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# The Estimation of Caloric Expenditure Using Three Triaxial Accelerometers

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I am submitting herewith a dissertation written by Tyrone Gene Ceaser entitled "The Estimation of Caloric Expenditure Using Three Triaxial Accelerometers." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Kinesiology.

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# The Estimation of Caloric Expenditure Using Three Triaxial Accelerometers

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Degree

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Tyrone Gene Ceaser

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## Dedication

I would like to dedicate this dissertation to the individual who has stood by me for the last 4 years. Tammara, you are truly a Godsend. There is no way I would have made it through this process had it not been for you. From being stuck on the mountains in Gatlinburg, to working 70+ hours per week just so I could move to Knoxville, you truly put yourself and you desires aside, just to see me succeed. You also know what I went through before I met you, and you have made it a long, forgotten memory of another lifetime. For that, I am eternally grateful. I will do nothing short of spending the rest of my life making you the happiest woman in the world.

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## Abstract

Accelerometer-based activity monitors are commonly used to measure physical activity energy expenditure (PAEE). Newly designed wrist and hip-worn triaxial accelerometers claim to accurately predict PAEE across a range of activities. **Purpose:** To determine if the Nike FuelBand (NFB), Fitbit (FB) and ActiGraph GT3X+ (AG) estimate PAEE in various activities. **Methods:** 21 healthy, college-aged adults wore a NFB on the right wrist, a FB on the left hip, and AG on the right hip, while performing 17 activities. AG data were analyzed using Freedson's kcal regression equation. PAEE was measured using the Cosmed K4b$^2$ (K4). Repeated measures ANOVAs were used to compare mean differences in PAEE (kcal/min). Paired sample t-tests with Bonferroni adjustments were used to locate significant differences. **Results**: For each device, the mean difference in PAEE was significantly different from the K4 (NFB, -0.45 $\pm$ 2.8, FB, 0.48 $\pm$ 2.27, AG, 0.64 $\pm$ 2.59 kcal/min, $p = 0.01$). The NFB significantly overestimated most walking activities (e.g., regular walking; K4, 3.1 $\pm$ 0.2 vs. NFB, 4.6 $\pm$ 0.2 kcal/min) and activities with arm movements (e.g., sweeping; K4, 3.0 $\pm$ 0.8 vs. NFB, 4.7 $\pm$ 0.4 kcal/min, $p <$ 0.05). The NFB trended towards overestimating sport activities (basketball; K4, 10.8 $\pm$ 0.8 vs. NFB, 12.2 $\pm$ 0.5 kcal/min) (racquetball; K4, 9.6 $\pm$ 0.8 vs. NFB 11.1 $\pm$ 0.5 kcal/min). The FB and the AG significantly overestimated walking (K4, 3.1 $\pm$ 0.2; FB, 5.4 $\pm$ 0.3, AG, 5.8 $\pm$ 0.4 kcal/min, $p = 0.01$) and underestimated PAEE of most activities with arm movements (e.g., Air Dyne, K4 5.6 $\pm$ 0.2; Fitbit, 0.3 $\pm$ 0.2; AG, 0.2 $\pm$ 0.1 kcal/min, $p < 0.05$) (racquetball, K4, 9.6 $\pm$ 0.8 kcal/minute vs. FB, 7.4 $\pm$ 0.6 kcal/minute, vs. AG, 6.5 $\pm$ 0.4 kcal/minute, $p < 0.05$). **Conclusion:** The NFB overestimated PAEE

during most activities with arm movements and tended to overestimate sport activities, while the AG and FB overestimated walking and underestimated activities with arm movements. Overall, the wrist-worn NFB had similar accuracy to the waist-worn triaxial accelerometers; however, none of the devices were able to estimate PAEE across a range of activities.

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# Chapter 1

Introduction

It is well documented that regular physical activity (PA) can be beneficial to health and quality of life in adults [1-3]. However, most Americans do not accumulate enough PA to achieve the minimum health benefits. According to the Centers for Disease Control and Prevention (CDC), 25 percent of Americans do not participate in any kind of leisure-time physical activity, and 35 percent of Americans do not meet the PA recommendations [4]. In light of the health risks associated with insufficient PA among U.S. citizens, the Physical Activity Guidelines Committee Report was issued in 2008. Furthermore, the American Heart Association (AHA) in conjunction with the American College of Sports Medicine (ACSM), emphasized that adults should accumulate 150 minutes of moderately intense PA or 75 minutes of vigorous PA per week in bouts 10 or more minutes [5]. The lack of regular PA among adults has also prompted key organizations to establish new goals for increasing PA among Americans. *Healthy People 2020* goals include reducing the prevalence of no-leisure-time PA among adults and increasing the proportion of adults who meet the current PA recommendations [6].

The measurement of PA is important for identifying trends in PA levels and implementing nationwide health recommendations for disease prevention. Traditionally, self-report methods (surveys, questionnaires) have been used for the assessment of PA levels. More recently, researchers have transitioned to the use of PA monitors (e.g. pedometers and accelerometers) instead self-report methods. This is partly due to inherent limitations of self-report methods that can lead to inaccurate assessments of PA.

Although PA monitors also have limitations [7, 8], objectively-measured PA has been more strongly associated with health outcomes compared to self-reported PA [9].

Traditionally, PA monitors were able to detect the number of steps taken over time. A number of studies have documented the validity and reliability of activity monitors and their ability to track steps [10-13] , and in many cases, their ability to increase PA adherence [14, 15]. More recently, PA monitors, specifically accelerometer-based devices, have undergone significant changes and now include improvements such as, increased data storage, online synchronization, and ability to capture the galvanic response [8, 13, 16-18]. Unlike pedometers, many accelerometers are equipped with piezoelectric technology, which makes them less likely to have measurement error. Another major feature of accelerometer-based devices is the ability to detect static, as well as dynamic, acceleration which is sometimes used to differentiate between walking, sitting, and standing. Additionally, triaxial accelerometer-based devices are able to detect motion in the vertical, horizontal, and diagonal planes. These measurement capabilities in accelerometer-based devices give them an advantage over pedometers in that accelerometer-based devices provide other information in addition to steps such as PA patterns (e.g. intensity).

Researchers have also developed prediction equations that relate accelerometer 'counts' to energy expenditure for different types of activities such as walking and running [19-22]. Traditionally, this has been done by performing calibration studies to determine the linear relationship between counts and energy expenditure. Due to inherent limitations (e.g., band-pass filtering and the inability to investigators to precisely quantify a count) with some types of accelerometers, more researchers have begun to use raw acceleration data to develop prediction models and equations. Currently, pattern recognition is emerging as a method for interpreting accelerometer-based output to predict energy expenditure. Pattern recognition or "machine-learning" assigns different categories or classes to data. Pattern recognition has been used in several newly designed accelerometer-based devices [23-25]. Types of pattern recognition include Hidden Markov Models (HMMs) and Artificial Neural Networks (ANNs).

## Statement of the Problem

Most accelerometer-based devices are designed to be worn on the hip. However, these devices are limited, in that they are not capable of capturing physical activities performed with the upper body (e.g., the arms). Thus, large commercial companies have created more technologically advanced hip-worn (Fitbit) and wrist-worn devices (Nike) that may be capable of detecting a greater variety of activities involving simultaneous upper and lower limb movement (e.g., basketball, household activities). However, it has not yet been determined whether these devices are capable of accurately assessing PA and energy expenditure across a wide range of activities.

## Statement of Purpose

The purpose of this dissertation is to determine the accuracy of three triaxial accelerometer-based activity monitors for measuring energy expenditure and steps (the Nike FuelBand, the Fitbit, and the GT3X+).

## Significance of the Study

Accelerometer-based devices are now being used in assessing nationwide PA patterns. As the design and development of accelerometer-based devices continues to increase, it is imperative that researchers continue to investigate the ability of these devices to accurately assess PA-related variables (i.e. steps and energy expenditure). Additionally anecdotal evidence suggests that the use of PA monitors is becoming more widely accepted by the general population for tracking PA habits.

## List of Terms

**Accelerometer-based Physical Activity Monitor**: Portable device used for quantifying physical activity by measuring the acceleration associated with human movement.

**Pattern Recognition**: Also known as 'machine learning', pattern recognition is a mathematical process in which a particular label (variable) is assigned a specific value.

**Physical Activity Energy Expenditure (PAEE):** Energy expenditure associated with that above normal resting values. Physical activity energy expenditure is also known as 'net' energy expenditure.

**Triaxial Accelerometer**: An accelerometer capable of detecting accelerations in three planes (anterior-posterior, medial-lateral, and vertical).

# Chapter 2: Review of Literature

Physical activity (PA) is any muscular movement resulting in energy expenditure above that of resting values [26, 27]. PA is a multi-dimensional behavior, characterized by frequency, mode, intensity, and duration. Taken together, these variables characterize PA energy expenditure (PAEE). Exercise, a subcategory of PA, is planned, structured, and often done for the purpose of maintaining or increasing physical fitness [26].

The impact of regular PA on health and well-being has been a longstanding focus of many health professionals and researchers [3, 27, 28]. The plethora of evidence collected over the past 40 years has been cited in a variety of health reports [2, 29, 30] developed with the intent of increasing public awareness and knowledge of regular PA and its associated health outcomes, and to provide safe and effective guidelines for maintaining a physically active lifestyle [2, 30]. In spite of the evidence cited in health reports and National Physical Activity Recommendations, PA levels among U.S. citizens are low and have been for some time. National attention pertaining to insufficient PA among U.S. citizens dates back to the early 1990's [31]. Due to the insufficient PA levels among Americans and the impact of insufficient PA on disease and disease risk, the Surgeon General's Report on Physical Activity and Health was published in 1996 [30]. This report emphasized the importance of regular PA and the negative impact that insufficient PA has on various health outcomes. The Surgeon General's Report also emphasized the benefits of regular, moderate PA on health and overall wellness. The report concluded that Americans can receive health-related benefits with as little as 30 minutes of PA on most days of the week [30]. Currently, the Department of Health and Human Services (DHHS) recommends that adults achieve a weekly minimum of 150 minutes of moderate PA or 75 minutes of vigorous activity in bouts of at least 10 minutes [3]. Additionally, Americans should engage in muscle-strengthening activities at least two times per week. However, most Americans do not meet the national PA recommendations. In 2008, less than half of all American adults met the guidelines [4], and approximately 25-30% of Americans reported no leisure-time PA (LTPA). Sex and age are related to the volume of PA that people accumulate. More men than women meet the PA recommendation. Approximately 60% of young adults age 18-24 meet the PA recommendations, but less than 40% of adults 65 years and older met the PA recommendations [4].

What is known for sure is that increasing daily PAEE over is directly related to lowering disease risk [2, 3, 29, 32, 33]. In light of the fact that most Americans do not meet the recommended levels of PA, it is important that current and future research identify strategies to increase PA levels and decrease the associated disease risks linked to sedentary behavior and inadequate PA. It is well documented that high levels of PA decrease risk for heart disease [1, 34-38], and research has shown that PA accumulated in bouts as small as 10 minutes (towards the 150-minute-per-week goal) can be beneficial to decreasing the risk for certain chronic diseases [39-42].

## Self-Report and Physical Activity Monitors

### Self-Report of Physical Activity

Understanding habitual PA levels and relating those habits to health-related risks and benefits depend on accurate and precise measurement techniques. PA is a multi-dimensional behavior and measurement techniques continue to evolve. It is essential that

PA assessment methodologies, self-report and objective, are valid, reliable, and accurate in the population of interest. Four domains are typically used to classify PA: leisure-time PA (LTPA), transportation-related PA (TPA), domestic PA (DPA), and occupation-related physical activity (OPA). Traditionally, PA levels were assessed using self-report methods. Self-reports can be self-administered or interviewer-directed and include diaries, questionnaires/surveys, and PA logs. Since many self-report methods have been tested and utilized in large populations, researchers are able to describe PA levels on a population level, and thus, much of the epidemiological evidence linking PA to disease risk is based on self-report from national surveys [43, 44]. However, self-report methods have several significant flaws. First, self-report presents a burden to the subject, because it forces the individual to complete real-time activity logs, to rely on recall ability or, on some instruments, the ability to recall previous PA patterns over an extended period. Second, some national surveys, such as the Behavioral Risk Factor Surveillance System (BRFSS), include a limited number of questions used to describe and summarize total PA behavior. For example, 2008 and 2010 BRFSS only contained one question related PA levels (During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?). The scope of the question is limited, because it only determines the prevalence of leisure-time physical inactivity. Essentially, it does not capture the intensity or frequency of the activity. However, the 2011 BRFSS does include questions regarding the frequency and mode of PA, which enables researchers to identify the prevalence of individuals meeting the PA guidelines. However, BRFSS provides a limited amount of detail relating to PA patterns. Population surveys taken out of context may lead to a misrepresentation of PA patterns at a population level. Lastly, self-reports are subject to reporting bias, because subjects have a tendency to underreport unwanted and/or unfavorable/unexpected outcomes [45, 46].

## Objective Monitoring

Although there are some advantages to using self-report (e.g. assessing a large sample at a relatively low cost), research has shown that objective monitoring, or PA monitors (pedometers, accelerometers, etc.), are valid and reliable tools for assessing PA [47-51]. Arguably, PA monitors are better than self-report methods for a number of reasons. One reason that objective monitoring is generally believed to be more valid than subjective data is due to their stronger correlation with health biomarkers [9]. Second, although hip-mounted PA monitors lack the ability to assess upper-body activities and are limited to measurements of hip accelerations, they assess ambulatory movement throughout the day, and thus give a more detailed indication of daily, ambulatory PA. For example, walking is a common form of LTPA among American adults [31, 52, 53]. However walking is difficult to accurately assess using subjective methods. Objective devices (e.g., accelerometer-based activity monitors) provide more detailed (e.g., walking patterns, time, distance, energy expenditure) information about the activity. Essentially, this results in a more detailed approach to PA measurement. Third, objective monitoring has also been used to determine the effectiveness of interventions with the overall goal of increasing PA [15, 54]. This is important, because understanding the impact of objective monitoring on PA adherence and how these devices are best used to encourage PA is critical for increasing PA levels.

**The StepWatch**

One common PA monitor used to detect physical activity is the StepWatch (SW) (Orthocare Innovations), which detects steps. The device is relatively small, measuring 70 x 50 x 20mm and weighing less than 40 grams. The SW is an ankle-mounted PA monitor worn on the lower leg, just above the lateral malleolus of the fibula. The device is secured to the leg using an elastic band with velcro. The battery life of the SW is approximately 7 years, and it can record data for up to 2 months between downloads. Unlike many PA monitors, the SW does not have a digital display, so the user cannot receive any real-time feedback on PA patterns. The SW synchronizes with a portable docking station (connected to a computer by USB) that communicates using an infrared beam enclosed within the SW, which then allows for data download and management. The SW output is available as steps taken over time, and the SW software allows for the adjustment and analysis of steps taken at a slow (<30 steps$\cdot$minute$^{-1}$), moderate (30-80 steps$\cdot$minute$^{-1}$), and/or medium (>80 steps$\cdot$minute$^{-1}$) pace [55]. To date, the SW is one of the most valid and reliable tools for detecting ambulatory activity in several populations (i.e., healthy, obese, elderly, and diseased) [50, 56-60].

Several studies have compared the accuracy of the SW PA monitor to other PA monitors such as pedometers. In 1999 Shepard et al. [58] investigated the accuracy of the StepWatch during brisk walking, slow walking, and stair walking. Twenty-nine subjects wore a Sportline pedometer on the hip and the SW on the lateral ankle. Compared to the

Sportline pedometer, the SW had a lower mean error score during all activities (0.54%, SW vs. 2.82%, Sportline pedometer). Authors also found that the SW performed similarly in normal weight and obese individuals, whereas the Sportline pedometer did not, yielding a significant correlation between error score and body mass index ($r = 0.792$, $p < 0.0001$). In 2005, Karabulut et al. [61] compared the accuracy of the StepWatch and another ankle-mounted device [Activity Monitoring Pod 331 ($AMP_{ankle}$)] to 2 waist-mounted pedometers [New Lifestyles NL-2000 ($NL_{waist}$) and Digiwalker SW-701 ($SW\text{-}701_{waist}$)] under laboratory and field conditions. In phase one, subjects (n = 20) were asked to walk at treadmill speeds of 27-107$m \cdot min^{-1}$. In phase two, subjects were asked to participate in leg swinging, heel tapping, stationary cycling, and car driving. Finally, 15 subjects wore the pedometers over a 24-hour period. Results indicated that the SW was more accurate at detecting steps during treadmill walking compared to all other devices (mean score within 1% of actual steps measured with a hand counter for all treadmill speeds). Additionally, during the 24-hour monitoring period, the $AMP_{ankle}$ recorded 18%, the $NL_{waist}$ 11%, and the $SW\text{-}701_{waist}$ recorded approximately 15% fewer steps than the SW, which lead Karabulut et al. [61] to conclude that the SW was more capable of counting steps during a wide range of activities and walking speeds compared to other ankle-mounted and hip-mounted devices.

In 2005, Foster et al. [57] also examined the accuracy of the SW under several different conditions. Their study included lean (n = 10) and obese (n = 10) individuals who engaged in treadmill walking (1, 2, and 3 mph) and over ground walking (hallway walking at 1 and 1.85 mph). Each subject wore three devices (Accusplit, Omron HF-100, and the SW). Foster et al. [57] found that that the mean accuracy for the SW was 99.7 ± 0.67% during all treadmill speeds, whereas the other devices produced a larger amount of variance (SD = 4-13 steps) across treadmill speeds (98% accuracy for Omron HF and Accusplit at 3 mph vs. 61 ± 3.3% at 1 mph, Omron HF and 26 ± 2.8%, Accusplit 1 mph). Authors concluded that the StepWatch was far more accurate than the other devices, particularly at low speeds.

**Accelerometers**

Accelerometer-based PA monitors, or accelerometers, are portable devices used to classify PA by measuring acceleration during human movement [24, 62, 63]. Most accelerometers contain a transducer, (common types include piezoelectric, piezoresistive, or variable capacitive) that detect acceleration in one to three orthogonal planes (anteriorposterior, mediolateral, and vertical) [64]. The functional capability of an accelerometer depends on the type of transducer within the unit. Unlike pedometers, summed accelerations (e.g., counts) from accelerometers can be used to classify PA patterns (bout frequency, intensity, and duration) over time. Accelerometers can be grouped based on presence or absence of passive components (i.e., requires little or no power consumption), as well as those that are sensitive to static accelerations (i.e., acceleration due to gravity) [64]. Since accelerometers measure accelerations along one to three axes, they are able to determine the bout frequency and intensity of human movement. Unlike pedometers, accelerometers are not affected by tilt, which gives accelerometers a measurement advantage over pedometers, which can be affected by tilt [57, 64].

**The History of Accelerometers in Physical Activity Research**

Initial designs of the accelerometer for use in PA measurement date back to the 1950's [65]. Given their relatively high cost and bulky design [65, 66], accelerometers developed during the 1950's did not gain much traction in research, and were not very useful for the measurement of PA. However, with the advancement of science and technology, the measurement of human motion using accelerometers resurfaced during the 1970's [63, 67, 68]. During this time period, Morris [63] suggested that the use of accelerometers for detecting human motion had many advantages over other methods, and he eventually designed the first cantilever-based accelerometer with strain gauge elements. By the early 1980's, the use of accelerometer-based devices for measuring human motion and energy expenditure received attention from other researchers. Specifically, Wong, Webster, Montoye and Washburn [69] examined the accuracy of modified ceramic phonocartridge accelerometers to measure energy expenditure compared to the criterion measurement (microcomputer-based Beckman metabolic function cart). Compared to the two other PA monitors used in the study (a mechanical pedometer and a graphical multi-meter activity displaying monitor), the modified ceramic phonocartridge accelerometer had the best correlation with oxygen consumption. This finding was significant, because it provided strong evidence for the development and use of accelerometer-based activity monitors capable of estimating energy expenditure and PA levels.

**The Concept behind Accelerometry for the Measurement of Human Motion**

Acceleration is the change in speed over time. Since human acceleration requires the use of muscle mass, and muscle mass requires energy to perform work, measuring acceleration is a good indicator of the amount of energy expended during movement. Although accelerometers can be worn in several different locations (e.g., lower leg, arm, hip), the hip is perhaps the most common place for accelerometer. This is primarily because the hip is near the center of mass (i.e., the torso), and it can be inferred that the measurement of acceleration at the hip is a great representation of most human locomotion. Technically speaking, accelerometers contain inertial sensors that measure acceleration along various axes, or the angular motion around one or multiple axes using a combination of accelerometers and/or gyroscopes [51]. Most accelerometers operate based on a sensing element, which incorporates a seismic mass coupled with a mechanical suspension system. Changes in acceleration will cause the seismic mass to deflect. Thus, acceleration of the seismic mass is calculated based on the physical displacement of the seismic mass. Acceleration is typically measured in gravitational units (g, in which 1g is approximately equal to $-9.8 m \cdot s^{-2}$) [51, 64, 70, 71].

## Monitor Placement

Accelerometer output is primarily dependent on two major factors: the position of the accelerometer on the body and the sensor properties of the accelerometer. Studies have shown that accelerometers can be worn in multiple positions on the body (i.e., hip, wrist, leg, and ankle) [72], with few studies suggesting that one location has measurement advantage over the others. Traditionally, accelerometers placed on the lower leg/ankle are primarily used to detect ambulatory movement. However, a number of the previously designed accelerometers are worn on the hip. Thus, for movement requiring the ‘whole body’ (e.g., walking), areas in closer proximity to the center of mass are ideal locations.

Recently, more speculation has emerged pertaining to the accuracy of the wrist and/or arm as a location for accelerometer placement. Few accelerometers have been solely designed for the arm or the wrist. However, wrist and arm locations may offer a potential measurement advantage over other locations, because upper body activities may be captured by wearing accelerometers in these areas. Whether a wrist/arm-mounted accelerometer provides greater measurement accuracy over traditional waist/hip-mounted accelerometers is yet to be determined.

**Piezoelectric Sensors**

Since the mid-1980's, a number of accelerometer-based PA monitors have been developed for the study of human movement. Initial accelerometer designs during the 1980's and early 1990's centered around piezoelectric technology [69]. The piezoelectric sensor functions similar to a spring-loaded system. In a spring-loaded system, once an external acceleration is applied, a small mass within the accelerometer applies a force to the spring, which causes it to stretch or compress. The acceleration is then calculated from the displacement of the spring [64]. In a piezoelectric design, a sensing element within the unit bends due to the applied external acceleration. The bending causes the seismic mass within the unit to produce a voltage proportional to the applied external acceleration. Piezoelectric accelerometers are typically lightweight, small, and provide a range of 9-45 days of continuous measurement. Piezoelectric accelerometers are able to detect dynamic changes in acceleration, but they are not able to detect static acceleration (i.e., acceleration due to gravity) [64, 70]. Piezoelectric pedometers have an advantage over traditional spring-loaded pedometers, because piezoelectric pedometers are not affected by high body mass index (BMI), waist circumference, and tilt angles, all of which have been shown to affect the accuracy of spring-loaded pedometers [73, 74]. Examples of accelerometers piezoelectric accelerometers include the AM7164 (ActiGraph, Pensacola, FL), the RT3 (StayHealthy, Monrovia, CA), and the Actical (Philips Respironics, Chichester, UK).

**Piezoresistive and Capacitive Sensors**

To date, many accelerometer-based PA monitors incorporate the use of piezoresistive or variable capacitance sensors. A piezoresistive accelerometer consists of a cantilever beam and a seismic mass. The piezoresistors are arranged in a Wheatstone bridge configuration (i.e., an electrical circuit in which an unbalancing of the sensing elements results in a corresponding electrical signal), in which the electrical resistance increases with an increase in applied external acceleration forces [51, 64]. The size of the voltage is proportional to the amount of acceleration. Unlike piezoelectric accelerometers, piezoresistive accelerometers are capable of measuring constant acceleration such as gravity, and thus are equipped to measure static and dynamic accelerations. Common examples of piezoresistive accelerometers include the Intelligent Device for Energy Expenditure, (IDEAA), and the $\text{Tracmor}_D$ (Philips New Wellness Solutions).

Differential capacitance accelerometers operate by the use of a differential capacitor with a central plate attached to the moving mass and fixed external plate. An applied acceleration unbalances the capacitor, creating a voltage output proportional to the amplitude to the acceleration. Advantages to using a differential capacitance accelerometer include the low power consumption, the relatively large output level, and the fast response to human motion [51, 64]. The GT1M and the GT3X (both developed by ActiGraph) are commonly used capacitive accelerometers.

Current accelerometer-based PA monitors (piezoresistive and differential capacitive resistors) contain micro-electro-mechanical accelerometers (MEMs). Relatively new in design, MEMs are equipped with relatively small (micro-scale) structural components that consist of a micro processing unit and several other sensors that function alongside the main microprocessor unit [71]. In essence, the MEMs give many accelerometers the capacity to detect human movement in multiple planes (i.e. biaxial and triaxial) without compromising the measurement capability of the accelerometer. More recently, accelerometer-based PA monitors equipped with MEMs technology have become available for consumer use (e.g., IDEAA monitor, Actical), and are typically inexpensive compared to many other devices capable of detecting human motion [75].

**The ActiGraph**

ActiGraph is a major manufacturer of several commonly used accelerometers for measuring human motion. Since 1993, ActiGraph has developed several accelerometer models, beginning with the 7164. Since the 7164, three new models were introduced (GTM, GT3X, and GT3X+) from ActiGraph . Each of ActiGraph's PA monitors are capable of compiling activity counts (the sum of accelerations over a user specified time period) and composite vector magnitudes from one to three axes [17, 76].

Relatively small in size, the 7164 measures 5.1 x 3.8 x 1.5 cm and weighs approximately 43 grams. The 7164 is uniaxial and measures acceleration in the vertical plane of human movement [77]. The 7164 has a cantilever beam design, in which external accelerations ignite a small charge within the unit proportional to the amount of acceleration applied. The charge is then filtered and digitized by an analog/digital (A/D) converter at a rate of 10 cycles per second (10Hz). The 7164 is most commonly worn on the waist [77].

Generally speaking, walking causes up-and-down movements at the hip and oscillatory movements at the wrist [77]. When properly worn on the hip (i.e. just above the anterior superior iliac spine), the 7164 stores information on vertical accelerations within user-defined sampling intervals (epochs). The sampling interval is predetermined by the user (1, 10, 15, and 30 seconds). As information is digitized and filtered, the data are stored within the accelerometer's random access memory (RAM). The device is powered by a single 2430 lithium coin cell battery. Data from the 7164 unit are downloaded using a reader interface unit (RIU) through a serial port to a computer. Once downloaded, data can be viewed in a spreadsheet format [77].

Advances in microchip technology over the past decade have led to the improved design and functional capacity of accelerometer-based PA monitors. During the early 2000's, the 7164 from Computer Science Application was replaced by GT1M model, and the manufacturer, Computer Science Applications become known as ActiGraph. Although the accelerometer output is similar to the 7164 [17], the GT1M has several advanced measurement capabilities. Primarily, the accelerometer includes a miniaturized, dual-axis, MEMs accelerometer, which includes a capacitive sensor that detects external accelerations based on variances in the capacitance, or the potential energy of the sensor. This enables the accelerometer unit to detect both static (acceleration due to gravity) and dynamic acceleration. The GT1M capacitive sensor (Analog Devices, Norwood, MA) is smaller than the 7164 (5.1 x 3.8 x 1.5 cm), measuring 4 x 4 x 1.5mm. In 2008, ActiGraph unlocked dual axes capabilities in the GT1M, which enabled the GT1M with the capability of detecting accelerations in the antero-posterior and vertical planes [76].

Following the production of the GT1M, ActiGraph developed the GT3X in 2009, and discontinued production of the GT1M. Currently, the ActiGraph GT3X is one of the most advanced accelerometer-based activity monitors. The GT3X is triaxial, capable detecting motion in three orthogonal planes (vertical, horizontal, and diagonal). Unlike previous versions of the ActiGraph, the GT3X provides activity counts and vector magnitudes from three orthogonal planes, compiling a more comprehensive assessment of human motion. Both (GT1M and GT3X) models include a 12-bit A/D converter, which samples at 30Hz, contrary to the older 7164, which samples at 10Hz. However the GT3X has greater memory storage capabilities (4MB vs. 1 MB) and a longer battery life (22 days vs. 14 days) than the GT1M [17, 78].

The most current version of the ActiGraph is the GT3X+. The GT3X+ has an external, water-resistant casing. The GT3X+ is somewhat smaller (4 x 6 x 3 x 3) than previous versions. The battery is composed of a single cell prismatic lithium ion polymer (3.7V). The circuit board includes the following components: tin plated surface, a solder mask, and a surface mounted capacitive accelerometer with resistors. The ActiGraph GT3X+ measures accelerations ranging from +/- 6 g's, and uses a twelve-bit A/D convertor. The ActiGraph GT3X+ also includes an inclinometer and an ambient light sensor, and can collect and store data for approximately 40 days at a sampling rate of 30Hz without external charging. Unlike its predecessors, the GT3X+ has a unique feature, in that the unit initially collects raw data at a user-defined sampling rate of 30-100Hz. Filtering and epoch selection are adjusted following data collection. This allows researchers to manipulate multiple accelerometer parameters (epoch length, ambient light detection, filtering, etc.) after wear-time has ended.

As previously discussed, a number of MEMs-based PA monitors have been developed for the measurement of physical activity, and have become one the most widely used activity monitors. Furthermore, accelerometers have been studied for their accuracy for measuring PA patterns and for predicting energy expenditure in laboratory settings [10, 20, 79] as well as in free-living settings [18, 21, 22, 80, 81].

**Predicting Energy Expenditure from Accelerometer-Based Activity Monitors during Laboratory and Free-living Activity**

To date, most accelerometer-based activity monitors store acceleration data as activity counts [7, 50, 62]. Activity counts reflect the duration and intensity of activity over a user-specified period (e.g., 30 seconds, 1 minute) known as epochs [62, 70]. To translate accelerometer counts into physiologically meaningful data, calibration is required. Thus, calibration studies are necessary to quantify the relationship between accelerometer counts and PA. A 'value' calibration is necessary to evaluate accelerometer count variation across a wide range of activities [82, 83]. In many calibration studies, accelerometer counts are directly compared against measured oxygen consumption ($VO_2$) during a variety of activities: sport-specific activities, household activities, and other activities of daily living. Accelerometer counts are then used in regression equations to develop prediction equations that provide an estimate of energy expenditure during activities of various bout frequencies, intensities, and durations [69, 82, 83].

The current understanding of accelerometer-based PA monitors has greatly improved over the last two decades, and has resulted in an array of prediction equations designed to estimate energy expenditure. Previous and current prediction equations are primarily based on two types of activities: dynamic (i.e., walking and running) and static (i.e., sitting and lying down). Several previously developed prediction equations were used to convert raw accelerometer counts to energy expenditure. The initial research underlying the relationship between accelerometer counts and energy expenditure found relatively high correlations between accelerometer counts and indirect calorimetry during walking, running, and other laboratory-based activities (e.g., lying, standing, and/or a series of increasing treadmill speeds as a test protocol; $r = 0.80 - 0.90$) [7, 20, 21]. However, these studies were limited, because they did not examine the accuracy of accelerometer prediction equations during lifestyle and field-based activities. Therefore, more studies were conducted to determine how well previously developed prediction equations predicted energy expenditure during lifestyle activities such as gardening and household chores [7, 21, 22].

A number of studies investigating the validity of accelerometers to predict energy expenditure were published during the mid-1990s. Freedson and colleagues [20] were one of the first groups to determine the validity of the first ActiGraph models (CSA 7164). In their study, subjects (n=50) performed treadmill walking and running at three speeds (4.8, 6.7, and 9.7 km/hr) while wearing the CSA accelerometer on the hip. Freedson et al. [20] developed an energy expenditure prediction equation based on accelerometer counts: $\text{kcal} \cdot \text{min}^{-1} = (0.00094 * \text{cnts} \cdot \text{min}^{-1}) + (0.1346 * \text{mass in kg}) - 7.37418$ ($r^2 = 0.82$, SEE = +/- 1.40 $\text{kcal} \cdot \text{min}^{-1}$). They found a high correlation ($r = 0.93$) between the actual and predicted energy expenditure during all treadmill walking and running speeds.

Although Freedson's group was able to show a strong correlation between CSA counts and oxygen consumption during walking and running, there was still a need to determine the accuracy of accelerometer-determined prediction equations during field-based activities. Thus, several studies were undertaken to determine the accuracy of accelerometer-based PA monitors in the field. Hendelman's group [21] investigated the accuracy of hip-worn accelerometers (CSA and Tritrac accelerometer) in the field during several different activities (over ground walking at a self-selected pace, golf, and indoor and outdoor household activities). Although the correlation between accelerometer counts and oxygen consumption during walking was strong ($r = 0.77$, CSA; Tritrac, $r = 0.89$), the correlation was not as strong during the field-based activities (CSA, $r = 0.59$, Tritrac, $r = 0.62$). Nichols et al. [84] conducted a similar calibration study with the CSA accelerometer, in which they sought to show a linear relationship between CSA accelerometer counts and oxygen consumption. In their study, 30 participants walked on a treadmill at 3.2, 6.4, and 9.7 km/hr at a 0% grade and at 6.4 km/hr on a 5% grade. Another sample of 30 participants performed field-based activity, which included a brisk walk and jog at a self-selected pace on a 400-meter track. Oxygen consumption was measured using an automated metabolic cart (SensorMedics Vmax 29, Anaheim, CA). Results confirmed a linear correlation between $VO_2$ and CSA accelerometer counts during walking and running activities ($r^2 = 0.89$, standard error = 3.72 $ml \cdot kg^{-1} \cdot min^{-1}$). However, there were significant differences between CSA counts in the laboratory setting and the field-based setting ($p < 0.05$) during activities of varying intensities. This finding led investigators to conclude that prediction equations developed from walking and running activities were not as accurate during field-based activities. Given the limitations of accelerometers to predict energy expenditure during field-based activities, several hypotheses were tested to improve the measurement capabilities of the accelerometer by either changing the location of the unit, the prediction equation, and/or the instrument.

Swartz et al. [22] investigated the accuracy of accelerometer devices worn at multiple sites (hip only versus hip and wrist) during activities from six different categories: yard work, housework, recreation, family care, occupation, and conditioning. The Cosmed K4 $b^2$ was used as the criterion for oxygen consumption. Their results indicated that wearing the CSA accelerometer on the wrist, in addition to the waist, added more accuracy, in that it explained roughly 3% more of the variance in energy expenditure than wearing the CSA accelerometer on the hip only (hip only, 31.3% vs. hip and wrist combined, 34.7%). However, authors concluded that the additional 3%

explained by wearing the CSA accelerometer on the wrist was not significant enough to warrant wearing multiple monitors.

A number of other strategies were undertaken to improve the estimation of energy expenditure using accelerometers. In 2005, Crouter et al. [81] investigated an alternative to using previously developed regression equations to predict energy expenditure. Unpublished data previously collected by Crouter et al. [81] suggested that accelerometer counts during walking and running varied less than accelerometer counts from other types of activities. More specifically, they hypothesized that walking and running activities could be distinguished based on the coefficient of variation for 6-to-10-second epochs over a 1-minute period, and that an appropriate regression model would yield a more precise estimate of energy expenditure across a broader range of activities. Based on this finding, Crouter et al. [81] developed and tested a 2-regression model to predict energy expenditure from accelerometer counts over a wide range of laboratory-based activities and activities in the field. Their study included 48 subjects who performed three exercise routines of a light, moderate, and vigorous nature. Participants wore an (model 7164) accelerometer on the hip. The coefficient of variation (CV) per 10 seconds was used to identify the activity as walking/running or another activity. Depending on the CV (either $\leq$10 or $\geq$10), an appropriate regression (walk/run, or a lifestyle/leisure) model was applied. The Cosmed K4 b$^2$ was used as the criterion measure for oxygen consumption. Their results illustrated that the 2-regression model was more accurate for energy expenditure prediction compared previously developed regression equations. In a sample of 34 adults, Rothney et al. [85] conducted a study to determine the validity of the two-regression model for predicting energy expenditure using the GT1M. Their study compared the accelerometer-derived activity counts to whole-room indirect calorimetry and doubly labeled water (DLW). Their study found that the 2-regression model overestimated total energy expenditure by only 10.2 ± 11.4% (1,282 ± 125 vs. 1,174 ± 152 MET-min, $p<0.001$), indicating fairly good agreement between the 2-regression model and room calorimetry. Currently the 2-regression model developed by Crouter et al. [81] is an accepted model for predicting energy expenditure from accelerometer counts.

An overestimation of energy expenditure during light activities and an underestimation of energy expenditure during vigorous activities are a common issue in PA research. In 2006, Crouter et al. [80] also compared the accuracy of previously published regression equations (n=15 equations) [20, 21, 84, 86-90] designed to estimate energy expenditure during a variety of activities. Several accelerometers (Actical, ActiGraph, and AMP-331) were compared. In general, investigators found the prediction equations overestimated sedentary/light activities such as sitting and walking [20-22, 84, 87, 90], and underestimated vigorous activities. Thus, investigators have concluded that most count-based regression equations perform well only during activities from which the regression equation was modeled, and do not accurately predict energy expenditure across a variety of activities. A number of reasons can be cited for these findings. First, accelerometers only detect accelerations with respect to the axis of measurement. For example, if the accelerometer is placed on the hip or waist, upper-body movement is undetected by the accelerometer. Furthermore, accelerometers cannot detect activities with additional energy expenditure such as walking while carrying a box, uphill running, or resistance training. Although some trixial accelerometers can also detect postural changes, they cannot detect additional resistance applied during uphill or downhill walking and running. Additionally, count-based PA monitors are subject to the "plateau phenomenon" [8, 50]. While the accelerometer is able to discern between walking speeds of 2-5 mph, it is not able to differentiate running speeds between 6 and 12 mph. Previous research has illustrated that ActiGraph counts plateau at speeds $\geq$ 6 mph [8, 50]. For example, King et al. [91] compared the accuracy of five different devices (CSA, TriTrac-R3D, RT3, SenseWear Armband, and the BioTrainer-Pro) for measuring energy expenditure across three walking speeds and four running speeds. They found that neither the CSA nor the Biotrainer illustrated a linear relationship with energy expenditure with speeds greater than 161 $m \cdot min^{-1}$. Likewise, Barge et al. [86] also found that the CSA model 7164 leveled off at treadmill speeds greater than 9 $km \cdot h^{-1}$, which in turn, caused an underestimation of $VO_2$ by 10% at 10 $km \cdot h^{-1}$ and approximately 50% at 16 $km \cdot h^{-1}$. Ultimately, this causes walking and running-based accelerometer prediction equations to misclassify some vigorous activities. To the researcher's knowledge, there are no accelerometer-based activity monitors designed to circumvent this issue.

The inability of accelerometer-based PA monitors to detect differences during various running speeds, their inability to determine when loads are being carried, and difficulty in distinguishing walking on an incline are limitations to the technology. Furthermore, the overestimation and underestimation of energy expenditure using accelerometer counts during lifestyle and laboratory/structured PA is often cited as a limitation to most, if not, all accelerometer-based prediction equations. Essentially, unique relationships exist between human movement patterns and energy expenditure during certain activities. However, accelerometer prediction equations based on movement patterns will likely underestimate energy expenditure (and total PA levels) from lifestyle activities and lifestyle equations will likely overestimate general activity such as walking and running. Thus, it is improbable that a single prediction equation will accurately detect a wide range of activities. Therefore, researchers have begun to investigate alternatives to solely relying on accelerometer counts for the estimation of energy expenditure and PA classification. Other alternatives include wearing the unit in a different location, using raw acceleration units (e.g. gravitational units) instead of accelerometer counts, and using more complex equations to estimate energy expenditure.

Traditionally, accelerometers are worn on the hip for PA assessment. However, more research has begun to investigate alternative wear sites. The National Health and Nutrition Examination Survey (NHANES), one of the few national surveys that rely on objective monitoring for PA assessment, began reporting accelerometer-derived PA levels of adults in 2003. Initially, participants wore the 7164 accelerometer on the hip. Beginning in 2011, NHANES changed the unit location for PA assessment to the wrist. During the 2003-2004 NHANES cycle, only 26% of the respondents who participated in the PA assessment wore the 7164 for at least 7 days [92]. This is important, because much of the awareness concerning PA levels among U.S. citizens is shaped from national survey data, and wear-time compliance on the hip has not proven to be reliable on a national scale. This could be due to a number of reasons. For instance, accelerometers worn on the waist must be removed during occasions such as when changing clothes, sleeping, and during high-contact sports. Additionally, some formal occasions may require the removal of a hip-worn accelerometer. These types of events are likely contributing to a decreased accelerometer wear-time period. Another issue with hip-worn accelerometers is the classification of non-wear time versus sedentary time. For example, if a researcher observes a pattern of 'zero counts' from the accelerometer over a specified time period, it is difficult to determine whether the accelerometer was removed, or, if it was truly sedentary time. If data are classified as sedentary time, and the device was actually removed, PA will be underestimated, and sedentary time will be overestimated. Although PA monitoring will never capture 100% of PA, researchers may be able to avoid some of these issues with wrist-worn devices. Conclusively, wrist-worn devices may be more suitable for PA measurement, and may also enhance wear-time compliance [93].

**Pattern Recognition**

Another proposed strategy to increase the accuracy of predicting PA is using a mathematical technique known as pattern recognition or "machine learning". In pattern recognition, classification algorithms are applied and, 'trained', to learn and recognize patterns associated with a particular activity. Several types of pattern recognition are commonly used in PA research. In an Artificial Neural Network (ANN), inputs (i.e., independent variables) and outputs (dependent variables) are included in the model, and a processing layer exist between the inputs and outputs [71, 94] that further categorizes and classifies the activity based on user inputs. Thus, the processing layer can be manipulated through learned algorithms. Supervised and unsupervised learning are examples of learned algorithms. In supervised learning, once the inputs and outputs are applied to the ANN, self-learning occurs until a prediction error reaches a preset threshold [71, 94]. On the other hand, Hidden Markov Models (HMMs) function in conjunction with a Markov Chains (MC), which identify activities as individual “states”. Once applied to the MC, a HMM determines the model state based on observable parameters (e.g., accelerometer counts). More recently, several studies have developed and tested algorithms based on Artificial Neural Networking to predict energy expenditure, PA type, or both [23, 25, 95]. Researchers have used ANNs to detect many types of activities and their associated energy expenditure (e.g. ascending and descending stairs, soccer, tennis) [71, 96-98]. With the advancement of technology and the need to better understand and detect physical activity, more investigations have included the application of pattern recognition algorithms to accelerometer data [99-101].

## Newly Designed Physical Activity Monitors

### Nike FuelBand

In February of 2012, Nike released a new PA monitor known as the Nike FuelBand. The device is worn on the wrist and includes a triaxial accelerometer. The Nike FuelBand is available in three different sizes (small, 14.7 cm; medium, 17.2 cm; large, 19.7cm), and includes a sizing tool and ‘links’, that allow for the adjustment of the FuelBand for a more snug fit on the wrist. Additionally, the FuelBand has 20 color light-emitting diodes (LED) for a digital display. The FuelBand displays time, steps taken, and calories burned, which allows the user to monitor real-time PA data. Additionally, the

Nike FuelBand also gives a proprietary unit of measurement known as 'Fuel', calculated based on the energy cost and other activity-based parameters unspecified by the manufacturer. The Nike FuelBand also comes with a USB charging cable and charging stand, which are connected to a compatible computer for data uploading. Once the user downloads the software (Nike Plus™), height, weight, Fuel Points Goal™, and hand dominance are uploaded to the FuelBand, and a user profile is created. As the user progresses through the day, the LED display on the FuelBand progresses from red to green, indicating the user's daily goal progress. The FuelBand also includes Bluetooth software, allowing for compatibility with Bluetooth-enabled phones (currently, this is only available to use with the Apple IOS operating system and the Android operating system). The Nike FuelBand also includes an "Airplane" mode, which disables radio connections. The FuelBand is currently available from Nike for $150 [102]. To date, there is no previously published research regarding the accuracy of the device to detect human motion, PA, and/or energy expenditure. Although proprietary testing of the FuelBand has been conducted by Nike, the results of that testing have not been made public knowledge. It is therefore unclear if the activity-based outcome variables (steps, fuel points, distance and calories) from the Nike FuelBand are solely dependent upon raw accelerometer data, or, if accelerometer data were treated with a pattern recognition algorithm.

**The Fitbit**

The first version of the Fitbit was released in the fall of 2008. The Fitbit is a MEMs-based triaxial accelerometer capable of detecting PA and energy expenditure.

The Fitbit measures 5.5cm x 19.5cm x 14mm and weighs slightly fewer than 12 grams. The Fitbit is not waterproof and thus should not be used during water-based activities such as swimming. Similar to the Nike FuelBand, the Fitbit features a single-button control, which allows the user to cycle through several outputs using an organic light-emitting diode (OLED) display which indicates calories burned, steps taken, miles, time, floors climbed, and a flower which grows with increasing PA throughout the day. There is also an option for the user to include an optional greeting and user-specified 'chatter' for daily encouragement. The Fitbit includes a base station operating on an ultra-low powered 2.4 GHz ANT radio transceiver. The unit is also capable of wireless synchronizing, if the unit is within 15 feet of the base station. The rechargeable lithium-ion polymer battery can operate for 5-7 days without charging. The Fitbit provides minute-by-minute data on PA and energy expenditure using internet-based software. During initialization, the user uploads information on height, weight, gender, and age, which are used to calculate resting energy expenditure based on a prediction equation from the Food and Drug Administration (FDA) [103]. However, for more detailed data regarding PA patterns and energy expenditure, the user must purchase additional software packages from the manufacturer.

The Fitbit Ultra, the most recent version of the Fitbit, is similar to the model designed in 2008. However, the most current unit includes an altimeter, which detects the vertical climb up stairs and hills [103]. Similar to the Nike FuelBand, the Fitbit is also new, and to the researcher's knowledge, no previous research has been published on the Fitbit.

If proven valid and reliable, the Nike FuelBand and the Fitbit have promising potential for consumer use. They are relatively easy to use, lightweight, and unlike traditional accelerometers, capable of providing real-time feedback on PA patterns and energy expenditure. This is especially important, due to the fact those PA monitors (i.e. monitors with a real-time, digital display) have been shown to enhance PA levels [15]. Although little is currently known about either device, it is speculated that consumer use of these devices will be high, given that these companies design other products (weight scales, clothing, shoes, sport-related equipment, etc.) that are endorsed by celebrated individuals (i.e., professional athletes). Essentially, this enhances the marketability of their products, particularly among young adults. Therefore, it is important that future research examine whether or not these devices are capable of accurately detecting PA and energy expenditure under both laboratory and field conditions.

# Chapter 3: The Estimation of Energy Expenditure using Triaxial Accelerometers

## Abstract

**Background**: Accelerometer-based activity monitors (accelerometers) have become the standard for monitoring physical activity (PA) patterns. Consumer use of PA monitors has also gained considerable traction among U.S. citizens. However it is not known if current triaxial accelerometers, worn on different body locations, can predict energy expenditure (EE) across a wide range of activities. **Purpose:** To determine if three triaxial accelerometers can predict EE across a range of activities. **Methods:** 21 healthy, college-aged adults wore a Nike FuelBand on the right wrist, a Fitbit on the left hip, and ActiGraph GT3X+ (ActiGraph) on the right hip, while performing 17 lifestyle and recreational activities. EE was measured using the Cosmed K4b$^2$. ANOVA repeated measures were used to compare mean differences in net EE (kcals $\cdot$ min$^{-1}$). Paired sample t-tests with Bonferroni adjustments were used to locate significant differences. **Results**: For each device, the mean difference in EE was significantly different from the criterion measure (FuelBand, -0.45 $\pm$ 2.8, Fitbit, 0.48 $\pm$ 2.27, ActiGraph, 0.64 $\pm$ 2.59 kcal$\cdot$min$^{-1}$, $p < 0.01$). The Nike FuelBand significantly overestimated most walking activities and activities involving significant arm movement (sweeping; Cosmed, 3.0 $\pm$ 0.8 vs. Nike FuelBand, 4.7 $\pm$ 0.4 kcals per minute, $p < 0.05$) (regular walking; Cosmed, 3.1 $\pm$ 0.2 vs. Nike FuelBand, 4.6 $\pm$ 0.2 kcals $\cdot$ min$^{-1}$). The Fitbit and the ActiGraph performed similarly across most activities, underestimating EE of activities requiring arm movement (Air Dyne; Cosmed 5.6 $\pm$ 0.2; Fitbit, 0.3 $\pm$ 0.2; ActiGraph, 0.2 $\pm$ 0.1 kcals $\cdot$ min$^{-1}$, $p < 0.05$). **Conclusion:** For any given individual, the error in EE prediction from one of the tested devices could be quite large. The wrist-worn Nike FuelBand captured the EE during several of the activities requiring arm movement, and sport activity, while the hip-

worn ActiGraph GT3X+ and Fitbit performed similarly, but underestimating activities with arm movement. Therefore, wrist-worn and hip-worn moderately predict EE during some activities, but still suffer from similar limitations seen with previously designed accelerometer-based devices.

Keywords: kilocalories, sensor, physical activity, exercise

**Introduction**

Accelerometer based-physical activity (PA) monitors, or accelerometers, are devices capable of detecting motion by measuring acceleration along an axis of movement [50, 62, 70]. Over the past 25 years, the use of accelerometers to measure PA in research has increased because they have been shown to provide valid and objective measures of this human behavior.

There have been several advances in accelerometer technology over the last three decades [62]. Some accelerometers have piezoelectric sensors with an inertial mass on the end of a cantilevered beam. When exposed to acceleration, the mass causes the beam to deflect and to compress a piezoelectric crystal, resulting in an electrical current being generated. These early accelerometers were capable of detecting dynamic accelerations due to body movements, but required individual calibration (i.e., assuring that accelerometers accurately measure acceleration signals following exposure to external forces such as mechanical shakers). Later developments led to piezeoresistive and capacitive accelerometers that use electrical currents powered by a battery. When these devices are exposed to acceleration, the resistance to flow of electrical current, or the charge separation, is altered [62, 98]. The manufacturing process for the capacitive accelerometers with solid-state circuitry results in much more consistent responses, eliminating the need for individual calibration. In addition, these newer accelerometers are capable of detecting static, as well as dynamic, acceleration. Over the past decade, advances in technology have led to smaller (i.e., microelectromechanical or MEMS) accelerometers capable of detecting movement in three orthogonal planes (i.e., triaxial) [51, 64, 98], which may potentially improve estimates of PAEE.

Memory capacity of accelerometer-based PA monitors has also increased over the past two-and-a-half decades. The CSA ActiGraph originally had 64 KB of memory, while the ActiGraph GT3X+ now has 516 MB of memory [50]. This has allowed data to be stored in smaller and smaller increments. Rather than storing accelerometer "counts" in 1-min epochs, it is now common practice to store raw acceleration data at 30-100 Hz. With these advances in computer memory chips, it has become possible to use new methods of analyzing accelerometer data. One of these methods is "pattern recognition", a form of artificial intelligence that uses sophisticated mathematical algorithms based on machine learning. Essentially, increased storage capacities and more complex mathematical algorithms for accelerometers may produce more precise estimates of PAEE.

Accelerometers can be worn in multiple locations such as the hip, wrist, thigh, and ankle [7, 94]. Traditionally, accelerometers are primarily worn on the hip. Hip-worn accelerometers have proven to be valid for quantifying PA levels and patterns [10, 18, 20, 21, 74, 79, 104, 105]. Previous studies have shown that hip-worn accelerometers are capable of detecting PA across a range of activities [10, 18, 20, 21, 74, 79, 104, 105]. However, hip-worn accelerometers are limited, because their positioning limits their ability to detect additional EE associated with upper-body movements and thus they tend to under-estimate the EE of ambulatory activity requiring significant upper-body movement (e.g., basketball and racquet sports) and intermittent lifestyle activities [7, 20, 21, 79, 82, 83, 89]. Furthermore, hip-worn accelerometers can be burdensome to the participant leading to a decrease in wear-time compliance when compared to wrist accelerometers [106].

Given the current limitations of hip-worn accelerometers, wrist-worn accelerometers may have an advantage over hip worn accelerometers, because they may be able to capture additional activities requiring significant upper body movements. Recently, there has been an increase in the number of accelerometer-based PA monitors designed solely for consumer use that are worn on the wrist (e.g. Jawbone, San Francisco, CA and Nike FuelBand, Beaverton, OR). Furthermore, the National Institutes of Health (NIH) began using a wrist-worn accelerometer for the National Health and Nutrition Examination Survey (NHANES) starting in 2011, due to a desire to increase wear-time compliance and to obtain an objective measure of sleep.

Recently, several companies developed new triaxial accelerometers aimed at detecting PA levels. Nike, Fitbit, and Actigraph have released triaxial accelerometers capable of detecting movement and estimating EE [78, 102, 103]. With the increase in the production of accelerometers and their potential to provide more detailed information regarding PA patterns, as well as their potential to encourage PA, researchers must determine whether these devices accurately detect PA and the associated EE. It is also important to determine whether or not newly developed triaxial accelerometers are capable of predicting EE across a wide variety of activities such as sedentary, household and recreational activities. Therefore, the purpose of this study was to determine the accuracy of three newly developed, triaxial accelerometers (Nike FuelBand, Fitbit, and ActiGraph GT3X+) across a wide range of activities.

**Materials and Methods**

The study included 21 participants (14 males, 7 females). The University of Tennessee, Knoxville's Institutional Review Board approved the study protocol prior to participant recruitment and data collection. All participants provided informed consent prior to testing. The participants were 18-45 years old, body mass index (BMI) between 18.5 $kg \cdot m^{-2}$ and 29.9 $kg \cdot m^{-2}$, regularly active (at least 150 minutes per week of moderate activity or 75 minutes per week of vigorous activity), free of any musculoskeletal limitations, and capable of performing all activities in the study (We asked participants about their ability to engage in vigorous activities, such as racquetball and basketball, for approximately 10 minutes per activity.). Only those individuals who reported meeting the PA guidelines and indicated ability to perform the sports in question were allowed to participate in the study. Individuals not meeting these criteria were excluded from the study.

Testing sessions consisted of 3 separate visits. During the first visit to the laboratory, participants were briefed on the nature of the study and completed an informed consent form and a PA readiness questionnaire (PAR-Q) [107] to screen for potential conditions that indicated the individual should not engage in moderate-to-vigorous exercise**.** Subsequently, their height (cm) was measured with a standard stadiometer and weight (kg) was measured with an electronic scale (Tanita Body Composition analyzer, Model BC-418). Subjects then completed one of three PA routines.

All participants performed one to three activity routines of varying intensities (Table 1), with each participant completing at least one routine.

**Table 1. Routines used in the study.**

| | |
|---|---|
| **Routine 1 (sedentary/walking)** | |
| | Seated computer work |
| | Standing |
| | Walking, self-paced |
| | Walking with an umbrella* |
| | Walking with a backpack** |
| | Walking up and down stairs |
| **Routine 2 (housework/yard work)** | |
| | Vacuuming |
| | Sweeping |
| | Washing dishes |
| | Mowing (push mower) |
| | Raking |
| **Routine 3 (sports/exercise)** | |
| | Racquetball |
| | Basketball |
| | Elliptical |
| | Air Dyne bike |
| | Treadmill, 9.3 km/hr |
| | Treadmill, 12.0 km/hr |

All walking activities performed on an outdoor track at self-selected pace.
* - Umbrella was held in dominant hand.
** - Backpack weighed 4.5kg.
All routine activities consisted of 8-minutes bouts.

Each activity routine consisted of 5-6 activities, and one routine was completed per day. The order in which routines were completed was randomized, but the order in which the activities were completed was consistent across each routine. The routines were as follows:

*Routine 1*: computer work, standing, self-paced walking, self-paced walking with an umbrella in the dominant hand, self-paced walking with a backpack, and walking flights of stairs.

*Routine 2*: vacuuming, sweeping, washing dishes, mowing (using a push mower), and raking.

*Routine 3:* racquetball, basketball, elliptical, Air Dyne biking, treadmill running at 9.7 km/h, and treadmill running at 12.0 km/h.

A total of 21 participants performed at least two of three routines. Specifically, 21 participants performed Routines 1 and 2, and 20 participants performed all three routines. Each activity was performed for eight minutes. Participants were given a 3-4 minute rest between each activity. During each activity routine, oxygen consumption ($VO_2$) was measured using indirect calorimetry (Cosmed K4 $b^2$ , Rome, Italy). Previous research in our laboratory has validated $VO_2$ values from the Cosmed K4 $b^2$ [108]. Prior to each test, the K4 $b^2$ was calibrated according to the manufacturer's instructions. This consisted of performing a room air calibration and a reference gas calibration using 16.00% oxygen and 3.98% carbon dioxide. The flow turbine was calibrated using a 3.0-liter syringe (Hans-Rudolph). An additional delay calibration was performed to account for the lag time that occurs between the expiratory flow measurement and the gas analyzers assessment of the gas fractions. The Cosmed K4 $b^2$ was used as the criterion measure for EE (net kilocalories per minute). In order to estimate resting EE, participants also wore the Cosmed K4 $b^2$ while lying supine for approximately 15 minutes prior to performing routines on day 1.

*ActiGraph GT3X+ accelerometer*: The ActiGraph GT3X+ (ActiGraph) accelerometer was securely placed over the right hip using a nylon belt. The ActiGraph was initialized using Actilife 5 (ActiGraph) computer software. Data from the ActiGraph were collected at a rate of 100 Hz with 30-second epoch lengths. At the completion of each routine, data were uploaded from the ActiGraph to a laboratory computer using a standard universal serial bus (USB) drive.

*Nike FuelBand*: The Nike FuelBand (Nike, Beaverton OR), a bracelet-sized device, was placed around the dominant wrist. The Nike FuelBand is available in three sizes (small, medium, and large) and comes pre-packaged with additional extenders that allow individuals to adjust the size of the Nike FuelBand. The Nike FuelBand was initialized using web-based software (http://nikeplus.nike.com/plus/setup/fuelband) in which personalized data (height, weight, and age) is stored within the software, and synchronized with the Nike FuelBand to estimate net EE during activity.

*The Fitbit:* The Fitbit (San Francisco, CA) was placed on a belt around the waist of each participant, at the anterior iliac crest. Similar to the Nike FuelBand, the Fitbit was initialized using web-based software (www.fitbit.com/start) and individualized data (gender, age, height, weight, and stride rate) were used in estimating gross EE during PA.

**Measures**

***Kilocalories***

Breath-by-breath measurements were collected using the Cosmed K4b$^2$ and averaged over 1-minute periods. Net kilocalories per minute (kcal$\cdot$min$^{-1}$) was the variable of interest. For the Cosmed K4 b$^2$, the last 4 minutes of each activity was used in the final analysis. The kcal$\cdot$min$^{-1}$ values for the last 4 minutes of each activity were averaged to obtain a net kcal$\cdot$min$^{-1}$ value. In order to obtain net kilocalories from the Cosmed K4 b$^2$, resting metabolic rate was subtracted from the average gross kilocalorie value (per activity) given by the Cosmed K4 b$^2$. For the Nike FuelBand and Fitbit, an initial kcal value was subtracted from the final kcal value at the end of each activity to obtain the total kilocalories per activity. The FuelBand provides an estimate of PAEE, thus can be directly compared with the net kcal per min obtained from the Cosmed. The Fitbit estimates gross kilocalories (PAEE + kilocalories expended at rest) using a combination of the Mifflin St. Jeor equation [109, 110] for resting metabolic rate and other undisclosed equations to compute the activity EE using proprietary algorithms [109, 110]. Therefore, PAEE for the Fitbit was estimated by subtracting resting metabolic rate (i.e., gross EE minus resting metabolic rate using the Mifflin St. Jeor equation) from the average kcal$\cdot$min$^{-1}$ value derived for each activity. For the ActiGraph, data were downloaded to a computer, and a kilocalorie value for each bout of activity was derived from the software. The combination equation consisting of a standard work-energy theorem and the Freedson prediction equation [20] was used to calculate EE from accelerometer counts. Accelerations less than or equal to 1952 counts$\cdot$min$^{-1}$ are converted to kcals using the work-energy theorem. Likewise, accelerations totaling greater than 1952 counts$\cdot$min$^{-1}$, are converted to kcal$\cdot$min$^{-1}$ using the Freedson kcal equation was used:

Work energy Theorem: *kilocalories = Counts × 0.0000191 × Mass*

Freedson: *kilocalorie$\cdot$min$^{-1}$ = (0.00094×Counts + (0.1346×Mass-7.37418).*

*According to ActiGraph's website [111], these equations were developed to determine PAEE [111], which is synonymous with net EE (i.e., EE in excess of the resting EE).*

## Measures

### *Statistical Approach*

All data were analyzed using SPSS 19 for Windows (SPSS Inc., Chicago, IL). An alpha level of 0.05 was set as an indicator of statistical significance. Repeated measures ANOVAs were used to determine significant differences in measured and predicted net EE (net kcal$\cdot$min$^{-1}$) for all activities. Paired sample t-tests with Bonferroni adjustments were used to locate significant differences across devices.

Modified Bland-Altman plots were used to illustrate the variability in individual error scores (measured kilocalories per min – predicted kilocalories per min) across activities (n = 17 activities for kilocalories per min) and devices (Nike FuelBand, Fitbit, and Actigraph). Data points below zero indicate an overestimation, while data points above zero indicate an underestimation.

## Results

Due to device error and the inability of several individuals to complete some of the activities, data were missing for some participants, and thus were excluded from the final analysis (three of 21 individuals were excluded for routine 1 and routine 2, and five of 20 subjects were excluded for routine 3). As a result, the final analysis included 18 individuals who completed routine 1 and 2, and 15 individuals who completed routine 3.

Table 2 shows the physical characteristics of participants.

**Table 2. Physical characteristics of study participants.**

| | |
|---|---|
| Age (y) | 24.5 $\pm$ 2.6 (21 – 30) |
| Height (cm) | 176.8 $\pm$ 8.6 (156.0 – 192.0) |
| Body mass (kg) | 75.8 $\pm$ 16.5 (50.0 – 112.0) |
| BMI ($kg \cdot m^{-2}$) | 23.9 $\pm$ 3.6 (18.2 – 33.0) |
| Resting EE ($kcal \cdot min^{-1}$): | 1.3 $\pm$ 0.4 (0.87 – 1.72) |

n = 21
Male = 14
Female = 7

**Table 3 Compares the actual (Cosmed K4b$^2$) and predicted (Nike FuelBand, Fitbit, and ActiGraph GT3X+) net EE (net kcals·min$^{-1}$) across 17 activities.**
**a: Nike FuelBand significantly different from criterion measure ($p < 0.05$).**
**b: Fitbit significantly different from criterion measure ($p < 0.05$).**
**c: ActiGraph significantly different from criterion measure ($p < 0.05$).**

| Activity | Cosmed K4b$^2$ | FuelBand | Fitbit | ActiGraph GT3X+ |
|---|---|---|---|---|
| Computer Work (a,c) | 0.4 ± 0.0 (0.1 – 0.5) | 0.0 ± 0.0 (0.0 – 0.0) | 0.3 ± 0.05 (0.3 – 0.4) | 0.0± 0.0 (0.0 – 0.0) |
| Standing (a,c) | 0.2 ± 0.1 (0.1 – 0.3) | 0.0 ± 0.0 (0.0 – 0.0) | 0.1 ± 0.1 (-0.1 – 0.3) | 0.0 ± 0.0 (0.0 – 0.0) |
| Self-paced Walking (a,b,c) | 3.1 ± 0.2 (2.8 – 3.5) | 4.6 ± 0.2 (4.2 – 5.1) | 5.4 ± 0.3 (4.8 – 6.0) | 5.8 ± 0.4 (4.9 – 6.7) |
| Walking with Umbrella (b,c) | 3.3 ± 0.2 (3.0 – 3.8) | 3.5 ± 0.5 (2.5 – 4.5) | 5.2 ± 0.3 (4.5 – 6.0) | 5.8 ± 0.5 (4.7 – 6.9) |
| Walking with Backpack (a,b,c) | 3.6 ± 0.2 (3.2 – 3.9) | 4.7 ± 0.2 (4.3 – 5.1) | 5.0 ± 0.3 (4.6 – 6.0) | 5.6 ± 0.5 (4.5 – 6.8) |
| Walking up-and-down Stairs | 6.7 ± 0.4 (6.0 – 7.6) | 6.0 ± 0.4 (5.1 – 7.0) | 7.0 ± 0.4 (6.1 - 8.0) | 6.7 ± 0.6 (5.5 – 8.0) |
| Vacuuming (c) | 2.6 ± 0.2 (2.1 – 3.0) | 2.7 ± 0.4 (2.0 – 3.5) | 2.2 ± 0.1 (1.9 – 2.5) | 0.7 ± 0.1 (0.6 – 0.9) |
| Sweeping (a,b,c) | 3.0 ± 0.8 (2.5 – 3.3) | 4.7 ± 0.4 (4.0 – 5.5) | 2.0 ± 0.2 (1.5 – 2.3) | 1.0 ± 0.2 (0.7 – 1.3) |
| Dishwashing (a,b,c) | 1.5 ± 0.1 (1.2 – 1.8) | 3.0 ± 0.3 (2.5 – 3.6) | 0.2 ± 0.1 (0.1 – 0.3) | 0.1 ± 0.5 (0.0 – 0.2) |
| Mowing (a,b,c) | 5.3 ± 0.4 (4.6 – 6.1) | 6.8 ± 0.5 (5.8 – 7.9) | 4.3 ± 0.4 (3.6 – 5.1) | 3.7 ± 0.4 (2.7 – 4.8) |
| Raking (a,b,c) | 3.5 ± 0.2 (3.0 – 3.9) | 8.0 ± 0.5 (7.0 – 9.0) | 2.5 ± 0.1 (2.2 – 2.8) | 1.2 ± 0.1 (1.0 – 1.3) |
| Racquetball (b,c) | 9.6 ± 0.8 (7.9 – 11.2) | 11.1 ± 0.5 (9.9 – 12.3) | 7.4 ± 0.6 (6.1 – 8.6) | 6.5 ± 0.4 (5.7 – 7.4) |
| Basketball (c) | 10.8 ± 0.8 (9.0 – 12.5) | 12.2 ± 0.5 (11.2 – 13.3) | 8.8 ± 0.6 (7.4 – 10.2) | 8.3 ± 0.8 (9.0 – 12.5)* |

| | | | | |
|---|---|---|---|---|
| Elliptical (a,c) | 5.0 ± 0.2<br>(4.5 – 5.5) | 3.1 ± 0.4<br>(2.3 – 4.0) | 5.5 ± 0.4<br>(4.7 – 6.3) | 7.6 ± 0.4<br>(6.7 – 8.5) |
| Air Dyne<br>(b,c) | 5.6 ± 0.2<br>(5.2 – 6.1) | 4.9 ± 0.5<br>(3.9 – 6.0) | 0.3 ± 0.2<br>(0.0 – 0.1) | 0.2 ± 0.1<br>(0.0 – 0.5) |
| Treadmill<br>9.7km/h (a,c) | 9.7 ± 0.4<br>(8.9 – 10.7) | 12.7 ± 0.7<br>(11.3 – 14.1) | 10.8 ± 0.6<br>(9.5 – 12.1) | 10.9 ± 0.5<br>(9.8 – 12.0) |
| Treadmill<br>12.0km/h | 11.9 ± 0.6<br>(10.5 – 13.3) | 10.8 ± 0.8<br>(8.9 – 12.6) | 10.3 ± 0.9<br>(8.3 – 12.2) | 11.2 ± 0.7<br>(10.5 – 13.2) |

Table 3 Compares the actual (Cosmed K4b2) and predicted (Nike FuelBand, Fitbit, and ActiGraph GT3X+) net EE (net kcals.min-1) across 17 activities.

a: Nike FuelBand significantly different from criterion measure ($p < 0.05$).

b: Fitbit significantly different from criterion measure ($p < 0.05$).

c: ActiGraph significantly different from criterion measure ($p < 0.05$).

.

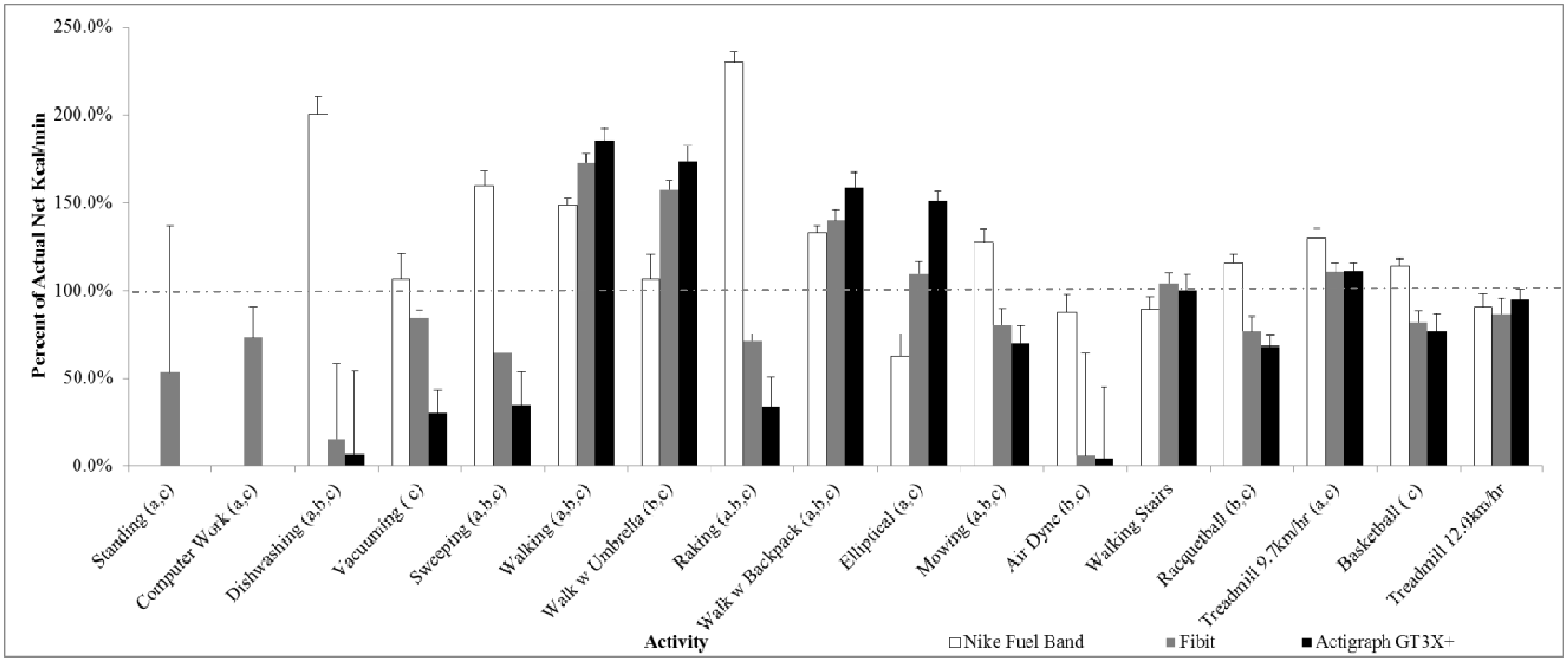


***Figure 1: Illustrates the percent of actual (Cosmed K4 $b^2$) net kcals per minute across all activities and 3 devices (Nike FuelBand, Fitbit, and ActiGraph GT3X+).***

a: Nike FuelBand significantly different from criterion measure $p < 0.05$ level.

b: Fitbit significantly different from criterion measure $p < 0.05$ level.

c: ActiGraph significantly different from criterion measure at $p < 0.05$ level

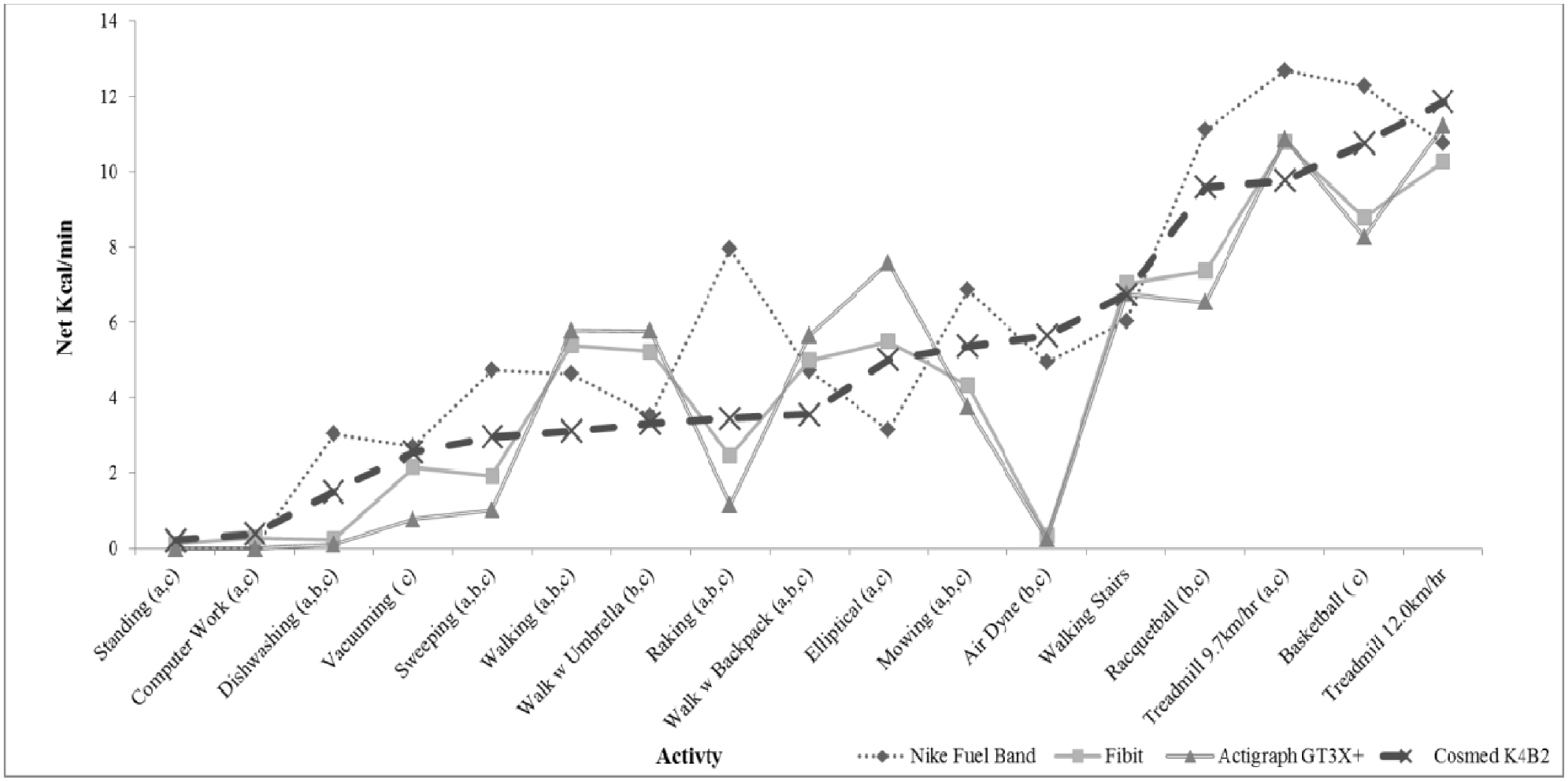


***Figure 2: Measured (Cosmed K4b$^2$) and estimated net kilocalories per minute (kcal·min$^{-1}$) across activities of varying intensities*.**

a: Nike FuelBand significantly different from criterion ($p < 0.05$ level); b: Fitbit significantly different from criterion ($p < 0.05$).

c: ActiGraph significantly different from criterion ($p < 0.05$).

Figures 3a, 3b, and 3c show modified Bland-Altman Plots for individual error scores for EE (kcals per minute) for the Nike FuelBand (Figure 3a), Fitbit (Figure 3b), and the ActiGraph (Figure 3c).

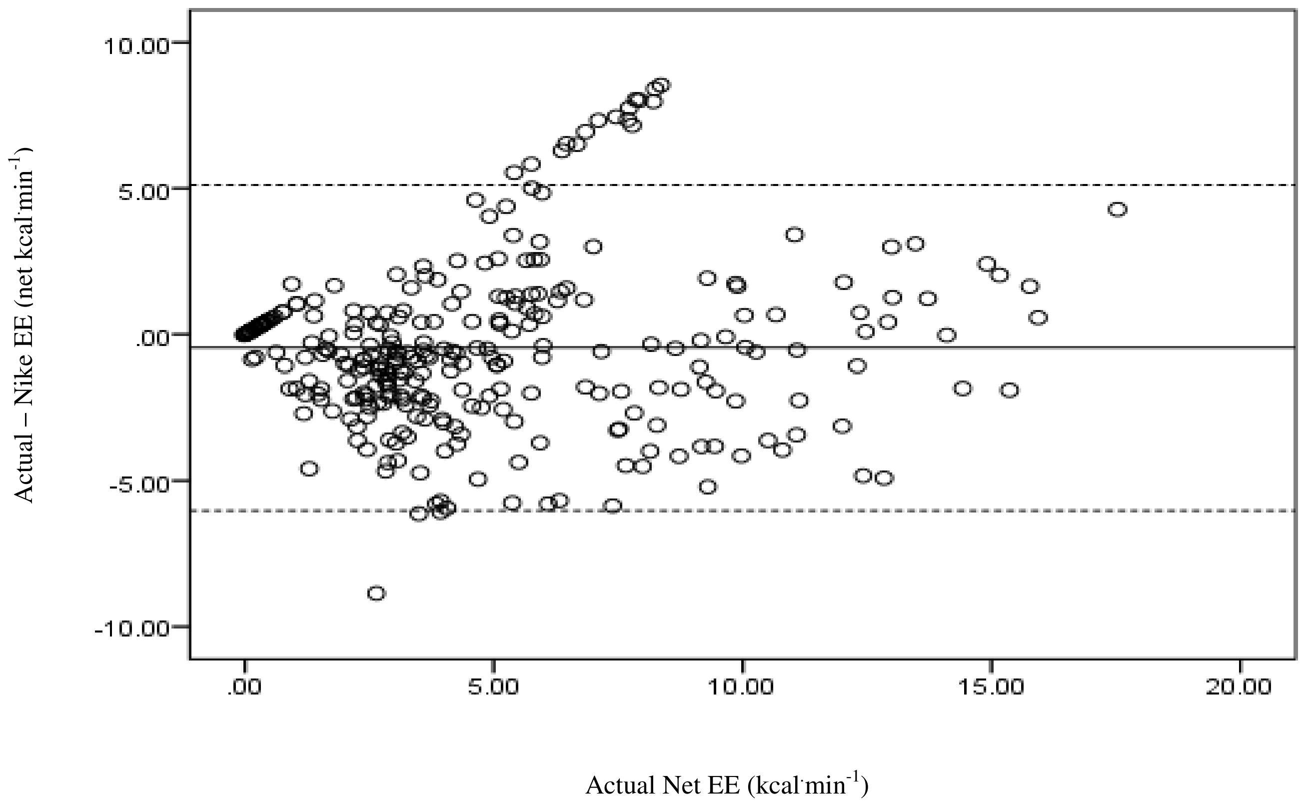


***Fig (3a): Modified Bland-Altman plot depicting individual error scores for the Nike FuelBand (kcal·min$^{-1}$) for all activities***. Dashed lines represent the 95% limits of agreement. Solid line represents the mean difference.

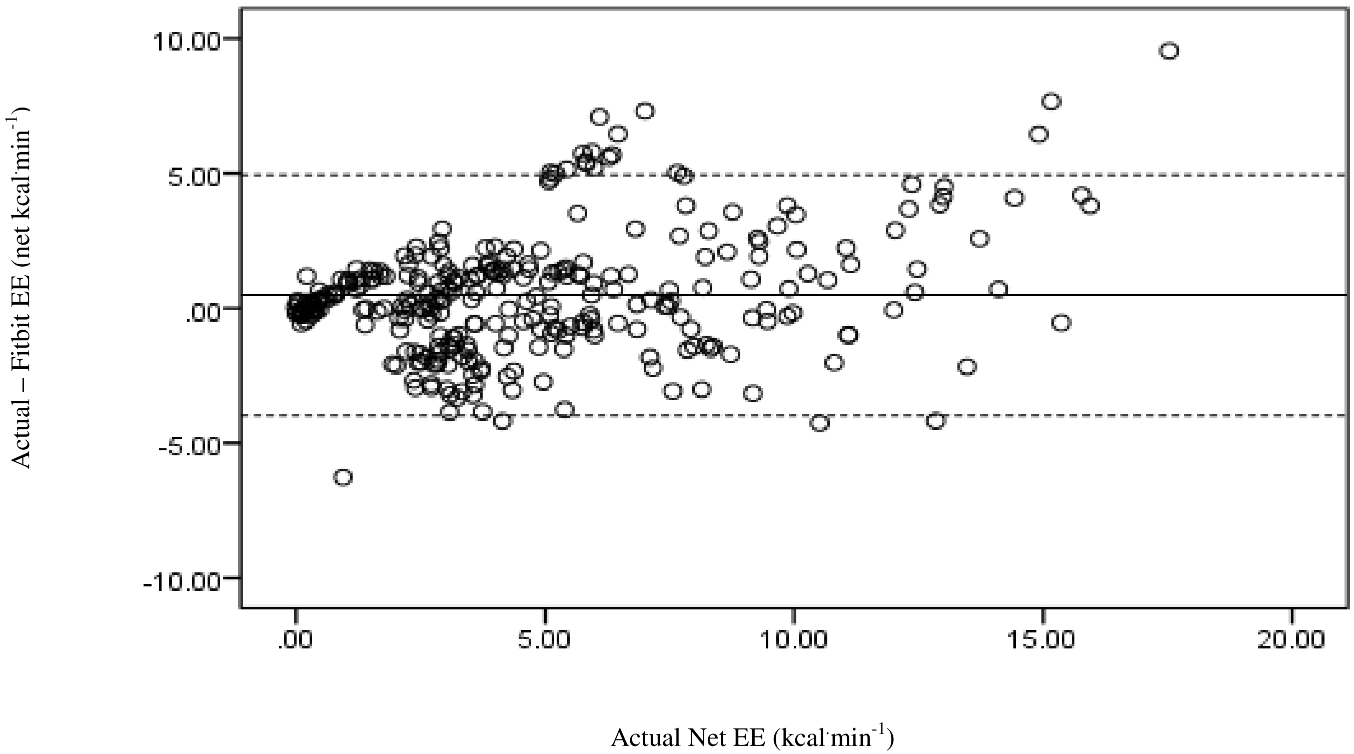


***Fig (3b): Modified Bland-Altman plot depicting individual error scores for the Fitbit (kcal·min$^{-1}$) for all activities.*** Dashed lines represent the 95% limits of agreement. Solid line represents the mean difference.

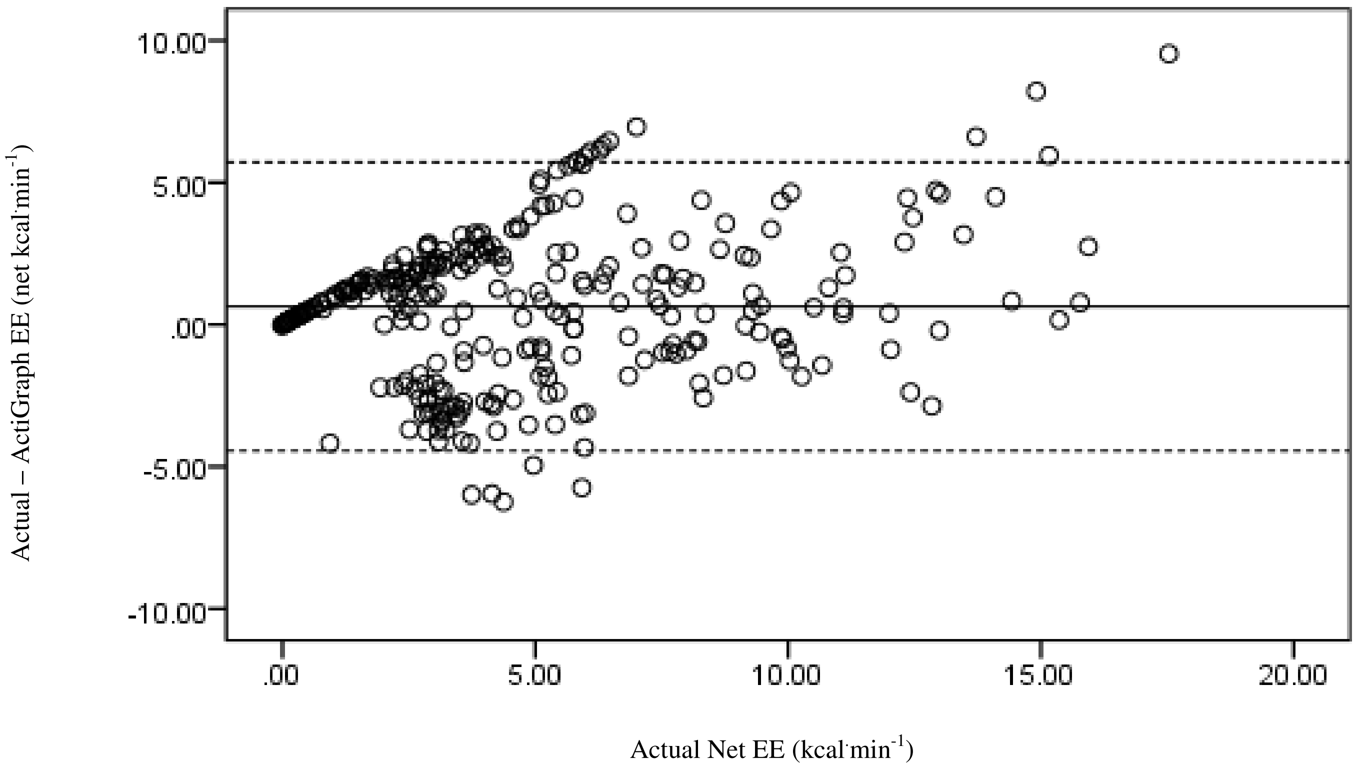


***Fig (3c): Modified Bland-Altman plot depicting individual error scores for the ActiGraph (kcal·min$^{-1}$) for all activities***. Dashed lines represent the 95% limits of agreement. Solid line represents the mean difference.

The Nike FuelBand significantly overestimated the energy cost of 7 out of the 17 total activities included in the study (Table 1, Figures 1 and 2), and underestimated the energy cost of 3 of the 17 activities. More specifically, during nearly all the walking activities, the Nike FuelBand significantly overestimated EE. The only exception to this was during the umbrella activity in which arm movement was limited (Table 3). During household activities requiring significant arm movement, the Nike FuelBand significantly overestimated EE (sweeping; Cosmed, 3.0 $\pm$ 0.8 vs. Nike, 4.7 $\pm$ 0.4 kcals per minute, $p = 0.00$) (Dishwashing; Cosmed, 1.5 $\pm$ 0.1 vs. Nike, 3.0 $\pm$ 0.3 kcals per minute, $p < 0.05$). During sport activities, however, the FuelBand performed somewhat better than during household activities. There were no significant differences between the Nike FuelBand and the criterion measure during racquetball and basketball (Figure 2). During stationary exercises that required equipment and significant arm movement (i.e., elliptical and Air Dyne biking), the FuelBand accurately predicted EE (Table 3, Figure 2), but did not accurately predict EE for the elliptical machine involving arm movement (Cosmed, 5.0 $\pm$ 0.2 vs. Nike, 3.1 $\pm$ 0.4 kcals per minute, $p < 0.05$). The FuelBand accurately predicted EE during the faster running speed (Table 3), but was significantly different from the criterion measure during the slower running speed (Cosmed, 9.7 $\pm$ 0.4 vs. Nike, 12.7 $\pm$ 0.7 kcals per minute, $p < 0.05$)

Similar to the Nike FuelBand, the Fitbit and the ActiGraph overestimated nearly all walking activities (Table 3). The Fitbit and the ActiGraph gave remarkably similar values for most activities. In general, the Fitbit and the ActiGraph significantly underestimated several of the same activities (e.g., dishwashing, sweeping, and racquetball). For example, the Fitbit and the ActiGraph recorded close to 0 kcals per minute during household activities requiring significant arm movements (e.g., dishwashing and sweeping), and they recorded over 2-3 calories per minute less than the criterion measure during racquetball (Cosmed, 9.6 $\pm$ 0.8 kcals per minute vs. Fitbit, 7.4 $\pm$ 0.6 kcals per minute, vs. ActiGraph, 6.5 $\pm$ 0.4 kcals per minute, $p < 0.05$). It can also be observed from Figure 1 that the Fitbit and the ActiGraph were unable to capture the additional EE resulting from upper body movements on the Schwinn Air Dyne. Additionally, they were unable to accurately predict the EE associated with the elliptical machine (Table 3).

The modified Bland-Altman Plots (Figure 3) indicated that the Nike FuelBand, on average when all activities were combined, differed from the criterion value by -0.46 $\pm$ 2.84 $kcals \cdot min^{-1}$ ($p = 0.01$) indicating a slight overestimation by the Nike FuelBand. In comparison, EE (net $kcal \cdot min^{-1}$) from the Fitbit differed from the Cosmed $K4b^2$ by 0.48 $\pm$ 2.28 $kcal \cdot min^{-1}$ ($p = 0.00$), while the mean difference between the Cosmed $K4b^2$ and the ActiGraph was 0.64 $\pm$ 2.6 $kcal \cdot min^{-1}$ ($p = 0.000$). The 95% prediction intervals were roughly + 5 MET, for all three devices. Thus, the Nike FuelBand, Fitbit, and ActiGraph had limited accuracy for predicting EE across a wide range of activities.

**Discussion**

Although the Nike FuelBand, Fitbit, and ActiGraph accurately predicted EE for several of the activities, our results suggest that, collectively, these newly-designed triaxial accelerometers had limited ability to predict EE across a range of activities. Out of 17 total activities, both the wrist-worn FuelBand and the waist-worn Fitbit accurately predicted 7 out of 17 possible activities. Thus it appears that, overall, the wrist-mounted and hip-mounted device performed similarly for predicting EE across a range of activities. However, when considering all activities together, the mean bias for the FuelBand and Fitbit went in opposite directions (Nike; -0.455 $\pm$ 2.84 kcals$\cdot$min$^{-1}$, p = 0.01, Fitbit; 0.482 $\pm$ 2.28 kcal$\cdot$min$^{-1}$, p = 0.00). Furthermore, the wrist-mounted and hip-mounted devices differed in their accuracy for predicting the EE of specific activities.

The Nike FuelBand overestimated most of the household activities as well as most of the walking activities (Table 3). The FuelBand tended to overestimate household activities requiring arm movements (Routine 2, Table 2), and waking activities during which arms swung freely by the participant's side. The FuelBand performed the best during the sport activities, and accurately predicted EE during one of the stationary exercises (Schwinn Air Dyne) and during the fastest treadmill speed (12.0 km/h). Thus, it appears that the Nike FuelBand overestimates EE during low-to-moderate lifestyle activities such as self-paced walking and household activities, but adequately predicts EE during sport activities. The overestimation during low to moderate intensity activities and activities requiring significant arm movement may be explained by the placement of the FuelBand on the wrist. For example, the Nike FuelBand dramatically overestimated the EE of raking by over 200% (Figure 1). During dishwashing, and activities requiring almost no lower body movement and significant arm movements, the Nike FuelBand also overestimated EE by over 150% (Figure 1), indicating that the FuelBand is very sensitive to exaggerated arm/wrist movement. Although the Nike FuelBand does not appear to perform superiorly to the Fitbit and the ActiGraph, the Nike FuelBand has the ability to capture EE associated with upper body movements and may perform superior to hip worn-accelerometers to predict EE during activities requiring significant arm movement.

The ActiGraph and the Fitbit underestimated EE during activities requiring arm movements, and overestimated EE during most of the walking activities. Both devices also underestimated sport activities, and the ActiGraph significantly underestimated the slower treadmill speed (9.7 $km \cdot h^{-1}$). Although the ActiGraph significantly overestimated EE during the slower treadmill speed, the predicted EE from the ActiGraph was not significantly different from the Fitbit (ActiGraph, 10.9 $\pm$ 0.5 vs. Fitbit, 10.8 $\pm$ 0.6 kcals per minute, $p = 1.00$). Therefore, comparing the Fitbit to the Actigraph, the two devices performed similarly during most activities.

Our study used a previously developed algorithm to predict EE from the ActiGraph. The algorithm is derived from a combination of the Freedson kcal equation [20] and a work/energy theorem to calculate caloric expenditure [111]. Furthermore, it only uses the vertical axis on the ActiGraph GT3X+ to produce accelerometer counts for EE. This is significant, because previous research has found that triaxial accelerometers are advantageous to uniaxial designs [112-114] when estimating EE during PA. Thus, when using the combination equation with the ActiGraph GT3X+, it is likely that EE for some activities (especially those involving significant movements in the horizontal plane) may be underestimated. Nevertheless, several prediction equations do exist that incorporate vector magnitude counts of three axes. However, further research is needed to develop algorithms based on raw, triaxial acceleration data, and to determine the accuracy of newly-developed prediction equations.

Previous research has shown that accelerometer-based activity monitors often exhibit a 'plateau' effect during faster treadmill speeds, in which filtering mechanisms within the accelerometer prevent the device from discerning the differences in EE during treadmill speeds greater than approximately 9.5 – 10km/hr [8, 17]. Specifically in our study, when comparing the 9.7km/hr treadmill run to the 12.0km/hr treadmill run, it appeared that the ActiGraph, Fitbit, and the Nike FuelBand suffered from the plateau effect, in which filtering mechanisms prevented the accelerometers (mainly the Nike FuelBand), from detecting differences in treadmill speeds greater than approximately 9.5 - 10km/hr. Although none of the devices were significantly different from the measured $kcal \cdot min^{-1}$ at the faster treadmill speed, it appeared that the filtering limitation may have caused EE during faster running speeds to be somewhat similar to the EE seen for the FuelBand, Fitbit, and ActiGraph at the slower treadmill speed. The ability to differentiate among high intensity activities (e.g., various running speeds) is a major limitation to currently available accelerometers.

Pattern recognition or 'machine learning' has been proposed as a potential method of converting accelerometer counts to EE. Previous research has shown that wrist-worn accelerometers and hip-worn accelerometers have similar accuracy, but limited data is available regarding the accuracy of pattern recognition applied to wrist-worn accelerometers [93]. According to a website containing Fitbit source code (developed by Fitbit engineers) [109], physical activity EE is computed using 'proprietary algorithms' based on the user's actigraphy data. Currently, it is unknown if the Nike FuelBand uses pattern recognition to estimate EE because the device uses proprietary algorithms. More research is needed to determine if the use of pattern recognition would enhance estimates of EE across a range of activities and at multiple locations (i.e., hip and wrist).

Neither the FuelBand nor the Fitbit were able to predict energy expenditure across a range of activities. Therefore, it would be impractical to utilize these devices as criterion measures during experiments in which energy expenditure is the main outcome variable. However, given their novelty and popularity, the Nike FuelBand and Fitbit do have the potential to encourage PA among previously inactive or low active individuals. The general public can utilize these devices as rough estimates of energy expenditure during activity.

In summary, these triaxial accelerometer-based activity monitors were not able to accurately predicting EE across all activities. Wrist-worn devices tended to overestimate EE during activities requiring arm movement, whereas hip-worn devices underestimate activities requiring arm movement. Furthermore, both devices performed similarly across walking activities. Overall, the accuracy of the waist-worn Fitbit and wrist-worn Nike FuelBand were similar to that of the Actigraph. However, none of the devices accurately predicted EE across a wide range of activities.

## List of References


1. Kampert, J.B., et al., *Physical activity, physical fitness, and all-cause and cancer mortality: a prospective study of men and women.* Annals of Epidemiology, 1996. **6**(5): p. 452-457.

2. Pate, R.R., et al., *Physical activity and public health: A recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine.* Journal of the American Medical Association, 1995. **273**(5): p. 402-407.

3. Physical Activity Guidelines Advisory Committee, *Physical Activity Guidelines Advisory Committee Report*, 2008, U.S. Department of Health and Human Services Washington, DC.

4. Centers for Disease Control and Prevention. *Physical Activity Statistics*. 2008 [cited 2011 February 27]; Available from: http://www.cdc.gov/nccdphp/dnpa/physical/stats/.

5. Haskell, W.L., et al., *Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association.* Medicine & Science in Sports & Exercise, 2007. **39**(8): p. 1423-1434.

6. Koh, H.K., *A 2020 vision for healthy people.* New England Journal of Medicine, 2010. **362**(18): p. 1653-1656.

7. Bassett, D.R., Jr., *Validity and reliability issues in objective monitoring of physical activity.* Research Quarterly for Exercise and Sport, 2000. **71**(2 Suppl): p. S30-6.

8. John, D., B. Tyo, and D.R. Bassett, *Comparison of four actigraph accelerometers during walking and running.* Medicine & Science in Sports & Exercise, 2010. **42**(2): p. 368-374.

9. Atienza, A.A., et al., *Self-reported and objectively measured activity related to biomarkers using NHANES.* Medicine & Science in Sports & Exercise, 2011. **43**(5): p. 815-821.

10. Bassett, D.R., Ainsworth, B.E., Swartz, A.M., Strath, S.J., O'Brien, W.L., and King, G.A., *Validity of four motion sensors in measuring moderate intensity physical activity.* Medicine & Science in Sports & Exercise, 2000. **32**(9): p. S471-S480.

11. Crouter, S.E., et al., *Validity of 10 electronic pedometers for measuring steps, distance, and energy cost.* Medicine & Science in Sports & Exercise, 2003. **35**(8): p. 1455-1460.

12. Schneider, P.L., et al., *Accuracy and reliability of 10 pedometers for measuring steps over a 400-m walk.* Medicine & Science in Sports & Exercise, 2003. **35**(10): p. 1779-1784.

13. Silcott, N.A., et al., *Evaluation of the omron HJ-720ITC pedometer under free-living conditions.* Medicine & Science in Sports & Exercise, 2011. **43**(9): p. 1791-1797.

14. Hatano, Y., *Use of the pedometer for promoting daily walking exercise.* Journal of International Council for Health, Physical Education, and Recreation, 1993. **29**(4): p. 4-8.

15. Bravata, D.M., et al., *Using pedometers to increase physical activity and improve health: a systematic review.* Journal of the American Medical Association, 2007. **298**(19): p. 2296-2304.

16. Jakicic, J.M., et al., *Evaluation of the sensewear pro armband (TM) to assess energy expenditure during exercise.* Medicine & Science in Sports & Exercise, 2004. **36**(5): p. 897-904.

17. John, D. and P. Freedson, *ActiGraph and actical physical activity monitors: A peek under the hood.* Medicine & Science in Sports & Exercise, 2012. **44**(1S): p. S86-S89.

18. Welk, G.J., et al., *Field validation of the MTI ActiGraph and bodymedia armband monitor Using the IDEEA monitor.* Obesity, 2007. **15**(4): p. 918-928.

19. Crouter, S.E., K.G. Clowers, and D.R. Bassett, *A novel method for using accelerometer data to predict energy expenditure.* Journal of Applied Physiology, 2006. **100**(4): p. 1324-1331.

20. Freedson, P.S., E. Melanson, and J. Sirard, *Calibration of the computer science and applications, inc. accelerometer.* Medicine & Science in Sports & Exercise, 1998. **30**(5): p. 777-81.

21. Hendelman, D., et al., *Validity of accelerometry for the assessment of moderate intensity physical activity in the field.* Medicine & Science in Sports & Exercise, 2000. **32**(9): p. S442-S449.

22. Swartz, A.M., et al., *Estimation of energy expenditure using CSA accelerometers at hip and wrist sites.* Medicine & Science in Sports & Exercise, 2000. **32**(9): p. S450-S456.

23. Freedson, P.S., et al., *Evaluation of artificial neural network algorithms for predicting METs and activity type from accelerometer data: Validation on an independent sample.* Journal of Applied Physiology, 2011. **111**: p. 1804-1812.

24. Rothney, M.P., et al., *An artificial neural network model of energy expenditure using nonintegrated acceleration signals.* Journal of Applied Physiology, 2007. **103**(4): p. 1419-1427.

25. Staudenmayer, J., et al., *An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer.* Journal of Applied Physiology, 2009. **107**(4): p. 1300-1307.

26. Mcardle, Katch, and Katch, *Exercise Physiology: Physical Activity, Health, and Aging*, in *Exercise Physiology: Energy, Nutrition, and Human Performance*. Lipincott, Williams, and Wilkins 5th edition 2001. p. 886-887.

27. Caspersen, C.J., K.E. Powell, and G.M. Christenson, *Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research.* Public Health Rep, 1985. **100**(2): p. 126-31.

28. Simmons, R., et al., *Increasing overall physical activity and aerobic fitness is associated with improvements in metabolic risk: Cohort analysis of the ProActive trial.* Diabetologia, 2008. **51**(5): p. 787-794.

29. Thompson, P.D., et al., *Exercise and physical activity in the prevention and treatment of atherosclerotic cardiovascular disease: A Statement From the Council on Clinical Cardiology (Subcommittee on Exercise, Rehabilitation, and Prevention) and the Council on Nutrition, Physical Activity, and Metabolism (Subcommittee on Physical Activity).* Arteriosclerosis, Thrombosis, and Vascular Biology, 2003. **23**(8): p. e42-e49.

30. U.S. Department of Health and Human Services, *Physical Activity and Health: A Report of the Surgeon General* in *Atlanta GA: U.S. Department of Health and Human Services,*

*Center for Disease Control and Prevention, National Centers for Chronic Disease Prevention and Health Promotion*1996.

31. Crespo, C.J., et al., *Leisure-time physical activity among U.S. adults: results from the Third National Health and Nutrition Examination Survey.* Archives of Internal Medicine, 1996. **156**(1): p. 93-98.

32. Weller, I. and P. Corey, *The impact of excluding non-leisure energy expenditure on the relation between physical activity and mortality in women.* Epidemiology, 1998: p. 632-635.

33. Lamonte, M.J. and B.E. Ainsworth, *Quantifying energy expenditure and physical activity in the context of dose response.* Medicine & Science in Sports & Exercise, 2001. **33**(6): p. S370-S378.

34. Hu, F.B., et al., *Walking compared with vigorous physical activity and risk of type 2 diabetes in women.* Journal of the American Medical Association, 1999. **282**(15): p. 1433-1439.

35. Lee, I., H.D. Sesso, and R.S. Paffenbarger, *Physical activity and coronary heart disease risk in men: does the duration of exercise episodes predict risk?* Circulation, 2000. **102**(9): p. 981-986.

36. Manson, J.A.E., et al., *Walking compared with vigorous exercise for the prevention of cardiovascular events in women.* New England Journal of Medicine, 2002. **347**(10): p. 716-725.

37. Manson, J.E., et al., *A prospective study of walking as compared with vigorous exercise in the prevention of coronary heart disease in women.* New England Journal of Medicine, 1999. **341**(9): p. 650-658.

38. Rockhill, B., et al., *Physical activity and mortality: a prospective study among women.* American Journal of Public Health, 2001. **91**(4): p. 578-583.

39. Donnelly, J., et al., *The effects of 18 months of intermittent vs. continuous exercise on aerobic capacity, body weight and composition, and metabolic fitness in previously sedentary, moderately obese females.* International journal of obesity and related metabolic disorders, 2000. **24**(5): p. 566-572.

40. Jakicic, J.M., et al., *Effects of intermittent exercise and use of home exercise equipment on adherence, weight loss, and fitness in overweight women.* Journal of the American Medical Association, 1999. **282**(16): p. 1554-1560.

41. Murphy, M., et al., *Accumulating brisk walking for fitness, cardiovascular risk, and psychological health.* Medicine & Science in Sports & Exercise, 2002. **34**(9): p. 1468.

42. Murphy, M.H., A.M. Nevill, and A.E. Hardman, *Different patterns of brisk walking are equally effective in decreasing postprandial lipaemia.* International Journal of Obesity, 2000. **24**(10): p. 1303-1309.

43. Assah, F.K., et al., *Accuracy and validity of a combined heart rate and motion sensor for the measurement of free-living physical activity energy expenditure in adults in Cameroon.* International Journal of Epidemiology, 2011. **40**(1): p. 112-120.

44. Healy, G.N., et al., *Sedentary time and cardio-metabolic biomarkers in U.S. adults: NHANES 2003–2006.* European Heart Journal, 2011. **32**(5): p. 590-597.

45. Sallis, J. and B. Saelens, *Assessment of physical activity by self-report: status, limitations, and future directions.* Research Quarterly for Exercise and Sport, 2000. **71**(2 Suppl): p. S1-S14.

46. Shephard, R., *Limits to the measurement of habitual physical activity by questionnaires.* British journal of sports medicine, 2003. **37**(3): p. 197-206.

47. Bouten, C.C., et al., *A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity.* IEEE Transactions on Biomedical Engineering, 1997. **44**(3): p. 136-147.

48. Macfarlane, D.J., et al., *Convergent validity of six methods to assess physical activity in daily life.* Journal of Applied Physiology, 2006. **101**(5): p. 1328-1334.

49. Plasqui, G. and K.R. Westerterp, *Physical activity assessment with accelerometers: An evaluation against doubly labeled water.* Obesity, 2007. **15**(10): p. 2371-2379.

50. Bassett, D. and D. John, *Use of pedometers and accelerometers in clinical populations: Validity and reliability issues.* Physical Therapy Reviews, 2010. **15**(3): p. 135-142.

51. Yang, C.C. and Y.L. Hsu, *A review of accelerometry-based wearable motion detectors for physical activity monitoring.* Sensors, 2010. **10**(8): p. 7772-7788.

52. U.S. department of Health and Human Services and Office of Disease Prevention and Health Promotion, *Physical activity guidelines advisory committee report*: Washington, DC U.S. Department of Health and Human Services, 2008.

53. Kruger, J., et al., *Prevalence of transportation and leisure walking among US adults.* Preventive medicine, 2008. **47**(3): p. 329-334.

54. Richardson, C.R., et al., *A meta-analysis of pedometer-based walking interventions and weight loss.* The Annals of Family Medicine, 2008. **6**(1): p. 69-77.

55. Orthocare Innovations. *StepWatch Overview*. 2012 April 2 ]; Available from: http://orthocareinnovations.com/pages/stepwatch.

56. Coleman, K.L., et al., *Step activity monitor: long-term, continuous recording of ambulatory function.* Journal of Rehabilitation Research and Development, 1999. **36**(1): p. 8-18.

57. Foster, R.C., et al., *Precision and accuracy of an ankle-worn accelerometer-based pedometer in step counting and energy expenditure.* Preventive Medicine, 2005. **41**(3-4): p. 778-783.

58. Shepherd, E.F., et al., *Step activity monitor: increased accuracy in quantifying ambulatory activity.* Journal of Orthopedic Research, 1999. **17**(5): p. 703-708.

59. Storti, K.L., et al., *Gait speed and step-count monitor accuracy in community-dwelling older adults.* Medicine & Science in Sports & Exercise, 2008. **40**(1): p. 59-64.

60. Mudge, S., N.S. Stott, and S.E. Walt, *Criterion validity of the stepwatch activity monitor as a measure of walking activity in patients after stroke.* Archives of Physical Medicine and Rehabilitation, 2007. **88**(12): p. 1710-1715.

61. Karabulut, M., S.E. Crouter, and D.R. Bassett, *Comparison of two waist-mounted and two ankle-mounted electronic pedometers.* European journal of applied physiology, 2005. **95**(4): p. 335-343.

62. Chen, K.Y. and D.R. Bassett Jr, *The technology of accelerometry-based activity monitors: current and future.* Medicine & Science in Sports & Exercise, 2005. **37**(11): p. S490-S500.

63. Morris, J., *Accelerometry--a technique for the measurement of human body movements.* Journal of Biomechanics, 1973. **6**(6): p. 729-732.

64. Mathie, M.J., et al., *Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement.* Physiological Measurement, 2004. **25**: p. R1-R20.

65. Culhane, K., et al., *Accelerometers in rehabilitation medicine for older adults.* Age and ageing, 2005. **34**(6): p. 556-560.

66. Saunders, J., V.T. Inman, and H.D. Eberhart, *The major determinants in normal and pathological gait.* The Journal of Bone and Joint Surgery (American), 1953. **35**(3): p. 543-558.

67. Gage, H., *Accelerographic analysis of human gait.* Washington DC: American Society for Mechanical Engineers, 1964.

68. Saunders, J., V.T. Inman, and H.D. Eberhart, *The major determinants in normal and pathological gait.* Journal Of Bone And Joint Surgery American Volume, 1953. **35**(3): p. 543-558.

69. Wong, T.C., et al., *Portable accelerometer device for measuring human energy expenditure.* IEEE Transactions on Biomedical Engineering, 1981. **28**(6): p. 467-71.

70. Bonomi, A. and K. Westerterp, *Advances in physical activity monitoring and lifestyle interventions in obesity: a review.* International Journal of Obesity, 2011. **36**: p. 167-177.

71. Godfrey, A., et al., *Direct measurement of human movement by accelerometry.* Medical Engineering & Physics, 2008. **30**(10): p. 1364-1386.

72. Bouten, C.V.C., et al., *Effects of placement and orientation of body-fixed accelerometers on the assessment of energy expenditure during walking.* Medical and Biological Engineering and Computing, 1997. **35**(1): p. 50-56.

73. Crouter, S.E., P.L. Schneider, and D.R. Bassett, *Spring-levered versus piezo-electric pedometer accuracy in overweight and obese adults.* Medicine and Science in Sports and Exercise, 2005. **37**(10): p. 1673-1679.

74. Melanson, E.L., et al., *Commercially available pedometers: considerations for accurate step counting*. Preventive Medicine, 2004. **39**(2): p. 361-368.

75. Pyle, J. and P. Emerald, *Convection-based technology offers the lowest-cost accelerometers and tilt sensors.* Auto Technology, 2002. **2**: p. 60-63.

76. Sasaki, J.E., D. John, and P.S. Freedson, *Validation and comparison of actigraph activity monitors.* Journal of Science and Medicine in Sport, 2011. **14**(5): p. 411-416.

77. Tryon, W.W. and R. Williams, *Fully proportional actigraphy: a new instrument.* Behavior Research Methods, 1996. **28**(3): p. 392-403.

78. ActiGraph. *ActiGraph GT1M monitor and actilife lifestyle monitor software version 1.0 user manual*. 2006 February 24]; Available from: http://dl.theactigraph.com/ActiLife5-PUB10DOC10-D.pdf.

79. Melanson Jr, E.L. and P.S. Freedson, *Validity of the computer science and applications, inc.(CSA) activity monitor.* Medicine and Science in Sports and Exercise, 1995. **27**(6): p. 934-940.

80. Crouter, S.E., J.R. Churilla, and D.R. Bassett, *Estimating energy expenditure using accelerometers.* European Journal of Applied Physiology, 2006. **98**(6): p. 601-612.

81. Crouter, S.E., K.G. Clowers, and D.R. Bassett, *A novel method for using accelerometer data to predict energy expenditure.* Journal of Applied Physiology, 2005. **100**(4): p. 1324-1331.

82. Matthew, C.E., *Calibration of accelerometer output for adults.* Medicine and Science in Sports and Exercise, 2005. **37**(11): p. S512-S522.

83. Welk, G.J., *Principles of design and analyses for the calibration of accelerometry-based activity monitors.* Medicine and Science in Sports and Exercise, 2005. **37**(11): p. S501-S511.

84. Nichols, J., et al., *Assessment of physical activity with the computer science and applications, inc., accelerometer: laboratory versus field validation.* Research Quarterly for Exercise and Sport, 2000. **71**(1): p. 36-43.

85. Rothney, M.P., et al., *Validation of the ActiGraph Two–Regression Model for Predicting Energy Expenditure.* Medicine and Science in Sports and Exercise, 2010. **42**(9): p. 1785-1792.

86. Brage, S., et al., *Reexamination of validity and reliability of the CSA monitor in walking and running.* Medicine and Science in Sports and Exercise, 2003. **35**(8): p. 1447-14454.

87. Brooks, A.G., et al., *Predicting walking METs and energy expenditure from speed or accelerometry.* Medicine and Science in Sports and Exercise, 2005. **37**(7): p. 1216-1223.

88. Heil, D.P., et al., *Body size as a determinant of activity monitor output during overground walking.* Online Journal of Exercise Physiology. **6**: p. 1-11.

89. Leenders, N., T. Nelson, and W. Sherman, *Ability of different physical activity monitors to detect movement during treadmill walking.* International Journal of Sports Medicine, 2003. **24**(1): p. 43-50.

90. Yngve, A., et al., *Effect of monitor placement and of activity setting on the MTI accelerometer output.* Medicine and Science in Sports and Exercise, 2003. **35**(2): p. 320.

91. King, G.A., et al., *Comparison of activity monitors to estimate energy cost of treadmill exercise.* Medicine and Science in Sports and Exercise, 2004. **36**(7): p. 1244-1251.

92. Troiano, R.P., et al., *Physical activity in the United States measured by accelerometer.* Medicine and Science in Sports and Exercise, 2008. **40**(1): p. 181-8.

93. Zhang, S., et al., *Physical activity classification using the GENEA wrist worn accelerometer.* Medicine & Science in Sports & Exercise, 2012. **44**(4): p. 742-748.

94. Chau, T., *A review of analytical techniques for gait data. Part 2: neural network and wavelet methods.* Gait & Posture, 2001. **13**(2): p. 102-120.

95. Oshima, Y., et al., *Classifying household and locomotive activities using a triaxial accelerometer.* Gait & Posture, 2010. **31**(3): p. 370-374.

96. Baek, J., et al., *Accelerometer signal processing for user activity detection.* Lecture Notes in Computer Science, 2004. **3215**: p. 610-617.

97. Ermes, M., et al., *Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions.* IEEE Transactions on Information Technology in Biomedicine 2008. **12**(1): p. 20-26.

98. Yang, J.Y., J.S. Wang, and Y.P. Chen, *Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers.* Pattern Recognition Letters, 2008. **29**(16): p. 2213-2220.

99. Lester, J., T. Choudhury, and G. Borriello, *A practical approach to recognizing physical activities.* Pervasive Computing, 2006: p. 1-16.

100. Lester, J., et al. *A hybrid discriminative/generative approach for modeling human activities*. in *Proceedings of the 19th International Joint Conference on Artificial Intelligence*. 2005.

101. Tapia, E.M., et al. *Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor*. in *Wearable Computers, 11th IEEE International Symposium*. 2007 p. 37-40. Institute of Electrical and Electronics Engineers.

102. Nike. *Nike Plus Fuel Band*. 2012 [cited 2012 February 21]; Available from: http://nikeplus.nike.com/plus/products/fuelband.

103. Fitbit. *Fitbit Technical Specs*. 2012 [cited 2012 February 21]; Available from: http://www.fitbit.com/product/specs.

104. Welk, G.J., J. Almeida, and G. Morss, *Laboratory calibration and validation of the Biotrainer and Actitrac activity monitors.* Medicine & Science in Sports & Exercise, 2003. **35**(6): p. 1057-1064.

105. Welk, G.J., et al., *A comparative evaluation of three accelerometry-based physical activity monitors.* Medicine & Science in Sports & Exercise, 2000. **32**(9): p. S489-S497.

106. Evenson, K.R. and J.W. Terry Jr, *Assessment of differing definitions of accelerometer nonwear time.* Research Quarterly for Exercise and Sport, 2009. **80**(2): p. 355-362.

107. Chisholm, D., et al., *PAR-Q Validation Report: The evaluation of a self-administered pre-exercise screening questionnaire for adults.* BC Ministry of Health and Health and Welfare Canada, Victoria, 1978.

108. McLaughlin, J., et al., *Validation of the cosmed K4b2 portable metabolic system.* International Journal of Sports Medicine, 2001. **22**(4): p. 280-284.

109. Friedman, E. and P. Risenberg. *Fitbit API*. Welcome to the fitbit API 2012 [cited 2012 August 15]; Available from: https://wiki.fitbit.com/display/API/Fitbit+API.

110. Roberts, D. *DIY Biomechanics*. Fitbit lab 2012 February 7 2012 [cited 2012; Available from: http://www.diybiomechanics.com/2012/02/07/fitbit-lab/.

111. Actigraph. *What is the difference between the energy expenditure algorithms?* 2012 [cited 2012 August 15]; Available from: http://support.theactigraph.com/faq/difference-energy-expenditure-algorithms.

112. Ayen, T. and H. Montoye, *Estimation of energy expenditure with a simulated three-demensional accelerometer.* Journal of Ambulatory Monitoring, 1988. **1**: p. 293-301.

113. Bouten, C.V., et al., *Assessment of energy expenditure for physical activity using a triaxial accelerometer.* Medicine and Science in Sports and Exercise, 1994. **26**(12): p. 1516-1523.

114. Plasqui, G., et al., *Measuring Free-Living Energy Expenditure and Physical Activity with Triaxial Accelerometry.* Obesity Research, 2012. **13**(8): p. 1363-1369.

# Appendices

# Appendix A

## Estimation of Steps using three Triaxial Accelerometers

### Introduction

The measurement of physical activity energy expenditure (PAEE) is crucial for understanding the relationship between PA and health outcomes. Using data from the current study, the Nike FuelBand and Fitbit have shown limited accuracy for predicting energy expenditure (EE), in $kcal \cdot min^{-1}$over a range of activities. However, it is unknown if these devices (Fitbit and Nike FuelBand) are able to detect steps, relative to a criterion measure, during the same activities. In addition to determining if these devices could predict energy expenditure ($kcal \cdot min^{-1}$), a secondary purpose was to determine whether the Nike FuelBand and the Fitbit could predict steps ($steps \cdot min^{-1}$) taken during several of the activities used in this study.

### Methods

Methodologies for the Nike FuelBand and Fitbit are described elsewhere (Chapter 3). The StepWatch 3 (Orthocare Innovations, Oklahoma City, OK) (SW) pedometer was the criterion measure and was worn around the left ankle, just above the lateral malleolus. The SW was secured to the ankle using an elastic strap. The participant's height was entered into the SW software. Additionally, within the SW software, the user selects pre-programmed speeds (normal and quick stepping) based on the activity. For our walking activities, the SW speed was set to 'normal'. For the running activities, the SW was set to the 'quick-stepping' speed. All devices were initialized using the same computer to ensure time synchronization between the devices. Total steps per minute ($steps \cdot min^{-1}$) for activities were compared for the Nike FuelBand, the Fitbit, and the SW. The SW software does not include a 'uniformed' step rate setting, which is consistent across activities of varying step rates. Thus, we limited the step analysis to 10 of the 17 activities (regular walking, walking with an umbrella, walking with a backpack, walking up-and-down stairs, vacuuming, sweeping, mowing, raking, treadmill running at 9.7 km/hr, and 12 km/hr). The SW was the criterion measure for steps.

**Statistical Analysis**

One-sample t-tests were used to determine mean differences between the Nike FuelBand and the SW, and the Fitbit and SW. We also developed modified Bland-Altman plots to illustrate the variability in individual error scores for steps per min, across 10 activities and two devices (Fitbit and Nike FuelBand). Data points below zero indicate an overestimation, while data points above zero indicate an underestimation.

**Results and Discussion**

Figure 4a and 4b show modified Bland-Altman plots depicting individual error scores for steps$\cdot$min$^{-1}$ for the Nike FuelBand (Figure 4a) and Fitbit (Figure 4b).

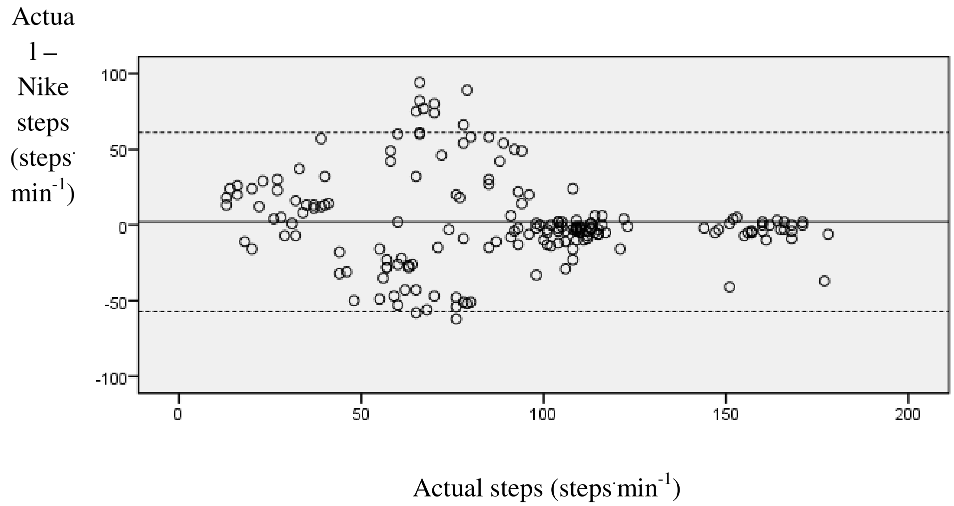


***Fig (4a): Modified Bland-Altman plot depicting individual error scores for the Nike FuelBand (steps·min$^{-1}$) for 10 activities.*** Dashed lines represent the 95% limits of agreement. Solid line represents the mean difference.

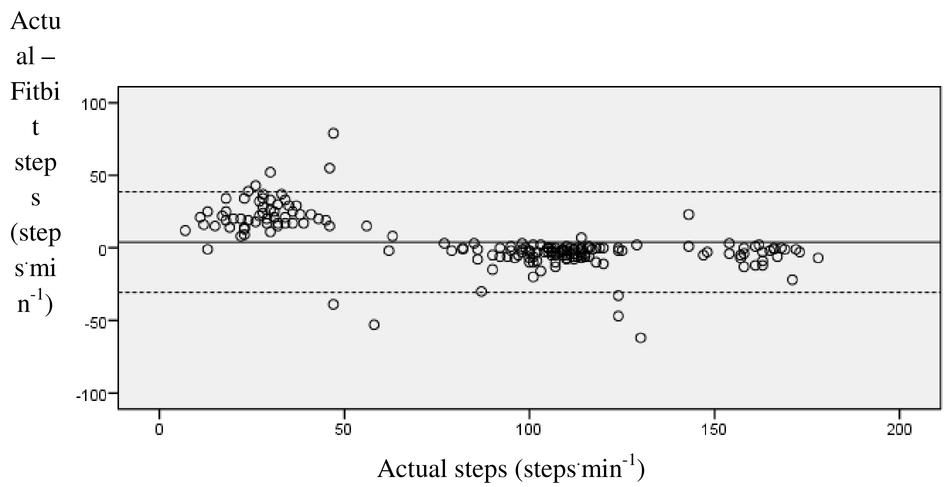


***Fig (4b): Modified Bland-Altman plot depicting individual error scores for the Fitbit (steps·min$^{-1}$) for 10 activities.*** Dashed lines represent the 95% limits of agreement. Solid line represents the mean difference.

The mean difference between the Fitbit and the StepWatch was 3.93 ± 17.7 steps·minute$^{-1}$ (p = 0.03). The mean difference between the Nike FuelBand and the StepWatch was 1.98 ± 30.1 steps·minute$^{-1}$, but the mean difference between the two devices was not significant (p = 0.38). The 95% prediction intervals were nearly twice as wide for the FuelBand as for the FitBit (Figures 4a and 4b). Thus it appears that the Fitbit had a significantly larger mean error than the FuelBand, but the FuelBand had greater individual variation. As seen with kilocalories, the individual error in predicting steps·minute$^{-}$1 across a range of activities could be quite large. Thus, caution should be exercised when using the Fitbit and the FuelBand for measuring steps during PA.

# Appendix B

**INFORMED CONSENT FORM**

The Estimation of Caloric Expenditure and Physical Activity using Accelerometer-based Physical Activity Monitors

Investigator Contact Information:
Tyrone Ceaser
University of Tennessee
Department of Kinesiology, Recreation, and Sport Studies
HPER 303
1914 Andy Holt Ave.
Knoxville, TN 37923
Telephone: (865) 974-5091 Email: tceaser@utk.edu

**Study Purpose**

The purpose of this study is to determine whether newly-designed motion sensor devices (accelerometer-based physical activity monitors) can accurately estimate the calories burned and steps taken during different activities. In order to be eligible for this study, you must be healthy, regularly active, and able to complete the activities included in this study.

**Testing Protocol**

You will be asked to come to the Applied Physiology Lab on 3 separate occasions for 1.5 to 2 hours per visit. On each visit you will perform a different exercise routine. On the first visit, you will be given information about this study and asked to sign an informed consent form (this form). You will also be asked to complete a form about your health. Once these are completed, your height and weight will be measured. You will then be fitted with several different devices that will measure the amount of calories you burn at rest and during each activity you perform. You will wear a total of 6 different devices (2 on the hip, 1 on the ankle, 1 on each wrist, and 1 around your torso that will be connected to a facemask which will allow you to breathe normally). All of the devices are safe, and will not harm you in any way. Once you have been fitted with these devices, you will begin your first exercise routine. Each activity will last for 8 minutes, and you will have 2-4 minutes to rest in between each activity. The order in which you do each of the following activity routines will be randomized. In other words, the activities you perform on day 1 may not necessarily be routine 1.

For routine 1, you will perform the following activities: seated computer work, standing, walking with arms swinging by side, walking with an umbrella, walking while holding onto backpack strap, and walking up-and-down stairs. The walking activities in routine 1 will be done on the university outdoor track and field complex at a self-selected pace.

For routine 2, you will perform the following activities: Vacuuming, sweeping, washing dishes, lawn mowing, and raking. These activities will be done in and around the Applied Physiology Lab in the HPER building.

For routine 3, you will perform the following activities: Racquetball, basketball, elliptical machine, Air Dyne (requires arm and leg movement while on a stationary cycle), slow treadmill running (6 mph), and fast treadmill running (7.5 mph). These activities will be done in the HPER building.

**Risks**

There are health risks associated with any type of moderate-to-strenuous exercise. These include muscular discomfort, dizziness, headaches, abnormal blood pressure responses, and heart attack. However, the health risks that come with exercise are minimal for people who are healthy and exercise regularly. People who are at increased risks for these types of responses will not be included in the study.

**Emergency Medical Treatment**

In the event that you are injured during this research project, the University of Tennessee does not automatically pay for the treatment of injuries. If physical injury is suffered in the course of research, or for more information, please notify the investigator in charge Tyrone Ceaser (865) 974-5091.

**Benefits**

There are no direct benefits to participating in this study. However, you will be given an opportunity to see how different devices work to measure calorie expenditure. We will also measure your height and weight and provide you with that information.

**Compensation**

There will be no compensation for your participation in this study.

**Confidentiality**

All data collected will be treated as confidential. We will identify you in our records by an identification number and not by any personal identifiers such as name, date of birth, etc. Data will be stored in a locked file in the HPER building.

**Contact Information**

For the duration of the study, you will be contacted and notified by phone and/or email concerning upcoming visits to the lab and/or problems you may be experiencing. If you have any questions about participating in this research study (or you experience any adverse effects as a result of participating in this study), contact Tyrone Ceaser , The University of Tennessee, 1914 Andy Holt Avenue, Knoxville, TN, 37996 or (865) 974-5091. Furthermore, if you have questions about your rights as a participant, please contact the University of Tennessee, Knoxville Office of Research Compliance Officer at (865) 974-3466.

**Participation**

Your participation in this study is completely voluntary. You are under no obligation to participate in this study and may decline to continue participation at any time during the study. In the event that you do not finish the study, any data collected from you may be used for research, unless you specify otherwise. If you do not wish for your data to be used for research, please let the researcher (Tyrone Ceaser) know, and it will be destroyed.

---

Consent

By signing this consent form, I am indicating that I have read this form and agree to take part in this study. I have received a copy of this form.

___________________________________
Print Name

___________________________________ __________________
Your signature Date

___________________________________ __________________
Researcher's Signature Date

# Appendix C

Physical Activity Readiness Questionnaire Form

PHYSICAL ACTIVITY READINESS QUESTIONNAIRE (PAR-Q)

Regular physical activity is fun and healthy, and increasingly more people are starting to become more active every day. Being more active is very safe for most people. However, some people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age and you are not used to being very active, check with your doctor.

| **No** | **Yes** | |
|---|---|---|
| ☐ | ☐ | 1. Has your doctor ever said that you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor? |
| ☐ | ☐ | 2. Do you feel pain in your chest when you do physical activity? |
| ☐ | ☐ | 3. In the past month, have you had chest pain when you were not doing physical activity? |
| ☐ | ☐ | 4. Do you lose your balance because of dizziness or do you ever lose consciousness? |
| ☐ | ☐ | 5. Do you have a bone or joint problem that could be made worse by a change in your physical activity? |
| ☐ | ☐ | 6. Is your doctor currently prescribing drugs (for example water pills) for your blood pressure of heart condition? |
| ☐ | ☐ | 7. Do you know of <u>any other reason</u> why you should not do physical activity? |

Please note: If your health changes so that you then answer YES to any of these questions, tell your fitness or health professional. Ask whether you should

**If you answered YES to one or more questions**

Talk to your doctor by phone or in person BEFORE you start becoming much more physically active of BEFORE you have a fitness appraisal. Tell your doctor about the PAR-Q and which questions you answered YES.

- You may be able to do any activity you want as long as you start slowly and build up gradually. Or you may need

| | |
|---|---|
| change your physical activity plan. | to restrict your activities to those which are safe for you. Talk to your doctor about the kinds of activities you wish to participate in and follow his/her advice.<br>• Find out which community programs are safe and helpful for you. |

| **If you answered NO to all questions** | Delay becoming much more active if: |
|---|---|
| If you have answered NO honestly to all PAR-Q questions, you can be reasonably sure that you can:<br>• Start becoming much more physical active – begin slowly and build up gradually. This is the safest and easiest way to go.<br>• Take part in a fitness appraisal – this is an excellent way to determine your basic fitness so that you can plan the best way for you to live actively. | • You are not feeling well because of a temporary illness such as a cold or a fever – wait until you feel better, or<br>• If you are or may be pregnant – talk to your doctor before you start becoming more active. |

I understand that my signature signifies that I have read and understand all the information on the questionnaire, that I have truthfully answered all the questions, and that any question/concerns I may have had have been addressed to my complete satisfaction.

Name (please print)___________________________

Date______________________________________________________

Signature_________________________________________________

# Vita

Tyrone Ceaser was born in Los Angeles California. He resided in California for several years, and then relocated to Marion, South Carolina by way of adoption. Tyrone has 3 biological brothers, 1 biological sister, and 7 siblings by way of adoption. Tyrone attended Marion High School in Marion, South Carolina, After graduation, he attended Winthrop university in Rock Hill, South Carolina, where he obtained a bachelor's degree in Athletic Training. After completion of his bachelor's degree, Tyrone relocated to Chralotte, North Carolina, where he accepted a teaching assistantship and completed his Master's degree in Clinical Exercise Physiology. Immediately following his master's degree, Tyrone relocated to Knoxville, Tennessee, where he accepted a graduate teaching associate assistantship and graduate with a Doctorate degree in Kinesiology. He is currently a post-doctoral fellow at Gramercy Research Group in Winston-Salem, North Carolina.