online flyers, and word of mouth. Prior to testing, each participant signed an informed consent approved by the University's Institutional Review Board (IRB).

SenseWear Armband – Mini Fly

Participants wore a SWA-MF (55mm x 62mm x 13mm; 45.4g) (BodyMedia Inc., Pittsburgh, PA) on the upper left arm. The core SWA-MF device currently sells for $99, with an optional display device selling for an additional $29. The license that accesses more advanced software which is used by researchers to analyze the data is approximately $2,000; it provides access to raw data from each sensor, summary sheets for clinicians, and energy expenditure graphs. Without the license, consumers have access to a brief summary of energy expended and amount of time in each intensity level (sedentary, moderate, vigorous, and very vigorous). For this study, software version 7.0 was used, allowing data to be uploaded from the SWA-MF monitor to the software on the computer.

Data Collection

Participants were instructed to fast for three hours and to refrain from exercise for 24 hours prior to being tested. Once in the lab, participants completed a heath history questionnaire to determine their eligibility. Once eligibility was established, anthropometric assessments were taken, including: height (m), weight (kg), and waist circumference (cm). After body measurements were taken, participants were organized into one of three BMI categories: normal weight (18.5-24.9 $kg \cdot m^{-2}$), overweight (25-29.9 $kg \cdot m^{-2}$), or obese (≥30 $kg \cdot m^{-2}$). Participants were then fitted with the SWA-MF, which is physical activity monitor that is worn over the left triceps. Next, participants were connected to a ParvoMedics TrueOne 2400 metabolic cart (ParvoMedics, Sandy, UT) via a Hans Rudolf uni-directional breathing valve and hose. The ParvoMedics system

measures energy expenditure via indirect calorimetry. The gas analyzers were calibrated, prior to testing, using room air and a gas tank of known concentrations of gases (16.0% O_2, 4.01% CO_2). A 3-Liter syringe was used to calibrate the Hans Rudolf pneumotachometer to measure the expired ventilation.

The study protocol began with 15 minutes of seated rest, followed by treadmill walking at a speed of 50 $m \cdot min^{-1}$ for 8 minutes, then a seated recovery for 15 minutes, and finally treadmill walking for 8 minutes at 75 $m \cdot min^{-1}$. The ParvoMedics cart determined the measured energy expenditure ($kcal \cdot min^{-1}$) by continuously collecting information on oxygen consumption data and displayed the output in Calories (kcal) at 60-second intervals. The SWA-MF data were downloaded after each test using BodyMedia software version 7.0 and stored on a laboratory computer. The BodyMedia software contains propriety algorithms which are not released to the public. Therefore results of any analysis need to attribute the validity and accuracy to the combination of the SenseWear Armband model and the software version used. The SWA-MF collected data for each minute and quantified energy expenditure in Joules. Joules were then converted to kcals (using the conversion factor of 4.184 joules to one calorie) to allow comparison between the two devices. Energy expenditure (kcal/min) was determined for each activity (seated rest, treadmill walking at 50 $m \cdot min^{-1}$, recovery, treadmill walking at 75 $m \cdot min^{-1}$), as well as the total testing session.

Statistical Analysis

Statistical analyses were performed using SPSS Version 21 for Windows (IBM Corp, Armonk, New York). The overall significance level was set at α = 0.05. Means and standard deviations for the participant's characteristics (age, BMI, and waist circumference) and values for total energy expenditure over the total testing session were calculated. Error scores (ParvoMedics (measured) minus SWA-MF (predicted)) were created for energy expenditure (kcal·min^{-1}). A positive error score indicates an under-estimation of energy expenditure by the SWA-MF and a negative error score indicates an over-estimation by the SWA-MF. Physical characteristics and energy expenditure for the total testing session were split according BMI. One-way ANOVAs were used to test for differences in age, waist circumference, and energy expenditure during the total testing session among BMI groups.

A two-way repeated measures ANOVA (BMI group x condition) was used to analyze the error scores (measured minus predicted) for energy expenditure. Any significant differences were then followed up using contrasts to determine if the error scores were significantly different.

Bland-Altman plots were used to graphically represent the error scores of individuals in each BMI category, for the total energy expended during the entire testing session. The SWA-MF error scores were plotted on the y-axis. The average of the measured and predicted energy expenditure values were plotted on the x-axis. Mean error score and 95% prediction interval (95%PI) are displayed on each plot. Individual

accuracy is represented by narrow 95%PI, along with mean bias and r^2 close to zero. Data points below zero indicate an overestimation by the SWA-MF, and data points above zero indicate an underestimation.

Results

The participants' physical characteristics are shown in **Table 3.1**. Of the 46 participants, 32.6% were normal weight (n = 15), 37.0% were overweight (n = 17), and 30.4% were obese (n = 14).

Table 3.1. Descriptive characteristics of participants

Variable	All Participants (N = 46)	Normal weight (n = 15)	Overweight (n = 17)	Obese (n = 14)
Age (y)	27.1 (0.5)	24.8 (7.5)	27.6 (5.7)	29.1 (9.2)
Percent Female	67.4%	86.7%	52.9%	64.3%
BMI (kg·m^{-2})	27.9 (5.4)	22.6 (1.3)	27.4 (1.8)	34.3 (4.1)
Female Waist Circumference (cm) (n= 31)*	80.9 (11.4)	71.8 (4.7)	80.5 (6.3)	94.7 (8.8)
Male Waist Circumference (cm) (n= 15)*	93.7 (8.5)	80.3 (2.5)	93.3 (6.1)	99.8 (6.5)

Mean (SD); Body Mass Index (BMI): normal weight (18.5-24.9 kg·m^{-2}), overweight (25-29.9 kg·m-^{2}), obese (≥30.0 kg·m^{-2}). * Significantly different among BMI categories, p<0.001.

Error scores (kcal·min^{-1}) for each condition are shown in **Table 3.2.** The repeated measures ANOVA showed that the main effect of BMI group ($p = 0.543$), and the interaction effect (BMI group x condition) ($p = 0.381$) were not statistically significant. However, the repeated measures ANOVA did show a main effect of the four conditions ($p < 0.001$). Specifically, rest, recovery, and 75 m·min^{-1} treadmill walk had error scores that were not significantly different from each other ($p > 0.05$), but treadmill walking at 50 m·min^{-1} differed from all other conditions ($p < 0.001$).

The one-sample t-test showed that the SWA-MF significantly underestimated energy expenditure compared to the measured values during the resting condition by 0.21 kcal·min^{-1} ($p < 0.001$), and during the recovery by 0.27 kcal·min^{-1} ($p < 0.001$). The SWA-MF significantly overestimated energy expenditure during treadmill walking at 50 m·min^{-1} by 0.70 kcal·min^{-1} ($p < 0.001$). The SWA-MF was not significantly different from the measured values during treadmill walking at 75 m·min^{-1} ($p = 0.672$). The one-way ANOVA showed no effect for BMI group on energy expenditure over the total testing session (mean error 0.01 kcal·min^{-1}; $p = 0.913$).

Figure 1 shows the Bland-Altman plots for the energy expended over the total testing session, for normal weight, overweight, and obese individuals. Patterns in the plots did not show bias toward over- or underestimation of the SWA-MF during the total testing session. In general the mean bias was between -0.09 and 0.09 kcal·min^{-1}. The 95%PIs were highest for the overweight group, (-1.16, 1.20 kcal·min^{-1}) and smaller for the normal weight, (-0.70, 0.87 kcal·min^{-1}), and obese, (-0.88, 0.70 kcal·min^{-1}) groups.

Table 3. 2. Energy expenditure (kcal·min^{-1}) error scores (measured minus predicted) for all participants at rest, treadmill walking at 50 m·min^{-1}, recovery, treadmill walking at 75 m·min^{-1}, and total testing session.

Condition	Error Score	95% CI		p- value
		Lower	Upper	
Seated Rest	0.21	0.12	0.29	$p < 0.001$
Treadmill Walk (50 m·min^{-1})	-0.70	-1.06	-0.34	$p < 0.001$
Recovery	0.27	0.18	0.35	$p < 0.001$
Treadmill Walk (75 m·min^{-1})	-0.07	-0.40	0.26	$p = 0.672$
Total testing session	0.01	-0.13	0.15	$p = 0.913$

.

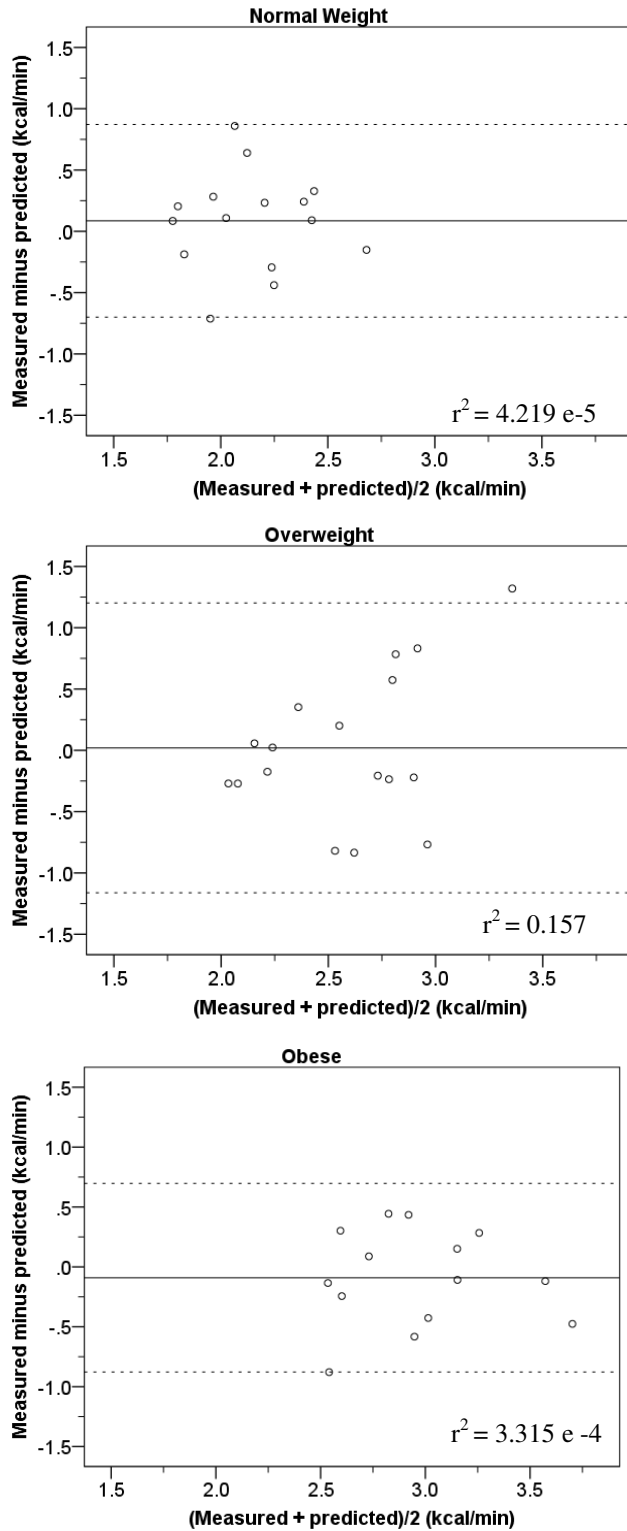**Figure 3.1 –** Bland Altman plots depicting error scores (measured (ParvoMedics) minus predicted (SenseWear Armband-MF)) (kcal·min[-1]) for the total bout in normal weight, overweight, and obese individuals. Solid line represents the mean bias; the dashed lines represent the 95% prediction interval.

Discussion

  The primary finding of this study was that the validity of the SWA-MF is not affected by BMI category (i.e. normal weight, overweight, obese). A secondary finding is that the SWA-MF underestimated energy expenditure during seated rest and recovery, and overestimated energy expenditure of treadmill walking at 50 m·min^{-1}. However, The SWA-MF was found to be accurate for estimating the energy cost of treadmill walking at 75 m·min^{-1} and during the total testing session.

  This is the first study to assess the accuracy of the SWA-MF across three BMI categories. Based on our results, the SWA-MF can be used for normal weight, overweight, or obese individuals without a bias error in estimation in any group based on BMI. This finding supports BodyMedia in their promotion for the use of the SWA-MF in overweight and obese population to be used as a tool in maintaining or losing weight.

  During seated rest and recovery, the SWA-MF significantly underestimated energy expenditure by 14% and 16%, respectively. While previous studies have not looked at short periods of rest, SenseWear Armbands have been previously reported as valid for estimating resting metabolic rate. Fruin, et al. (74), assessed the SenseWear Pro2, software 4.0, for estimating resting metabolic rate along with different treadmill walking speeds and grades. The study found the SenseWear Pro2 to be reliable (r = 0.93 ($p < 0.001$)) and was highly correlated with indirect calorimetry ((r = 0.74 ($p < 0.004$)) for estimating resting metabolic rate. Malavolti, et al. (76) examined the accuracy of the SenseWear Pro2 to estimate resting metabolic and found no significant

differences between the resting energy expenditures of the measured and predicted

values. The seated resting and recovery bouts in our study were significantly different

than the measured values; this may be due to the difference between the postures of

supine rest and sitting. The ability for the SenseWear Armband to integrate posture into

its algorithms for estimating energy expenditure may help to give more accurate

measures during seated and sedentary time.

During treadmill walking at 50 m·min^{-1}, the SWA-MF significantly overestimated

energy expenditure by 16%, but no significant differences were found while walking at

75 m·min^{-1} between the measured and predicted values. SenseWear Armband monitors

have previously been shown to overestimate energy expenditure during walking. One of

the initial studies on the SenseWear Armbands by Jakicic, et al. (25) found the

SenseWear Pro1, software 3.0, to significantly underestimate treadmill walking at 80.4

m·min^{-1} by 14.9 ±17.5 kcals, which was 6.9 ± 8.5%. Results from that study encouraged

recommendations for BodyMedia to create activity specific algorithms to increase the

accuracy of the energy estimates. Changes were made to both the software and

monitor, and since these changes studies have had similar findings to our current study

of overestimation at slow walking speeds (23, 48, 74, 78). The SenseWear Pro2 was

tested by Fruin, et al. (74), and King, et al. (48), using software 4.0 during treadmill

walking speeds of 54, 80, and 107 m·min^{-1}. Fruin, et al. (74) found the SenseWear Pro2

to significantly overestimated energy expenditure by 13-27% at 80.5 and 107.3 m· min^{-1},

but energy expenditure was significantly underestimated by 22% while walking at 107.3

m· min^{-1} with a 5% grade. King, et al (48), found high correlations for energy expenditure

between measured and predicted values at all walking speeds. The SenseWear

Armband Pro3, software 6.1 was assessed by Dudley, et al. (23) and Mann, et al. (78).

These studies found that road walking was significantly overestimated by 0.8 kcal·min^{-1}

and treadmill walking at 50 m·min^{-1} was significantly overestimated by 0.33 kcal·min^{-1}

(23, 78).

The majority of the previous studies used healthy, normal weight participants, but

two studies focused on obese individuals and had similar findings for slow walking

speeds. Papazoglou, et al. (26) found that the SenseWear Pro2 significantly

overestimated energy expenditure by an average of 1.82 kcal·min^{1} in obese individuals

(BMI ≥ 30 kg·m^{-2}) while walking at 50 m·min^{-1}. Similarly, Browning, et al. (27) found that

the SenseWear Armband Pro2, software 6.0, significantly overestimated energy

expenditure by 71.6 ± 46.7%, in bariatric patients with a BMI >40 kg·m^{-2}. The SWA-MF

and software 7.0, used in the current study, have reduced the prediction error on a

group basis compared to these previous versions.

For the total testing session, the mean bias for the SWA-MF was within 1

kcal·min^{-1} of the measured energy expenditure. In addition this was not different

between normal weight, overweight, and obese BMI groups. However the individual

error was large, as can be seen in the Bland-Altman plots. During the total session,

individual activities were significantly different from measured values, but the over- and

under-estimation balanced each other so that over the total testing time the mean error

was close to zero. The SWA-MF may not predict individual activities well, but over the

course of a testing period it may provide an accurate measure of energy expenditure. Future studies should investigate how the SWA-MF compares to total daily expenditure.

To our knowledge, this is the first study to assess the validity of the SWA-MF for estimating the energy cost of walking across three BMI categories. Limitations of this study are that only four activities were examined (seated rest, recovery, and two walking speeds on a treadmill) and the sample size was small. In addition, BMI is not the most accurate indicator of adiposity. Future research studies should consider categorizing individuals using different body composition measures when testing the SWA-MF, and including a greater array of activities.

Conclusion

Results of this study support that the SWA-MF is acceptable and provides similar mean biases among BMI categories. From both past research and our findings, a trend is shown that the SenseWear Armband commonly overestimates energy expenditure at slower treadmill walking speeds (< 75 m·min^{-1}), but validity improves at faster treadmill walking speeds (≥ 75 m·min^{-1}). During seated rest and recovery the SWA-MF significantly underestimated energy expenditure, but if algorithms were changed to incorporate posture accuracy would likely improve.

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APPENDICES

APPENDIX A

INFORMED CONSENT FORM

_____

<u>Title of Research:</u> Accuracy of the SenseWear Pro3 Armband During Rest and Treadmill Walking Across BMI Categories

<u>Principal Investigator:</u> Bethany Forseth

<u>Location:</u> Applied Physiology Laboratory, 1914 Andy Holt Ave, The University of Tennessee, Knoxville, TN

_____

Purpose/Objective

You are invited to participate in a research study on the accuracy of the SenseWear Pro 3 Armband, a wearable physical activity monitor.
The purpose of this study is to determine the accuracy of the SenseWear Pro 3 Armband across BMI categories during rest and walking.

The SenseWear Pro 3 Armband will be placed over the triceps muscle on the right arm, and will estimate calories under resting conditions and during treadmill walking. Simultaneously, the Parvomedics cart will collect data on your oxygen consumption and carbon dioxide production; these measurements will serve as the criterion measure to show how many calories were actually expended.

INFORMATION ABOUT PARTICIPANTS' INVOLVEMENT IN THE STUDY

After reading and signing the informed consent, and filling out the Health History Questionnaire (HHQ), we will measure your height, weight, triceps skinfold, and waist circumference. After the measurements are taken, you will be fitted with the SenseWear Pro3 Armband and a mouthpiece (and noseclips) connected to a hose leading to the ParvoMedics cart. You will then be asked to rest in a seated position for 15 minutes, followed by walking on the treadmill at 50 m/min (1.86 mph) for 8 minutes, seated rest for another 15 minutes, and then walking at 75m/min (2.8mph) for 8 minutes. Should you decide to end your participation in the study at any time, you are free to do so.

Because this is an activity-based study, we do ask that you wear comfortable athletic clothing, including a short-sleeved shirt and appropriate footwear. You should not exercise for 24 hours before your visit, and you should refrain from eating/drinking anything (except water) for 3 hours prior to your visit.

Initials _____

RISKS

Potential risks include abnormal heart rate or blood pressure responses, muscle strains or pulls, falls, and, in rare instances, heart attack, stroke or sudden death. To reduce these risks, you will only be invited to participate if you are comfortable with walking unassisted at 75m/min (2.8mph) for 8 minutes and do not have any contraindications to exercise. If you should have a serious injury during the course of the study, testing will be stopped immediately and you will receive appropriate medical treatment.

However, in the event of an injury, UT does not automatically provide compensation for medical care.

BENEFITS

Anticipated benefits to this study include new knowledge on the accuracy of the SenseWear Pro3 armband. The results could lead to more accurate tools to monitor physical activity in different populations.

You will also receive a free Omron pedometer and a handout that will include your current weight status, resting energy expenditure measures, and a personalized walking program.

CONFIDENTIALITY

Your data will be kept confidential throughout the study. All subject information will be coded and data will be secure, only being made available to those researchers and staff involved in the study.

EMERGENCY MEDICAL TREATMENT
All testing will be conducted in the Health and Physical Education and Recreation (HPER) building at the University of Tennessee – Knoxville campus. In the unlikely event of an adverse response to the during the physical activity protocols, you will receive appropriate treatment from trained clinicians

INVESTIGATOR CONTACT INFORMATION

If you have questions at any time about the study or the procedures (or you experience adverse effects as a result of participating in this study), you should immediately contact the principal investigator, Dr. David Bassett, 325 HPER Building, The University of Tennessee, Knoxville, TN, 37996, (865) 974 – 8766. If you have questions concerning your rights as a participant, contact Ms. Brenda Lawson with the Compliance Section of the Office of Research at (865)974-3466.

Initials _____

PARTICIPATION

Your participation in this study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled. If you withdraw from the study before the data collection is completed your data will be returned to you or destroyed.

_____

STATEMENT OF CONSENT

"I have read the above information. I have received a copy of this form. I agree to participate in this study."

_____
Participant's Name

_____   _____
Participant's Signature   Date

_____   _____
Investigator's Signature   Date

APPENDIX B

Name: _____

Address: _____

City: _____ **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 _____   Asian _____   Hispanic _____

    Black / African American _____   Native Hawaiian / Pacific Islander _____   Other _____

Personal Physician: _____ **Location:** _____

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

Name of Medication	Reason for Taking	For How Long?

Please Turn Over

61

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

Bethany MaryAlice Forseth was born in Bloomington, Minnesota. In 2008 graduated from Thomas Jefferson High School, with one year of Post-Secondary Education Option (PSEO) completed. Following high school, Bethany was honored to attend the University of Wisconsin – La Crosse. While there she completed a Bachelors of Science in Exercise and Sport Science with an emphasis in Fitness in the spring of 2012. The cold winters persuaded Bethany to move down south and attend the University of Tennessee, where she completed a Master of Science in Kinesiology – Exercise Physiology. Bethany, against the will of her now-warmed-and-thinned-blood, will continue her graduate education in fall of 2014 as a doctoral candidate at the University of Wisconsin – Milwaukee.