Monitors-Based Measurement of Sedentary Behaviors and

Light Physical Activity in Adults

by

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ABSTRACT

Having accurate measurements of sedentary behaviors is important to understand relationships between sedentary behaviors and health outcomes and to evaluate changes in interventions and health promotion programs designed to reduce sedentary behaviors. This dissertation included three projects that examined measurement properties of wearable monitors used to measure sedentary behaviors. Project one examined the validity of three monitors: the ActiGraph GT3X+, activPAL™, and SenseWear 2. None of the monitors were equivalent with the criterion measure of oxygen uptake to estimate the energy cost of sedentary and light-intensity activities. The ActivPAL™ had the best accuracy as compared with the other monitors. In project two, the accuracy of ActiGraph GT3X+and GENEActiv cut-points used to assess sedentary behavior were compared with direct observation during free-living conditions. New vector magnitude cut-points also were developed to classify time spent in sedentary- and stationary behaviors during free-living conditions. The cut-points tested had modest overall accuracy to classify sedentary time as compared to direct observation. New ActiGraph 1-minute vector cut-points increased overall accuracy for classifying sedentary time. Project 3 examined the accuracy of the sedentary sphere by testing various arm elevation- and movement-count configurations using GENEActiv and ActiGraph GT3X+ data obtained during free-living conditions. None of the configurations were equivalent to the criterion measure of direct observation. The best configuration of the GENEActiv was: worn on the dominant wrist at 15 degrees below the horizontal plane with a cut-point <489 for each 15-second interval. The best configuration for the ActiGraph was: worn on the non-dominant wrist at 5° below the horizontal plane with a cut-point of <489 counts for each 15-second

interval. Collectively, these findings indicate that the wearable monitors and methods examined in this study are limited in their ability to assess sedentary behaviors and light intensity physical activity. Additional research is needed to further understand the scope and limitations of wearable monitors and methods used to assess sedentary behaviors and light intensity physical activity.

DEDICATION

I dedicate this dissertation to my family with special feelings of love and gratitude to my wife, Adriana Ruelle-Gómez for her patience, love, support, and push for continuous personal improvement. Gracias por todo, mi amor.

I also dedicate this dissertation to my son, David Flórez-Ruelle who has motivated me to be a better person. Son remember to dream, enjoy what you do, work hard, and persist; thus, your dreams will turn into reality.

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TABLE OF CONTENTS

APPENDIX Page

LIST OF TABLES

Table Page

Table Page

LIST OF FIGURES

Chapter 1

INTRODUCTION

For more than 50 years, the health effects of physical activity have been studied extensively. Research has shown a positive relationship between physical activity and positive health outcomes.[1] Levels of physical activity that expend an energy expenditure of at least 500 kcal per week in moderate and intensity activities or where adults accumulate at least 150 minutes per week in moderate-intensity activities or 75 minutes per week in vigorous-intensity activities reduce the risks for morbid health conditions and premature mortality.[2,3] In 1978, Paffenbarger et al.[2] reported that physical activity energy expenditure was inversely related to the risk of a first heart attack in men. In 1989, Leon et al.[4] observed that leisure time physical activity was inversely related to coronary heart disease and overall mortality in middle-aged men at high risk for coronary heart disease. Further, Helmrich et al.[1] showed an inverse association between physical activity and type 2 diabetes among male college students. Collectively, these and other studies support the observation that regular physical activity is positively related to good health and disease prevention.[5]

Within the past 15 years, there has been a growing body of evidence showing that sedentary behaviors are a distinct risk factor independent of physical activity and that sedentary behaviors are related to multiple adverse health outcomes in adults.[6–9] Sedentary behaviors are defined as any waking behavior characterized by an energy expenditure $\leq$1.5 metabolic equivalents (METs) while in a sitting or reclining posture.[10] As a referent, one MET is defined as the energy cost while sitting quietly. In the

Australian Diabetes, Obesity and Lifestyle Study (AusDiab), Dunstan et al.[6,11] found that among non-diabetic adults, self-reported television viewing time was positively associated with abnormal glucose metabolism and metabolic syndrome. In another study on sedentary behaviors, Wijndaele et al.[9] reported that increases in television viewing were associated with increases in waist circumference and diastolic blood pressure. As well, Howard et al.[8] showed that television viewing time was associated with an increased risk of colon cancer. The adverse health associations between sedentary behaviors also have been reported in other population-based studies that have included different types of sedentary behaviors, to include sitting and reclining behaviors.

The importance of understanding the health impact of sedentary behaviors and health relates to the prevalence of sedentary behaviors and the relationship with metabolic disease conditions. American adults spend at least 55% of their time sitting,[12] and only 3.5% attain sufficient physical activity to meet national physical activity recommendations.[13] Furthermore, in both developing and developed countries, the prevalence of sedentary behaviors is increasing and metabolic energy expenditure is decreasing in daily activities.[14] Thus, high exposure to sedentary behaviors can compromise the metabolic health for persons who are sedentary for prolonged periods of the day. The adverse health effects of prolonged sedentary periods also applies to persons who engage in enough physical activity to meet physical activity recommendations.[15]

As the study of sedentary behaviors is a new field, current interest in sedentary behaviors research is focused mainly in three areas. First, the physiological evidence of specific health effects of sedentary behaviors is unique to sedentary behaviors that are detrimental to health, independent of physical activity levels.[16,17] This area is of high importance as the evidence supporting sedentary behaviors as a chronic disease risk factor is in the early stages as compared with the enormous amount of evidence of the protective effects of moderate-to-vigorous intensity physical activity.[18] Second, the physiological evidence of specific health effects showing that 'breaking up' or having intermittent amounts of sedentary behaviors is better for health than uninterrupted sedentary behaviors.[19] Research in this area is important as some American adults spend as much as 96% of their free time in light-intensity physical activities and sedentary behaviors.[12] Additional research is needed to understand the optimal frequency, intensity, and duration of breaks between bouts of sedentary behaviors.[20] A third area of focus is the measurement of sedentary behaviors. Time spent in sedentary behaviors and the types of sedentary behaviors performed are measured with self-report questionnaires and daily records or logs (herein referred to as self-report methods) and/or accelerometer-based wearable monitors (herein referred to as wearable monitors). Another type of sedentary behavior assessment is direct observation of human movement (herein referred to as direct observation). Direct observation uses a systematic method to record sedentary and physical activity behaviors as an individual completes their daily activities.

Accurate measures of sedentary behaviors is important for surveillance systems to assess the prevalence of sedentary lifestyles, to determine the dose-response relationships between sedentary behaviors and health outcomes, and to plan and evaluate health promotion interventions.[21] The accurate measurement of sedentary behaviors encompasses several challenges. Self-report methods are cost-effective, readily accessible to the majority of the population, have a relatively low participant burden, and can be used to identify types of behaviors in the context in which the behaviors occur; however, self-report methods consistently demonstrate low-to-moderate criterion-related validity.[22,23] A major impediment to establishing the validity of self-report methods is the lack of an accepted criterion measure.[24] Self-report methods commonly are validated against accelerometer-based devices; however, accelerometers have their limitations in assessing sedentary behaviors. For example, low compliance for hip-mounted wearable monitors and reliance on activity counts without including posture allocations for each activity reduces the accuracy of sedentary time estimations. Thus, research related to the wearable monitors-based measurement of sedentary behaviors is needed to improve the accuracy of identifying sedentary behaviors. Few studies have used direct observation as a criterion measure of physical activities and sedentary behaviors.[25–27] Direct observation has distinct advantages over wearable monitors in that it allows identification of several sedentary behaviors characteristics. For example, direct observation allows recording of the type and context of sedentary behaviors according to when, where, and with whom the behaviors under observation occur. Because of the large amount of information collected, direct observation is labor intensive and it is difficult to estimate energy expenditure from the behaviors observed.[28]

Statement of the Problem

A challenge with wearable monitors-based measurement of sedentary behaviors is in the ability to distinguish sedentary behaviors from light-intensity physical activities that people perform during the day.[18,29] Two of the commonly used wearable monitors used to measure sedentary behaviors are the ActiGraph (ActiGraph LLC, Pensacola, FL, USA) and the activPAL™ physical activity logger (PAL Technologies Ltd, Glasgow, UK). Another less popular wearable monitor is the SenseWear 2 (SWA, BodyMedia Inc., Pittsburgh, PA, USA). The ActiGraph measures ambulatory movement using acceleration counts while the activPAL™ measures differences in posture during physical activity and sedentary behaviors. The SenseWear provides measures of movement in MET values. Unfortunately, the three wearable monitors are unable to differentiate between several types of movement. The ActiGraph is unable differentiate sedentary behaviors from light-intensity activities that yield zero or very few counts per minute, such as standing and other stationary activities.[21] Similarly, the ActiGraph has been shown to misclassify standing as a sedentary behavior.[30] The activPAL™ also has limitations in being unable to detect differences in movement intensities. For example, Harrington et al.,[31] showed the MET values from the activPAL™ during walking speeds ranging from 2- to 4 mph were significantly different from the energy costs of walking measured by oxygen uptake (P <0.0001). Further, since the activPAL™ sedentary behavior estimates are posture-based and the monitor is worn in the front of the thigh, it is difficult to differentiate sitting from lying behaviors since the monitor is horizontal in both conditions.[32]

Another problem with wearable monitors-based assessment of sedentary behaviors is a lack of consensus about the most appropriate protocol to analyze data arising from controlled movement settings.[24] One of the most common approaches to analyzing data from accelerometer-based devices is the cut-points approach which determines the time spent in varying movement intensities.[24,33,34] This approach assumes a linear relationship between movement counts per minute used to develop the cut-points and resulting amount of time spent in different intensity levels. Because of variability in movement, movement intensity does not increase linearly in all persons. Thus, using a cut-points approach to analyze data may lead to inaccurate estimates of time spent in different movement intensities.[35–37] To complicate the matter, only a few cut-points have been developed and validated to classify sedentary behaviors. These include values of 50 counts per minute,[35] 100 counts per minute,[12] 150 counts per minute,[25] and 500 counts per minute.[38] Notably, 100 counts per minute often is used to reflect time spent in sedentary behaviors, despite the observation that it underestimates sitting time by 5%.[25]

To date, cut-points used to estimate time spent in sedentary behaviors has been applied to uniaxial accelerometers that measure movement in a vertical plane only. With the development of tri-axial accelerometers that measure movement in the vertical, anteroposterior, and mediolateral planes, analytic methods allow a computed axis resulting in a combination of these three axes. This composite measure is referred to as the vector magnitude. In theory, analyzing the vector magnitude may provide an improved estimate of time spent in sedentary behaviors as compared with the use of the vertical axis only. To date, vector magnitude cut-points have not been developed to identify sedentary behaviors using the ActiGraph accelerometer; instead, they have been developed to estimate sedentary behaviors for the wrist-worn GENEActiv (ActivInsights, Cambs, United Kingdom). The GENEActiv is a tri-axial accelerometer that provides activity counts for the 3 axes noted previously and a composite vector to estimate movement duration and intensity. The vector magnitude cut-points have been evaluated in laboratory settings, and to lesser extent in free-living conditions.[39]

A persistent concern about using accelerometer-based wearable monitors is that current monitors have limited functional abilities to measure sedentary behaviors in agreement with the current definition of sedentary behaviors.[21] Instead, a more accurate assessment of sedentary behaviors includes estimating energy expenditure using MET values and posture. Both methods require complex, analytical approaches as opposed to the simple cut-point methods in use today. Complex approaches to estimating sedentary behaviors, such as machine learning techniques, are being gradually implemented;[26] however, they are still under development and beyond many researchers' understanding. Thus, such complex analytical methods are not practical at this time to measure sedentary behaviors for use by most researchers and practitioners.[40] Alternatively, the use of tri-axial accelerometers allow for an inclinometer feature of monitors to estimate posture allocations, which in addition to current cut-point scoring methods, may improve the assessment of sedentary behaviors without the complexity of machine learning techniques.[41] However, this feature has not been widely tested.[41–44] One method developed recently is referred to as the sedentary sphere, which allows for posture classification by estimating arm elevation combined with activity counts obtained from wrist-worn wearable monitors.[41] The sedentary sphere has shown to be a valid method to determine sedentary time in laboratory- and free-living settings, and across brands (i.e., GENEActiv and ActiGraph model GT3X+) when the accelerometer is worn on the non-dominant wrist.[44] The validity of the sedentary sphere method has not been tested when the wearable monitors are worn on the dominant hand and with different configurations, defined as activity count thresholds and arm elevation angles.

The current dissertation includes three projects that examined measurement properties of wearable monitors used in the assessment of sedentary behaviors. Project one assessed the criterion validity of three commonly used wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate the intensity of sedentary behaviors and light-intensity physical activities in adults as compared to the criterion method of indirect calorimetry (VO_2). Project two tested the accuracy of six uniaxial cut-points and two vector magnitude cut-points for the GENEActiv and the ActiGraph GT3X+ to classify sedentary and stationary time in free-living conditions as compared to the criterion of direct observation. Project two also developed optimal vector magnitude cut-points for the ActiGraph and the GENEActiv to classify sedentary time and stationary time based upon data collected in free-living conditions. Project three tested the accuracy of estimates of sedentary time computed by the sedentary sphere method with the GENEActiv and the ActiGraph GT3X+ during free-living conditions. The monitors were worn on the dominant and non-dominant wrist. Project three also tested the accuracy of the sedentary sphere method with different arm elevation angles and activity count thresholds.

Purposes and Hypotheses

The three projects were designed to utilize different wearable monitors to measure time spent in sedentary behaviors. The research hypotheses for each project are listed below.

Project One. Wearable monitors criterion validity for energy expenditure estimates in sedentary and light activities.

Project one purpose. To examine the validity of three wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate intensity for sedentary-to-light activities in adults as compared with oxygen uptake measured in $ml \cdot kg^{-1} \cdot min^{-1}$.

Project one hypothesis. There will be no difference between energy expenditure estimates for sedentary-to-light activities made by the tested wearable monitors

(ActiGraph GT3X+, activPAL™, and SenseWear 2) and energy expenditure estimates from the criterion measure of indirect calorimetry.

Project Two. Wearable monitors accuracy to classify sedentary and stationary time under free-living conditions.

Project two purpose 1. To test the accuracy of selected uniaxial and vector magnitude cut-points to classify sedentary and stationary time in free-living conditions.

Project two purpose 2. To develop optimal vector magnitude cut-points from the ActiGraph GT3X+ and GENEActiv to classify sedentary and stationary time using data obtained under free-living conditions.

Project two hypothesis 1. There will be no difference between sedentary and stationary classifications made by different cut-points for the ActiGraph GT3X+ (wrist and waist) and GENEActiv (wrist) and sedentary behaviors classifications from the criterion of direct observation.

Project two hypothesis 2. There will be no difference between free-living sedentary and stationary classifications made by the developed vector magnitude cut-points and free-living sedentary and stationary classifications from the criterion of direct observation.

Project Three. Accuracy of posture-based sedentary behavior estimates made by the sedentary sphere method in free-living settings.

Project three purpose 1. To test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and ActiGraph GT3X+

wearable monitors during free-living conditions in both dominant and non-dominant wrists.

Project three purpose 2. To test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and ActiGraph GT3X+ wearable monitors during free-living conditions with different angle and activity threshold configurations.

Project three hypothesis 1. There will be no difference between free-living sedentary behavior classifications made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors in both dominant and non-dominant wrists and free-living sedentary behaviors classifications from the criterion measure of direct observation.

Project three hypothesis 2. There will be no difference between free-living sedentary behavior classifications made by the different configurations of the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ and free-living sedentary behavior classifications from the criterion measure of direct observation.

Scope

This dissertation consists of three distinct research projects with the overall theme of the wearable monitors-based measurement of sedentary behaviors. The studies were designed to: A) examine the validity of wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate intensity for sedentary-to-light activities. B) test the accuracy of wearable monitors (GENEActiv and the ActiGraph GT3X+) to classify sedentary and stationary time in free-living using different cut-points and body locations (wrist and waist); and to develop optimal vector magnitude cut-points to classify sedentary and stationary time based upon data collected under free-living conditions. C) test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors during free-living conditions in both dominant and non-dominant wrists and with different angle configurations.

Assumptions

1. The oxygen cost of activities performed in the exercise physiology laboratory was accurately assessed using portable indirect calorimetry.
2. The accelerometer placements were made by strictly following research protocols, ensuring identical wearing setup among all enrolled participants.
3. For healthy adults, two observation days (weekday and weekend) with at least 6 hours per day, was sufficient to capture regular physical activity and sedentary behaviors in free-living conditions.
4. In the absence of motion, the gravitational component of the acceleration signal allows to determine the orientation of the monitor and therefore wrist position.

Limitations

1. Project one data were obtained in a laboratory setting with staged activities, limiting generalization of the results to free-living settings.
2. Participants in the three projects comprised a convenience sample of healthy adults, limiting generalization of the results to other populations.
3. Problems with initialization and downloading wearable monitors caused missing data which may introduce measurement error.

4. The generalization of the results of this dissertation is limited to populations composed of individuals who are similar to the participants studied.
5. By having two researchers conducting simultaneous observations, there is a potential bias in direct observation as one researcher observations may influence the other.

Significance of the Research

Despite the knowledge that sedentary behaviors are related to negative health outcomes independent of physical activity levels, some American adults spend at least 96% of their time in light-intensity physical activities and in sedentary behaviors, of which 55% of that time is spent sitting.[12] Having accurate measurement of sedentary behaviors is important to understand additional relationships between sedentary behaviors for surveillance, identifying health outcomes, and to evaluate changes in interventions and health promotion programs.[17]

This dissertation had a goal to increase understanding of the measurement of sedentary behaviors by: 1) examining the validity of commonly used wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2); examining the validity of two wearable monitors (GENEActiv and the ActiGraph GT3X+) to classify sedentary and stationary time in free-living settings using different cut-points and body locations (wrist and waist) (2a) and developing vector magnitude cut-points to classify sedentary and stationary time based upon data collected under free-living conditions (2b); and 3) testing the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors during free-living conditions in both dominant and non-dominant wrists (3a), and testing the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors during free-living conditions with different angle configurations (3b).

Findings in this dissertation have several implications for research in the measurement of sedentary behaviors. Project one results help to understand the degree to which light intensity physical activity is misclassified as sedentary behaviors and vice versa. Thus, future improvements in wearable monitors' accuracy to measure energy expenditure in the low end of the energy continuum could aim to overcome such limitations and successfully integrate sedentary behaviors and light-intensity physical activity to the entire activity intensity spectrum measurement. Project two results will add arguments to the ongoing debate on what is the most accurate uniaxial cut-point to classify sedentary time, and whether vector magnitude cut-points developed with free-living data will improve the assessment of sedentary behaviors. Project three will help to understand whether the combination of an inclinometer feature available in tri-axial accelerometers and cut-points will accurately measure sedentary behaviors in free-living settings. Project three results also may offer an alternative to complex analytical approaches such as machine learning to measure sedentary behaviors. Collectively, the three projects have the potential to help researchers and practitioners decide what type wearable monitor and data analysis best fits their needs in measuring sedentary behaviors.

Definition of Terms

- **Accelerometers**. Devices that measure body movements using changes in acceleration that are used to estimate the intensity of physical activity over time.[45] Accelerometers are also known as activity monitors or wearable monitors.

- **Activity counts.** Raw accelerations filtered, digitized, and integrated over a given sampling period.[46] A common way to express activity counts is integrating them into a 1-minute epoch.
- **Area under the receiver operating characteristic curve (AUC).** Is a plot of a test true-positive rate (y-axis) against the corresponding false-positive rate (x-axis) (i.e., sensitivity against 1-specificity). The AUC allows to combine sensitivity and specificity into a single measure of "diagnostic accuracy" which facilitates comparisons.[47]
- **Cut-points.** Levels of movement that are equivalent to different activity intensities.
- **Epoch.** User-specified time interval integrates a filtered digitized acceleration signal from an accelerometer.[48]
- **Glucose transporters (GLUT).** Different types of proteins that are critical to glucose uptake stimulated by three signals: basal metabolism (GLUT-1), insulin release (GLUT-4), and exercise (GLUT-4).[49]
- **Hazard Ratio.** The hazard ratio, sometimes called a relative hazard, is typically used to compare time to event data between two treatment groups.[50]
- **Inactive.** A person who is performing insufficient amounts of moderate-to-vigorous intensity physical activity; not meeting established physical activity guidelines.[10]
- **Lipoprotein lipase (LPL).** An enzyme that binds to circulating lipoproteins when present on the vascular endothelium and is essential for hydrolysis of the triglyceride contained in lipoproteins.[51]
- **Low-Frequency Extension.** A filter is designed to detect lower amplitude movements over standard filter in ActiGraph accelerometers.[52]

- **Metabolic Equivalent (MET).** The value of resting oxygen uptake relative to total body mass and is generally ascribed the value of 3.5 milliliters of oxygen per kilogram of body mass per minute.[53]
- **Odds Ratio (OR).** Is a measure of association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure.[54]
- **Physical Activity.** Any bodily movement produced by skeletal muscles that results in energy expenditure.[55]
- **Physical activity Absolute Intensity.** Refers to the energy or work required to perform an activity which does not take into account the physiologic capacity of the individual. For aerobic activities, absolute intensity may be expressed as the rate of energy expenditure in kilocalories per minute or multiples of resting energy expenditure expressed as METs and the speed of movement such as walking at 3 miles per hour or jogging at 6 miles per hour. Absolute intensity for physical activities is classified as light (1.6 to 2.9 METs), moderate (3.0 to 5.9 METs) and vigorous (6.0 > METs).[3]
- **Relative Risk (RR).** Is a measure of the risk of an outcome in one group compared to the risk of the outcome in another group.[56]
- **Sedentary behavior.** Any waking behavior characterized by an absolute energy expenditure of ≤1.5 METs while in a sitting or reclining posture.[10]
- **Vector magnitude.** A composite of accelerations from three orthogonal axes (vertical, anteroposterior, and mediolateral) of tri-axial accelerometers. For ActiGraph the vector magnitude is calculated as follows, Vector magnitude = √

($\text{Vertical}^2 + \text{anteroposterior}^2 + \text{mediolateral}^2$).[34] For the GENEActiv the vector magnitude is calculated as follows, Vector magnitude = $\Sigma\ [(x^2 + y^2 + z^2)^{1/2} - 1g]$.[57]

Chapter 2

REVIEW OF THE LITERATURE

This chapter provides an overview of the evolution of the sedentary behavior concept, the health outcomes related to sedentary behaviors, the physiological mechanisms how sedentary behaviors impact health, the prevalence of sedentary behaviors, and the measurement of sedentary behaviors.

Evolution of the Sedentary Behavior Concept

The term sedentary behavior is a relatively new term that has gained popularity in the new millennium. One of the initial definitions of sedentary behaviors was presented by Hamilton et al.[58] who defined sedentary behavior as primarily sitting and doing other activities that involve low levels of metabolic energy expenditure. According to Hamilton, some activities that could be deemed as sedentary behaviors are sitting or watching television. In 2008, Pate et al.[17] operationalized the concept of sedentary behavior by adding the specific range of energy expenditure values and made the differentiation between sedentary behaviors (1.0-1.5 METs) and light physical activities (1.6-2.9 METs). In 2010, Owen et al.,[16] complemented the existing definitions by making explicit that sedentary behaviors could happen in different contexts such as commuting, work sites, domestic environment and during leisure time.

A common practice in the physical activity literature has been to use the term sedentary to describe individuals who are not meeting physical activity guidelines, but not high amounts of sedentary time. Accordingly, too much sitting is different than too little exercising. In an attempt to disambiguate the term and to avoid confusion, the

Sedentary Behavior Research Network (SBRN) proposed a new definition of sedentary behavior as, "any waking behavior characterized by an energy expenditure ≤1.5 METs while in a sitting or reclining posture."[10] The SBRN also suggested that the term "inactive" should be used to describe those individuals who are not meeting physical activity guidelines as they have low levels of moderate-to-vigorous physical activity. The new definition of sedentary behaviors developed by the SBRN seems to have high acceptance within the academic community as evidenced by its broad use. As standing is usually difficult to classify, as either sedentary behavior or light intensity physical activity, the definition of sedentary behavior may change soon and may include both sedentary behaviors and standing still as stationary type of behaviors. It is important to notice that this classification is not been still recognized by the scientific community.

Health Outcomes Related to Sedentary Behaviors

The goal of this section of the literature review is to examine the evidence for the association between sedentary behavior exposures, breaks in sedentary time, and health outcomes and mortality attributed to sedentary behaviors.

Exposure to sedentary behaviors

Research on the deleterious effects of excessive amounts of sedentary behaviors can be traced to the middle of the 20th century. Morris et al.'s [59] seminal research conducted in the 1950's with the London bus drivers and ticket takers is one of the earliest published studies in which sedentary behaviors showed a negative health impact. The purpose of the study was to examine differences in the incidence of ischemic heart disease events between sedentary bus drivers and active ticket takers employed by the London Transit Authority. When comparing health outcomes, the drivers had a higher incidence of ischemic heart disease when compared with conductors (2.7 vs. 1.9 per 1,000 men-years of study). Although Morris et al. gave no explicit reference to sedentary behaviors in the study since the purpose of the study was to show the benefits of occupational physical activity, the study showed that occupational physical inactivity was a risk factor for developing ischemic heart disease.

Following Morris' study, most of the research in the 1960's through the 1990's focused on the associations between physical activity and varied health outcomes but not on sedentary behaviors. Two seminal studies were published by Paffenbarger in the 1970's (San Francisco longshoremen and the Harvard alumni studies) that highlighted the importance of active versus sedentary population groups. In the San Francisco Longshoremen's study, Paffenbarger et al.[60] compared the energy cost of occupational tasks of longshoremen with office clerks. In comparing mortality rates of longshoremen, who had a more active job of handling cargo, experienced a coronary death rate one-quarter lower than the less active clerks. In one of the first prospective cohort studies published about the health effects of leisure-time physical activity, Paffenbarger et al.[2] observed the exposure of low leisure-time physical activity energy expenditure on the risk of a first heart attack in men who attended Harvard University in the early-to-mid 20th century. The results showed a lower risk of a first heart attack in men who expended from 500- to 2,000 kilocalories per week (kcal/week) in leisure-time physical activities as compared with men who reported no leisure-time physical activity. The energy expenditure associated with the lowest risk was 2,000 kcal/week. In 1989, Leon et al.[4] reported the association of leisure-time physical activity metabolic activity units and the risks for all-cause mortality and disease-specific mortality rates in men with one or more coronary heart disease (CHD) risk factors enrolled in the Multiple Risk Factor Intervention Study. All-cause mortality and fatal and non-fatal CHD events were 20% lower for men with middle-to-high tertiles levels of leisure time physical activity (47 minutes/day and 124 minutes/day, respectively) as compared with men in the lowest tertile of leisure-time physical activity (15 minutes/day) ($P < 0.05$). An additional seminal study published in 1991 by Helmrich et al.[1] analyzed data from the University of Pennsylvania Cohort Study to show the effects of different doses of moderate-to-vigorous intensity physical activity on mortality attributed to type 2 diabetes. Results showed a 6% reduction in the risk of type 2 diabetes-related for every 500 kcal/day increment in physical activity energy expenditure. An overview of these and other studies supporting the association of physical activity (as compared with sedentary behaviors) and reduced morbidity and mortality is provided by the expert panel report of the 2008 U.S. Physical Activity Guidelines.[3]

Evidence supporting adverse associations between sedentary behaviors and health outcomes has increased in the past decades. The first studies, published in the 1990's and early 2000's, used cross-sectional and epidemiological prospective designs to show inverse associations between self-reported television viewing as a sedentary behavior with disease-specific morbidity and the presence various chronic disease risk factors. In 2004, Dunstan et at.,[6] studied the association between television viewing and the risk of having an abnormal glucose metabolism in 8,299 healthy Australian adults (55.4% women), aged 25 years or older. Television viewing was measured by self-reported total time spent watching TV or videos in the previous week. Abnormal glucose metabolism was based on an oral glucose tolerance test. The data were analyzed using odds ratios to determine the association between the exposure and the outcome. Results showed that television viewing for >14 hours per week had a significantly increased risk of having type 2 diabetes in men (OR = 2.40, 95% CI = 1.41 to 4.12) and women (OR = 2.20, 95% CI = 1.32 to 3.61). Alternatively, the risk of having an abnormal glucose metabolism among television watchers was significant higher for women (OR = 1.49, 95% CI = 1.12 to 1.99), but not for men (OR = 1.16, 95% CI = 0.79 to 1.70). The results were independent of several confounders such as age, education, family history of diabetes, cigarette smoking, diet, and physical activity. The authors concluded that physical activity has a protective effect and TV time has a deleterious effect on the risk of having abnormal glucose metabolism in adults.

Prospective studies have added evidence to the deleterious effects of sedentary behaviors on health. In 2008, Howard et al.,[8] studied the association between sedentary time and incidence of colon cancer in 488,720 participants from the NIH-AARP Diet and Health Study (40.27% women), aged 50–71 years at baseline. Sedentary behaviors were assessed by asking participants about the average number of hours per day they currently spent watching television or videos. Incidence of colon cancer was established by histologically confirmed incident colon and rectal cancer cases. The data were analyzed by using Cox proportional hazards regression to estimate relative risks (RR) and 95% confidence intervals (CI) of colon or rectal cancer with age as the underlying time metric. During an observation period of eight years, results showed that watching television more than 9 hours per day was significantly associated with an increased incidence of colon cancer in men (RR=1.61, 95% CI=1.14 to 2.27) but not in women (RR=1.45, 95% CI=0.99 to 2.12). These associations were independent of total physical activity, age, smoking and alcohol consumption, education, race, family history of colon cancer, diet, and menopausal hormone therapy. The authors concluded that time spent sedentary is associated with increased colon cancer risk.

In 2010, Wijndaele et al.,[9] conducted a 5-year prospective cohort study to identify the association between hours spent in television watching and cardiometabolic risk factors defines as waist circumference, triglycerides, HDL-cholesterol, systolic and diastolic blood pressure, and fasting plasma glucose in 3,846 healthy Australian adults. The mean age at baseline was 47.64 years (95% CI = 47.17 to 48.11) and 48.61 years (95% CI = 48.06 to 49.16) for women and men, respectively. Television viewing was measured by self-reported total time spent watching TV or videos in the previous week. Cardiometabolic risk factors were assessed in a laboratory setting with trained personnel. The data were analyzed with multiple linear regression modeling in which the change in the cardiometabolic risk variables was regressed against changes in TV viewing time. The results showed that for every 10 hours•week^{-1} increase in television viewing time there were significantly associated increases in waist circumference (men: 0.43 cm, 95% CI = 0.08 to 0.78 cm, P = 0.02; women: 0.68 cm, 95% CI = 0.30 to 1.05, P = 0.001), and diastolic blood pressure (women: 0.47 mm Hg, 95% CI = 0.02 to 0.92 mm Hg, P = 0.04). The associations were independent of baseline television viewing time and baseline physical activity and change in physical activity. The authors concluded that an increase in television viewing time is associated with adverse cardiometabolic biomarker changes.

Associations between sedentary behaviors and health outcomes also have been found in population-based studies that included varying types of sedentary behaviors than watching television. In 2003, Hu et al.,[61] analyzed the relationships between television watching and risks of obesity and type 2 diabetes in women (n = 50,277 for risks of obesity; n = 68,497 for risks of type 2 diabetes), aged 30 to 55 years, from the Nurses' Health Study. Sedentary time was assessed by asking participants to list their sitting time in watching television, sitting at work, sitting while driving, and other sitting such as meals and reading). Body weight was self-reported. A case of diabetes was considered when the participant reported one or more of the following criteria: 1) classic symptoms of type 2 diabetes plus elevated fasting plasma glucose concentrations, 2) two or more measures of elevated fasting plasma glucose concentrations in the absence of symptoms, and 3) current treatment with oral hypoglycemic agents or insulin. The data were analyzed using Cox proportional hazard models. The results showed that time spent watching television and sitting at work were positively associated with risks of obesity and type 2 diabetes. Each two hours per day increment of time spent watching television was associated with a 23% (95% CI = 17% to 30%) increase in obesity risk and a 14% (95% CI = 5% to 23%) increase in diabetes risk. Also, each two hours per day increment of time spent sitting at work was associated with a 5% (95% CI = 0% to 10%) increase in obesity risk and a 7% (95% CI = 0%-16%) increase in type 2 diabetes risk. The results were independent of age, smoking history, alcohol consumption, physical activity, family history of diabetes, and diet. The authors concluded that sedentary behaviors, especially television viewing, were associated with significantly elevated risk of obesity and type 2 diabetes.

In 2005, Brown et al.,[62] conducted a 5-year prospective cohort study to determine the relationship of hours spent sitting on weight gain in 8,071 women, aged 45 to 55 years, enrolled in the Australian Longitudinal Study on Women's Health. Self-reported sitting time and body weight data were obtained using a questionnaire developed for the study. The data were analyzed using multiple regression analyses. Results showed an increased mean 5-year weight change among women who spent more time sitting than in active behaviors (P for trend <0.0001). The results were independent of physical activity, menopause transition and hysterectomy, smoking transition, and body weight. The authors concluded that sitting time was independently associated with weight gain over a 5-year period in the cohort study of middle-age Australian women.

In 2009, Gierach et al.,[7] studied the association between sedentary time and incidence of endometrial cancer in 109,621 women from the NIH-AARP Diet and Health Study, aged 50–71 years at baseline. Sedentary behaviors were assessed by collapsing the answers to two different questions (time spent watching TV or videos during a typical 24-hour period over the past 12 months and the time spent sitting during a typical 24-hour period over the past 12 months) into a sedentary behavior category. Incidence of endometrial cancer was established by histologically confirmed incidents of the disease. The data were analyzed by using Cox proportional hazards regression with change in age as the time scale. Results showed the risk for endometrial cancer significantly increased with the number of hours of daily sitting (RR = 1.56, 95% CI = 1.22 to 1.99 for 7 or more hours per day). The results were independent of age, race, smoking status, number of births, ever use of oral contraceptives, and age at menopause. The authors concluded that the risk for endometrial cancer increased with number of hours of daily sitting.

Sedentary behaviors have also been associated with mortality. In 2009, Katzmarzyk et al.,[63] studied the relationship between sitting time and mortality among 17,013 Canadians (7,278 men and 9,735 women), aged 18–90 years. The amount of sitting time during work, school, and housework was obtained from a lifestyle questionnaire previously developed and validated for the study. Mortality was determined by linking the study database with the Canadian Mortality Database. The data were analyzed by Cox proportional hazards models. Results showed that time spent sitting was associated with increased mortality rates. For all-cause mortality, sitting three-fourths of the time had a HR = 1.36 (95% CI = 1.14 to 1.63) and sitting almost all of the time had a HR = 1.54 (95% CI = 1.25 to 1.91). For cardiovascular disease-related mortality, sitting three-fourths of the time had a HR = 1.47 (95% CI = 1.09 to 1.96) and sitting almost all of the time had a HR = 1.54 (95% CI = 1.09 to 2.17). For other causes of mortality, sitting three-fourths of the time had a HR = 1.65 (95% CI = 1.18 to 2.31) and sitting almost all of the time had a HR = 2.15 (95% CI = 1.47 to 3.14). The results were independent of age, smoking status, alcohol consumption, leisure-time physical activity, and scores on the Physical Activity Readiness Questionnaire (pass/fail/missing). The authors concluded that a dose–response association exists between sitting time and all-cause mortality and cardiovascular disease specific mortality.

In 2010, Patel et al.,[64] examined relation between leisure time spent sitting and physical activity on mortality in 123,216 adults (53,440 men and 69,776 women) from the American Cancer Society's Cancer Prevention Study II - Nutrition Cohort. Participants were aged 63.6 ± 6.0 years in men and 61.9 ± 6.5 years in women when enrolled in the study. Leisure time spent sitting was assessed by using the question, "During the past year, on an average day (not counting time spent at your job), how many hours per day did you spend sitting (watching television, reading, etc.)?" Deaths were identified by linking the study database to the National Death Index. The data were analyzed using Cox proportional hazards models with follow-up time in days as the time axis. Results showed that leisure-time sitting was positively associated with all-cause mortality rates in both women (3-5 hours per day RR = 1.13, 95% CI = 1.07 to 1.18; >6 hours per day RR = 1.34, 95% CI = 1.25 to 1.44) and men (3-5 hours per day RR = 1.07, 95% CI = 1.03 to 1.12; >6 hours per day RR = 1.17, 95% CI = 1.11 to 1.24). The results were independent of age, race, marital status, education, smoking status, body mass index, alcohol use, total caloric intake, comorbidities, and total physical activity. The authors concluded that the time spent sitting was independently associated with total mortality, regardless of physical activity level.

In 2012, Matthews et al.,[65] studied the association between overall sitting time and television viewing with mortality in 240,819 adults from the NIH-AARP Diet and Health Study, aged 50–71 years who did not report any cancer, cardiovascular disease, or respiratory disease at baseline. Television viewing was assessed by the question, "During a typical 24-hour period over the past 12 months, how much time did you spend watching television or videos?" Overall sitting was assessed by the question, "During a typical 24-hour period over the past 12 months, how much time did you spend sitting? Cause-specific mortality was assessed through linkage of the study data with the Social Security Administration Death Master File and the National Death Index. The data were analyzed using Cox proportional hazards models. Results showed that television viewing (≥7 h/d compared with <1 h/d) was positively associated with mortality; all-cause mortality (HR = 1.61, 95% CI = 1.47 to 1.76), cardiovascular mortality (HR = 1.85, 95% CI = 1.56 to 2.20), and cancer mortality (HR = 1.22, 95% CI = 1.06 to 1.40). The results were independent of age, sex, education, smoking, diet, race, and moderate-to-vigorous physical activity. The authors concluded that time spent in sedentary behaviors was positively associated with mortality and participation in high levels of moderate-to-vigorous physical activity did not fully mitigate health risks associated with prolonged time watching television.

The strength of this evidence is confirmed by meta-analyses and systematic reviews that support the findings. In a meta-analysis with morbidity and mortality outcomes, Biswas et al.[66] found significant association between sedentary behaviors with all-cause mortality (HR = 1.24, 95% CI = 1.09 to 1.41), cardiovascular disease mortality (HR = 1.18, 95% CI = 1.11 to 1.26), cardiovascular disease incidence (HR = 1.14, 95% CI = 1.00 to 1.73), cancer mortality (HR = 1.17, 95% CI = 1.11 to 1.24), cancer incidence (HR = 1.13, 95% CI = 1.05 to 1.21), and type 2 diabetes incidence (HR = 1.91, 95% CI 1.64 to 2.22). In 2011 Proper et al.,[67] conducted a systematic review of the literature on longitudinal studies for the relationship between sedentary behaviors and health outcomes. In total, 19 studies met their inclusion criteria, of which 14 were of high methodologic quality. Results shows moderate evidence for a positive relationship between time spent sitting and the risk for type 2 diabetes and strong evidence for time spent sitting and all-cause and cardiovascular disease mortality.

In summary of the health outcomes of sedentary behaviors, two topics emerged. First, spending more time in sedentary behaviors is adversely associated with health outcomes and increases pre-mature mortality. Associations between sedentary behaviors and morbidity include having an abnormal glucose metabolism (for women but not for men),[6] increased risks of developing type 2 diabetes (for men and women),[6,67] having a high diastolic blood pressure (for women),[9] developing colon cancer (in men but not for women),[8] and in developing endometrial cancer in women.[7] Exposure to sedentary behaviors increases waist circumference for men and women[9] and sedentary behaviors contributes to weight gain for women.[61,62] Sedentary behaviors also are associated with all-cause,[64–66] cardiovascular disease-related, [65,66] and other diseases-specific mortality rates.[63,65] Second, the associations between sedentary behaviors and morbidity and pre-mature mortality are independent of physical activity and other physical, sociodemographic, and behavioral confounders.[6–9,61–65]

Interruptions in sedentary behaviors

Recent research findings have shown that interrupting long periods of sedentary time into shorter periods may have a beneficial impact on health outcomes. One of the initial studies to examine the effects of interrupting sedentary behaviors was reported by Healy et al. in 2008.[68] The investigators conducted a cross-sectional study to examine the association of breaks in sedentary time with different biological markers of metabolic risk in 168 adults (65 men and 103 women), aged 53.4 years ± 11.8. Sedentary time was measured with a hip-mounted ActiGraph 7164 accelerometer during waking hours for seven consecutive days. A break was classified as an interruption in sedentary time (minimum 1 minute) in which the accelerometer counts were higher than 100 counts per minute. Metabolic risk markers included anthropometric measurements, an oral glucose tolerance test and blood lipids. Blood samples were assayed according to laboratory protocols. Data were analyzed using linear regression models. Results showed that breaks in sedentary time were beneficially associated with lower values for waist circumference (β = -0.16, 95% CI = -0.31 to -0.02, P = 0.026), BMI (β = -0.19, 95% CI = -0.35 to -0.02, P = 0.026), triglycerides (β = -0.18, 95% CI = -0.34 to -0.02, P = 0.029), and 2-h plasma glucose (β = -0.18, 95% CI = -0.34 to -0.02, P = 0.025). The results were independent of age, sex, employment, alcohol intake, income, education, smoking, family history of diabetes, diet quality, moderate- to vigorous-intensity time, mean intensity of breaks, and total sedentary time. The authors concluded that more interruptions in sedentary time were associated with lower metabolic risk values

In a cross-sectional study published in 2011, Healy et al.[69] reported the associations between objectively assessed sedentary time and breaks in sedentary time with cardio-metabolic and inflammatory risk biomarkers in 4,757 adults from the 2003/04 and 2005/06 US National Health and Nutrition Examination Survey (NHANES). Sedentary time was assessed by an ActiGraph 7164 accelerometer using a threshold of <100 counts per minute to depict sedentary time. Breaks in sedentary time were classified as counts per minutes in excess of 100 counts per minute within the sedentary periods. The accelerometer was worn on the right hip during waking hours (except for water-based activities) for 7 days. Cardio-metabolic and inflammatory risk biomarkers measured in all participants included waist circumference, resting systolic blood pressure, non-fasting serum measures of HDL, non-fasting C-reactive protein, triglycerides, plasma glucose, and insulin Additionally, half of the participants had measured fasting triglycerides, plasma glucose, and insulin. Data were analyzed with linear regression analysis. Results showed that breaks in sedentary time were beneficially associated with lower waist circumferences (P for trend <0.0001) and lower C-reactive protein values (P for trend = 0.001). The results were independent of age, socioeconomic status, race, smoking/alcohol use, dietary variables, moderate-to-vigorous physical activity, sedentary time, and medical history. The authors concluded that breaking up sedentary time had significant beneficial associations with cardio-metabolic health.

In addition to cross-sectional studies showing the benefit of interrupting sedentary behaviors on health outcomes, experimental studies have tested the effects of modifying sitting durations on cardiometabolic risk factors, particularly glucose levels. In 2012, Dunstan et al.,[70] conducted a cross-over trial to examine the effects of uninterrupted sitting time compared with sitting time that was interrupted by brief bouts of light- or moderate-intensity walking on postprandial levels of glucose and insulin in 19 overweight/obese adults (11 men and 8 women) with a mean age 53.8 ± 4.9 years. Participants completed three experimental conditions lasting one day each, 1) uninterrupted, continuous sitting, 2) continuous sitting with 2-minute breaks of light-intensity walking every 20 min, and 3) continuous sitting with 2-minute breaks of moderate-intensity walking every 20 min. Participants were randomly assigned to group conditions with >6 days of separation between the group tasks. The dependent variable was measured by obtaining hourly venous samples and analyzed using standard laboratory assays. Data were analyzed using generalized estimating equations. The results showed that interrupting sitting time with short breaks of light- and moderate-intensity walking lowered glucose metabolism (24.1%, $P < 0.01$ and 29.6%, $P < 0.0001$ for light and moderate intensity respectively) as compared to uninterrupted sitting. The authors concluded that interrupting sitting time with short bouts of light- or moderate-intensity walking lowers postprandial glucose and insulin levels in overweight/obese adults.

In 2013, Peddie et al.,[71] conducted a randomized crossover study to compare the effects of prolonged sitting, continuous physical activity combined with prolonged sitting, and regular activity breaks on postprandial metabolism in 42 women and 28 men, aged 25.9 ± 5.3 years. Enrolled participants completed three experimental conditions lasting 9 hours each 1) prolonged sitting, 2) walking 30 minutes and then sitting, and 3) walking 1 minute and 40 seconds every 30 minutes. Participants a consumed a meal-replacement beverage at 1, 4, and 7 hours during each 9 hour experiment. The order participants received treatments were assigned randomly and each condition was separated by a wash-out period of 6 days. The dependent variables of plasma glucose, insulin, and triglycerides were obtained from venous blood and analyzed using standard laboratory assays. Samples were obtained every hour from baseline to the end of the experiment, with additional blood samples obtained at 30 and 45 minutes after the consumption of each meal-replacement. Areas under the curve (AUC) were calculated for the dependent variables of insulin, glucose, and triglycerides. Data were analyzed using mixed models regression analysis. Results showed that the regular activity break intervention lowered insulin AUC by 866.7 IU · L^{-1} · 9 h-1 (95% CI = 506.0 to 1227.5 IU · L^{-1} · 9 h-1, P <0.001) compared with the prolonged sitting intervention and by 542.0 IU · L^{-1} · 9 h-1 (95% CI = 179.9 to 904.2 IU · L^{-1} · 9 h-1, P <0.001) compared with the physical activity intervention. The effects of the prolonged sitting and physical activity interventions on insulin AUC did not differ significantly from each other (difference: 324.7 IU · L^{-1} · 9 h-1, 95% CI = -38.0 to 687.4 IU · L^{-1} · 9 h^{-1}, P = 0.079). Alternatively, the regular activity break intervention lowered plasma glucose AUC by 18.9 mmol · L^{-1} · 9 h^{-1} (95% CI = 10.0 to 28.0 mmol · L^{-1} · 9 h-1, P <0.001) compared with the prolonged sitting intervention and by 17.4 mmol · L^{-1} · 9 h-1 (95% CI = 8.4 to 26.3 mmol · L^{-1} · 9 h^{-1}, P <0.001) compared with the physical activity intervention. The effects of the prolonged sitting and physical activity interventions on plasma glucose AUC did not differ significantly (difference: 1.6 mmol · L^{-1} · 9 h-1, 95% CI = 27.4 to 10.6 mmol · L^{-1} · 9 h^{-1}, P = 0.730). The effects of the physical activity (P = 0.098) and regular activity break (P = 0.284) interventions on triglyceride AUC were not significantly different from the effects of the prolonged sitting intervention. The authors concluded that regular activity breaks were more effective than continuous physical activity at decreasing postprandial glycemia and insulinemia in healthy, normal-weight adults.

In 2015, Bailey and Locke,[72] reported a crossover trial study that tested the effects of breaking up prolonged sitting time with standing or light-intensity walking on different cardiometabolic risk markers (plasma glucose, total cholesterol, HDL, triglycerides, and systolic/diastolic blood pressure) in 10 non-obese adults(7 men and 3 women) with a mean age of 24.0 ± 3.0 years. Participants completed three experimental conditions lasting 5 hours each, 1) uninterrupted sitting, 2) seated with 2-min bouts of standing every 20 min, and 3) seated with 2-min bouts of light-intensity walking every 20 minutes. Participants were randomly assigned to group conditions with a minimum wash-out period of 6 days between each condition. Before the beginning of each condition, two standardized test drinks were consumed and hourly blood samples and blood pressure readings were taken. Total cholesterol, HDL, and triglycerides were assessed at baseline and at 5 hours. The dependent variables of plasma glucose, total cholesterol, HDL, and triglycerides were obtained every hour from venous blood samples and analyzed using standard laboratory assays. Hourly blood pressure readings were taken by trained personnel. The data were analyzed by first calculating total area under the curve (AUC) for plasma glucose and blood pressure and, then AUC data were analyzed by using ANOVAs to explore between-trial differences. Effect sizes with eta squared were measured as an indicator for the strength of association (etas of .02 = small effect, .13 = medium effect, and .26 = large effect) between the independent and dependent variable. . Data from pre- and post-trial lipid parameters were analyzed by using repeated measures ANOVA to assess differences across conditions. Results showed a significant effect of condition with a large effect size (partial eta squared= 0.39) for glucose AUC ($F = 8.59$, $p = 0.001$). Glucose was lower after the activity-break condition (mean AUC = 18.5, 95% CI = 17.0 to 20.0 mmol L/5-h) as compared to the uninterrupted sitting condition (mean AUC = 22.0, 95% CI = 20.5 to 23.5 mmol L/5-h) and the standing-break conditions (mean AUC = 22.2, 95% CI = 20.7 to 23.7 mmol L/5-h). There was no significant effect of the condition for systolic blood pressure AUC and a small effect size (partial eta squared = 0.03) ($F = 0.45$, $p = 0.65$,). There was no significant condition effect but a small-to-medium effect size (partial eta squared = 0.08) ($F = 1.10$, $p = 0.35$,) for diastolic blood pressure AUC. There was no significant main effect for the condition on changes in total cholesterol ($F = 0.01$, partial eta squared = 0.00), HDL ($F = 0.09$, partial eta squared = 0.01), or triglycerides ($F = 1.45$, partial eta squared = 0.10) from baseline to 5-h. The investigators concluded that interrupting sitting time with frequent brief bouts of light-intensity activity, but not standing, imparts beneficial postprandial responses that may improve cardiometabolic health.

On the other hand, there is evidence showing that the beneficial effect of breaking sedentary time on glucose metabolism is also observed for standing breaks but not only light intensity physical activity as proposed by Bailey and Locke. For example, In 2016, Crespo et al.,[73] reported a randomized crossover full-factorial study that tested the effects of incremental intervals of standing, walking, and cycling to a sit-only condition on 24-h and postprandial glucose responses in nine (2 men, 7 women) overweight/obese (body mass index = 29 ± 3 $kg \cdot m^2$) adults with a mean age of 30 ± 15 years. Participants completed four experimental conditions 1) sitting, 2) standing, 3) cycling, and 4) walking during an 8-hours simulated workday. Standing, cycling, and walking intervals increased from 10 to 30 $min \cdot h^{-1}$ (2.5 h total) during an 8-h workday. Four meals were provided per condition. Participants were randomly assigned to group conditions with a minimum wash-out period of 7 days between each condition. The dependent variables were obtained through continuous interstitial glucose monitoring was performed for 24 hours for three consecutive days; different glucose metabolism metrics were calculated from the continuous glucose monitoring, including mean interstitial glucose and total area under the curve. The data were analyzed with linear mixed models to test for condition differences. Results showed that compared with sitting (5.7 ± 1.0 $mmol \cdot L^{-1}$), mean 24-h glucose during standing (5.4 ± 0.9 $mmol \cdot L^{-1}$), walking (5.3 ± 0.9 $mmol \cdot L^{-1}$), and cycling (5.1 ± 1.0 $mmol \cdot L^{-1}$) were lower (all $P < 0.001$). Similar results were observed during the 8-hours simulated workday and after-work evening hours. Compared with sitting, cumulative 6-h postprandial mean glucose was 5 to 12% lower during standing, walking, and cycling ($P < 0.001$). Also 6-h postprandial glucose integrated area under the curve was 24% lower during walking ($P < 0.05$) and 44% lower during cycling ($P < 0.001$). The authors concluded that replacing sitting with regular intervals of standing or light-intensity activity during an 8-h workday reduces 24-h and postprandial glucose and that these effects persist during after work evening hours, with cycling having the largest and most sustained effect.

Meta-analysis research designs have been used to examine the consistency of studies examining the relationship between breaks in sedentary behaviors and health outcomes. In 2015, Chastin et al.,[74] conducted a meta-analysis and systematic review to study the relationship between breaks in sedentary behavior with adiposity (BMI and waist circumference), cardiometabolic (glucose, insulin, triglycerides, and cholesterol), and inflammation markers (C-reactive protein). Studies were included that met the following criteria, 1) reported a measure of breaks in sedentary behaviors (observational studies) or used a design that included interruptions of sedentary behaviors (experimental studies), 2) reported at least one marker of cardiometabolic health as an outcome, 3) written in English, 4) included human subjects, and 5) were primary research articles. Thirteen articles were included in the analyses. Observational studies (n=7) were used for the systematic review and were analyzed by computing a Bayesian posterior probability of an association between breaks in sedentary behaviors and cardiometabolic markers. Experimental studies (n=6) were used for the meta-analysis and were analyzed using the inverse variance method modified for crossover trials. The results for observational studies did not find an association between breaks in sedentary behaviors and markers of glucose metabolism, cardiovascular health and inflammation; except for one study by Healy et al.,[69] which found a significant association with C-reactive protein. On the other hand, observational studies showed that breaks in sedentary behaviors were associated with positive outcomes in adiposity markers (BMI and waist circumference). The results for experimental studies in the meta-analysis showed that standing breaks do not produce significant effect in blood glucose (-2.26%, 95% CI = -12.63 to 8.12) compared to uninterrupted sitting. However, light-intensity physical activity breaks and moderate-to-vigorous physical activity breaks showed significant reductions in blood glucose postprandial response (-17.42%, 95% CI = -24.25 to -10.60 and -1.40%, 95% CI= -1.60 to -1.20 respectively). Moderate-to-vigorous physical activity breaks in sedentary time seemed to be more effective in reducing blood glucose than a single prolonged bout of moderate-to-vigorous physical activity. Regarding insulin levels, light-intensity physical activity breaks, and moderate-to-vigorous physical activity breaks showed significant reductions in insulin levels (-14.92%, 95% CI = -20.44 to -9.40 and -23.84%, 95% CI = -43.46 to -4.22 respectively). Standing breaks also were shown to have a significant effect on metabolic risk; however, data from only one study was available. Moderate-to-vigorous physical activity breaks also seemed to be more effective in reducing blood insulin level than a single prolonged bout of MVPA (17.98%, 95% CI = 9.43 to 26.52). Breaks in sedentary behaviors failed to have a significant effect on triglyceride levels (P=0.32). For cholesterol values, results from the two studies investigating the effects of breaks in sedentary behavior on cholesterol levels could not be pooled, but both reported null findings. The authors concluded that interrupting bouts of sedentary behavior with light-intensity activity might help control adiposity and postprandial glycemia.

In summary, three topics emerged from the research cited in this section. First, for healthy adults, interrupting sedentary time with breaks of light-to-moderate intensity is beneficial for maintaining normal glucose metabolism and to reduce adiposity metrics, such as waist circumference. These findings have been observed in observational studies, experimental studies, and in a meta-analysis. Additional research is needed to identify if the associations are independent of total sedentary time. Second, findings showing associations between health outcomes such as blood pressure and inflammatory markers are inconsistent and suggest that more research is needed to elucidate whether breaks in sedentary time are beneficial for altering these health conditions. Third, it is necessary to elucidate whether stationary standing during a sitting break is equally effective than light-to-moderate intensity physical activity to gain beneficial effects of breaking up sedentary time on health outcomes.

Physiological Mechanisms of Sedentary Behaviors

This section provides a brief overview of the physiological mechanisms for which high amounts of sedentary behaviors have a negative impact on health. As the deleterious effects of sedentary behaviors on metabolic health appear to be mediated by changes in lipoprotein lipase (LPL) activity and changes in muscle glucose transporters (GLUT) protein content,[75] this section will review these two proteins in relation to sedentary behaviors.

The LPL is an enzyme that catalyzes the hydrolysis of circulating chylomicrons and very low density lipoproteins by releasing their fatty acids for entry into tissue cells.[76] Low levels of LPL are associated with increased circulating triglyceride levels (hypertriglyceridemia) and decreased HDL cholesterol.[58] Hypertriglyceridemia is associated with increased risks of cardiovascular death, myocardial infarction, cardiovascular events, and possibly acute pancreatitis.[77] Low HDL is associated with increased risks for myocardial infarction, stroke, sudden death, and severe premature atherosclerotic disease in the proximal left main coronary artery.[78] LPL activity is reduced in response to both acute and chronic sedentary behaviors with the this response localized to slow oxidative muscle fibers.[51]

GLUT is a family of proteins required for the transfer of glucose across the lipid bilayer cellular membrane. Cells import glucose by a process of facilitative diffusion mediated by the GLUT family of proteins. Fourteen GLUT types are expressed in humans which include transporters for other substrates, including glucose.[79] The GLUT-4 protein is found in adipose tissues, skeletal muscle and cardiac muscle. It serves as a major mediator of glucose removal from the circulation and a key regulator of whole-body glucose homeostasis.[80] Sedentary behaviors affect carbohydrate metabolism through reductions in GLUT content.[75] Thus, with a reduced GLUT content, the regulation of circulating levels of glucose are modified representing an elevated risk for developing glucose intolerance and insulin resistance.

Prevalence of Sedentary Behaviors

This section describes the prevalence of sedentary behaviors in two U.S. studies and two international studies. The studies use questionnaires, records, and accelerometers to obtain data about time spent in sedentary behaviors.

In 2011, Bauman et al.,[81] reported the prevalence of sitting during a single day in the 2002-2004 International Prevalence Study (IPS). The IPS was a cross-sectional study of physical activity and sitting time in 20 countries who volunteered to participate in the study. Sitting time was obtained with a single question from the International Physical Activity Questionnaire (IPAQ) that asked participants to recall their hours spent sitting on a usual weekday. A total of 49,493 adults, aged 18–65 years, reported spending an average of 5.8 ± 3.39 hours/day sitting. The countries with the highest median values for sitting time (>360 minutes/day) were Taiwan, Norway, Hong Kong, Saudi Arabia, and Japan. The countries with the lowest median values for sitting time (<180 minutes/day) were Portugal, Brazil, Colombia, and the U.S.

The American Time Use Survey (ATUS) is a population-based survey designed to provide nationally representative estimates of how, where, and with whom Americans spend their time. The ATUS uses a stratified random sample drawn from households that have completed the Current Population Survey with a sampling frame weighted to be representative of the U.S. civilian non-institutional population.[82] Participants in the ATUS complete a detailed diary of time spent for one day in varied activities. Results from the 2015 ATUS (n = 10,900) showed that for periods classified as leisure time, Americans spent an average of 3.27 hours/day in sedentary behaviors during weekdays and 4.14 hours/day during weekends. Among the types of reported sedentary behaviors, watching television occupied the most time (2.56 and 3.29 hours/day for weekdays and weekends, respectively). Playing games while using a computer was the second most common sedentary behavior (0.39 and 0.50 hours/day for weekdays and weekends respectively). The third most common sedentary behavior was reading (0.32 and 0.35 hours/day for weekdays and weekends respectively). Cumulatively, sedentary behaviors accounted for two-thirds of the leisure time reported by American survey respondents.[83]

In 2007, Hagströmer et al.,[84] reported results from a cohort study using accelerometers to determine the time spent in sedentary time in a nationally representative sample of Swedish adults (56% women), aged 45 ± 15 years. A total of 1,114 participants wore an ActiGraph accelerometer (model 7164) for seven consecutive days except during water activities. 672 participants were included in the analyses who met the analytic inclusion criteria of having at least four days of valid accelerometer data. Sedentary time was defined as less than 100 counts per minute. Results showed an average sedentary time of 7.8 ± 1.5 hours/day.

In 2008, Matthews et al.,[12] reported sedentary time assessed by accelerometers in a sub-sample of the 2003-2004 National Health and Nutrition Examination Survey (NHANES). NHANES is a population survey that includes a representative sample of the U.S. civilian and noninstitutionalized population. In the sub-sample, 7,176 participants wore an ActiGraph accelerometer (model 7164) for seven consecutive days. 6,329 participants were included in the analyses who met the analytic inclusion criteria of at least one day of valid data. Sedentary time was computed as less than 100 counts per minute. Results showed the average monitor-wearing time was 13.9 hours/day. Participants were sedentary for 55% of the monitored time, totaling a 7.7 ± 0.04 hours/day, the combination of light-intensity activity and sedentary time makes up 96% of the average American's waking hours.

In summary, as evidenced by both self-report and wearable monitors-based measures, adults spend the much of their waking time in sedentary behaviors averaging nearly 8.0 hours/day. High amounts of time spent in sedentary behaviors are observed for global reports of sitting time and domain-specific sedentary behaviors (i.e., leisure time). This is demonstrated by an average of 5.8 hours/day of total sitting time, or 3.27 hours/day engaged in sedentary behaviors during leisure time.

Sedentary Behavior Measurement Methods

Sedentary behaviors have been measured using a variety of self-report methods and wearable monitors-based methods. These two methods are presented below in more detail.

Self-report methods

Self-report methods include a variety of tools used to assess a limited number of discretionary behaviors thought to be proxy variables of sedentary behaviors. Self-report methods include single item questions (e.g., time spent watching television or sitting time),[6] multiple sedentary behaviors questionnaires (e.g., watching television, playing computer/video games, and sitting while listening to music),[85] or domain-specific questionnaires (e.g., sitting at work).[86] Healy et al.[33] provide a detailed description of the validity and reliability for self-report questionnaires used to assess sedentary behaviors. Other self-report methods such as behavioral logs and short term recalls are used to identify detailed information about sedentary behaviors, although these methods are used less frequently than questionnaires. The reader is directed to Atkin et al.[24] for a description of other tools used to assess sedentary behaviors such as proxy-report questionnaires and diaries.

In general, self-report methods have shown acceptable-to-good test-retest reliability on the order of ρ=0.28–0.93 (Spearman's rho).[33] Concurrent validity correlation coefficients are in the low-to-moderate range (r =-0.02 to 0.40) when compared with direct measures of sedentary behaviors, such as accelerometers.[33] The highest concurrent validity correlation coefficients are observed for sedentary behaviors that are performed on a regular basis and for prolonged periods of time such as sitting at work and using a computer at home (r=0.69 to 0.74).[87] The lowest coefficients are observed for less regularly performed behaviors such as reading ρ=0.20.[88] Also, concurrent validity coefficients tend to be lower for a composite questionnaire of different sedentary behaviors than when assessed by a single item (e.g., sitting time).[24,33]

Self-report measures of sedentary behaviors have strengths and limitations that should be noted. Strengths are that self-report methods can be implemented on a large scale, are relatively inexpensive, do not alter the behavior under investigation,[33] and are useful to identify the type of behavior/context,[21] Limitations to their use include participant burden, systematic reporting errors, administration costs,[33] and difficulty in measuring breaks in sedentary time.[25] Despite the limitations, self-report measures of sedentary behaviors continue to be a primary source of data in the study of sedentary behaviors for surveillance and health outcomes.

Wearable Monitors-Based Methods

Technological advancements have allowed the development and popularization of several wearable monitors that are easily available to the general public and for the physical activity and sedentary behaviors researchers. This section focuses on research-grade wearable monitors used in sedentary behavior measurement that covers the following topics: types of wearable monitors, technical features, functioning principles, approaches to analyze data, and the validity and reliability of the measurement methods.

Types of wearable monitors used to measure sedentary behaviors. Wearable monitors are used to measure sedentary behaviors that can be classified as energy expenditure estimation monitors or posture classification monitors.[21] Among the several existing wearable monitors, two stand out as being commonly used as energy expenditure estimation monitors: the ActiGraph and the GENEActiv. A commonly used posture classification monitor is the activPAL™ physical activity logger. A recent approach has emerged in research to use either the ActiGraph or the GENEActiv wearable monitors to classify sedentary behaviors due to their tri-axial accelerometer-based inclinometer features.[44]

The ActiGraph is a tri-axial accelerometer that provides activity counts for separate axes (vertical, anteroposterior, and mediolateral) and a composite vector magnitude of its three axes to estimate movement duration and intensity. The ActiGraph usually is worn on the waist or on the wrist secured to the body with an elastic band. The ActiGraph uses a Windows compatible software package (ActiLife®) to initializing the device, extract data from the recorded activity, and to analyze recorded data. ActiLife® software has several versions; 9.0.0.0 - April 2012 the newest. A useful feature of the ActiLife® software is that it allows data analysis using several options. For example, data can be summarized and analyzed using different user-defined time epochs ranging from one second and longer. It also is possible to choose different wear time determination algorithms or different cut-points to estimate movement duration and intensity. The ActiLife® software allows data to be exported as raw accelerations or as an epoch-compressed file into .csv format. The processed outputs from the ActiLife® software include a time stamp, time in selected intensity cut-point ranges, total counts per axis, vector magnitude counts, time in sedentary breaks, steps count, and steps per minute. The advantage of the ActiLife® software is that it allows for easy analysis of physical activity and sedentary behavior data without the need to have extensive data programming experience. An important limitation of the ActiLife® software is that the purchased license is required to process all of the records from the ActiGraph wearable monitors.

The GENEActiv is a tri-axial accelerometer that provides activity counts for separate axes (vertical, anteroposterior, and mediolateral) and a composite vector magnitude of its three axes to estimate movement duration and intensity. The GENEActiv is worn on the wrist secured to the body with a factory strap. The

GENEActiv uses a Windows compatible software package (GENEActiv PC Software) that allows one to initialize the device and to extract data from the recorded activity. GENEActiv PC Software has several versions; v3.1 - April 2016 is the newest. Data can be summarized using different user-defined time epochs ranging from one second and higher. The software also allows data to be exported as raw accelerations or as an epoch-compressed file into .csv format. Processed outputs from the GENEActiv PC software include a time stamp, averages of the individual axes, and vector magnitude.

The activPAL™ is a uniaxial accelerometer that identifies walking, sitting, standing, steps, and instantaneous cadence using proprietary algorithms [89]. The activPAL™ usually is worn on the anterior aspect of the thigh (midline) attached to the skin using double-sided medical tape. The activPAL™ uses a Windows compatible software package (activPAL™ Professional Research Edition). The activPAL™ software has several versions; v7.2.32 – October 2014 the newest. The software allows one to initialize the device and to extract data from the activity recorded. Once the data are downloaded, they are summarized over 15 seconds epochs which allows data to be exported to .csv format. Outputs from the activPAL™ include a time stamp, steps count, MET values, sedentary time, upright time, stepping time, sedentary-to-upright movements, and upright-to-sedentary movements.

Technical features and functioning principle of wearable monitors used to measure sedentary behaviors. Technical features may vary across brands; however, accelerometer-based wearable monitors used to measure sedentary behaviors may share the following characteristics and functioning principles. A single wearable monitor (unit) can integrate one or several types of sensors, namely motion, physiological, and contextual sensors.[90] Examples of sensors are accelerometers (motion sensor), skin temperature sensors (physiological sensor) and light sensors (contextual sensor). Accelerometers are the most common type of sensor placed in wearable monitors, which have yielded a common practice of naming them as accelerometers, although a more precise name would be accelerometer-based wearable monitors. Older models of accelerometer-based wearable monitors included single vertical axis accelerometers (e.g., ActiGraph GT1M); modern models include tri-axial accelerometers (e.g., ActiGraph GT3X+ and GENEActiv).

Most of the accelerometer-based wearable monitors use the same underlying functioning principle of measuring and recording the frequency and amplitude of acceleration of the body segment to which they are attached. Often, a proprietary algorithm applies a digital filter to the raw data to eliminate any acceleration noise outside of the normal human activity frequency bandwidth. A typical bandwidth filter for a hip or waist worn accelerometer is 0.2 to 3.0 Hz, which is supposed to filter out acceleration signals that are likely not to be reflective of human movement.[90] Then, using a manufacturer's software, the filtered data are integrated (summed or averaged) over a specified interval of time referred to as an epoch. The epoch data are exported in the form of timestamped movement counts (also known as activity counts), absolute body positions, or other user-defined variables, such as breaks in sedentary time. Some of the wearable monitors, including the ActiGraph and GENEActiv, allow for user defined epochs while other wearable monitors, such as the activPAL™, summarizes data in predefined epochs. The activPAL™ summarizes data in a 15-second epoch.

Tri-axial accelerometers allow obtaining activity counts in individual axes (vertical, anteroposterior, and mediolateral) or composite measures (vector magnitude). Additionally, tri-axial accelerometers allow the use of an accelerometer-based inclinometer feature with which estimations of a subject's body segment position and posture are possible. Thus, when there is a change in one's position, it is possible to establish an angle between the wearable monitor (attached to a pre-defined body segment) and a constant vector given by the gravity. For example, the ActiGraph GT3X+ classifies as standing an angulation between 0º to 17º, sitting 17º to 65º, or lying >65º.[91]

Accelerometers also allow to record and download a raw signal that is not filtered. The raw acceleration signal is characterized by several features in multiple domains, being time and frequency the two most common domains.[92] Examples of features for the time domain are: mean, standard deviation, percentiles, lag-1-autocorrelation; while, total signal power and frequency of the signal with most power are features within the frequency domain. As raw signal features provide the possibility of improved estimates, as compared to the traditional activity count cut-points, its use is becoming increasingly popular for physical activity and sedentary behavior measurement research.

Approaches to analyze data from wearable monitors used to measure sedentary behaviors. While there is not a standard approach used to analyze sedentary behavior data, the most common approach is to analyze accelerometer-based wearable monitor data using a cut-points approach. Cut-points are numerical values for the acceleration of movement intensity (activity counts) that reflects differences in the energy cost of movement. Higher numerical cut-points reflect higher energy costs of movement. Cut-points are derived from prediction equations in which accelerometer counts are regressed against energy expenditure values in kilocalories or in oxygen uptake values (ml/kg/min).[35] Cut-points that reflect sedentary behaviors are usually established for activity counts equivalent to ≤ 1.5 METs. Several thresholds of activity counts have been proposed to classify sedentary time from the ActiGraph accelerometer: 50 counts per minute,[35] 100 counts per minute,[12] 150 counts per minute,[25] and 500 counts per minute.[38] Among these cut-points, 100 counts per minute is the most commonly used threshold. Even though modern accelerometer-based wearable monitors are capable of measuring acceleration in three axes, existing ActiGraph cut-points include the vertical axis only. There also are published vector magnitude cut-points that classify sedentary behaviors with the GENEActiv accelerometer (217, 386, and 77 counts per minute for left wrist, right wrist and waist respectively).[39]

In addition to the selection of a cut-point, the determination of accelerometer wear time is a common approach for free-living assessment of sedentary behaviors. Establishing wear-time parameters is important as accelerometers will collect data even when the monitor is not worn by a subject. If wear-time versus non-wear time is not differentiated, it is possible for the investigator to misclassify non-wear time as time spent in sedentary behaviors instead of time when the monitor was not being worn. With the established amount of wear time, researchers can flag a day as a “valid” or “not-valid” day regarding a minimum amount of required accelerometer wear time hours per day. Non-wear time is usually defined as an interval of at least 60 consecutive minutes of zero activity intensity counts, with allowance for 1-2 minutes of miscellaneous counts between 0 and 100.[13] There are different approaches that are available to classify non-wear time.[13,65,93–95] Typically, to exclude non-wear time it is necessary to run an automated computer program mediated for classification algorithms. Customizable parameters also can be used to classify wear time. For example, the ActiLife® software (used for ActiGraph wearable monitors), provides a process to evaluate vector magnitude for non-wear classification.[96] It has been recommended that a minimum wear time of 13 $h \cdot d^{-1}$ is needed to provide a valid daily measure for sedentary and light intensity activities,[97] and to include at least 4 days for analyses.[98] However, as some investigators have used one day of accelerometer data for data analysis, variation exists for the valid number of days required to include data into the analyses.[65]

Sophisticated techniques in data analysis have been developed in attempt to overcome limitations of existing accelerometer scoring methods.[26,99] Overall, these new techniques allow for automatic classification of different activities by posture (e.g., standing, sitting, and reclining), movement types (e.g., walking, running, and intermittent activities), the use of more densely sampled data (e.g., 100 Hz versus 30 Hz), and the integration of multiple information sources (e.g., accelerometry and GPS technology).[33]

One of these emerging methods for data analysis is the sedentary sphere. In 2014, Rowlands et al.[41] presented this method for classifying sedentary behaviors based on posture and activity counts from the GENEActiv. The sedentary sphere has also been used to classify posture from ActiGraph data.[44] This method, allows an application for posture classification by a simple premise of arm elevation that, combined with activity counts, can provide estimates of sedentary behaviors.[41] The sedentary sphere uses the gravitational component of the acceleration signal to determine the orientation of the monitor; hence, the wrist position can also established, which in combination with activity counts allows for estimates of the most likely posture. The sedentary sphere uses the following directions. (1) If the arm is elevated to > 15 degrees above the horizontal plane and the activity counts are less than 489 counts per each 15-second epoch (light-to-moderate intensity), the posture is classified as siting and/or lying (sedentary). (2) If the arm is hanging to <15 degrees below the horizontal plane and the activity counts are less than 489 counts per each 15-second epoch and, posture is classified as standing (non-sedentary). (3) If the activity counts are greater than 489 counts per each 15-second epoch regardless of wrist elevation, posture is classified as standing (non-sedentary). The value of the sedentary sphere is that, without the need of significant computational resources or data science experience, it avoids the limitations of using solely the cut-points approach to determine time spent in sedentary behaviors.

Even more sophisticated approaches, commonly recognized as human activity classification models are under development. Many of the human activity classification models involve multi-stage processes in which the raw recorded data (or signal) is divided into a number of small time segments referred to as windows. From each window, one or more features are derived to characterize an acceleration signal. Examples of features extracted from the accelerometer's signal are: standard deviation, percentiles, correlations between axes, total signal power, frequency of the signal with most power, etc.[92] The derived features are then used as inputs to a classification algorithm (e.g., decision trees or artificial neural networks) that associates each window with an activity type. Although these emerging techniques show considerable promise for more accurate assessments of sedentary behaviors, challenges arise for their implementation. For example, the complexity of these approaches may require highly dedicated computational resources or skills that may be beyond many researchers' experience.

In summary, regardless of the approach used to analyze data from wearable monitors, the two most common outputs used in research are the volume and breaks of sedentary behaviors.[24] Other metrics such as the number of breaks per hour of sedentary behaviors are receiving interest from the sedentary behavior research community, however, the metrics are still under examination.[100] Also, new sophisticated techniques that integrate more features from the accelerometer's signal are under development; however, its complexity is a limiting factor to their use physical activity and sedentary behaviors research.

Validity of wearable monitors used to measure sedentary behaviors. The purpose of this section is to review the validity of the most commonly used wearable monitors to measure sedentary behaviors. The validity of energy expenditure estimations, posture classification methods and machine learning methods will be reviewed.

The ActiGraph and the GENEActiv are devices used predominantly to measure sedentary behaviors using energy expenditure estimations. Specific to the ActiGraph, the cut-point value that has received the most of the attention is 100 counts per minute. The accuracy of using 100 counts per minute to reflect sedentary behaviors has been tested by several studies. Matthews et al.[69] compared the ActiGraph cut-point of 100 counts per minute to reflect sedentary behaviors with values obtained from a criterion monitor, Intelligent Device for Energy Expenditure and Activity (IDEEA). In a sample of 19 adults (mean age = 40.1 years), the results showed moderate correlations between the two monitors when assessing sedentary time ($r = 0.59$, $p < 0.01$).

In addition to testing 100 counts per minute as a cut-point for sedentary behaviors, Kozey-Keadle et al.[25] tested the criterion validity of five ActiGraph cut points (50, 100, 150, 200 and 250 counts per minute) against a criterion measure of direct observation. In a sample of 20 adults (mean age = 46.5 years), the results showed that the 100 counts per minute underestimated sedentary time by 4.9% and that 150 counts per minute had the lowest bias, but overestimated sedentary time by 1.8%. In a third study, Lyden et al.[100] assessed the criterion validity of the ActiGraph cut-points of 100 and 150 counts per minute to estimate sedentary behaviors, the absolute number of breaks, and the break-rate against a criterion measure of direct observation of sedentary behaviors. In a sample of 13 adults (mean age = 24.8 years), results showed that both ActiGraph cut-points 100 and 150 significantly overestimated all sedentary time metrics (total sedentary time, absolute number of breaks, and break-rate) measured in the study.

There is limited evidence of the validity of other published ActiGraph cut-points used to classify sedentary behaviors. For example, Silva et al.[38] reported using 500 counts per minute to classify sedentary behaviors, but has provided no evidence for the validity of the cut-point. Alternatively, Esliger et al.[39] compared vector magnitude cut-points for the GENEActiv accelerometer to reflect sedentary behaviors, light-, moderate-, and vigorous-intensity physical activity against a criterion measure of indirect calorimetry. In a sample of 60 adults (mean age = 49.4 years), the results for sedentary behaviors showed that the GENEActiv demonstrated high values for the area under the receiver operating characteristic curve (AUC) for each monitor location (Left wrist AUC = 0.98, 95% CI = 0.98 to 0.99; Right wrist AUC = 0.98, 95% CI = 0.97 to 0.99; and Waist AUC = 0.97, 95% CI = 0.96 to 0.98).[39]

The most common device used to assess sedentary behaviors by posture classification is the activPAL™; however, the ActiGraph[41–44] and GENEActiv[41,44] wearable monitors have been evaluated for their ability to reflect postures with the monitors accelerometer-based inclinometer feature. Despite the popularity of the activPAL™, few studies have assessed the criterion validity of the activPAL™ to assess sedentary behavior by body postures in adults. Instead, the majority of the studies have assessed the validity of the activPAL™ to count steps.[24] Several studies have shown convergent validity for the activPAL™ against questionnaires,[30] and other monitors that are not considered to be criterion measures for the movement domains studied.[33,101,102] A likely problem for these studies is that the activPAL™ is commonly used as the criterion to estimate sedentary time.

Several studies have assessed the validity of the activPAL™ to measure postural changes. Grant et al.[89] assessed the criterion validity of the activPAL™ as a measure of posture against a criterion measure of direct observation. In a sample of 10 adults (mean age = 43 ± 10.6 years), the results showed high agreement as expressed by a mean percentage difference of 0.19% (limits of agreement: 0.68% to 1.06%) for time spent sitting. Steeves et al.[103] assessed the criterion validity of the activPAL™ as a measure of posture against a criterion measure of direct observation. In a sample of 21 adults (mean age = 37.9 ± 14.2 years), the results showed that the activPAL™ correctly classified different sitting positions most of the time (self-selected sitting posture 95.2%, legs crossed at the knee 100%, 90-degree hip and knee angles 100%, legs crossed with ankle on opposite knee 100%), but only correctly classified sitting with legs outstretched 85.7% and sitting on a laboratory stool 5% of the time.

Studies also have evaluated the ability of the activPAL™ to assess sedentary behaviors and breaks in sedentary behavior. Kozey-Keadle et al.[25] tested the criterion validity of the activPAL™ to assess sedentary behaviors against a criterion measure of direct observation. In a sample of 20 adults (mean age = 46.5 years), the results showed that the activPAL™ underestimated sedentary time by 2.8%. Lyden et al.[100] assessed the criterion validity of the activPAL™ to estimate sedentary time, absolute number of breaks and break-rate against a criterion measure of direct observation. In a sample of 13 adults (mean age = 24.8 ± 5.2 years), the results showed a small but not significant bias for the activPAL™ as compared to the criterion measure (sedentary time = 1.6%, 95% CI = -0.1 to 3.4; absolute number of breaks = 0.3%, 95% CI = -7.0 to 7.7; and break rate = 1.0%, 95% CI = -9.1 to 7.0).

As the activPAL™ is limited in distinguishing between sitting and lying due to the thigh being horizontal in both of these postures, Basset et al.[32] tested whether placing a second activPAL™ monitor on the torso would allow the detection of seated versus lying postures against a criterion measure of direct observation. In a sample of 15 adults (mean age = 25 ± 9.4 years), results showed a high level of agreement between the two-accelerometer technique and the criterion measure (kappa = 0.968, P <0.001). By using this approach lying down and sitting were correctly classified 100% of the time.

Even though the activPAL™ is the most common device used to assess sedentary behaviors by posture classification, other accelerometer-based wearable monitors also are able to classify sedentary behaviors by using an accelerometer-based inclinometer feature. One of the few published studies of the accuracy of accelerometer-based inclinometer feature was demonstrated in a free communication poster presented at the

2010 ACSM annual meeting by McMahon et al.[42] . In a sample of 10 participants, the results showed the ActiGraph GT3X inclinometer functioned accurately classified 40% and 96.5% of the time spent in standardized and free-sitting activities, respectively and 80% and 30% for standardized and free-lying activities, respectively when compared to direct observation. Similarly, Peterson et al.[43] tested the accuracy of the inclinometer feature of the ActiGraph GT3X+ accelerometer. In a sample of 28 adults (age range 18 to 20), the results showed that when compared to direct observation the ActiGraph GT3X+ correctly classified sedentary behaviors 65% of the time (95% CI = 59.1 to 73.9).

The accuracy of posture classification from wrist-mounted GENEActiv using the sedentary sphere method has been examined in few studies. Rowlands et al.[41] tested the convergent validity between the sedentary sphere method with GENEActiv data and the activPAL™ for posture classification. The study included three different samples, 1) Free-living sample n=13, mean age = 34.5 years in which participants wore an extra thigh-mounted GENEActiv (next to the activPAL™), 2) Laboratory-based sample n=25, mean age = 39.8 years, and 3) Hospital in-patients sample n=10, mean age = 75.9 years). The results showed fair-to-substantial agreement between the wrist-mounted GENEActiv and the activPAL™ (free-living kappa = 0.65, SD = 0.25; laboratory-based kappa = 0.59, SD = 0.50; and hospital in-patients kappa = 0.38, SD = 0.11). The posture classification from the GENEActiv worn at the thigh (free-living sample) had the highest agreement with the activPAL™ (kappa = 0.90, SD = 0.40).[41] In a subsequent study, Rowlands et al.[44] tested the convergent validity for the sedentary sphere method with GENEActiv data, the ActiGraph GT3X+ data, and the activPAL3™ to classify sedentary behaviors by posture. In a sample of 34 adults (mean age = 27.2 years) that wore the wearable monitors during laboratory and free-living settings, results showed a moderate-to-substantial agreement among the tested wearable monitors (GENEActiv vs. activPAL3™ kappa = 0.50, 95% CI = 0.45 to 0.54; GENEActiv vs. ActiGraph kappa = 0.62, 95% CI = 0.56 to 0.68; and ActiGraph vs. activPAL3™ kappa = 0.49, 95% CI = 0.44 to 0.53). More recently, Pavey et al.[102] tested the convergent validity for the sedentary sphere with GENEActiv data and the activPAL3™ to classify sedentary behaviors by posture. In a sample of 57 adults (mean age = 28.1 years), the results showed slight underestimation of the total sedentary time for GENEActiv compared with the activPAL3™ (as showed by the Bland-Altman plots, mean difference = −3.44 minutes per day, limits of agreement = −144 to 137 minutes per day), and a moderate agreement as shown by a Mean kappa = 0.53 SD = 0.12.

Literature on the validity of the use of machine learning methods (also known as human activity classification models) to measure physical activity and sedentary behaviors have increased in the last decade. Available literature is scattered showing the efficacy of different models to perform activity recognition,[104–108] and to lesser extent, the validity of such methods to estimate sedentary behaviors. For example, in 2014, Lyden et al.,[26] in a sample of thirteen participants (5 males, 8 females), aged 24.8 ± 5.2 years, developed and studied the validity of two machine-learning methods (soj-1x and soj-3x for uniaxial and tri-axial hip-mounted ActiGraph data respectively) to estimate free-living MET-hours, sedentary time, and time spent in light, moderate and vigorous physical activity data against a criterion measure of direct observation. Both methods (soj-1x and soj-3x) were developed using hybrid machine learning approaches that combine artificial neural networks and decision trees. The data were analyzed using repeated measures linear mixed models, percent bias, intraclass correlation coefficient (ICC) and root mean squared error (rMSE). Results for sedentary minutes for the Soj-1X method showed %bias= 8.8 (95% CI= 1.1 to 16.4) with significant differences from direct observation, rMSE= 50.1 (95% CI= 31.7 to 68.5), and ICC= 0.72 (95% CI= 0.37 to 0.89) showing significant correlations with direct observation. Results for sedentary minutes for the Soj-3X method showed %bias= 0.5 (95% CI= -4.5 to 5.6) with no significant differences from direct observation, rMSE= 25.5 (95% CI= 15.4 to 35.6), and ICC= 0.91 (95% CI= 0.78 to 0.97) showing significant correlations with direct observation. Overall, differentiating sedentary behavior from light intensity activities in free-living individuals was superior with the soj-3x compared with the soj-1x.

In summary, the validity of most of the methods used to assess sedentary behaviors is still under assessment. The lack of accepted criterion measures to assess sedentary behaviors is problematic as available monitors are not yet capable of successfully integrating energy expenditure and posture assessments when measuring sedentary behaviors. Promising methods based on machine learning methods are also under development but its validity and applicability is still limited.

Direct Observation

Direct observation is a method of collecting evaluative information in which the researcher watches the subject in his or her usual environment without changing that environment.[109] There are several sampling methods available to conduct direct observation, including focal, instantaneous, and scan sampling methods, which are the most likely methods to be used in physical activity and sedentary behaviors research. Focal sampling refers to a technique in which the researcher observes one individual for an established length of time to make a record with the duration or frequency of the observed behaviors. Instantaneous sampling is a technique in which the researcher records an individual's current activity at preselected moments in time (e.g., every 5 minutes). Scan sampling is similar to instantaneous sampling with the difference that instead one individual, the researcher is observing a group of individuals.[110]

Direct observation has a long tradition in research in different applied disciplines such as psychology, sociology, and zoology. However, its use in physical activity research has been overlooked as a viable methods as it requires a significant amount of work in relation to obtaining data and may be monotonous and time consuming for researchers.[111] Some advantages of using direct observation in physical activity research includes its ability to provide detailed information about the physical activity type, duration, intensity, and the context in which the observed behaviors occur.[112] Limitations of direct observation include a potential for observers to be biased, participants' reactivity to being observed, and the labor-intensive nature of the sampling. Considerable time is required for researchers to travel to and to collect data in the participant environment.[112]

The main applications of direct observation in the physical activity field has been derived from the research led by McKenzie et al.[112] McKenzie and colleagues developed several systems that have been designed to directly observe people in their environments are described briefly. The Behaviors of Eating and Activity for Children's Health: Evaluation System (BEACHES) was designed to measure children's physical activity, sedentary and eating behaviors at home and in selected environmental, social and physical, settings that may influence these events.[113] The System for Observing Fitness Instruction Time (SOFIT) was designed to measure simultaneous measurement of student activity levels, lesson contexts in which the lessons occur, and teacher interactions relative to promoting physical activity and fitness.[114] The System for Observing Play and Leisure in Youth (SOPLAY) was designed to measure the number of participants and their physical activity levels during play and leisure opportunities in targeted areas.[115] The System for Observing Play and Active Recreation in Communities (SOPARC) was developed to measure the number of participants and their physical activity levels in park and recreation settings.[116] Last, the System for Observing Children's Activity and Relationships during Play (SOCARP) was designed to measure children's physical activity levels on the playground while simultaneously assessing the contextual variables of social group size, activity type, and pro- and anti-social interactions with peers.[117] A common characteristic for all of the direct observations systems developed by McKenzie and colleagues is that they allow for time spent in activity level classifications such as sedentary, walking, moderate and vigorous.

More recently, direct observation has been used as a criterion measure in sedentary behaviors research. In 2011, Kozey-Keadle et al.,[25] examined the criterion validity of wearable monitors to assess sedentary behaviors in a sample of 20 overweight inactive office workers, five men and fifteen women, aged 46.5 ± 10.7 years. Participants were directly observed for two 6-hour periods while wearing an activPAL™ and an ActiGraph GT3X. The criterion measurement was direct observation using focal sampling with duration coding to record either sedentary (sitting and lying down) or non-sedentary behaviors. In 2013, Lyden et al.,[26] used direct observations as the criterion to develop and validate two machine-learning algorithms to estimate physical activity and sedentary behaviors in free-living settings. Participants were directly observed on three separate occasions for 10-hours periods while wearing an ActiGraph GT3X on their right-hip. The criterion measure was direct observation using focal sampling with duration coding to record participant behavior by activity type, intensity, and duration.

In summary, direct observation has been sparsely used for physical activity research in some specific contexts.[112–116] Its use as a criterion measure for sedentary behaviors research is increasing in recent years.[25,26] Some advantages of using direct observation for sedentary behaviors research includes, it provides detailed information about the type, duration, and the context in which the observed behaviors occur.

Chapter 3

METHODS

This chapter includes the methods used in the three separate studies that compose chapters 4 to 6 of this dissertation. These studies focused on the assessment of sedentary behaviors based on wearable monitors. Project one examined the validity for energy expenditure estimations during sedentary and light activities made by wearable monitors in laboratory conditions. Project two tested the accuracy of different uniaxial cut-points to classify sedentary and stationary time in free-living conditions and developed vector magnitude cut-points to classify sedentary and stationary time. Project three examined the accuracy of posture-based sedentary behavior estimates made by the sedentary sphere method in free-living settings. The independent variables are abbreviated as IV and the dependent variables as DV for the explanation of the analysis.

Project One - Wearable monitors criterion validity for energy expenditure estimates in sedentary and light activities.

Purpose

To examine the validity of three wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate intensity for sedentary-to-light activities in adults as compared with oxygen uptake measured in ml•kg^{-1}•min^{-1} (1PA).

Null Hypothesis

There will be no difference between energy expenditure estimates for sedentary-to-light activities made by the tested wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) and energy expenditure estimates from the criterion measure of indirect calorimetry (1HA).

Sample

A convenience sample of sixteen participants (n = 8 men, n = 8 women) with an age range 19-47 years (mean age 25.38 ± 8.58 years), body mass index (BMI) range 18.8-35.0 kg/m^2 (mean 24.6 ± 4.6 kg/m^2) were enrolled in the study.

Independent Variables

Energy expenditure estimates were made by each monitor under assessment with their name and abbreviation as follows:

- ActiGraph (IVA)
- activPAL™ (IVB)
- SenseWear Pro 2 (IVC)

The independent variables were operationalized as dichotomous variables: sedentary behaviors (0) and light-intensity physical activities (1) levels. Sedentary behaviors values were assigned to energy expenditure estimates <1.5 METs while light-intensity values were assigned to energy expenditure estimates ≥1.5 METs.

Dependent Variables

Energy expenditure measured by oxygen uptake in ml/kg/min for seven sedentary-to-light activities (Cleaning a kitchen; Standing while reading; Sitting while typing; Sitting while gaming; Treadmill walking at 1.0 mph (0.45 m/s), 1.5 mph (0.67 m/s), and 2.0 mph (0.90 m/s)) performed by the participants in a randomly assigned order during seven minutes each. The dependent variable was operationalized as a dichotomous variable: sedentary behaviors (0) and light-intensity physical activities (1) levels. Sedentary behaviors values were assigned to activities with an energy expenditure <1.5 METs while light-intensity values were assigned to activities with an energy expenditure ≥1.5 METs.

Covariates

No covariates were included in this study.

Procedures Required to Test Hypotheses

- The independent variables (IVA, IVB, and IVC) were standardized to METs and classified as sedentary or light-intensity for each activity performed.
- The dependent variable (DV) was standardized to METs.
- The first two minutes (minutes 1-2) and the final minute of data (minute 7) of each activity were dropped from the analysis.
- Analyses were conducted by averaging the four 1-minute epochs of each activity into a one variable reflecting the average energy cost for the activity.

Statistical Analyses

- Computed Mean Percent Error (MPE) for each of the three wearable monitors relative to the criterion measure (IVA vs. DV, IVB vs. DV, and IVC vs. DV).
- Performed Equivalency testing for each of the wearable monitors relative to the criterion value (IVA, IVB, and IVC vs. DV).
- Prepared Bland-Altman plots for each of the three wearable monitors relative to the criterion measure (IVA vs. DV, IVB vs. DV, and IVC vs. DV).

- Computed kappa statistics for each of the three wearable monitors relative to the criterion measure (IVA vs. DV, IVB vs. DV, and IVC vs. DV).
- Computed sensitivity and specificity for each of the wearable monitors relative to the criterion value (IVA vs. DV, IVB vs. DV, and IVC vs. DV).

All analyses are statistically significant at $P<.05$.

Inclusion and Exclusion Criteria

Inclusion. Healthy adults with a BMI in the normal-to-obese type 1 category (BMI 18.5 to 34.9), ages 18-65, and able to walk unassisted on a motorized treadmill at 2.0 mph were included for study participation.

Exclusion. Persons with any disability that could inhibit daily physical activity, vulnerable population such as cognitively impaired, persons unable to provide their own consent, and pregnant women were excluded from study participation.

Project Two - Wearable monitors accuracy to classify sedentary and stationary time under free-living conditions.

Purposes

Purpose 1. To test the accuracy of time spent in free-living sedentary and stationary behaviors using selected cut-points obtained from ActiGraph GT3X+ uniaxial measures and GENEActiv vector magnitude measures as compared with the criterion measure of direct observation.

Purpose 2. To develop optimal vector magnitude cut-points from the ActiGraph and GENEActiv to classify sedentary and stationary time using data obtained under free-living conditions.

Null Hypotheses

Null Hypothesis 1. There will be no difference between free-living sedentary and stationary behaviors classifications made by the selected cut-points and free-living sedentary and stationary behaviors classifications from the criterion of direct observation.

Null Hypothesis 2. There will be no difference between free-living sedentary behavior classifications made by the developed vector magnitude cut-points and free-living sedentary behavior classifications from the criterion of direct observation.

Sample

A convenience sample of twenty participants (n = 10 men, n = 10 women) with and age range 21-46 years (mean age 30.25 ± 6.43 years), body mass index range 18.51-29.76 kg/m^2 (mean 22.7 ± 3.1 kg/m^2) was enrolled in the study. By chance all of the participants were right-handed.

Independent Variables

Independent variables for purpose 1 (IVA1 to IVA22). Sedentary and stationary time (1-minute) classifications for each monitor at selected body locations (left wrist, right wrist, right hip), and for varying cut-points (ActiGraph single axis cut-points of 50, 100, 150, 200, 250, and 500 counts per minute and GENEActiv vector magnitude cut-points of 217 and 386 counts per minute) for a total of 22 computed independent variables. An example of combinations of independent variables for the ActiGraph and the GENEActiv are below.

- ActiGraph Left Wrist 50 Counts per minute
- ActiGraph Right Wrist 50 Counts per minute
- ActiGraph Right Hip 50 Counts per minute
- GENEActiv Left Wrist 217 Counts per minute
- GENEActiv Right Wrist 386 Counts per minute

Each of the independent variables (IVA1 to IVA22) were operationalized as a dichotomous variable having the levels of, non-sedentary (0) when the tested monitor had a value above the respective cut-point and sedentary (1) when the tested monitor had a value bellow the respective cut-point. For example, for an ActiGraph cut-point of 50 counts per minute, an activity with 45 counts per minute would correspond to a computed variable equal to 1 and classified as sedentary.

Independent variables for purpose 2 (IVB1 to IVB26). Cut-points used to classify time as sedentary or stationary for each monitor at selected body locations (left wrist, right wrist, right hip), and for varying epoch lengths (1-minute, 15-second, and 1-second) for a total of 26 computed independent variables. An example of combinations of independent variables for the ActiGraph and the GENEActiv are below.

- ActiGraph Left Wrist 1-minute sedentary epoch
- ActiGraph Left Wrist 1-minute stationary epoch
- ActiGraph Right Wrist 15-second sedentary epoch
- ActiGraph Right Hip 15-second sedentary epoch

- GENEActiv Left Wrist 1-second sedentary epoch
- GENEActiv Right Wrist 1-second sedentary epoch

Independent sedentary variables (IVB1 to IVB13) were operationalized as a dichotomous variable having the levels of, non-sedentary (0) when the tested monitor had a value above the respective cut-point and sedentary (1) when the tested monitor had a value bellow the respective cut-point. For example, using a cut-point of 455, an ActiGraph worn on the left-wrist yields a 15-second epoch with 300 counts. The corresponding computed variable would be equal to 1 indicating the behavior is sedentary.

Independent stationary variables (IVB14 to IVB26) were operationalized as a dichotomous variable having the levels of, non-stationary (0) when the tested monitor had a value above the respective cut-point and stationary (1) when the tested monitor had a value bellow the respective cut-point. For example, using a cu-point of 18 counts per second, an ActiGraph right-wrist 1-second epoch with 15 counts per second would be equal to 1 and that the behavior is stationary.

Dependent Variables (Criterion Variables from Direct Observation)

The criterion measure was direct observation with focal sampling and duration coding for conditions for six activity categories (walking, running, sports/exercise, household chores, standing, and sitting/lying down), in five different contexts (household, transportation, occupation, sports/conditioning and leisure). Activity types were coded as: walking = 1, running = 2, sports/exercise = 3, household chores = 4, standing = 5, sitting/lying down = 6, private = 7, unobserved = 8, and error = 9. Activity context were coded as: household = 1, transportation = 2, occupation = 3, sports/conditioning and leisure= 4, and leisure = 5. The minimum duration for each code was one second. Each of the activity categories is described below:

- Walking. This activity category included walking for all locomotion purposes, walking in flat or inclined surfaces, and walking up or down stairs. Incidental or incomplete steps that didn't result in moving from one place to another were not included in this category (e.g., weight shifting).
- Running. This activity category included continuous and short bouts of running or jogging (e.g., jogging for exercising or short runs to cross the street).
- Sports and conditioning exercise. This activity category included playing sports or performing continuous or intermittent conditioning exercises. Other exercises different than running or jogging were included in this category (e.g., weight lifting, yoga, Pilates, or gym classes).
- Household chores. This activity category included housekeeping activities such as dish washing, gardening, vacuuming, and doing the laundry.
- Standing. This activity category included standing with or without upper body movements while bearing the body weight in one or both lower limbs. Incidental or incomplete steps that didn't result in moving from one place to another were included in this category.
- Sitting and lying down. This activity category included various body positions in which the body weight was not supported by the participant's feet. Instead, the body weight was supported by the buttocks, thighs or back; this included sitting, sitting in a laboratory stool, reclining and lying down (supine and prone).

- Private. When during the data collection sessions the participant required private time (e.g., restrooms use), researchers recorded this time as ‘private’ and resumed the activity recording as soon as the participant finished the private activity.
- Unobserved. When the participant was available to be observed but out of the sight of the researchers (e.g., turning corners), researchers recorded this time as ‘unobserved.’
- Error. When researcher made an error or unable to determine an accurate coding for a given activity.

Participants were observed directly in their free-living environment by two independent researchers for 6-hours on two days, a weekday and a weekend day. Each researcher independently recorded each activity performed on an IPad tablet. Every time a participant changed the activity, researchers made an annotation reflecting the new activity. A commercially available app, Timestamped Field Notes app was used to make annotations.[118]

Six dichotomous dependent variables were computed from the direct observation data; 2 dichotomous 1-minute criterion variables (sedentary and stationary).2 dichotomous 15-second criterion variables (sedentary and stationary), and 2 dichotomous 1-second criterion variables (sedentary and stationary).

The 1-minute sedentary variable (sedentary or non-sedentary) was created in which the seconds of sitting and lying down were considered sedentary activities; a minute was considered sedentary when most of its seconds where sedentary (i.e., between 31-60 seconds per minute). The 1-minute sedentary variable was operationalized as dichotomous variable with values of (0) for non-sedentary minute and (1) sedentary minute. The 1-minute stationary variable (stationary or non-stationary) was calculated using the same criteria as listed for the 1-minute sedentary variable except that standing, sitting and lying down were considered stationary type of activities. The 1-minute stationary variable was operationalized as dichotomous variable with values of (0) for non-stationary minute and (1) stationary minute.

The two 15-second criterion variables (sedentary and stationary) were computed using the same criteria as listed for the 1-minute sedentary and 1-minute stationary variables, except that the duration was 15-second epoch rather than 1-minute epoch.

The 1-second sedentary variable (sedentary or non-sedentary) was created in which the seconds of sitting and lying down were considered sedentary activities. The 1-second sedentary variable was operationalized as dichotomous variable with values of (0) for non-sedentary second and (1) sedentary second. The 1-second stationary variable (stationary or non-stationary) was calculated using the same criteria as listed for the 1-second sedentary variable, except that standing, sitting and lying down were considered stationary type of activities. The 1-second stationary variable was operationalized as dichotomous variable with values of (0) for non-stationary second and (1) stationary second.

Covariates

No covariates were included in the study analyses.

Procedures Required to Test the Hypotheses.

The observations obtained from the direct observation and the wearable monitors were randomly divided into a training dataset (50%) and a testing (50%) dataset. The training dataset was used to develop new equations to measure sedentary behaviors. The testing dataset was used to determine the validity of the new equations.

Statistical Analyses

Several computations were made to test hypothesis 1, to determine the accuracy of the selected 1-minute cut-points to classify an activity obtained from direct observation as sedentary or stationary.

- Percent Errors were computed for each of the tested wearable monitors, cut-points and locations relative to the criterion measures obtained from direct observation (IVA1 to IVA22 vs. 1-minute sedentary criterion variable, and IVA1 to IVA22 vs. 1-minute stationary criterion variable).
- Kappa statistics were computed for each of the tested wearable monitors, cut-points and locations relative to the criterion measure obtained from direct observation (IVA1 to IVA22 vs. 1-minute sedentary criterion variable, and IVA1 to IVA22 vs. 1-minute stationary criterion variable).
- Sensitivity and specificity were computed for each of the tested wearable monitors, cut-points and locations relative to the criterion measure obtained from direct observation (IVA1 to IVA22 vs. 1-minute sedentary criterion variable, and IVA1 to IVA22 vs. 1-minute stationary criterion variable).

To test hypothesis 2, the development of vector magnitude cut-points, the following procedures were used to analyze the data.

- Using the training dataset, receiver operating characteristic (ROC) curve analyses was conducted and optimal cut-points were obtained using the minimum distance method for 1-minute, 15-second, and 1-second epochs.
- Using the testing data set, computed percent error for each of the tested wearable monitors, estimated cut-points and locations relative to the criterion measure obtained from direct observation (IVB1 to IVB26 vs. 1-minute sedentary criterion variable, IVB1 to IVB26 vs. 1-minute stationary criterion variable, IVB1 to IVB26 vs. 15-second sedentary criterion variable, IVB1 to IVB26 vs. 15- second stationary criterion variable, and IVB1 to IVB26 vs. 1-second sedentary criterion variable, IVB1 to IVB26 vs. 1-second stationary criterion variable).
- Using the testing data set, computed kappa statistics for each of the tested wearable monitors, estimated cut-points and locations relative to the criterion measure obtained from direct observation (IVB1 to IVB26 vs. 1-minute sedentary criterion variable, IVB1 to IVB26 vs. 1-minute stationary criterion variable, IVB1 to IVB26 vs. 15-second sedentary criterion variable, IVB1 to IVB26 vs. 15-second stationary criterion variable, and IVB1 to IVB26 vs. 1-second sedentary criterion variable, IVB1 to IVB26 vs. 1-second stationary criterion variable).
- Using the testing data set, computed sensitivity and specificity for each of the tested wearable monitors, estimated cut-points and locations relative to the criterion measure obtained from direct observation (IVB1 to IVB26 vs. 1-minute sedentary criterion variable, IVB1 to IVB26 vs. 1-minute stationary criterion variable, IVB1 to IVB26 vs. 15-second sedentary criterion variable, IVB1 to IVB26 vs. 15- second stationary criterion variable, and IVB1 to IVB26 vs. 1-

second sedentary criterion variable, IVB1 to IVB26 vs. 1-second stationary criterion variable).

All analyses were regarded as statistically significant with a $P < .05$.

Inclusion and Exclusion Criteria.

Inclusion. Healthy adults with a BMI in the normal- to-overweight category (BMI 18.5 to 29.9), ages 18-65, and able to freely ambulate by walking and/or running were included for study participation.

Exclusion. Persons with any disability that could inhibit daily physical activity, vulnerable population such as cognitively impaired, persons unable to provide their own consent, and pregnant women were excluded from study participation.

Project Three. Accuracy of posture-based sedentary behavior estimates made by the sedentary sphere method in free-living settings

Purposes

Purpose 1. To test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and ActiGraph GT3X+ wearable monitors during free-living conditions in both dominant and non-dominant wrists.

Purpose 2. To test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and ActiGraph GT3X+ wearable monitors during free-living conditions with different angle configurations.

Null Hypotheses

Null Hypothesis 1. There will be no difference between free-living sedentary behavior classifications made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors in both dominant and non-dominant wrists and free-living sedentary behaviors classifications from the criterion measure of direct observation.

Null Hypothesis 2. There will be no difference between free-living sedentary behavior classifications made by the different configurations of the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ and free-living sedentary behavior classifications from the criterion measure of direct observation.

Sample

A convenience sample of twenty participants (n = 10 men, n = 10 women) with and age range 21-46 years (mean age 30.25 ± 6.43 years), body mass index range 18.51-29.76 kg/m^2 (mean 22.7 ± 3.1 kg/m^2) participated in the study. By chance all of the participants enrolled in this study were right-handed.

Independent Variables

Independent variables for purpose 1 (IVA1 to IVA4). Sedentary time estimates made by the sedentary sphere method (15-second epoch) from each monitor under assessment (ActiGraph and GENEActiv) and location (non-dominant wrist and dominant wrist) for a total of 4 computed independent variables.

- GENEActiv non-dominant (IVA1)
- GENEActiv dominant (IVA2)
- ActiGraph non-dominant (IVA3)

- ActiGraph dominant (IVA4)

Independent variables were operationalized as a dichotomous variable having the levels of, non-sedentary (0) and sedentary (1) according to the sedentary sphere classifications.

Independent variables for purpose 2 (IVB1 to IVB20). Sedentary time estimates made by different configurations of the sedentary sphere method (15-second epoch) from each monitor under assessment (ActiGraph and GENEActiv) and location (non-dominant-wrist and dominant wrist) for a total of 20 computed independent variables.

- Configurations 2-5 (IVB1 to IVB16). Varying arm elevation thresholds (5, 10, 20, 25 degrees below the horizontal plane, respectively) and with the intensity classified as light-to-moderate (<489 counts per 15-second epoch).
- Configuration 6 (IVB17 to IVB20). the arm elevation threshold is constant at 15 degrees below the horizontal plane and applied vector magnitude sedentary cut-points for 15-second epoch developed previously (GENEActiv non-dominant 65 counts per 15-second epoch, GENEActiv dominant 61 counts per 15-second epoch, ActiGraph non-dominant 455 counts per 15-second epoch, and ActiGraph dominant 495 counts per 15-second epoch).

Independent variables were operationalized as a dichotomous variable having the levels of, non-sedentary (0) and sedentary (1) according to the sedentary sphere classifications.

Dependent Variables (Criterion Variables from Direct Observation)

The technique used to collect data was direct observation with focal sampling and duration coding for conditions for six activity categories (walking, running, sports/exercise, household chores, standing, and sitting/lying down), in five different contexts (household, transportation, occupation, sports/conditioning and leisure). Activity types were coded as: walking = 1, running = 2, sports/exercise = 3, household chores = 4, standing = 5, sitting/lying down = 6, private = 7, and unobserved = 8. Activity context were coded as: household = 1, transportation = 2, occupation = 3, sports/conditioning and leisure= 4, and leisure = 5. The minimum duration for each observation code was one second.

A 15-second dichotomous sedentary criterion variable was created for each activity category in which sitting and lying down seconds were coded as sedentary activities. Each 15-second time period was considered sedentary when most of the seconds where in sedentary behaviors (i.e., between 9-15 seconds per 15-second epoch). The dependent variable was operationalized as dichotomous variable with values of (0) for non-sedentary and (1) sedentary.

Covariates

No covariates were included in this study.

Procedures Required to Test Hypotheses

A SAS program was created in order to replicate the data process made by the sedentary sphere Excel spreadsheets.

Statistical analyses

- Performed Equivalency testing for each of the sedentary sphere configurations to the criterion value (IVA1 to IVA4 vs. dependent variable, and IVB1 to IVB20 vs. dependent variable).
- Computed Percent Errors for each of the wearable monitors and configurations of the sedentary sphere relative to the criterion measure obtained from direct observation (IVA1 to IVA4 vs. dependent variable, and IVB1 to IVB20 vs. dependent variable).
- Presented Bland-Altman plots for each of the wearable monitors and configurations of the sedentary sphere relative to the criterion measure obtained from direct observation (IVA1 to IVA4 vs. dependent variable, and IVB1 to IVB20 vs. dependent variable).
- Computed kappa statistic for each of the wearable monitors and configurations of the sedentary sphere relative to the criterion measure obtained from direct observation (IVA1 to IVA4 vs. dependent variable, and IVB1 to IVB20 vs. dependent variable).
- Computed sensitivity and specificity for each of the wearable monitors and configurations of the sedentary sphere relative to the criterion measure obtained from direct observation (IVA1 to IVA4 vs. dependent variable, and IVB1 to IVB20 vs. dependent variable).

Inclusion and exclusion criteria

Inclusion. Healthy adults with a BMI in the normal to overweight category (BMI 18.5 to 29.9), ages 18-65, and able to freely ambulate by walking and/or running were included for study participation.

Exclusion. Persons with any disability that could inhibit daily physical activity, vulnerable population such as cognitively impaired, persons unable to provide their own consent, and pregnant women were excluded from study participation.

Chapter 4

WEARABLE MONITORS CRITERION VALIDITY FOR ENERGY EXPENDITURE IN SEDENTARY AND LIGHT ACTIVITIES

Abstract

Background. Wearable monitors (WMs) are used to estimate the time spent in sedentary behaviors (SBs) and light-intensity physical activities (LPAs) and their associated energy cost; however, the accuracy of WMs in measuring behaviors on the lower end of the intensity spectrum is unclear. The aim of this study was to assess the validity of 3 WMs (ActiGraph GT3X+; *activ*PAL, and SenseWear 2) in estimating the intensity of SB and LPA in adults as compared with the criterion measure of oxygen uptake measured by indirect calorimetry (oxygen uptake, VO_2).

Methods. Sixteen participants (age: 25.38 ± 8.58 years) wore the ActiGraph GT3X+, activPAL, and SenseWear devices during 7 sedentary-to-light activities. VO2 (mL/kg/min) was estimated by means of a portable gas analyzer, Oxycon Mobile (Carefusion, Yorba Linda, CA, USA). All data were transformed into metabolic equivalents and analyzed using mean percentage error, equivalence plots, Bland-Altman plots, kappa statistics, and sensitivity/specificity.

Results. Mean percentage error was lowest for the *activ*PAL for SB (14.9%) and LPA (9.3%) compared with other WMs, which were >21.2%. None of the WMs fell within the equivalency range of ±10% of the criterion mean value. Bland-Altman plots revealed narrower levels of agreement with all WMs for SB than for LPA. Kappa statistics were low for all WMs, and sensitivity and specificity varied by WM type.

Conclusion. None of the WMs tested in this study were equivalent with the criterion measure (VO_2) in estimating sedentary-to-light activities; however, the *activ*PAL had greater overall accuracy in measuring SB and LPA than did the ActiGraph and SenseWear monitors.

Keywords: Accelerometers, Accuracy, Low intensity, Metabolic estimations, Objective measurement, Sedentary behaviors.

Introduction

Sedentary behavior (SB) is an important determinant of health.[24] Accurate assessment of this behavior is useful for epidemiological research and to evaluate changes for interventions and programs.[35] Self-report has been the most common method to quantify SB, however, its validity is still under assessment.[39,65] Therefore, objective measurement with sophisticated wearable monitors has emerged to overcome self-reporting biases, yet, many challenges encompass its use.[25,33,36,37,119] To date, the treatment and understanding of the data obtained from wearable monitors is still very limited.[33,120] Further, most of the available wearable monitors have been extensively evaluated for accuracy to estimate moderate-to-vigorous physical activity (PA) and not SB or light intensity physical activity (LPA).

As many of the adults from developed and developing countries spend most of their time in SB and LPA,[121] it is critical to assess the validity of wearable monitors for SB and LPA. Early work in understanding energy expenditure (EE) has described the lack of ability for wearable monitors to measure EE in the sedentary-to-light intensity spectrum.[72] More recently, Calabro et al.[40] assessed the validity of a variety of wearable monitors to estimate EE during light- to- moderate intensity activities finding a percent error ranging from 9.5 to 30.5. Even though their work provides important information to consider a wearable monitor when there is interest in tracking low intensity activities, several questions remain related to what are the most valid and reliable objective wearable measures of SB and LPA.

Currently, there are many types of wearable monitors' brands available (e.g., ActiGraph, activPAL™, SenseWear) to measure PA and SB that have been extensively evaluated for accuracy to estimate moderate-to-vigorous PA. However, their ability to estimate EE on the lower end of the intensity spectrum, such as SB and LPA, is less well known. For example, the ActiGraph, a triaxial accelerometer (ActiGraph LLC, Pensacola, FL, USA), measures acceleration in three individual axes (vertical, antero-posterior, and medial-lateral) and provides activity counts for separate and for a composite vector magnitude of these three axes; however, the primary determination of SB using the ActiGraph is often based on only one axis using an intensity threshold of <100 counts per minute (cpm). There has been some concern about the accuracy of this threshold as it has underestimated sitting time by 5%. While a 150 cpm seems to be a more accurate cut-point for the Actigraph,[25] there are several proposed cpm thresholds to classify SB: 50 cpm,[35] 100 cpm,[65] 150 cpm,[25] and 500 cpm.[38] In another example of a monitor to measure SB and LPA, the activPAL™ PA logger (PAL™ Technologies Ltd, Glasgow, UK) is a uniaxial accelerometer and inclinometer that identifies walking, sitting, standing, steps, and instantaneous cadence.[89] The activPAL™ has shown accuracy for distinguishing sitting/lying down from standing postures and classifying time stepping;[25,122] however, the estimated metabolic equivalents (METs) values from the activPAL™ at various speeds (2 mph to 4 mph) are significantly different ($P < 0.0001$) from the criterion of oxygen uptake.[31] A third example of a monitor to measure SB and LPA is the SenseWear Armband 2 (BodyMedia, Pittsburgh, PA, USA), that integrates information from a bi-axial accelerometer and other physiological sensors (heat flux, temperature, and galvanic skin response) to provide estimates of EE using a proprietary algorithm.[123] This wearable monitor overestimates EE at various walking/running speeds ranging from 2 mph to 8 mph ($P < 0.0001$) as compared to the criterion of oxygen uptake.[124]

The accuracy (validity) for each of these wearable monitors for estimating EE during sedentary-to-light activities is unclear. One way to assess validity of the wearable monitors is to compare their outputs against a criterion measure (criterion validity). The criterion validity describes the relationship between wearable monitors outputs and physiological measures that reflect more directly the energy cost of the activity. Thus the goal of this study was to examine the validity of three wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate intensity for sedentary-to-light activities in adults as compared with oxygen uptake measured in ml•kg^{-1}•min^{-1}. We hypothesized that the validity of EE estimates made by the tested wearable monitors (ActiGraph, activPAL™, and SenseWear) would be low as most of the wearable monitors are validated for measuring moderate to vigorous PA but not SB nor LPA.

Materials and methods

Participants

A convenience sample of sixteen participants (n = 8 men, n = 8 women) with an age range 19-47 years (mean age 25.38 ± 8.58 years), body mass index range 18.8-35.0 kg/m^2 (mean 24.6 ± 4.6 kg/m^2), no contraindications for exercise (assessed with the physical activity readiness questionnaire - PAR-Q),[125] and ability to walk unassisted on a motorized treadmill at 2.0 mph participated in the study. Prior to participation, all participants read and signed an informed consent document approved by the Arizona State University institutional review board.

Procedures

Participants were instructed to avoid vigorous exercise the day before the testing and to eat their usual diet. Each participant performed seven sedentary-to-light activities in a randomly assigned order. Activities close to the light-intensity activity threshold of 1.5 METs were selected based on values listed in the 2011 Compendium of Physical Activities.[126] Every activity was performed for 7 min, with 4 min of rest between activities. Participants were instructed to be silent during the monitoring periods. The activities were performed twice, with at least 24 hours between trials. Participants were instructed to perform the activities as follows:

1) Treadmill walking at 1.0 mph (0.45 m/s), 1.5 mph (0.67 m/s), and 2.0 mph (0.90 m/s) – to walk using their normal gate at each speed, and not to use the handrails for support.
2) Cleaning a kitchen (cleaning) – to simulate cleaning a kitchen and dishes using a dry rag. Tasks included clearing dishes off a counter space, simulating washing and drying dishes, placing dishes in a cupboard, and wiping the counter.
3) Standing while reading (reading) – to stand in place and read a book silently.
4) Sitting while typing (typing) – to sit at a computer to type a given a paragraph. Participants were instructed to sit up straight and maintain that posture while typing.
5) Sitting while gaming (gaming) – to be seated and quietly play a board game, which required the participant to put five objects in a defined order. Participants also rolled a dice and moved their game piece a number of spaces based on their score obtained from ordering the objects. Participants competed against the researcher to more accurately simulate playing a board game.

Wearable Monitors

Each participant wore the three wearable monitors under assessment and the criterion monitor simultaneously during the seven selected activities. The criterion measure, oxygen uptake in $ml \cdot kg^{-1} \cdot min^{-1}$, was measured with the Oxycon Mobile portable metabolic unit (CareFusion, Yorba Linda, CA, USA);[127] the Oxycon Mobile was calibrated before each test according to the manufacturer's specifications.

The ActiGraph was worn on an elastic belt on the right hip. The ActiGraph was initialized to collect data at 30 Hz. The activPAL™ was worn on the anterior and medial portion of the right thigh attached to the skin by a hypoallergenic medical tape. The SenseWear Armband was worn on the left upper arm of the individual using the factory elastic strap.

Data management and processing

Researchers kept a written record of the time each activity was performed; for example, walking 1 mph was performed 1:00 PM to 1:07 PM. Upon finishing data collection, data were downloaded from each of the wearable monitors to a desktop computer. Data from two trials performed by each of the sixteen participants were included for data analysis resulting in a maximum of 32 trials.

To ensure that a steady state of VO_2 had been attained during each activity and to avoid small discrepancies between start and stop times for each activity, the first two minutes (minutes 1-2) and the final minute of data (minute 7) were dropped from the analysis. Accordingly, minutes 3-6 of each activity were utilized to identify the activity intensity for each wearable monitor. This process yielded four 1-minute-epochs for each subject in each activity.

Capabilities for data summarizing and measurement units are different among the selected wearable monitors; as a result, data output lengths were standardized to a one-minute epoch and the measurement units were standardized to METs. A MET is defined as the energy cost of a specific activity divided by a standard resting EE of 3.5 ml•kg^{-1}•min^{-1}. Table 1 summarizes how the measurement units for the criterion and the wearable monitors output values were transformed into METs.

Table 1 - Calculations used to obtain metabolic equivalents (METs) from monitors and the criterion measure

Monitor	Original Units	Equation used to calculate METs
Oxycon Mobile	ml•kg^{-1}•min^{-1}	ml•kg^{-1}•min^{-1} / 3.5
Actigraph	Counts Per Minute (CPM)	1.439008 + (0.000795 x CPM) [a]
activPAL™	MET•h	MET•h / 60
SenseWear	METs	No conversion needed

[a] From: Freedson PS, Melanson E, Sirard J. Calibration of the computer science and applications, inc. accelerometer. Med Sci Sports Exerc. 1998 May;30(5):777-81.

Statistical analysis

Analyses were conducted by averaging the four 1-minute epochs of each activity into a one variable reflecting the average energy cost for the activity. The variables were stratified into two groups according to their MET values; SB (<1.5 METs: reading, typing, and gaming), and LPA (≥1.5 METs: walking 1 mph, walking 1.5 mph, walking 2 mph, and cleaning). As each participant completed two trials for each activity, we performed a test-retest reliability analysis (ICC) for each wearable monitor prior to comparison to the criterion measure.

Mean Percent Error (MPE) was calculated to assess the proportion of error for each of the three wearable monitors relative to the criterion measure. MPE was calculated using the equation: MPE = [(Measured Score – True Score)/True Score] x 100. The true score was the criterion value (VO_2 in METs) and the measured score was the MET value obtained from each wearable monitor. A positive MPE indicated a MET value overestimation for the wearable monitor whereas a negative MPE indicated a MET value underestimation for the wearable monitor.[128]

Equivalency testing was used to examine whether the MET value for each of the wearable monitors was statistically equivalent to the criterion MET value. Equivalence testing is an alternative approach to testing for significant differences between means.[129] Equivalence testing requires researchers to identify a clinically-meaningful range (i.e., equivalence zone) which permits comparisons between the values for wearable monitors and the criterion values in the equivalence zone. If the full 90% CI range of a wearable monitor lies within the equivalence zone then it can be concluded (with an α <0 .05) that the wearable monitor value is equivalent to the criterion value. Based on previous published work,[130] we established ±10% of the criterion mean MET value as the equivalence zone, by choosing the same values we will facilitate comparisons when needed.

Bland-Altman plots[131] were used to show the distribution of the error and to assess systematic variation between the criterion MET value and each wearable monitor MET value. The Bland-Altman plot is a graphical method to compare two measurement techniques. In this method, the difference score between two measures (i.e., criterion MET value- the wearable monitor MET value) is plotted against the averages of the two measures. The error distribution can be observed within three horizontal reference lines that are drawn: mean difference (zero deviation line), upper limit of agreement (+1.96 SD), and lower limit of agreement (-1.96 SD). In order to provide a statistical reference for systematic bias between the criterion MET value and each wearable monitor MET value, the difference score between methods is regressed upon the average of the two scores. Thus, the regression line provides information whether the wearable monitor value becomes more or less accurate at varying levels of the criterion value. A flat regression line in the Bland-Altman plot indicates that the MET estimate of the wearable monitor varies in the same manner as the criterion value, a positive slope indicates that the wearable monitor is positively biased when compared to the criterion MET value, and a negative slope indicates that the wearable monitor is negatively biased when compared to the criterion MET value. The White test was used to examine the presence of heteroscedasticity.[132]

Kappa statistic was used to observe agreement between each wearable monitor and the criterion value for classifying activities while taking into account the agreement occurring by chance.[133] Data were dichotomous indicator variables for SB (0) or LPA (1). The kappa value interpretation is based on recommendations from Landis and Koch[134] as follows: 0–0.2 = slight agreement, 0.2–0.4 = fair agreement, 0.4–0.6 = moderate agreement, 0.6–0.8 = substantial agreement, and 0.8–1.0 = almost perfect agreement.

Sensitivity and specificity were calculated to measure the accuracy of the wearable monitors to classify an activity as SB or LPA. Sensitivity is the proportion of true positives (i.e., correct MET category for the wearable monitor and the criterion value) that are correctly identified by the wearable monitor (true positive proportion).

Sensitivity was calculated using the formula: Sensitivity = True positives / (True positives + False negatives).[135] A sensitivity value close to 1 shows that the wearable monitor is able to accurately classify a high proportion of the activities into the correct category; a sensitivity value close to 0 indicates that the wearable monitor fails to classify activities into the correct category. Specificity refers to the proportion of true negatives (i.e., correct exclusion of the wearable monitor and the criterion value from the incorrect category) that are correctly classified by the wearable monitor (true negative proportion). Specificity was calculated using the formula: Specificity = True negatives / (False positives + True negatives).[135] A specificity value close to 1 shows that the wearable monitor is able to exclude a high proportion of the activities from being classified into the incorrect category. A specificity value close to 0 indicates that the wearable monitor is unable to exclude activities from being classified into the incorrect category. Significance was set at the $p < 0.05$ probability level. All analyses were performed using SPSS Version 21 (IBM Corporation, Armonk, NY, USA) and SAS Version 9.3 (SAS Institute Inc., Cary, NC, USA).

Results

ICC test-retest values were high for all wearable monitors (0.94, 0.97, 0.99, and 0.85 for Oxycon Mobile, ActiGraph, activPAL™, and SenseWear, respectively). Tables 2 and 3 present means, SD, and 95% CIs in METs for the criterion and all wearable monitors under assessment for SB and LPA respectively. MPE is presented for the ActiGraph, activPAL™, and SenseWear wearable monitors referenced to the criterion value. For both SB and LPA, MPEs were lowest for the activPAL™ and highest for the

SenseWear monitors. When SB and LPA were combined, MPEs were lowest for the ActiGraph and highest for the SenseWear.

Table 2 - Measured MET values for sedentary behaviors (<1.5 METs) and mean percent error (MPE)

		METs			
		Criterion	**Actigraph**	**activPAL™**	**SenseWear**
Standing reading	n[a]	30	21	15	29
	Mean	1.13	1.44	1.40	1.07
	(SD)	(0.18)	(0.00)	(0.00)	(0.07)
	[95% CI]	[1.07 - 1.20]	[1.44 - 1.44]	[1.40 - 1.40]	[1.05 - 1.10]
	MPE	NA	32.48	32.34	-2.55
Sitting typing	n[a]	31	22	16	30
	Mean	1.25	1.44	1.25	1.96
	(SD)	(0.17)	(0.01)	(0.00)	(0.77)
	[95% CI]	[1.19 - 1.32]	[1.44 - 1.45]	[1.25 - 1.25]	[1.68 - 2.25]
	MPE	NA	12.96	0.98	56.05
Sitting board games	n[a]	30	21	15	29
	Mean	1.17	1.44	1.27	1.67
	(SD)	(0.16)	(0.01)	(0.05)	(0.63)
	[95% CI]	[1.11 - 1.23]	[1.44 - 1.45]	[1.24 - 1.30]	[1.42 - 1.91]
	MPE	NA	21.67	12.36	41.05
All Sedentary Combined	n[a]	91	64	46	88
	Mean	1.18	1.44	1.30	1.57
	(SD)	(0.17)	(0.01)	(0.07)	(0.68)
	[95% CI]	[1.15 - 1.22]	[1.43 - 1.44]	[1.28 - 1.32]	[1.42 - 1.71]
	MPE	NA	22.22	14.89	31.79

[a] The number of valid data points is different due to monitor error

Table 3 - Measured MET values for light intensity activities (>1.5 METs) and mean percent error (MPE)

		METs			
		Criterion	**Actigraph**	**activPAL™**	**SenseWear**
Walking 1 mph	n[a]	31	22	16	29
	Mean	2.19	1.55	2.22	3.06
	(SD)	(0.27)	(0.10)	(0.44)	(0.53)
	[95% CI]	[2.09 - 2.28]	[1.51 - 1.60]	[1.98 - 2.46]	[2.86 - 3.26]
	MPE	NA	-29.88	0.06	40.68

Table 3 - Measured MET values for light intensity activities (>1.5 METs) and mean percent error (MPE)

		METs			
		Criterion	Actigraph	activPAL™	SenseWear
Walking 1.5 mph	n[a]	30	21	16	29
	Mean	2.46	1.80	2.94	3.45
	(SD)	(0.28)	(0.20)	(0.50)	(0.47)
	[95% CI]	[2.35 - 2.56]	[1.71 - 1.89]	[2.68 - 3.21]	[3.27 - 3.63]
	MPE	NA	-27.42	27.10	41.14
Walking 2 mph	n[a]	30	21	15	29
	Mean	2.74	2.35	3.41	3.86
	(SD)	(0.30)	(0.32)	(0.06)	(0.49)
	[95% CI]	[2.63 - 2.85]	[2.20 - 2.49]	[3.38 - 3.45]	[3.68 - 4.05]
	MPE	NA	-15.71	23.88	42.36
Cleaning kitchen	n[a]	30	21	15	29
	Mean	1.68	1.47	1.43	3.04
	(SD)	(0.32)	(0.03)	(0.04)	(0.74)
	[95% CI]	[1.56 - 1.80]	[1.45 - 1.48]	[1.41 - 1.46]	[2.76 - 3.32]
	MPE	NA	-11.20	-13.17	82.18
All Light Combined	n[a]	121	85	62	116
	Mean	2.26	1.78	2.50	3.35
	(SD)	(0.48)	(0.39)	(0.81)	(0.65)
	[95% CI]	[2.17 - 2.35]	[1.70 - 1.87]	[2.29 - 2.71]	[3.23 - 3.47]
	MPE	NA	-21.15	9.30	51.58

[a] The number of valid data points is different due to instrument error

Based upon the equivalence plots displayed in figure 1, none of the wearable monitors (and their associated CI) fell within the equivalency range of ±10% for the criterion mean. The ActiGraph fell above the equivalence zone for SB and below the zone for LPA; the activPAL™ provided estimates closest to the equivalency range for both SB and LPA; and, the SenseWear was over the equivalence range for both SB and LPA.

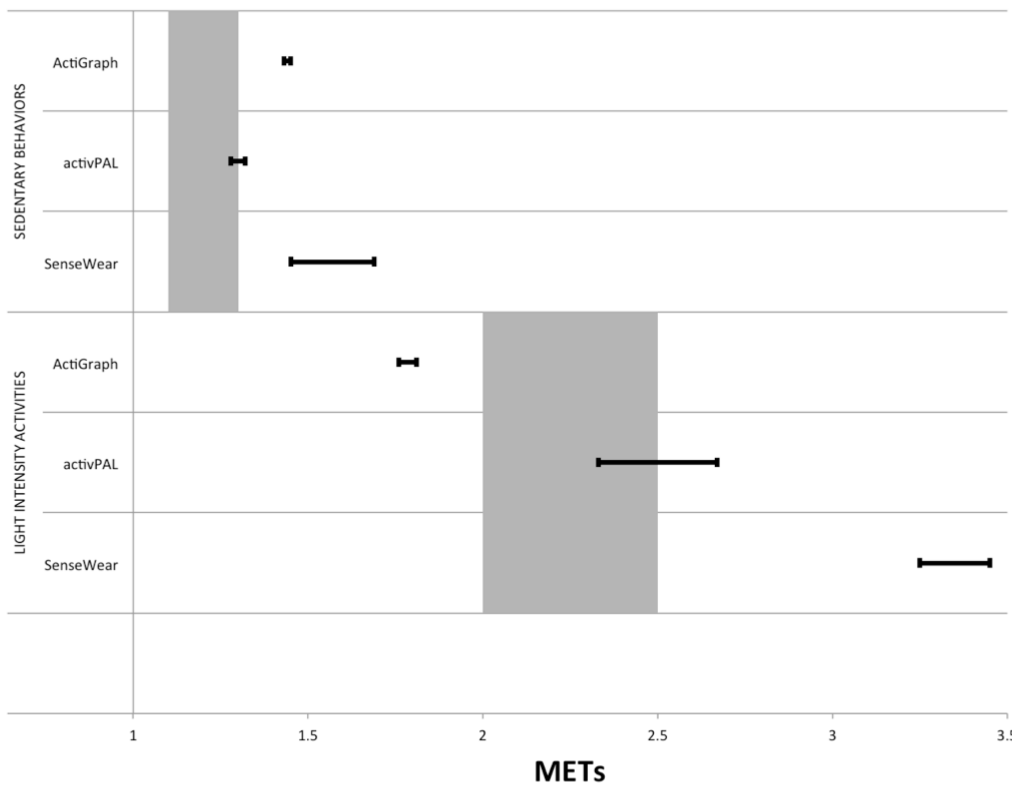


Figure 1 Equivalence Plots for Sedentary Behaviors and Light Intensity Physical Activities Compared with the Criterion Measure. Grey area represents +/-10% for the criterion mean (equivalence zone), black bars represents 90% confidence interval for the test monitor

Bland-Altman plots (Figure 2) revealed narrower levels of agreement for the wearable monitors when measuring SB (0.56, 0.55, and 1.62 METs for ActiGraph, activPAL™, and SenseWear, respectively) than when measuring LPA (1.42, 1.31, and 2.20 METs for ActiGraph, activPAL™, and SenseWear respectively). For SB, the ActiGraph and the activPAL™ had no pronounced variation across the intensity range, meanwhile the SenseWear showed a slight cluster of data points below the mean difference line. The variation for LPA was greater for all of the devices compared to the variation observed in SB; the ActiGraph had greater variation at higher intensity levels with a negative slope indicating a negative bias for EE as the intensity levels increased.

Heteroscedasticity was found for the that activPAL™ ($p = 0.11$) and SenseWear ($p = 0.30$) for SB but not for LPA.

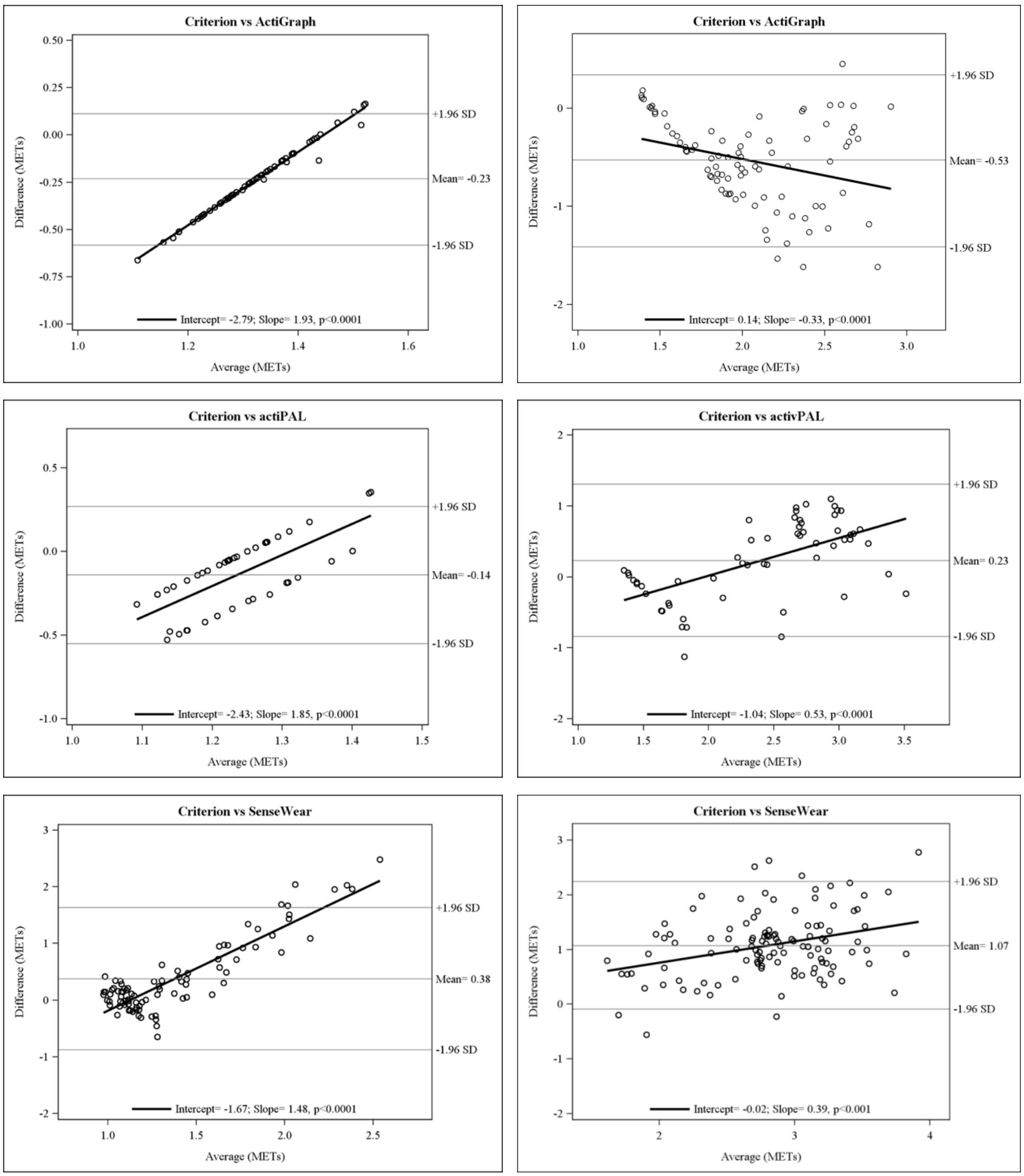


Figure 2 Bland-Altman plots for sedentary behaviors and light intensity physical activities MET values compared with the criterion value. Left panel shows sedentary behaviors, right panel shows light intensity physical activities.

Table 4 shows the kappa statistics for agreement between the wearable monitors and the criterion measure to classify SB and LPA as well as results for sensitivity and specificity. There was a slight overall agreement among the instruments for measuring SB. For LPA, the agreement was fair for the ActiGraph and moderate for the activPAL™. When data for SB and LPA were combined, the agreement increased markedly. For SB, both the ActiGraph and activPAL™ had high sensitivity but low specificity. For LPA, both the ActiGraph and activPAL™ had fair sensitivity and good specificity, meanwhile the SenseWear had good sensitivity but low specificity.

Table 4 - Kappa statistics, sensitivity, and specificity for the monitors MET values compared to the criterion MET values

		ActiGraph	**activPAL™**	**SenseWear**
Sedentary Behaviors	Kappa statistics	-0.03 (p=0.02)	0 (p=NA)	0.11 (p=0.08)
	Sensitivity	0.98	1.00	0.65
	Specificity	0.00	0.00	0.66
Light Intensity Activities	Kappa statistics	0.37 (p=0.01)	0.53 (p=0.14)	0 (p=NA)
	Sensitivity	0.73	0.84	1.00
	Specificity	1.00	1.00	0.00
Combined	Kappa statistics	0.64 (p=0.06)	0.80 (p=0.06)	0.58 (0.05)
	Sensitivity	0.98	1.00	0.57
	Specificity	0.68	0.81	0.98

Discussion

The aim of the present study was to examine the accuracy of three wearable monitors (ActiGraph GT3X+, activPAL™ and SenseWear 2) to estimate EE during sedentary and light-intensity physical activities in adults as compared with oxygen uptake measured by indirect calorimetry. The results showed overall low accuracy of the three wearable monitors to estimate EE in METs. These findings emphasize the need for more refinements in the low spectrum of the EE measurements given the necessity of accurately estimates of SB and/or LPA in the regard of its relation with mortality and chronic diseases.[16] The analyses are relevant as estimations made by the tested wearable monitors are often used in PA research and commonly used to quantify behaviors in the lower range of intensity. While the wearable monitors validity and reliability has been demonstrated in the moderate-to-vigorous EE spectrum, the tested wearable monitors showed considerable limitations in measuring the metabolic cost of SB and LPA. For example, Calabró et al.[40] examined the validity of EE estimates during sedentary-to-moderate intensity activities for different monitors compared to the Oxycon Mobile. They reported a 25.5% and 22.2% underestimation for the ActiGraph and activPAL™ monitors respectively. Their magnitude of underestimation is similar to what we found in the current study for the ActiGraph (21.15%), but differs for the activPAL™ (9.30%), the discrepancies found may be explained by the fact that their protocol included less structured activities that could have increased the amount of error for the ActivPAL™ monitor. Similarly, Kozey-Keadle et al.[25] conducted a study to examine the validity of two monitors to classify SB against direct observation as the criterion. They found that both the ActiGraph and activPAL™ monitors underestimated time spent in SB by 4.9% and 2.8%, respectively. They also tested the monitors for their ability to detect changes between sedentary and active. They found that the activPAL™ was more precise in measuring time in SB and more sensitive in detecting reductions in sitting time. Even though the Kozey-Keadle et al.[25] study and the current study used different metrics (Percentage Bias vs. MPE) and outcomes (time spent in SB vs. EE), the results are similar in the sense that the ActivPAL™ monitor performed best when estimating SB.

Possible explanations for the measurement error observed in the current study are that arm movements related to certain activities that might cause the SenseWear not to differentiate arm-movements (such as typing) from free ambulation. In addition, a small range of motion for the hip while walking at slow speeds on the treadmill may cause that the ActiGraph misclassified some LPA as SB. Another possible explanation of error measurement of the ActiGraph relates to the characteristics of the Freedson prediction equation used to estimate EE values.[136] The Freedson equation was validated using treadmill walking and running activities ranging from 3-9 mph. The EE estimates may be less accurate with lower intensity activities. We acknowledge the availability of other equations to estimate METs from the ActiGraph cpm in adults;[137–142] however, we are unaware of an equation to estimate EE during SB-to-LPA for the ActiGraph. Thus, we chose Freedson's equation[136] given its common use in the field and validity ($R^2 = 0.82$; SEE = ± 1.12 METs).

Among the three assessed wearable monitors, the activPAL™ was located in the anterior and medial thigh. The activPAL™ showed the lowest amount of error compared with the other wearable monitors (MPE = 14.89, MPE = 9.30 for SB and LPA, respectively). Thus, locating wearable monitors in the lower limbs seemed to be a more suitable location when measuring SB and LPA. These findings need further confirmation with wearable monitors placed in even more distal locations, such as the ankle. Alternatively, the activPAL™ may include a more sensitive transducer than the ActiGraph or SenseWear wearable monitors which may make it more suitable for SB and LPA.[90] However, this assertion has to be tested as we investigated the validity of the equations of each monitor not the transducers itself.

Interestingly, less error distribution was observed in the tested wearable monitors for SB than LPA. This was demonstrated by the Bland-Altman plots which revealed narrower levels of agreement for SB than LPA. In particular, the lowest limits of agreement were for the activPAL™ as compared with the other wearable monitors (0.55 METs for the SB and 1.31 METs for LPA). On the other hand, the heteroscedasticity test revealed that the variance of the residuals was not homogenous for the activPAL™ and SenseWear in SB. These results suggest a systematic bias in the two wearable monitors for assessing SB. In other words, the activPAL™ and SenseWear wearable monitors seem to have positive bias with heterogeneous error variation when assessing SB. Future research should be conducted to assess the sources of variability on the measurement of SB.

Despite the fact that all wearable monitors had high test-retest reliability (ICC=0.94, ICC=0.97, ICC=0.99, and ICC=0.85 for the OM, ActiGraph, activPAL™, and SenseWear respectively), all wearable monitors showed low agreement with the criterion measure to classify activities as either SB or LPA. When SB and LPA were combined into one category the agreement of the wearable monitors tended to be better than when evaluated separately (see kappa statistics in table 4). In a similar manner, the accuracy of the devices seemed to improve when SB and LPA were combined (see sensitivity and specificity results in table 4). This may have been due to having more data points with a greater range of values from low-to-light intensity EE. Also, it may be due to reduced variation in movement when performing SBs as compared with LPAs. These results highlight the importance of refining wearable monitors accuracy for the lower spectrum of the EE (sedentary-to-light).

When assessing the validity of wearable monitors for measuring SB, researchers should pay special attention to the criterion selection regarding the complexity of the behavior measured. Any waking behavior characterized by an EE ≤1.5 METs while in a sitting or reclining posture.[10] As a consequence, and whenever possible, a combination of criterion measures, should be considered (e.g., VO_2 for EE and direct observation for postural allocation). In the current study we aimed to examine the accuracy of wearable monitors to estimate EE of se dentary-to-light activities; thus, a criterion such as the VO_2 was needed to detect small differences between SB and LPA. However, a more comprehensive approach in classifying SB and LPA should include also the assessment of posture to fully address the ability of a device to detect SB. Among the selected activities for the current study there was one activity, standing while reading, that we classified as a SB. We considered that the very low EE of 1.13 METs and its lack of motion made this activity more an SB than an LPA type of activity. However, this assertion may not be applicable to everybody as the EE for standing may differ according to individual characteristics.[121]

There were several strengths to this study. First, participants wore the three wearable monitors and the Oxycon Mobile simultaneously so each activity could be monitored within a laboratory setting. Second, activities were randomized to prevent systematic bias in the measurement, which allowed the results to improve in accuracy. Last, activities were selected to be near the light-intensity activity threshold of >1.5 METs. This insured that activities performed would aid in understanding the accuracy of estimating EE in the lower end of the spectrum (sedentary-to-light).

With respect to the results for EE estimations for this study, it should be noted that the participants' resting metabolic rates were not measured and we used the standard MET value of 3.5 ml•kg^{-1}•min^{-1} to estimate resting EE units. This may have introduced error resulting in an overestimation of resting EE (10% and 15% for men and women, respectively) as reported for a recent systematic review.[143] Also, we observed that the MET values in the lower levels of the intensity spectrum for SB activities were quite homogeneous, which implies reducing the variance needed to obtain a substantial agreement. Additionally, we would like to notice that the seven sedentary-to-light activities may not be representative of the whole spectrum of sedentary-to-light EE; however, they were thoughtfully selected and randomly assigned order to avoid introducing systematic error. We acknowledge that the participants comprised a convenience sample of healthy adults and data were obtained in a laboratory setting with staged activities limiting generalization of the results to other populations (e.g., older adults). Missing data were caused by problems with wearable monitors initialization and an inability to save data to a spreadsheet. Although having missing data is a limitation, the data loss was random and did not represent a systematic bias.

Conclusion

As growing evidence demonstrates the associations between SB and morbidity and mortality more research and refinements in EE estimations and in the ability of wearable monitors to record SB-to-LPA is needed. Based on equivalency testing none of the wearable monitors tested in this study was equivalent with the criterion measure of oxygen uptake for estimating EE in SB-to-LPA. However, among the wearable monitors tested the activPAL™ had the highest overall criterion validity to measure both SB and LPA as compared with the ActiGraph and SenseWear wearable monitors.

Chapter 5

WEARABLE MONITORS ACCURACY TO CLASSIFY SEDENTARY AND STATIONARY TIME UNDER FREE-LIVING CONDITIONS

Abstract

Background. Uni-axial cut points are commonly used to estimate sedentary time (ST) from wearable monitors. However, it is likely that cut-points reflect stationary time (StT) rather than exclusively ST. Tri-axial vector magnitude cut-points (VMCP) provide an opportunity to accurately measuring ST and StT; however, its accuracy in free-living is to be determined. The aims of this study were (1) to test the accuracy of selected cut-points and VMCP to classify ST and StT in free-living conditions and (2) to develop optimal VMCP to classify ST and StT based upon data collected under free-living conditions.

Methods. Twenty participants (mean age = 30.25 ± 6.43 years) wore five wearable monitors, ActiGraph GT3X+ (each wrist and waist) and GENEActiv (each wrist). Two criterion measures (ST and StT) were determined from direct observation during 1 weekday and 1 weekend day. Data were analyzed using mean percent error, Bland-Altman plots, kappa coefficient, sensitivity, and specificity as compared two both criterion.

Results. Accuracy was low for tested cut-points regardless of the monitor location and criterion used. Across all accuracy metrics, ActiGraph 100 counts per minute, worn on the right-hip and ActiGraph 150 counts per minute, worn on the right-hip demonstrated moderate accuracy to identify StT but not ST. The ActiGraph right-hip cut-points had better accuracy to measure ST than left and right wrist cut-points. Estimated VMCP increased accuracy for measuring ST and StT regardless of the location worn.

Conclusion. ActiGraph cut-points (50, 100, 150, 200, 250, and 500 counts per minute) and GENEActiv VMCP (217 and 386 counts per minute) had limited overall accuracy to assess ST in free-living settings. The ActiGraph 100 counts per minute, worn on the right-hip and ActiGraph 150 counts per minute, worn on the right-hip accurately identified StT but not ST. Estimated VMCP increased the accuracy of measuring ST and StT in free living settings; the ActiGraph 2000 counts per minute, worn on the left-wrist and the ActiGraph 63 counts per minute, worn on the right-hip were the most accurate thresholds to classify ST and StT, respectively.

Key Words: Accelerometers, sedentary, objective measurement, cut-points, validity.

Introduction

Accelerometer-based wearable monitors have gained a strong interest in sedentary behavior and public health research as they can be used to measure total volume and breaks in sedentary time .[24] Cut-points traditionally have been used to assess sedentary time from wearable monitors. Cut-points are numerical values for the acceleration of movement intensity (activity counts) that reflect differences in the energy cost of movement. Higher numerical cut-points reflect higher energy costs and vice versa. Cut-points are derived from prediction equations in which accelerometer counts are regressed against energy expenditure values in kilocalories or in oxygen uptake values.[35] Cut-points that reflect sedentary behaviors have been established for activity counts equivalent to ≤ 1.5 METs and are summarized using 1-minute data-collection epochs. To date, several uniaxial cut-points for classifying ST with a hip-mounted ActiGraph have been proposed including 50,[35] 100,[12] and 150 counts per minute (CPM). Triaxial cut-points that classify sedentary time from a GENEActiv have been proposed including 217 and 386 CPM for left-wrist and right-wrist respectively.[39]

Despite their extensive use, using cut-points to reflect sedentary time has limitations. There is no consensus on which threshold is the most accurate cut-point to classify sedentary time and few cut-points have been tested in free-living conditions.[33] The development of existing cut-points have been limited mainly to laboratory-based simulations of free-living behaviors, which implies less variability in behavior patterns as compared to free-living settings. While the most commonly used cut-point for sedentary time is 100 CPM, this cut point has been observed to underestimate sedentary time by 5%.[25] Further, while derived from waist-mounted wearable monitors,[12] the 100 CPM has been applied to data obtained from wrist-mounted wearable monitors.[119] Other concerns about the use of the cut-points approach to estimate sedentary time is that it assumes a linear relationship between activity counts and energy expenditure estimates; however, cut-points-derived estimates of sedentary time reflect none or little movement and not all types of sedentary time. Accordingly, the cut-points can result in inaccurate estimates of sedentary time.[35–37] For example, time spent in light intensity physical activities such as dusting or washing dishes is classified as sedentary time.[120] Furthermore, there are recent findings of intra-individual variations in the energy cost of steady-state-standing with some individuals having little or no change in energy expenditure during standing relative to sitting.[121] Thus, it is likely that existing uniaxial sedentary cut-points reflect stationary types of behaviors (e.g., sitting and standing) rather than exclusively sedentary behaviors (e.g., sitting, lying down). As one's cardiometabolic health may be enhanced differentially by interrupting prolonged sitting time with frequent brief bouts of light-intensity activity and standing,[73] valid measurement of sedentary and stationary behaviors is likely important.

Tri-axial wearable monitors provide an opportunity to refine cut-points to measure sedentary and stationary time. Tri-axial wearable monitors display activity counts for separate axes (vertical, anteroposterior, and mediolateral) and a composite vector magnitude of its three axes. Accurate vector magnitude cut-points have been developed to estimate physical activity intensities for tri-axial GENEActiv and the ActiGraph monitors.[34,39,144] However, vector magnitude cut-points have not been developed to assess sedentary and stationary behaviors with the ActiGraph. Sedentary vector magnitude cut-points have been developed under laboratory settings for the

GENEActiv, however, the cut points have not been extensively tested in free-living settings.[39] Therefore, the aims of this study were (1) to test the accuracy of selected uniaxial and vector magnitude cut-points to classify sedentary and stationary time in free-living conditions and (2) to develop optimal vector magnitude cut-points to classify sedentary and stationary time based upon data collected under free-living conditions.

Materials and methods

Participants

A convenience sample of 20 adults was recruited for the study. Eligible participants were (a) 18-65 years of age; (b) normal to overweight body mass index (18.5 to 29.9 kg/m^2); and (c) without disease or disability that could inhibit daily physical activity (assessed by completing the Physical Activity Readiness Questionnaire - PAR-Q).[125] Participants were recruited through e-mail announcements and fliers placed on the Arizona State University campus. All enrolled participants provided informed consent prior to participation and the study protocol was approved by the Arizona State University Institutional Review Board.

Wearable monitors

The ActiGraph GT3X+ (ActiGraph LLC, Pensacola, FL, USA) and the GENEActiv (ActivInsights, Cambs, United Kingdom) wearable monitors were used in this study. The ActiGraph is a triaxial wearable monitor capable of recording accelerations in three axes (vertical, anteroposterior, and mediolateral). The ActiGraph GT3X+ measures accelerations ranging from 30-Hz up to 100-Hz in response to a magnitude range of ± 3 g. The GENEActiv is a triaxial wearable monitor capable of recording accelerations in three axes; it measures accelerations ranging from 10Hz up to 100Hz in response to a magnitude range of +/-8 g.

Participants wore five monitors simultaneously. One ActiGraph GT3X+ accelerometer on each wrist in the most proximal position using the manufacturer's adjustable wrist band, the monitors were placed with the brand logo oriented to be read by the participant. One GENEActiv accelerometer on each wrist in the most distal position next to the ActiGraph accelerometer, the monitors were placed with the serial oriented to be read by the participant. One ActiGraph accelerometer was worn on the hip over the right anterior superior iliac spine mounted with an elastic belt and with the USB cap oriented towards the participant's head.

ActiLife® software 6.11.5 and GENEActiv software 2.9 for ActiGraph and GENEActiv respectively were used to initialize and download wearable monitors. Wearable monitors were initialized to collect data at the highest possible resolution (100Hz). Data from the worn monitors were downloaded to .csv files in 1-, 15-, and 60-second epochs.

Before field data collection, monitors were tested for inter-monitor reliability by placing them in the same body location (left arm) during five different activities performed in a 10-minute period. Intraclass correlation coefficients (ICC) were calculated for inter-monitor reliability in the vertical axis using 1-minute data-collection epochs (ICC = 0.95 for ActiGraph, and 0.96 for GENEActiv wearable monitors).

Cut-points

To achieve the first aim of the study, we selected several uniaxial (vertical axis) cut-points for the ActiGraph wearable monitor to be tested (50,[35] 100,[12] 150,[25] 200, 250, and 500[38] CPM). Each cut-point was tested in three different body locations: left-wrist, right-wrist, and right-hip. In addition, we selected two vector magnitude cut-points, 217 and 386 CPM for the GENEActiv wearable monitors to be tested in the left and right wrist.[39]

For the second aim of the study, we estimated cut-points for 60-seconds epoch with ActiGraph (left, right wrist and right hip), 15-second epoch with ActiGraph (left, right wrist and right hip), 15-second epoch for GENEActiv (left, right wrist), 1-second epoch for ActiGraph (left, right wrist and right hip), and 1-second epoch for GENEActiv (left and right wrist) using receiver operating characteristic (ROC) curve analyses.

Criterion Measure: Direct Observation

Direct observation with focal sampling and duration coding were used to collect criterion data in real-time occurrence in free-living conditions for six activity categories (walking, running, sports and exercise, household chores, standing, and sitting and lying down), in five different contexts (household, transportation, occupation, sports and conditioning, and leisure). Each of the activity categories is described below:

- Walking. This activity category included walking for all locomotion purposes, walking in flat or inclined surfaces, and walking up or down stairs. Incidental or incomplete steps that didn't result in moving from one place to another were not included in this category (e.g., weight shifting).
- Running. This activity category included continuous and short bouts of running or

jogging (e.g., jogging for exercising or short runs to cross the street).

- Sports and conditioning exercise. This activity category included playing sports or performing continuous or intermittent conditioning exercises. Other exercises different than running or jogging were included in this category (e.g., weight lifting, yoga, Pilates, or gym classes).
- Household chores. This activity category included housekeeping activities such as dish washing, gardening, vacuuming, and doing the laundry.
- Standing. This activity category included standing with or without upper body movements while bearing the body weight in one or both lower limbs. Incidental or incomplete steps that didn't result in moving from one place to another were included in this category.
- Sitting and lying down. This activity category included various body positions in which the body weight was not supported by the participant's feet. Instead, the body weight was supported by the buttocks, thighs or back; this included sitting, sitting in a laboratory stool, reclining and lying down (supine and prone).

Additional observation categories were designed as follow:

- Private. When during the data collection sessions the participant required private time (e.g., restrooms use), researchers recorded this time as 'private' and resumed the activity recording as soon as the participant finished the private activity.
- Unobserved. When the participant was available to be observed but out of the sight of the researchers (e.g., turning corners), researchers recorded this time as 'unobserved.'

- Error. When researcher made an error or unable to determine an accurate coding for a given activity.

Enrolled participants were directly observed by two researchers in their free-living environment for 6-hours on two days, a weekday and a weekend day. Each researcher independently recorded activities in an iPad tablet; thus, every time a participant changed the activity, researchers made an annotation reflecting the new activity. A commercially available app, Timestamped Field Notes app (TFNA) was used to make annotations.[118] TFNA allows configuration of colored buttons for pre-defined observation categories. TFNA stores annotations in an offline database that later can be downloaded as a .txt file containing the timestamp and the observations made at each time point. Tablets were time synchronized with the same computer in which the wearable monitors were initialized and downloaded. At the end of each visit day, data from the tablet were downloaded and exported to a text file (.txt).

The sedentary criterion variable was a dichotomous variable including sitting and lying down for those observations in which both researchers had 100% agreement. A minute was considered sedentary when most of its seconds were sedentary (i.e., between 31-60 seconds per minute). The stationary criterion variable (stationary) was calculated with the same criteria except standing activities were included in the sedentary category.

Researchers training

Two researchers completed 24 hours of one-to-one supervised training consisting of:

- Two hours to become familiarized with the study protocols (including thorough explanations of activity categories), as well as tablets use.
- Two hours of training in direct observation techniques designed not to disrupt, disturb or modify the participant's natural behavior to every extent possible (e.g., in the case of reduced space locations where to place himself to be able to observe the participant without disturbing).
- Ten hours of direct observation practice using the tablets to record observations while watching a set of training videos of different members of our lab while doing their own activities at work and home environments.
- Ten hours of direct observation practice using the tablets in real-time occurrence with members of our lab while doing their own activities at work and home environments.

After the training, researchers completed a testing session of direct observation on a set of 8 different video clips with a total duration of 40 minutes (testing video set). The testing set was previously coded by two senior researchers in our lab; it was the result of several independent trials of video coding until there was full agreement between the two senior researchers. To be able to collect field data, researchers were required to have high agreement with the testing set; the agreement was measured with an ICC greater than 0.80.

Statistical analysis

Descriptive statistics were performed to characterize the sample by sex, age, and BMI. ICC was used to observe agreement between researchers' field observations. Several computations were made to measure the accuracy (first aim) of the selected cut-points to classify an activity as sedentary for each one of the aforementioned wearable monitors and locations. Percent Error (PE) was calculated to assess the proportion of error for each of the selected cut-points relative to the sedentary criterion measure. PE was calculated using the equation: PE = [(Monitor Total Sedentary Minutes – Criterion Sedentary Minutes) / Criterion Sedentary Minutes] x 100. A positive PE indicated an overestimation of sedentary time whereas a negative PE indicated underestimation.

Kappa was used to observe agreement between each cut-point and the sedentary criterion value for classifying activities as sedentary while taking into account the agreement occurring by chance.[133] Landis and Koch published categories to interpret the kappa values as follows: 0–0.2 = slight agreement, 0.2–0.4 = fair agreement, 0.4–0.6 = moderate agreement 0.6–0.8 = substantial agreement, and 0.8–1.0 = almost perfect agreement.[134]

Sensitivity and specificity were calculated to measure the accuracy of the selected cut-points to classify an activity as sedentary. Sensitivity measures the ability of a cut-point to correctly classify an activity as sedentary (true positives proportion). Sensitivity was calculated using the formula: Sensitivity = True positives / (True positives + False negatives). A sensitivity value close to 1 shows that the cut-point can correctly classify a high proportion of the activities as sedentary; a sensitivity value close to 0 indicates that the cut-point fails to classify activities as sedentary. Specificity measures the ability of a cut-point to correctly classify an activity as non-sedentary (true negatives proportion). Specificity was calculated using the formula: Specificity = True negatives / (False positives + True negatives). A specificity value close to 1 shows that the cut-point can correctly classify a high proportion of the activities as non-sedentary. A specificity value close to 0 indicates that the cut-point fails to classify activities as non-sedentary. PE, kappa, sensitivity, and specificity were also calculated to measure the accuracy (first aim) of the selected cut-points to classify an activity as stationary for each one of the aforementioned wearable monitors and locations as compared to the stationary criterion.

To develop vector magnitude cut-points (second aim), the observations were randomly divided into training (50%) and testing (50%) datasets. Using the training dataset, receiver operating characteristic (ROC) curve analyses were conducted with both criteria (sedentary and stationary). To determine the cut-points we used the minimum distance method. The minimum distance refers to the closest value to the optimal point at the upper-left corner of the ROC plot where Sensitivity=1 and 1-Specificity=0. The area under the ROC curve (AUC) was also calculated for each of the estimated cut-points. The AUC is an index of the accuracy of the ROC curve.[145] An AUC=1 means that the estimated cut-point is perfect in the classification of activities. An AUC=0.5 means that the estimated cut-point is no better than chance in the classification activities. An AUC=0 means that the estimated cut-point incorrectly classify all activities. To further test the accuracy of the estimated cut-points, PE, simple kappa coefficient, sensitivity, and specificity were computed in the testing dataset to compare the classifications made from the estimated cut-points with direct observation. ROC curve analyses were conducted using ROCPLOT macro for SAS.[146] All analyses were performed using SAS version 9.4.

Results

All 20 participants completed the study. Participants were 50% female. Participants' mean age was 30.25 (± 6.43) years and mean BMI was 22.7 (± 3.1) kg/m^2.

All of the participants enrolled in the study were right-handed. Due to device error 5.99 hours were missing for the GENEActiv on right wrist.

A total of 241.32 hours of free-living direct observation were conducted. The average length of free-living observation sessions was 5.97 ± 0.26 hours. Table 5 shows a breakdown for averages of the direct observation classification categories and contexts. There was a substantial agreement between researchers' observations (ICC=0.76, 95% CI = 0.75-0.77).

Table 5 - Minutes + standard deviation and percent of the observation period stratified by activity categories, context, and days of the week

	Weekdays		Weekends		Combined	
Total observation time (minutes)	7,180		7,314		14,494	
Activity	Minutes	%	Minutes	%	Minutes	%
Sitting/lying	187.4	52.3	140.5	38.5	163.9	45.4
Standing	64.6	18.1	79.0	21.6	71.7	19.8
Other non-	28.9	8.0	23.8	6.5	26.4	7.26
Unobserved	5.8 (6.8)	1.6	3.6 (7.5)	1.0	4.7 (7.2)	1.3
Private time	4.9 (6.0)	1.3	8.0 (13.9)	2.2	6.4 (10.7)	1.8
Context	Minutes	%	Minutes	%	Minutes	%
Sports/conditioni	15.9	4.4	19.8	5.2	17.9	4.7
Household	2.3 (8.8)	0.66	2.9 (13.2)	0.8	2.6 (11.1)	0.8
Transportation	16.4	4.7	21.2	5.8	18.8	5.2
Occupation	241.9	67.4	88	23.9	164.9	45.7
Leisure	28.6	8.0	148.8	41.1	88.7	24.7
	Minutes	%	Minutes	%	Minutes	%
Non-agreement	67.4	18.5	110.9	30.3	89.1	24.5

Cut-points accuracy

To assess the first study aim, we tested the accuracy of several selected uniaxial ActiGraph and vector magnitude GENEActiv cut-points to classify sedentary and stationary time as compared to the time spent in sedentary- (sitting and lying down) and stationary (sitting, lying, and standing) behaviors obtained from direct observation. Tables 6 and 7 show PE, kappa coefficient, sensitivity, and specificity for the tested cut-points for the sedentary and stationary criteria, respectively. The variable names reflect combinations of the type of monitor used (ActiGraph (AG) and GENEActiv (GA)), cut-point level (e.g., 50 CPM), and body location which the wearable monitors was worn on (e.g., left wrist).

Table 6 - Percent error, simple kappa, sensitivity, and specificity for selected sedentary cut-points as compared to the sedentary criterion

	Axis	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
AG50 left-wrist	1	-73.04	0.06 (0.05 to 0.07)	0.15 (0.15 to 0.16)	0.90 (0.90 to 0.91)
AG50 right-wrist	1	-72.05	0.08 (0.06 to 0.09)	0.17 (0.16 to 0.17)	0.91 (0.90 to 0.91)
AG50 right-hip	1	18.37	0.27 (0.26 to 0.29)	0.69 (0.68 to 0.70)	0.59 (0.58 to 0.60)
AG100 left-wrist	1	-66.66	0.08 (0.07 to 0.10)	0.19 (0.18 to 0.20)	0.88 (0.88 to 0.89)
AG100 right-wrist	1	-65.01	0.10 (0.09 to 0.11)	0.21 (0.20 to 0.22)	0.88 (0.88 to 0.89)
AG100 right-hip	1	35.53	0.29 (0.28 to 0.31)	0.78 (0.77 to 0.79)	0.52 (0.51 to 0.53)
AG150 left-wrist	1	-61.16	0.10 (0.09 to 0.12)	0.23 (0.22 to 0.24)	0.87 (0.86 to 0.88)
AG150 right-wrist	1	-58.96	0.13 (0.11 to 0.14)	0.25 (0.24 to 0.26)	0.87 (0.86 to 0.88)
AG150 right-hip	1	45.54	0.30 (0.28 to 0.31)	0.83 (0.82 to 0.84)	0.48 (0.47 to 0.49)
AG200 left-wrist	1	-55.33	0.12 (0.11 to 0.14)	0.27 (0.26 to 0.28)	0.85 (0.84 to 0.86)
AG200 right-wrist	1	-53.24	0.15 (0.14 to 0.17)	0.29 (0.28 to 0.30)	0.85 (0.85 to 0.86)
AG200 right-hip	1	52.47	0.30 (0.29 to 0.31)	0.86 (0.85 to 0.87)	0.45 (0.44 to 0.46)
AG250 left-wrist	1	-48.73	0.15 (0.14 to 0.17)	0.31 (0.30 to 0.32)	0.83 (0.83 to 0.84)
AG250 right-wrist	1	-47.74	0.17 (0.16 to 0.19)	0.33 (0.32 to 0.34)	0.84 (0.83 to 0.85)
AG250 right-hip	1	57.64	0.29 (0.28 to 0.30)	0.88 (0.87 to 0.89)	0.42 (0.41 to 0.43)
AG500 left-wrist	1	-22.00	0.24 (0.23 to 0.26)	0.48 (0.47 to 0.50)	0.76 (0.75 to 0.76)
AG500 right-wrist	1	-25.85	0.26 (0.24 to 0.27)	0.47 (0.46 to 0.49)	0.78 (0.77 to 0.79)
AG500 right-hip	1	72.71	0.25 (0.24 to 0.26)	0.93 (0.92 to 0.94)	0.34 (0.33 to 0.35)
GA217 left-wrist	3	-0.66	-0.29 (-0.31 to -0.28)	0.61 (0.60 to 0.62)	0.68 (0.67 to 0.69)
GA217 right-wrist[a]	3	-15.73	-0.26 (-0.28 to -0.25)	0.53 (0.52 to 0.54)	0.74 (0.73 to 0.75)
GA386 left-wrist	3	39.16	-0.36 (-0.37 to -0.34)	0.82 (0.81 to 0.83)	0.53 (0.52 to 0.54)

Table 6 - Percent error, simple kappa, sensitivity, and specificity for selected sedentary cut-points as compared to the sedentary criterion

	Axis	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
GA386 right-wrist[a]	3	28.38	-0.36 (-0.38 to -0.35)	0.78 (0.77 to 0.79)	0.58 (0.57 to 0.59)

[a] Due to device malfunctioning there was 5.99 missing hours on this device, accordingly analyses include only 235.33 hours.
The variable names reflect combinations of the type of wearable monitor used (ActiGraph (AG) and GENEActiv (GA)), and body location which the wearable monitor was worn on (e.g., left-wrist).

Table 7 - Percent error, simple kappa, sensitivity, and specificity for selected sedentary cut-points as compared to the stationary criterion

	Axis	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
AG50 left-wrist	1	-81.40	0.02 (0.01 to 0.03)	0.13 (0.12 to 0.14)	0.89 (0.88 to 0.90)
AG50 right-wrist	1	-80.74	0.01 (0.00 to 0.01)	0.13 (0.12 to 0.14)	0.88 (0.87 to 0.89)
AG50 right-hip	1	-18.26	0.20 (0.18 to 0.21)	0.61 (0.60 to 0.62)	0.60 (0.59 to 0.62)
AG100 left-wrist	1	-77.00	0.03 (0.02 to 0.04)	0.16 (0.16 to 0.17)	0.87 (0.87 to 0.88)
AG100 right-wrist	1	-75.90	0.02 (0.01 to 0.03)	0.17 (0.16 to 0.17)	0.86 (0.85 to 0.87)
AG100 right-hip	1	-6.38	0.25 (0.23 to 0.26)	0.70 (0.69 to 0.71)	0.55 (0.54 to 0.57)
AG150 left-wrist	1	-73.15	0.04 (0.03 to 0.05)	0.19 (0.19 to 0.20)	0.86 (0.85 to 0.87)
AG150 right-wrist	1	-71.61	0.03 (0.02 to 0.04)	0.20 (0.19 to 0.21)	0.84 (0.83 to 0.85)
AG150 right-hip	1	0.44	0.28 (0.26 to 0.29)	0.75 (0.75 to 0.76)	0.52 (0.51 to 0.54)
AG200 left-wrist	1	-69.19	0.05 (0.04 to 0.06)	0.22 (0.22 to 0.23)	0.84 (0.83 to 0.85)
AG200 right-wrist	1	-67.76	0.04 (0.03 to 0.05)	0.23 (0.22 to 0.24)	0.82 (0.81 to 0.83)
AG200 right-hip	1	5.28	0.29 (0.28 to 0.31)	0.79 (0.78 to 0.80)	0.50 (0.48 to 0.51)
AG250 left-wrist	1	-64.57	0.06 (0.05 to 0.07)	0.26 (0.25 to 0.27)	0.82 (0.81 to 0.83)
AG250 right-wrist	1	-63.91	0.05 (0.04 to 0.06)	0.26 (0.25 to 0.27)	0.80 (0.79 to 0.81)
AG250 right-hip	1	8.80	0.30 (0.29 to 0.32)	0.82 (0.81 to 0.82)	0.48 (0.46 to 0.49)
AG500 left-wrist	1	-46.20	0.10 (0.09 to 0.12)	0.40 (0.39 to 0.41)	0.73 (0.72 to 0.74)
AG500 right-wrist	1	-48.84	0.09 (0.08 to 0.10)	0.37 (0.36 to 0.38)	0.73 (0.72 to 0.75)
AG500 right-hip	1	19.25	0.31 (0.30 to 0.33)	0.88 (0.87 to 0.89)	0.40 (0.39 to 0.42)
GA217 left-wrist	3	-31.35	-0.14 (-0.15 to -0.12)	0.50 (0.49 to 0.51)	0.65 (0.63 to 0.66)
GA217 right-wrist[a]	3	-3.96	-0.18 (-0.19 to -0.16)	0.70 (0.70 to 0.71)	0.51 (0.50 to 0.52)
GA386 left-wrist	3	-41.80	-0.11 (-0.12 to -0.09)	0.42 (0.41 to 0.43)	0.69 (0.68 to 0.70)
GA386 right-wrist[a]	3	-11.33	-0.16 (-0.17 to -0.14)	0.65 (0.64 to 0.65)	0.54 (0.52 to 0.55)

[a] Due to device malfunctioning there was 5.99 missing hours on this device, accordingly analyses include only 235.33 hours.
The variable names reflect combinations of the type of wearable monitor used (ActiGraph (AG) and GENEActiv (GA)), and body location which the wearable monitor was worn on (e.g., left-wrist).

When compared to the sedentary criterion (sitting and lying down), none of the cut-points tested had outstanding accuracy (PE ranging from -73% to 72%; kappa <0.30; sensitivity <0.53; and specificity <0.91). Overall, ActiGraph hip cut-points showed better accuracy than wrist cut-points. The left-wrist cut-points tended to be less accurate than right-wrist and right-hip cut-points. Further, the left-wrist cut-points tended to have high negative percent error, (except for the GA217 and GA386), slight agreement (except for AG500), low-to-moderate sensitivity (except for GA217 and GA386), and high specificity (except for GA217 and GA386). With some exceptions, the right-wrist cut-points tended to have high negative percent error in excess of -25%, slight agreement with kappa's <0.17 (except for AG500), low-to-moderate sensitivity <0.53 (except for GA386), and high specificity > 0.74 (except for GA386). The right-hip cut-points tended to have moderate positive percent error (except for AG500), fair agreement, high sensitivity, and moderate specificity.

When stationary activities (standing, sitting and lying down) were included in the criterion variable, the ActiGraph hip cut-points were more accurate than the wrist cut-points. When compared to the wrist cut-points, the ActiGraph hip cut-points had a lower percent error and higher values for kappa, sensitivity, and specificity. The right-wrist GENEActiv cut-points were more accurate that the left-wrist cut-points. Among the tested cut-points AG150 right-hip was the most accurate stationary uniaxial cut-point.

Developing vector magnitude cut-points

To address the second aim, we estimated several vector magnitude cut-points to classify sedentary time based on the sedentary criterion (sitting + lying down) and stationary time based on the stationary criterion (standing + sitting + lying down).

Estimated cut-points included 1-minute epoch for the ActiGraph left-wrist, right-wrist, and right-hip. We also estimated a 15-second and a 1-second epoch for the ActiGraph left-wrist, right-wrist, and right-hip and the GENEActiv left-wrist and right-wrist. Tables 8 and 9 show values for AUC, PE, kappa, sensitivity, and specificity for the estimated cut-points (sedentary and stationary, respectively). The ROC graphics for the estimated cut-points are presented as supplemental material.

Table 8 - Percent error, kappa, sensitivity and specificity for estimated vector magnitude cut-points sedentary criterion

	VM CP	AUC	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
AG left-wrist[b]	2,000	0.702	12.98	0.33 (0.30 to 0.35)	0.69 (0.68 to 0.71)	0.63 (0.62 to 0.65)
AG right-wrist[b]	2,358	0.723	13.86	0.35 (0.33 to 0.37)	0.71 (0.70 to 0.73)	0.64 (0.63 to 0.66)
AG right-hip[b]	249	0.729	19.80	0.37 (0.35 to 0.39)	0.75 (0.74 to 0.77)	0.62 (0.61 to 0.64)
AG left-wrist[c]	455	0.672	16.17	-0.27 (-0.28 to -0.26)	0.67 (0.67 to 0.68)	0.60 (0.59 to 0.61)
AG right-wrist[c]	495	0.689	11.88	-0.30 (-0.31 to -0.29)	0.67 (0.66 to 0.68)	0.63 (0.62 to 0.64)
AG right-hip[c]	15	0.699	16.72	0.31 (0.30 to 0.32)	0.70 (0.69 to 0.71)	0.62 (0.61 to 0.62)
GA left-wrist[c]	65	0.685	19.25	-0.29 (-0.30 to -0.28)	0.70 (0.69 to 0.71)	0.59 (0.59 to 0.60)
GA right-wrist[a, c]	61	0.686	3.08	-0.28 (-0.29 to -0.27)	0.62 (0.61 to 0.63)	0.66 (0.66 to 0.67)
AG left-wrist[d]	5	0.647	16.39	0.26 (0.26 to 0.26)	0.67 (0.67 to 0.67)	0.59 (0.59 to 0.60)
AG right-wrist[d]	8	0.666	11.77	0.29 (0.28 to 0.29)	0.66 (0.66 to 0.67)	0.63 (0.62 to 0.63)
AG right-hip[d]	0	0.646	61.05	0.27 (0.26 to 0.27)	0.88 (0.88 to 0.88)	0.40 (0.40 to 0.40)
GA left-wrist[d]	2	0.664	14.41	-0.25 (-0.25 to -0.25)	0.65 (0.65 to 0.66)	0.60 (0.59 to 0.60)
GA right-wrist[a,d]	3	0.661	17.60	-0.25 (-0.26 to -0.25)	0.67 (0.67 to 0.67)	0.58 (0.58 to 0.59)

[a] Due to device malfunctioning there was 5.99 missing hours on this device, accordingly analyses include only 235.33 hours. [b] 1-minute epoch length. [c] 15-second epoch length. [d] 1-second epoch length.
The variable names reflect combinations of the type of wearable monitor used (ActiGraph (AG) and GENEActiv (GA)), and body location which the wearable monitor was worn on (e.g., left-wrist).
VMCP = Vector Magnitude Cut-Point, AUC = Area Under the curve.

Table 9 - Percent error, kappa, sensitivity and specificity for estimated vector magnitude cut-points stationary criterion

	VM CP	AUC	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
AG left-wrist[b]	2,365	0.611	-13.31	0.19 (0.17 to 0.21)	0.64 (0.63 to 0.65)	0.56 (0.54 to 0.58)
AG right-wrist[b]	2,411	0.601	-20.13	0.17 (0.15 to 0.19)	0.59 (0.57 to 0.60)	0.59 (0.58 to 0.61)
AG right-hip[b]	423	0.645	-5.50	0.25 (0.22 to 0.27)	0.71 (0.70 to 0.72)	0.54 (0.52 to 0.56)
AG left-wrist[c]	523	0.603	-14.85	-0.15 (-0.16 to -0.14)	0.62 (0.61 to 0.62)	0.56 (0.55 to 0.57)
AG right-wrist[c]	630	0.598	-15.51	-0.15 (-0.16 to -0.14)	0.61 (0.60 to 0.62)	0.56 (0.55 to 0.57)

Table 9 - Percent error, kappa, sensitivity and specificity for estimated vector magnitude cut-points stationary criterion

	VM CP	AUC	Percent error	Kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
AG right-hip[c]	63	0.638	-2.20	0.22 (0.21 to 0.23)	0.72 (0.71 to 0.72)	0.51 (0.50 to 0.52)
GA left-wrist[c]	77	0.620	-10.34	-0.16 (-0.17 to -0.15)	0.65 (0.64 to 0.66)	0.54 (0.53 to 0.55)
GA right-wrist[a,c]	91	0.602	-10.89	-0.15 (-0.16 to -0.14)	0.64 (0.64 to 0.65)	0.53 (0.53 to 0.54)
AG left-wrist[d]	6	0.600	-18.37	0.17 (0.17 to 0.18)	0.60 (0.59 to 0.60)	0.59 (0.59 to 0.59)
AG right-wrist[d]	18	0.599	-16.39	0.17 (0.17 to 0.17)	0.61 (0.61 to 0.61)	0.58 (0.57 to 0.58)
AG right-hip[d]	0	0.626	11.77	0.24 (0.24 to 0.25)	0.81 (0.81 to 0.81)	0.42 (0.42 to 0.43)
GA left-wrist[d]	3	0.613	-11.00	-0.15 (-0.15 to -0.15)	0.64 (0.64 to 0.64)	0.53 (0.53 to 0.54)
GA right-wrist[a,d]	4	0.597	-11.44	-0.14 (-0.14 to -0.14)	0.63 (0.63 to 0.63)	0.53 (0.52 to 0.53)

[a] Due to device malfunctioning there was 5.99 missing hours on this device, accordingly analyses include only 235.33 hours. [b] 1-minute epoch length. [c] 15-second epoch length. [d] 1-second epoch length.
The variable names reflect combinations of the type of wearable monitor used (ActiGraph (AG) and GENEActiv (GA)), and body location which the wearable monitor was worn on (e.g., left-wrist).
AUC = Area Under the curve, VMCP = Vector Magnitude Cut-Point.

For those vector magnitude cut-points estimated from the sedentary criterion (sitting + lying down), overall accuracy metrics tended to be better for 1-minute epochs and for wrist cut-points. As compared to the sedentary uniaxial cut-points, overall accuracy metrics were higher for the estimated vector magnitude cut-points. Among the estimated vector magnitude cut-points AG2000 left-wrist was the most accurate sedentary cut-point for the AUC of 0.702.

Vector magnitude cut-points estimated from the stationary criterion (standing + sitting + lying down) had accuracy metrics that were similar across the different time epoch lengths ranging from 1 minute to 1 second. As compared to the stationary uniaxial cut-points, the overall accuracy metrics were higher for the estimated vector magnitude cut-points. Among the estimated stationary vector magnitude cut-points, AG63 right-hip seemed to be the most accurate stationary cut-point for the AUC= 0.638.

Discussion

This study had two aims (1) to test the accuracy of selected cut-points to classify sedentary and stationary time in free-living conditions and (2) to develop vector magnitude cut-points to classify sedentary and stationary time. The major findings of this study were (a) an overall lack of accuracy for the tested uniaxial cut-points regardless of the location and criterion used, (b) AG100 right-hip and AG150 right-hip demonstrated moderate accuracy to differentiate stationary time but not sedentary time, (c) the tested ActiGraph right-hip uniaxial cut-points had better accuracy to measure sedentary time than left and right wrist cut-points, and (d) the estimated vector magnitude cut-points increased accuracy for measuring sedentary and stationary time regardless of the location and criterion used.

There was a lack of accuracy to classify sedentary and stationary time for the tested uniaxial cut-points regardless of the location and criterion used. The results for the accuracy metrics used to test uniaxial cut-points were not in favor of using a specific cut-point to measure sedentary time. All of the tested uniaxial cut-points demonstrated poor accuracy to classify sedentary time regardless the location. Overall the cut-points for the left-wrist wearable monitors tended to be less accurate than the cut-points right-wrist to measure sedentary time. This might be an effect of handedness; however, we could not test this hypothesis as all of the participants in our study were right-handed. We suggest that future studies consider testing whether handedness has an effect on the accuracy of a wrist mounted wearable monitors.

The AG100 right-hip and AG150 right-hip uniaxial cut-points accurately differentiated stationary time (standing, sitting, and lying down) but not sedentary time (sitting, and lying down). As wearable monitors measure body movements using changes in acceleration that are used to estimate the intensity of physical activities over time,[45] these findings are not surprising, on the contrary, suggest caution interpreting wearable monitors -derived measures of sedentary time and its associations to health-related outcomes. Interestingly, Kozey-Keadle et al.[25] reported that the AG100 right-hip and AG150 right-hip cut-points had similar error magnitude and direction for measuring sedentary time as compared to what we found for the same cut-points when measuring standing time. Metrics used and methodological differences between Kozey-Keadle et al. and our study may explain some of the differences. For example, Kozey-Keadle et al. used the low-frequency extension for the ActiGraph while we did not apply additional filters to the wearable monitors' signal. Another possible source for the differences is the sampling frequency which is not reported in their study. Finally, the criterion used by Kozey-Keadle et al. was derived from observations of a single researcher while ours were composed by two researchers. These conflicting findings add arguments to the ongoing debate on what is the most accurate uniaxial cut-point to classify sedentary time, and whether the cut-points approach is more reflective of stationary type of behaviors rather than sedentary behaviors. We suggest that future studies consider testing the accuracy for wearable monitors to assess sedentary time vs stationary time.

All of the tested uniaxial cut-points for the ActiGraph placed on the hip showed better accuracy to measure sedentary time than those for wrist locations regardless the cut-point used. This reduced accuracy for cut-points for wrist mounted wearable monitors is likely a result of participants' arms movements that occurred during sedentary activities (e.g., typing), resulting in an increment of false negative results for sedentary time. Overall the GENEActiv cut-points had a lower PE as compared to the ActiGraph. We believe that as the GENEActiv cut-points were validated for wrist locations,[39] it is understandable why the scores for PE were lower than those for the ActiGraph cut-points that were not specifically validated for wrist locations. These results might be an indicator that the hip is a better location to place wearable monitors when assessing sedentary time. The poor accuracy of the wrist-mounted ActiGraph wearable monitors to measure sedentary time is an issue that should be further investigated as data from wrist-mounted ActiGraph wearable monitors are being used to make estimates of sedentary time at the population level in the US.[119] Furthermore, when using the ActiGraph wearable monitors in a wrist-mounted fashion, it is important to use cut-points that have been validated for that specific location.

As compared to uniaxial cut-points, the estimated vector magnitude ActiGraph cut-points improved the accuracy of measuring sedentary and stationary time considerably by reducing the overall PE and increasing kappa, sensitivity, and specificity values. Among the estimated vector magnitude cut-points, AG2000 left-wrist was the most accurate cut-point to measure sedentary time. On the other hand, AG63 right-hip was the most accurate stationary cut-point. We believe that having cut-points that accurately differentiate standing, sitting and lying down from other physical activity types may be of interest for some researchers depending on the goal of their research. We acknowledge the limited accuracy of using cut-points to assess sedentary time. However, the cut-point approach remains the method of choice for many researchers and practitioners due to its simplicity and relatively low cost. Thus, until more complex approaches are easily accessible to researchers and practitioners to score wearable monitors data, the most accurate cut-points available should be used.

As strengths of this study, we note that researchers had an intensive training that resulted in a substantial agreement between their field observations. This agreement yielded a valid criterion with less observer bias as compared to other studies that have included observations from a single researcher.[25,100] In addition, we observed our participants in free-living settings for two days (weekday and weekend day) allowing us to capture a broad range of observations in different contexts.

An important limitation of this study is that there was no energy expenditure measurement to classify sedentary time, which could have led to erroneous classifications. Also, the study sample was comprised of healthy right-handed adults limiting generalization of the results to other populations (e.g., left-handed, older adults, etc.). Last, missing data were caused by problems with a wearable monitors recording that resulted in the GENEActiv right-wrist analyses with only 235.33 hours as compared to the other wearable monitors that included 241.32 hours.

Conclusion

This study showed that ActiGraph single axis cut-points (50, 100, 150, 200, 250, and 500 CPM) and GENEActiv vector magnitude cut-points (217 and 386 CPM) had limited overall accuracy to assess sedentary time in free-living settings. The AG100 right-hip and AG150 right-hip uniaxial cut-points demonstrated to be accurate to differentiate stationary time (standing, sitting, and lying down) but not sedentary time (sitting, and lying down). The estimated vector magnitude cut-points increased accuracy of measuring sedentary and stationary time in free living settings. The estimated AG2000 left-wrist and AG63 right-hip vector magnitude cut-points were the most accurate thresholds found to classify sedentary and stationary time respectively.

Supplemental Material

Supplemental Material 1 - ROC Plot for ActiGraph Left Wrist 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 2 - ROC Plot for ActiGraph Right Wrist 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 3 - ROC Plot for ActiGraph Right hip 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 4 - ROC Plot for ActiGraph Left Wrist 15-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 5 - ROC Plot for ActiGraph Right Wrist 15-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 6 - ROC Plot for ActiGraph Right hip 15-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 7 - ROC Plot for GENEActiv Left Wrist 15-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 8 - ROC Plot for GENEActiv Right Wrist 15-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 9 - ROC Plot for ActiGraph Left Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 10 - ROC Plot for ActiGraph Right Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 11 - ROC Plot for ActiGraph Right hip 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 12 - ROC Plot for GENEActiv Left Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 13 - ROC Plot for GENEActiv Right Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion.

Supplemental Material 14 - ROC Plot for ActiGraph Left Wrist 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 15 - ROC Plot for ActiGraph Right Wrist 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 16 - ROC Plot for ActiGraph Right hip 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 17 - ROC Plot for ActiGraph Left Wrist 15-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 18 - ROC Plot for ActiGraph Right Wrist 15-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 19 - ROC Plot for ActiGraph Right hip 15-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 20 - ROC Plot for GENEActiv Left Wrist 15-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 21 - ROC Plot for GENEActiv Right Wrist 15-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

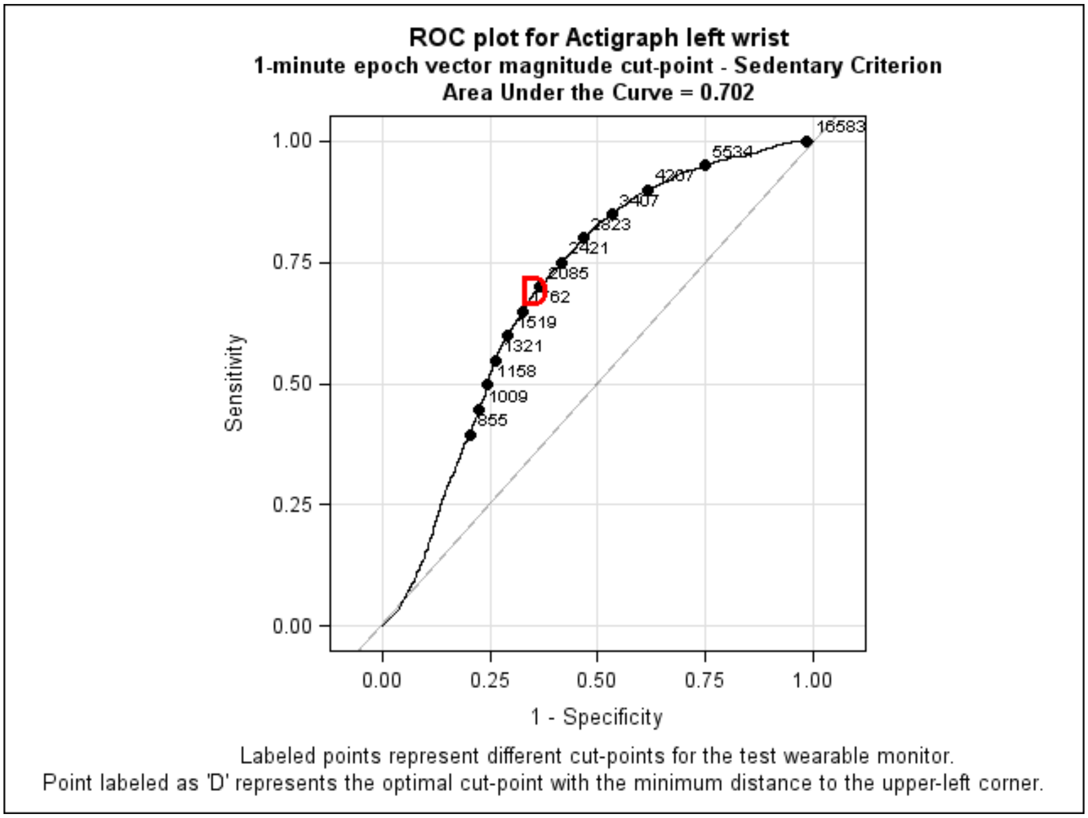
Supplemental Material 22 - ROC Plot for ActiGraph Left Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 23 - ROC Plot for ActiGraph Right Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

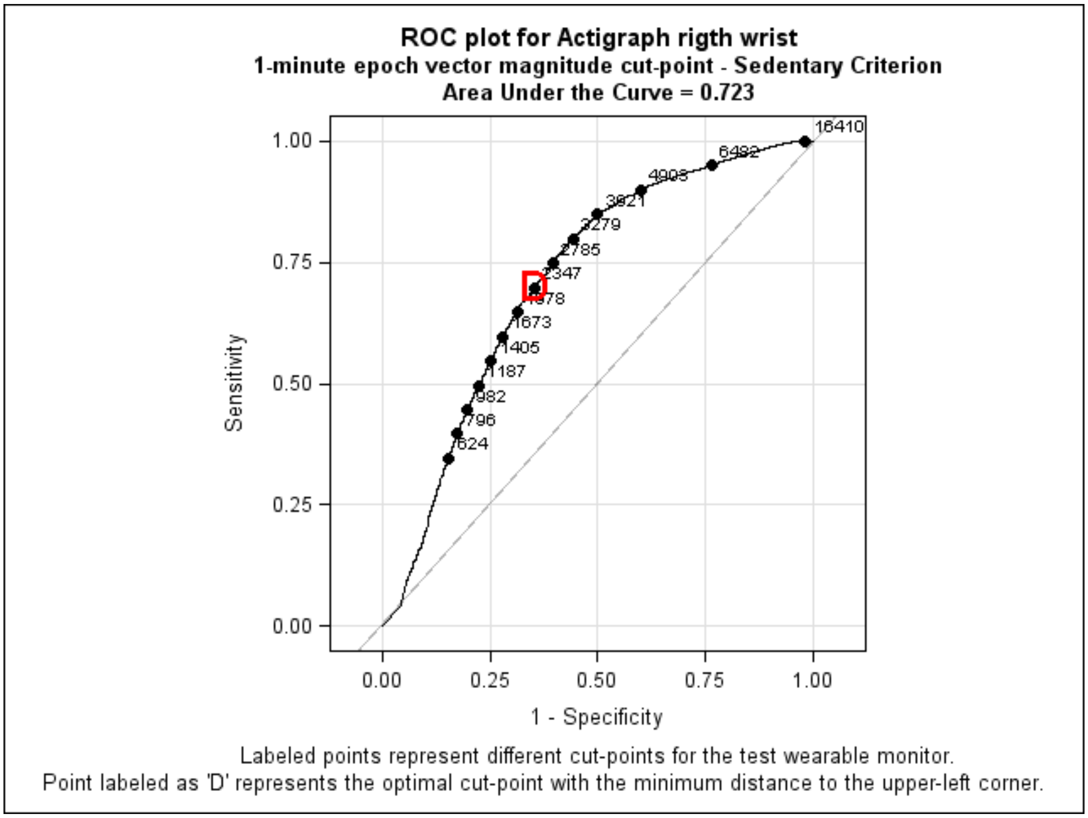
Supplemental Material 24 - ROC Plot for ActiGraph Right hip 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

Supplemental Material 25 - ROC Plot for GENEActiv Left Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion.

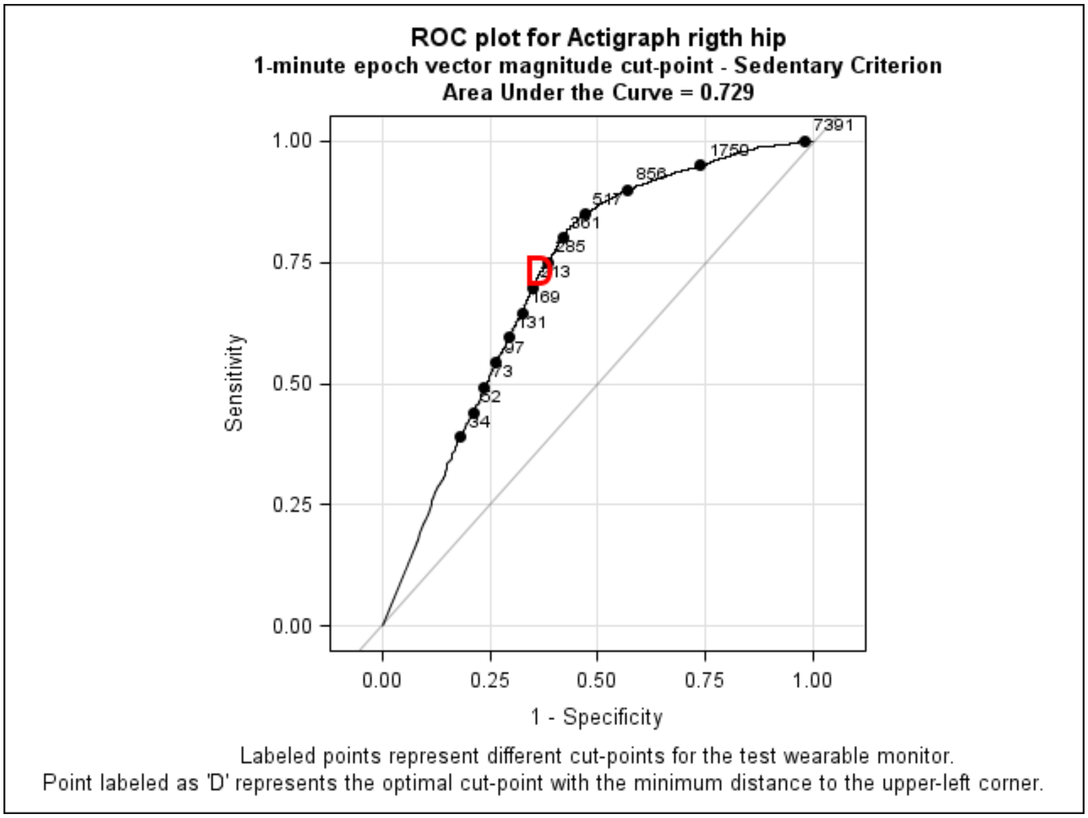
Supplemental Material 26 - ROC Plot for GENEActiv Right Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion.



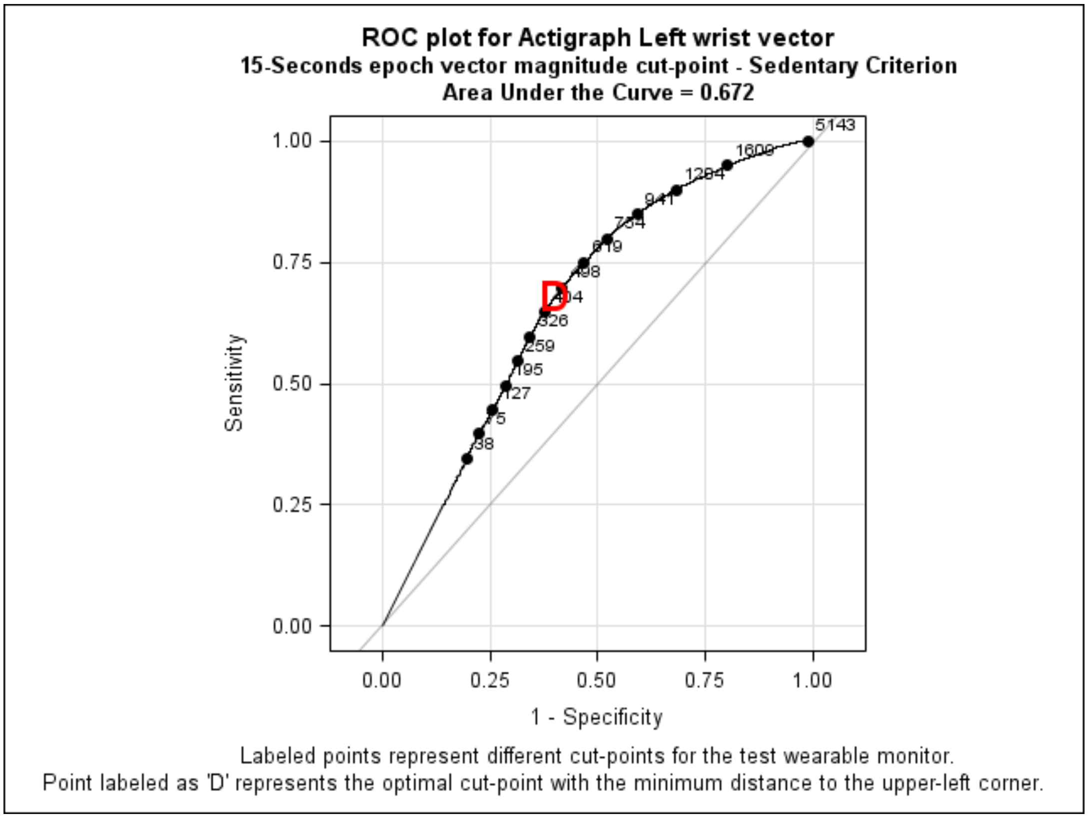
Supplemental Material 1 ROC Plot for ActiGraph Left Wrist 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion



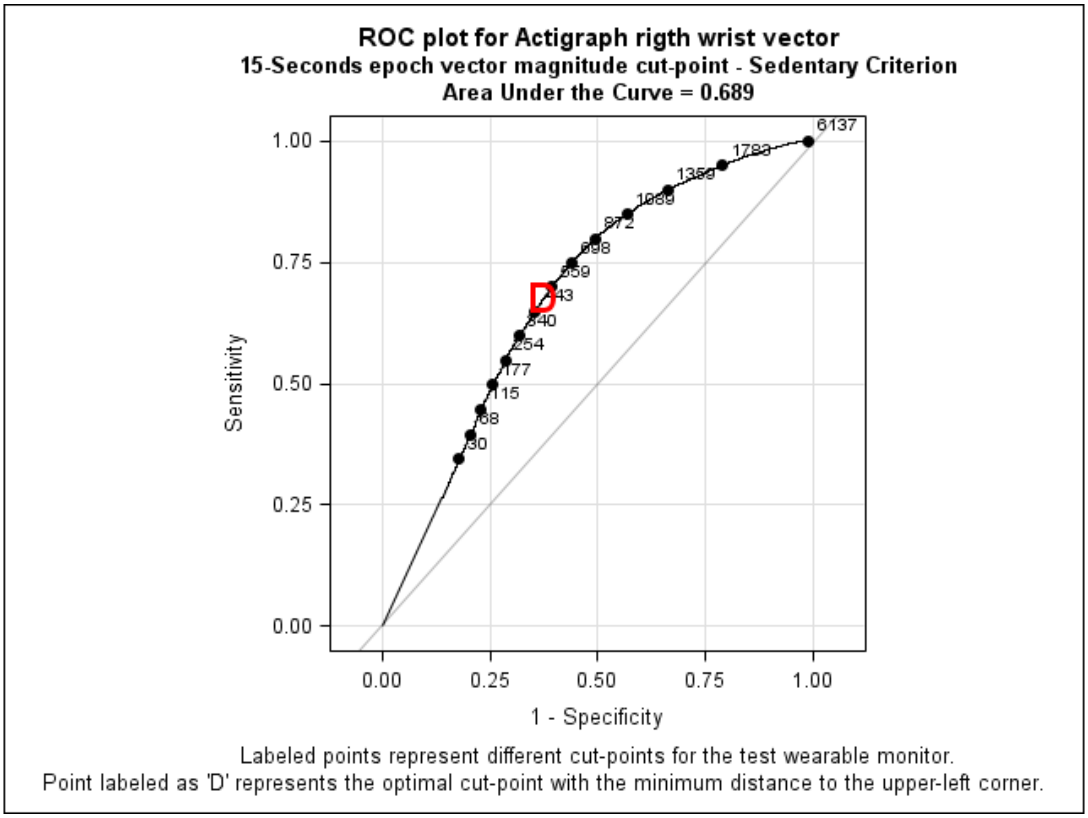
Supplemental material 2 ROC Plot for ActiGraph Right Wrist 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion



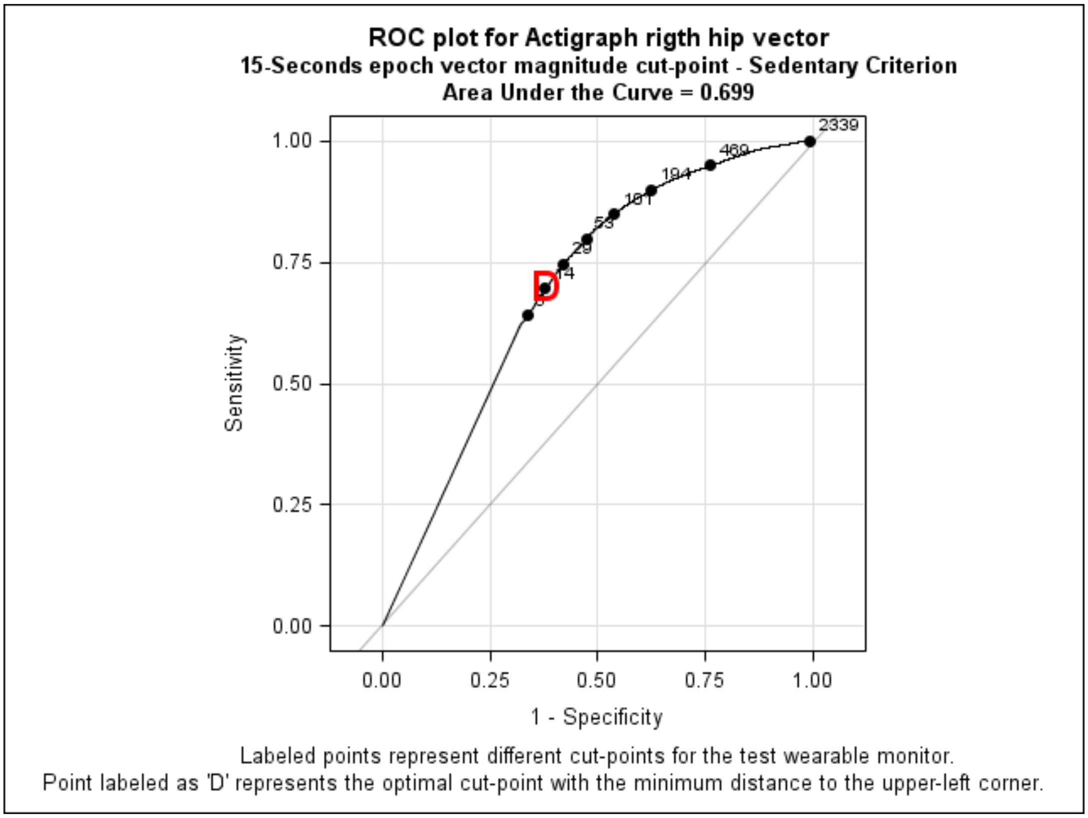
Supplemental material 3 ROC Plot for ActiGraph hip Wrist 1-minute Epoch Vector Magnitude Cut-point - Sedentary Criterion



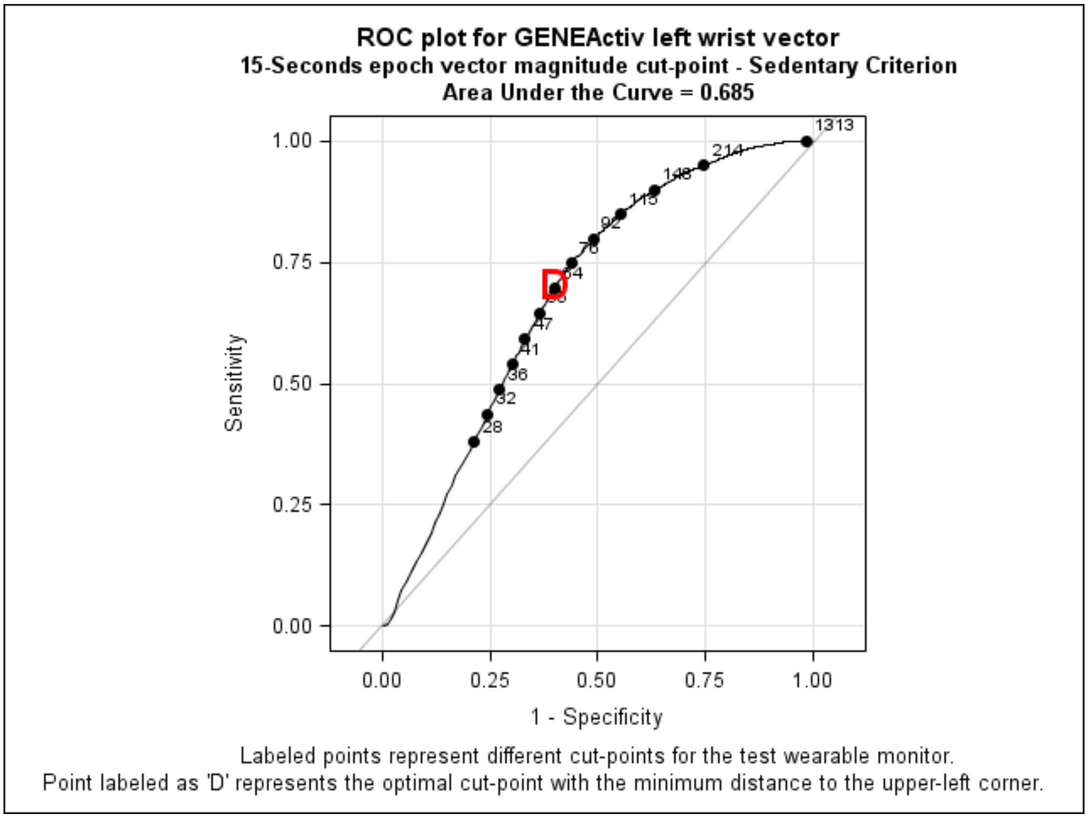
Supplemental material 4 ROC Plot for ActiGraph Left Wrist 15-seconds Epoch Vector Magnitude Cut-point - Sedentary Criterion



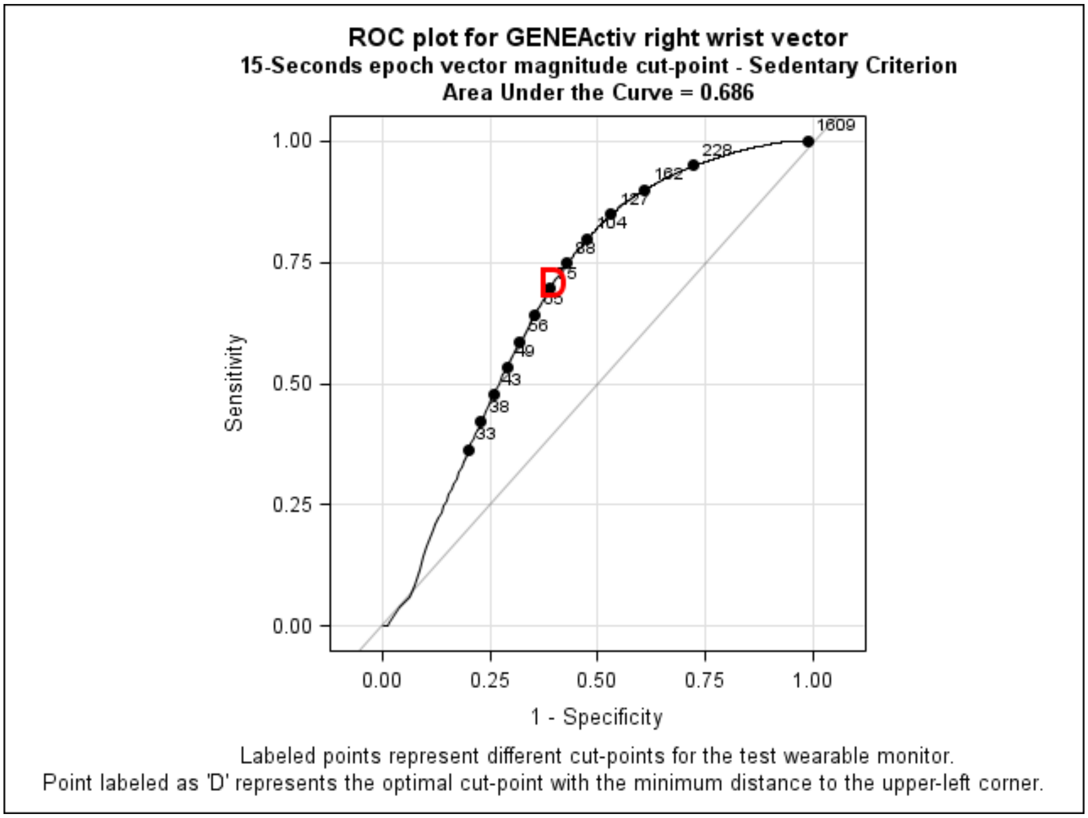
Supplemental material 5 ROC Plot for ActiGraph Right Wrist 15-seconds Epoch Vector Magnitude Cut-point - Sedentary Criterion



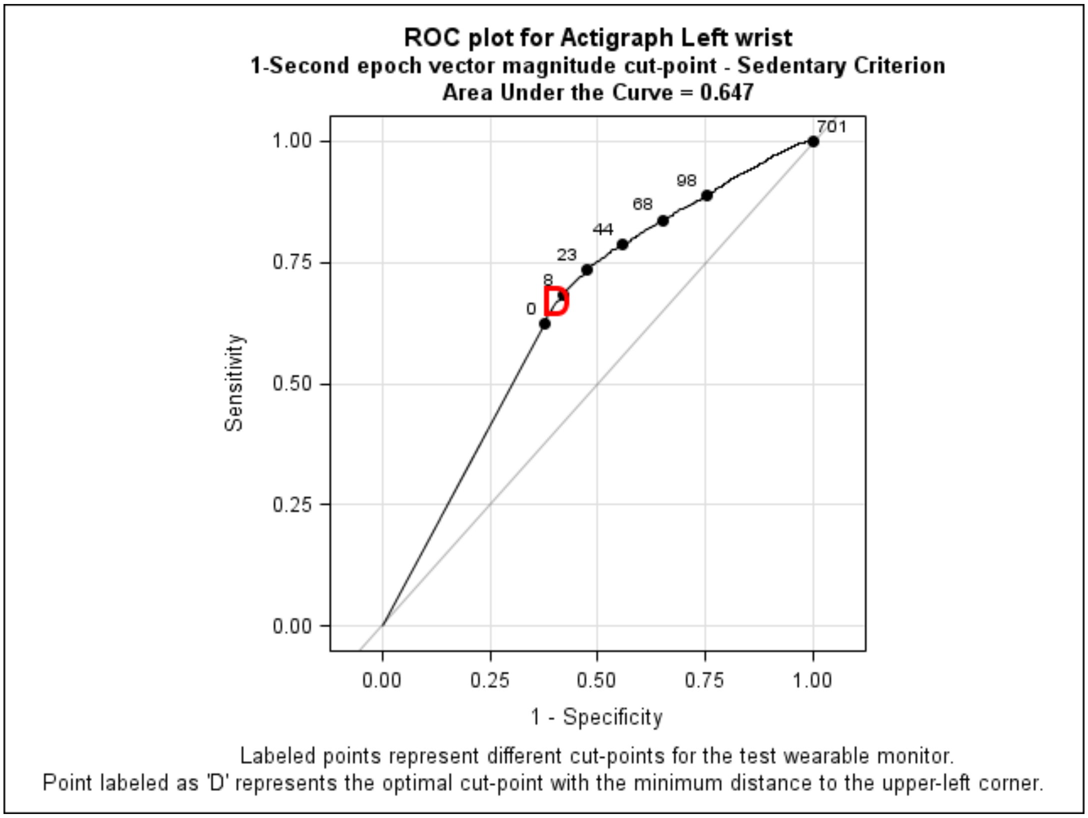
Supplemental material 6 ROC Plot for ActiGraph Right hip 15-seconds Epoch Vector Magnitude Cut-point - Sedentary Criterion



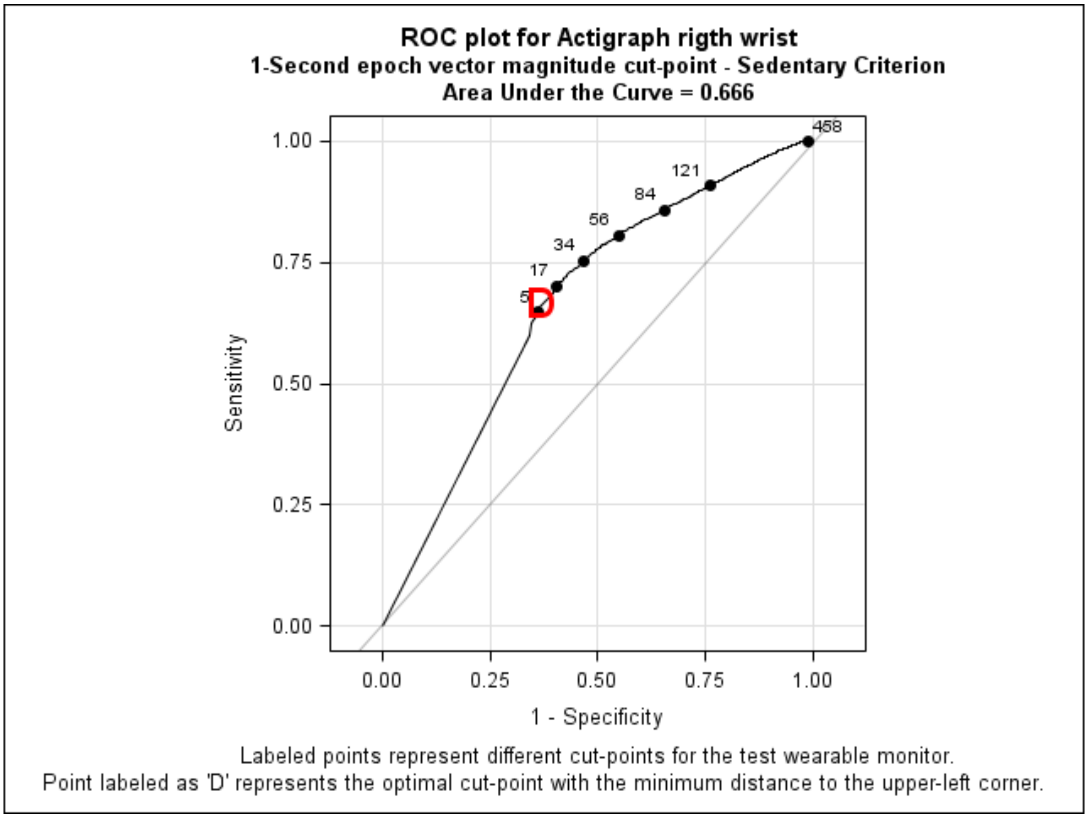
Supplemental material 7 ROC Plot for GENEActiv Left Wrist 15-seconds Epoch Vector Magnitude Cut-point - Sedentary Criterion



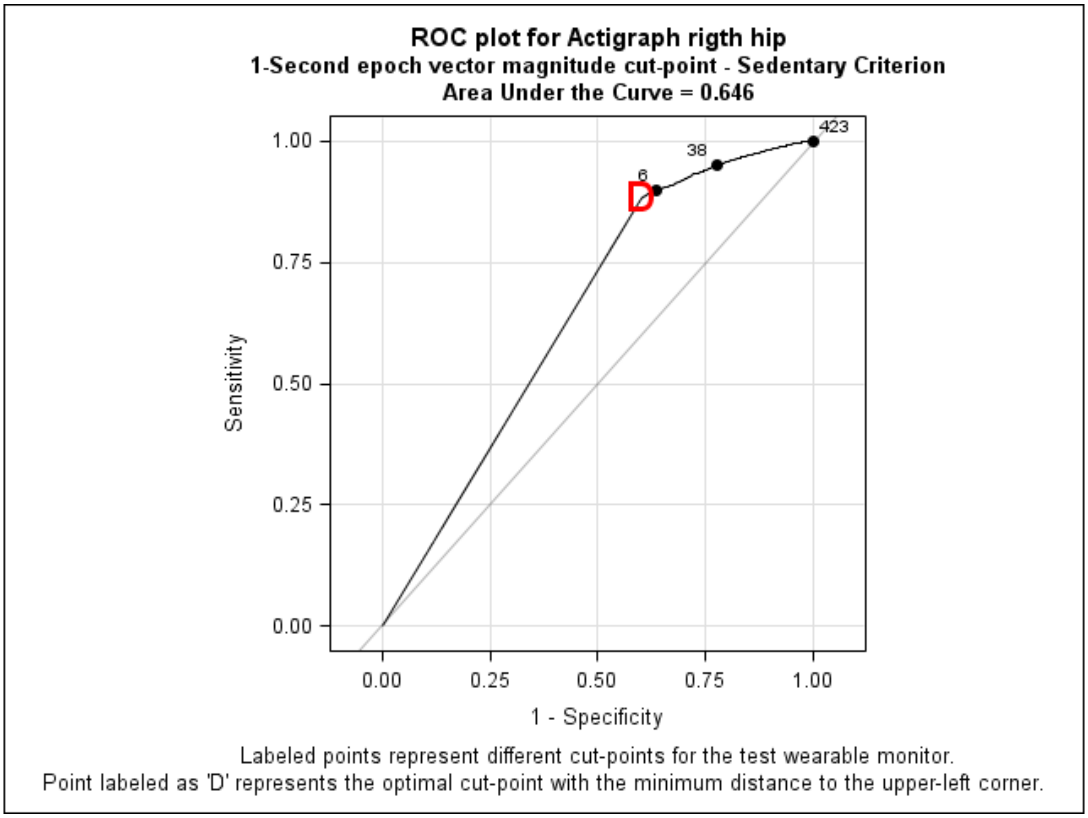
Supplemental material 8 ROC Plot for GENEActiv Right Wrist 15-seconds Epoch Vector Magnitude Cut-point - Sedentary Criterion



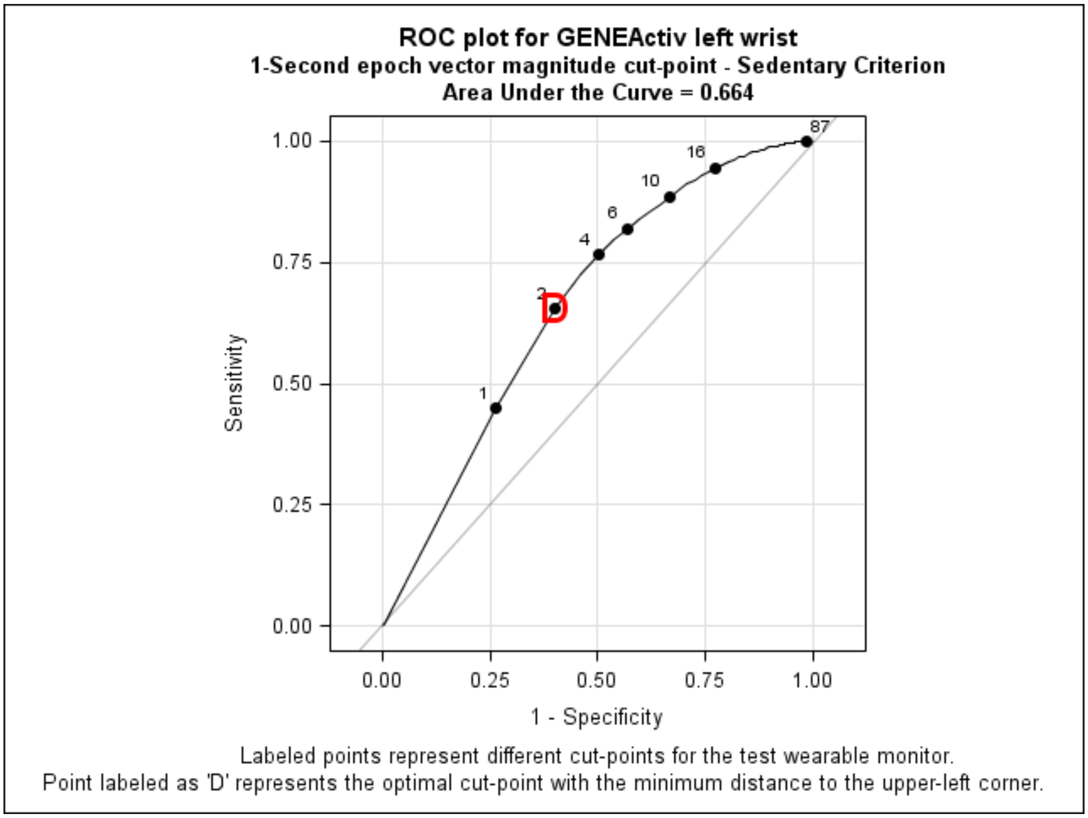
Supplemental material 9 ROC Plot for ActiGraph Left Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion



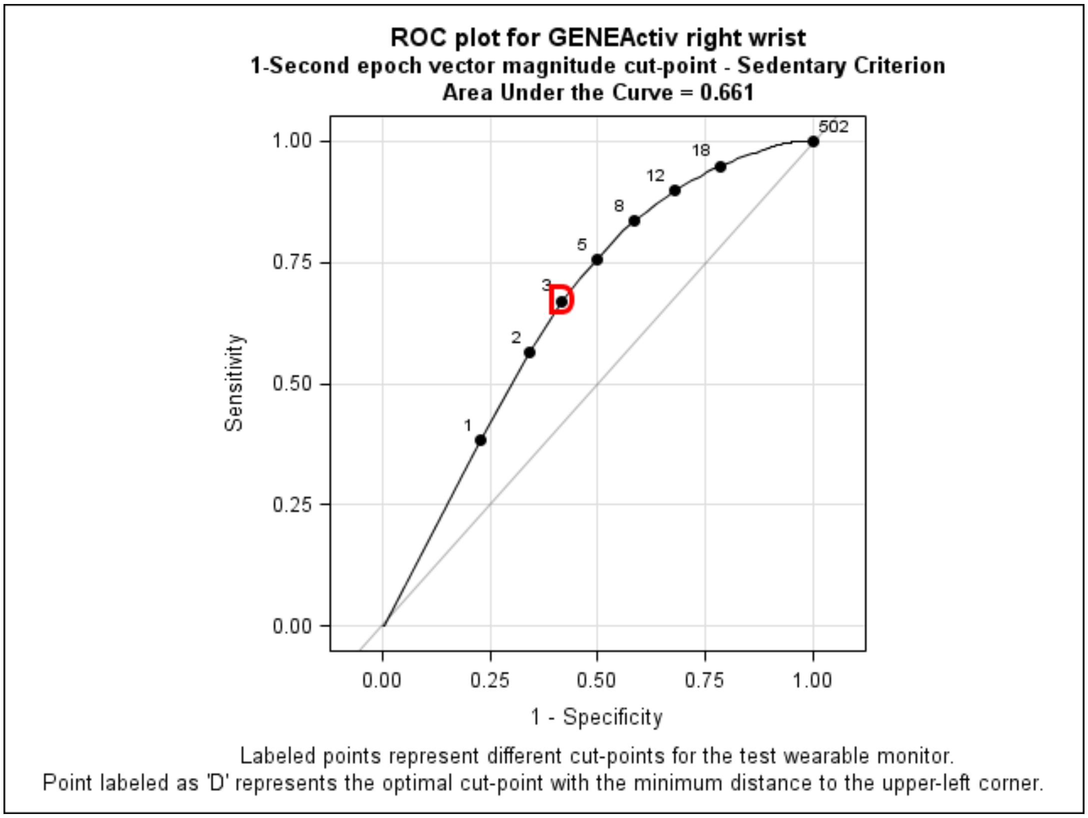
Supplemental material 10 ROC Plot for ActiGraph Right Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion



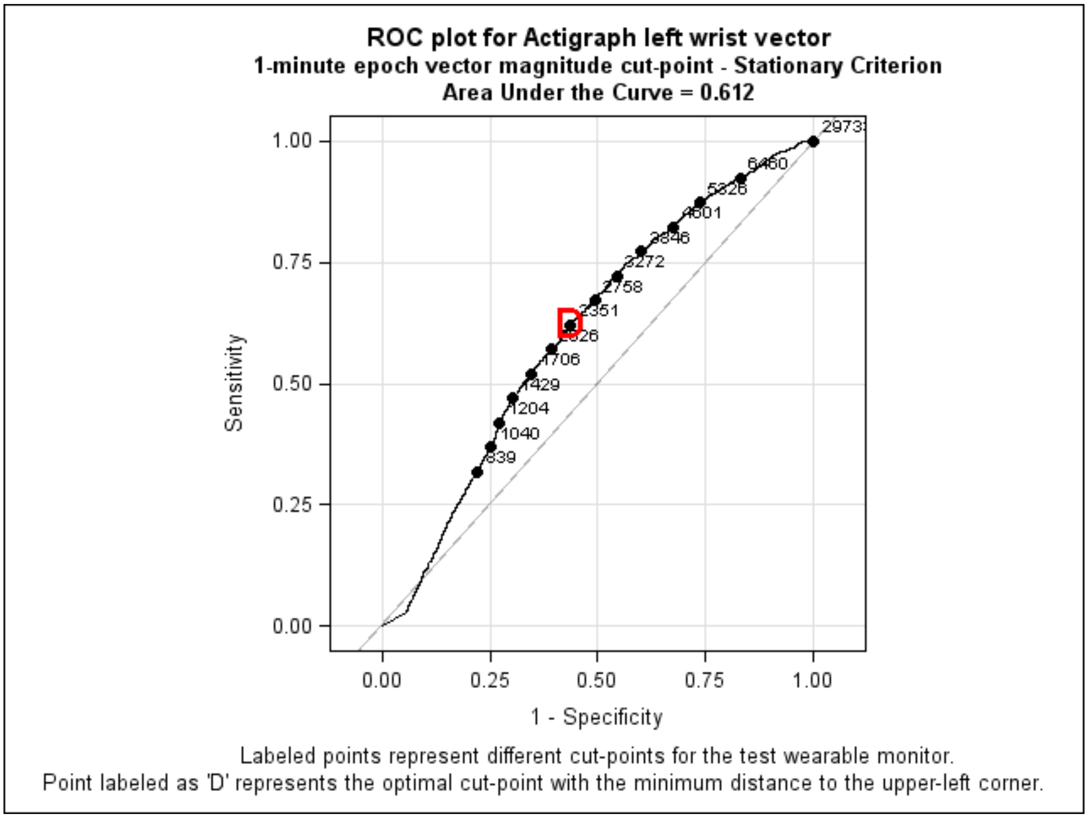
Supplemental material 11 ROC Plot for ActiGraph Right hip 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion



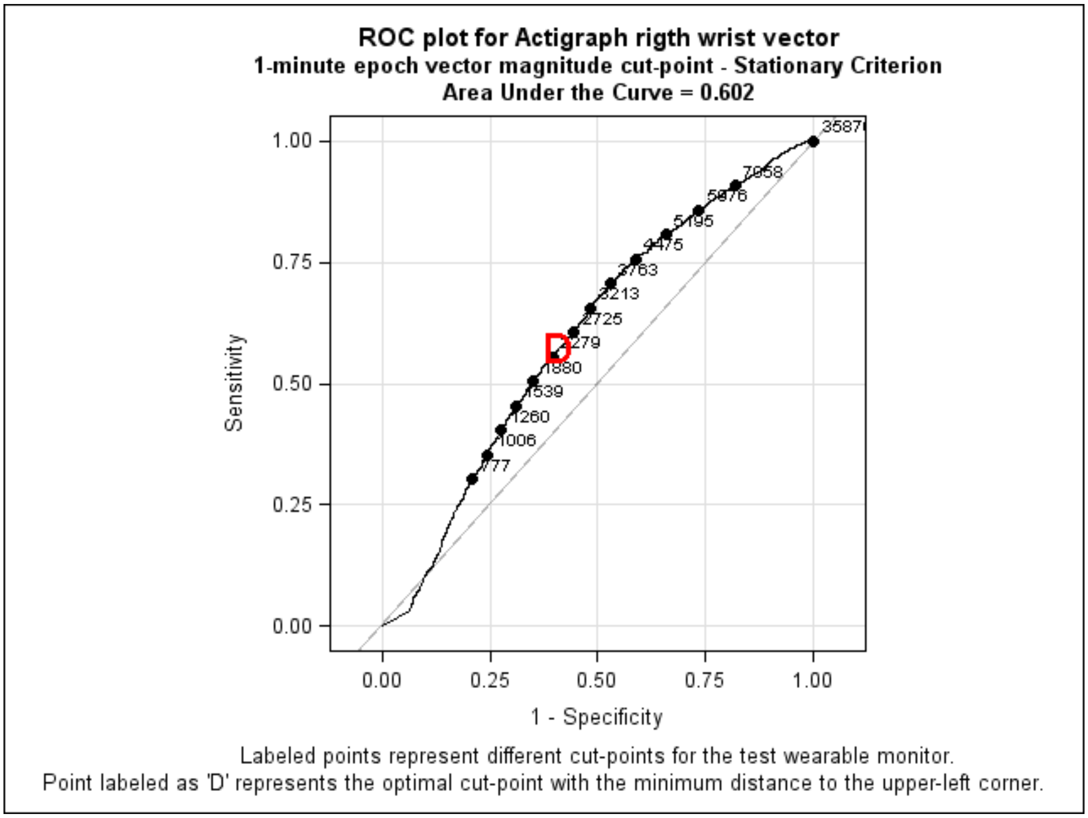
Supplemental material 12 ROC Plot for GENEActiv Left Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion



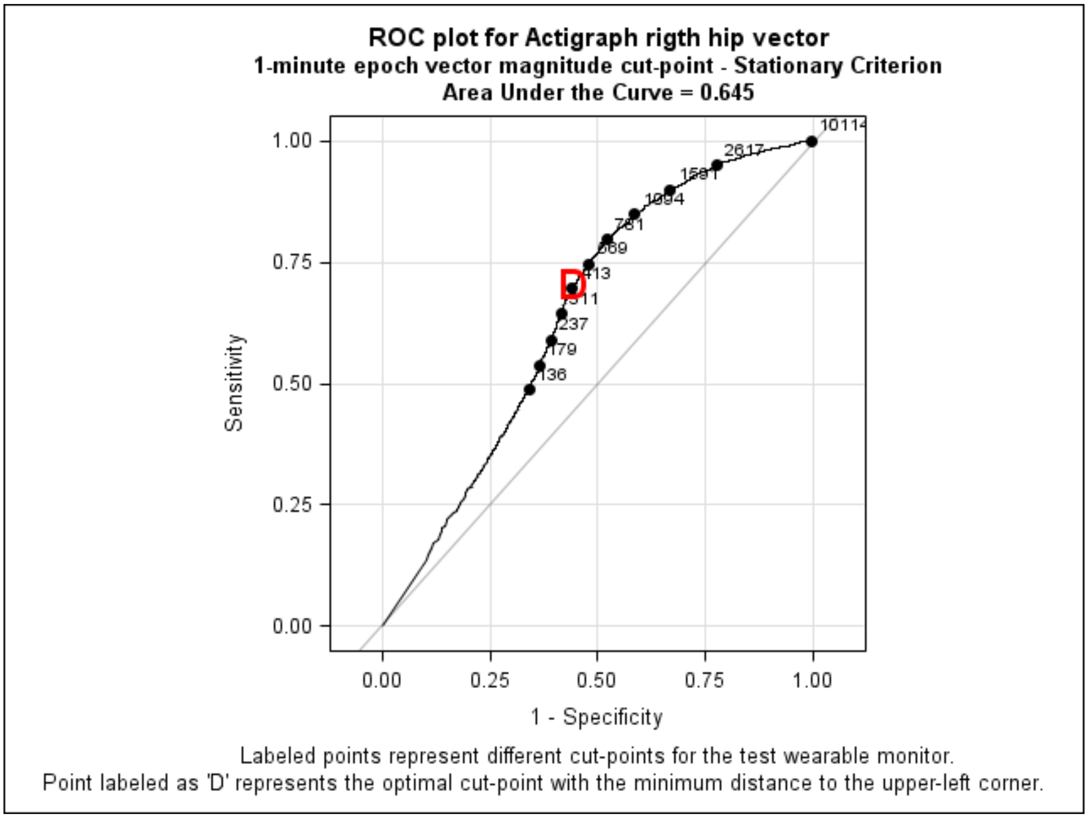
Supplemental material 13 ROC Plot for GENEActiv Right Wrist 1-second Epoch Vector Magnitude Cut-point - Sedentary Criterion



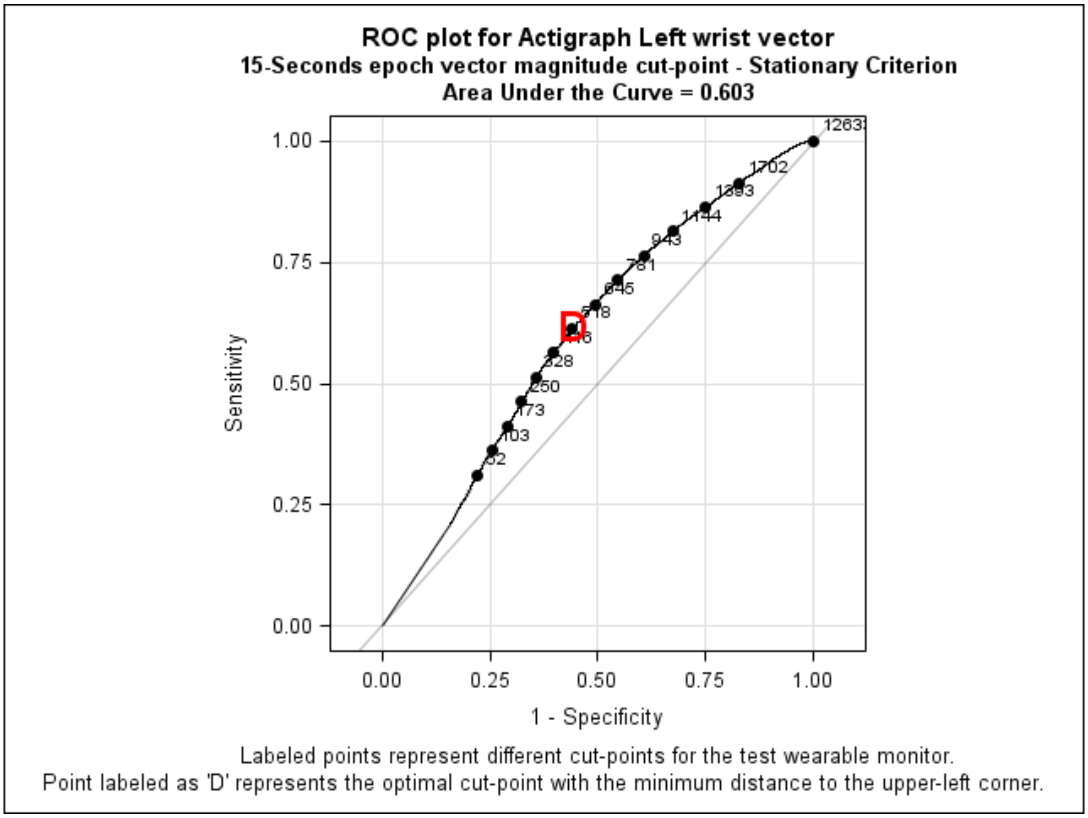
Supplemental material 14 ROC Plot for ActiGraph Left Wrist 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion



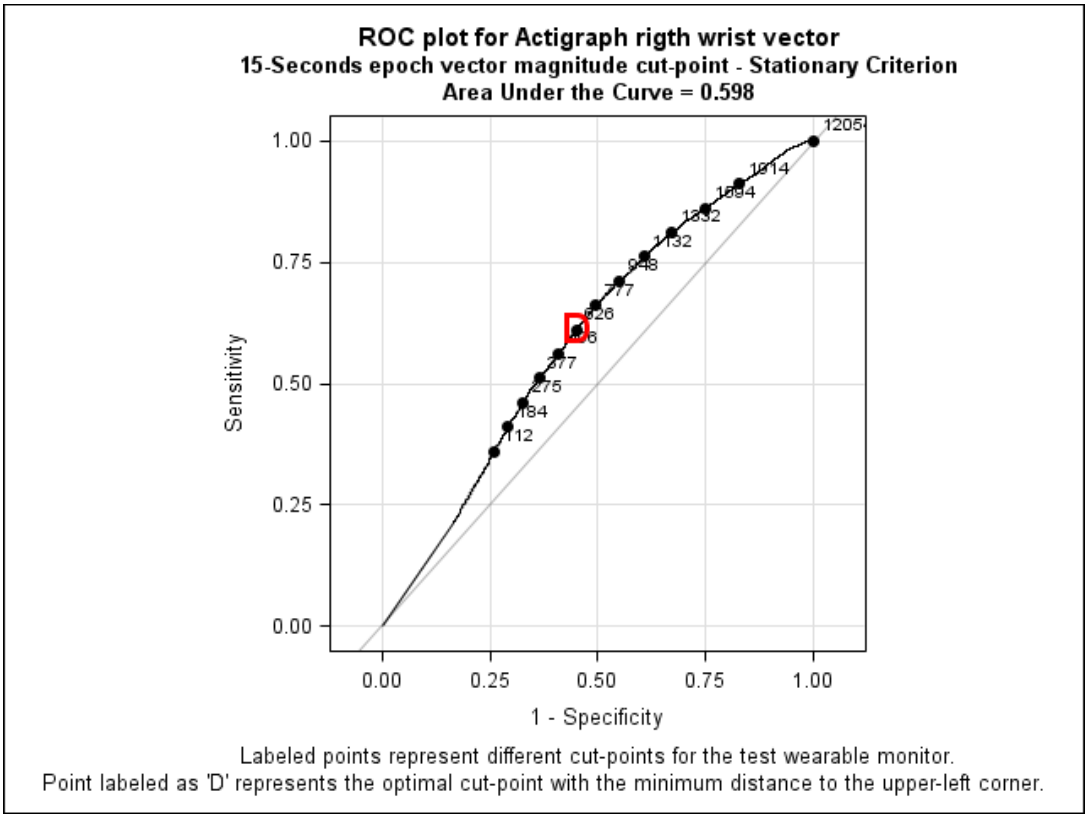
Supplemental material 15 ROC Plot for ActiGraph Right Wrist 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion



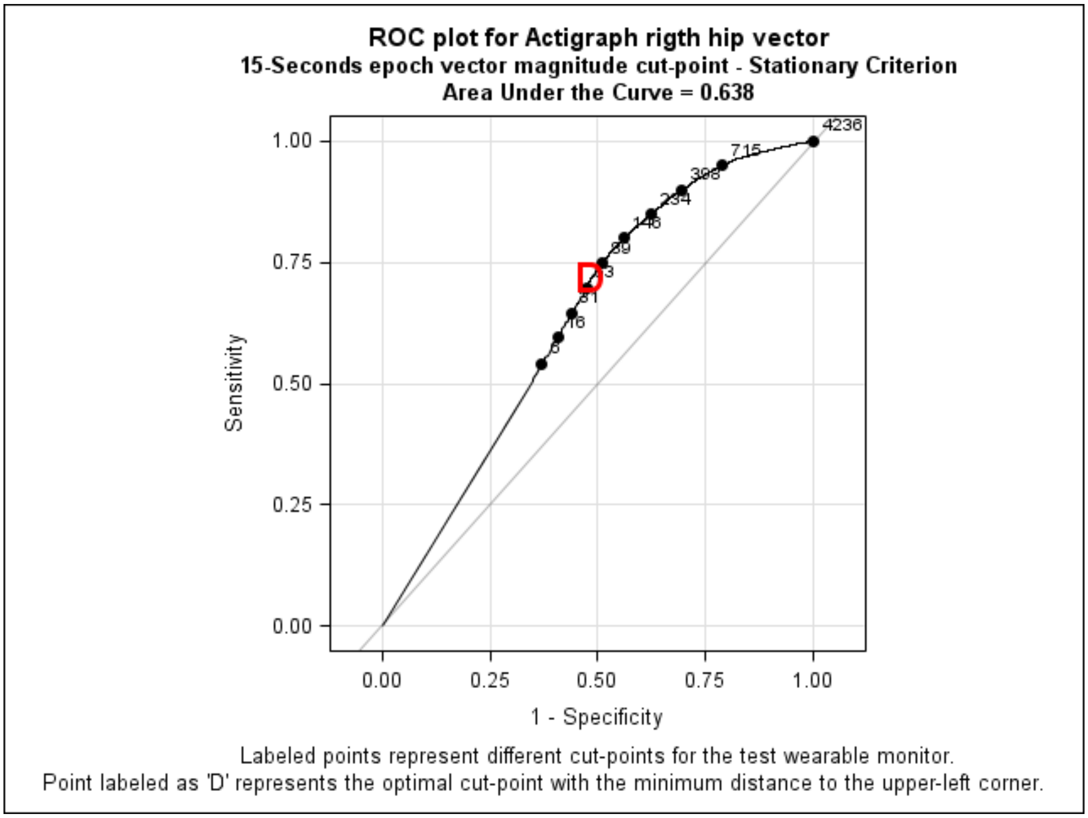
Supplemental material 16 ROC Plot for ActiGraph Right hip 1-minute Epoch Vector Magnitude Cut-point - Stationary Criterion



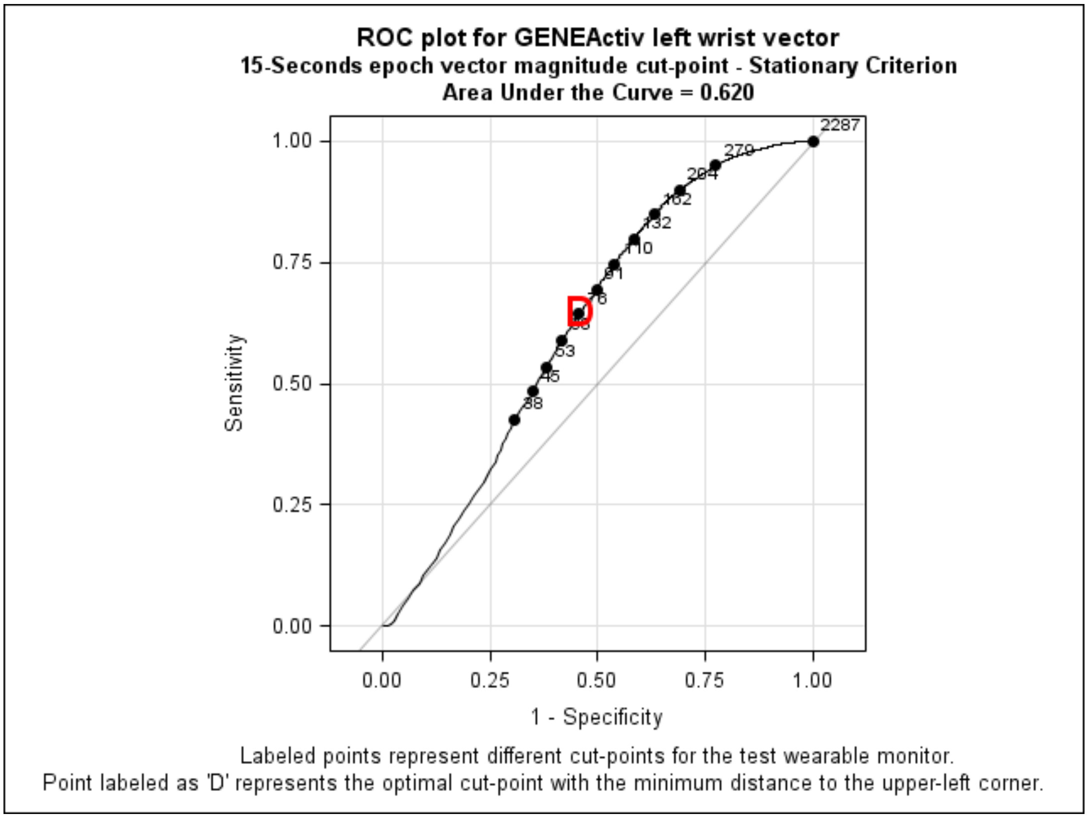
Supplemental material 17 ROC Plot for ActiGraph Left Wrist 15-seconds Epoch Vector Magnitude Cut-point - Stationary Criterion



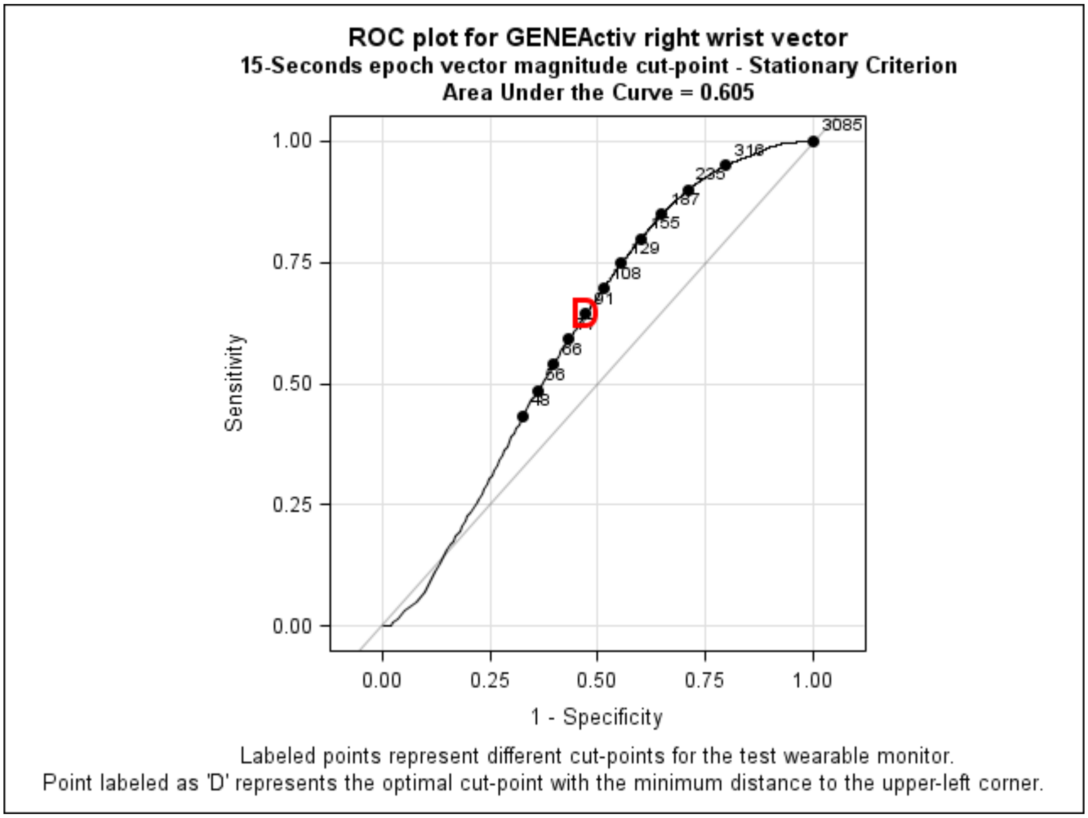
Supplemental material 18 ROC Plot for ActiGraph Right Wrist 15-seconds Epoch Vector Magnitude Cut-point - Stationary Criterion



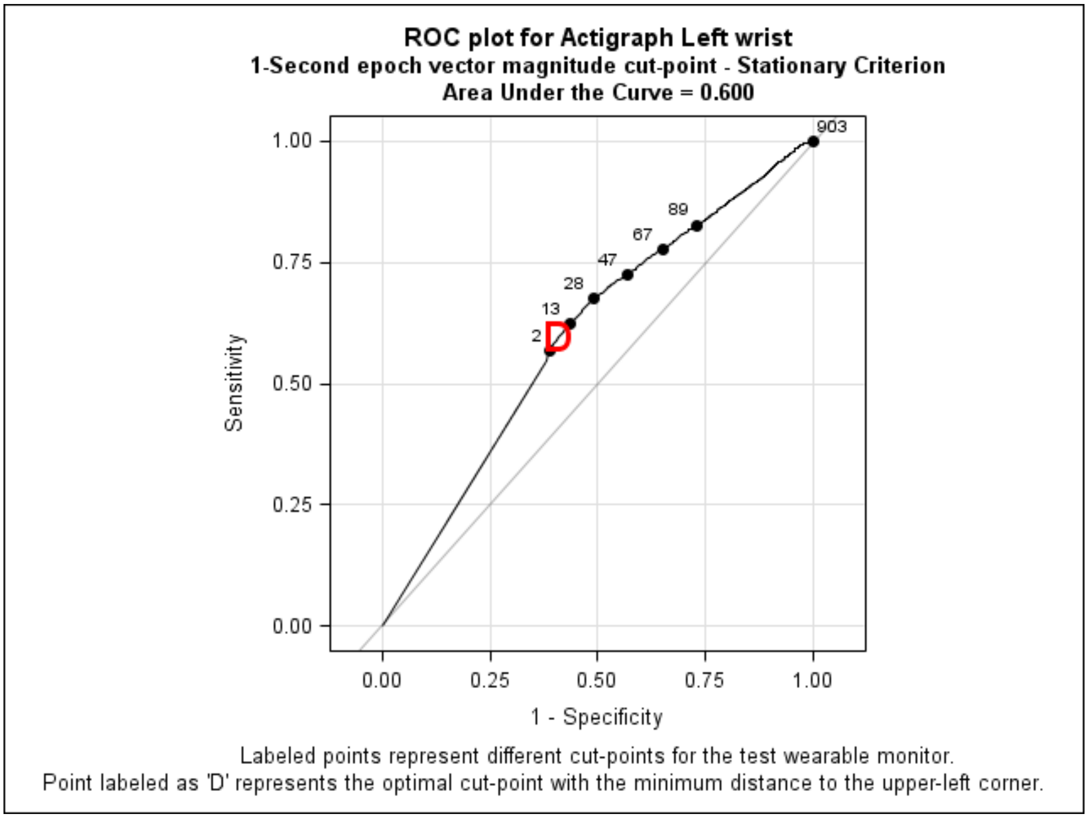
Supplemental material 19 ROC Plot for ActiGraph Right hip 15-seconds Epoch Vector Magnitude Cut-point - Stationary Criterion



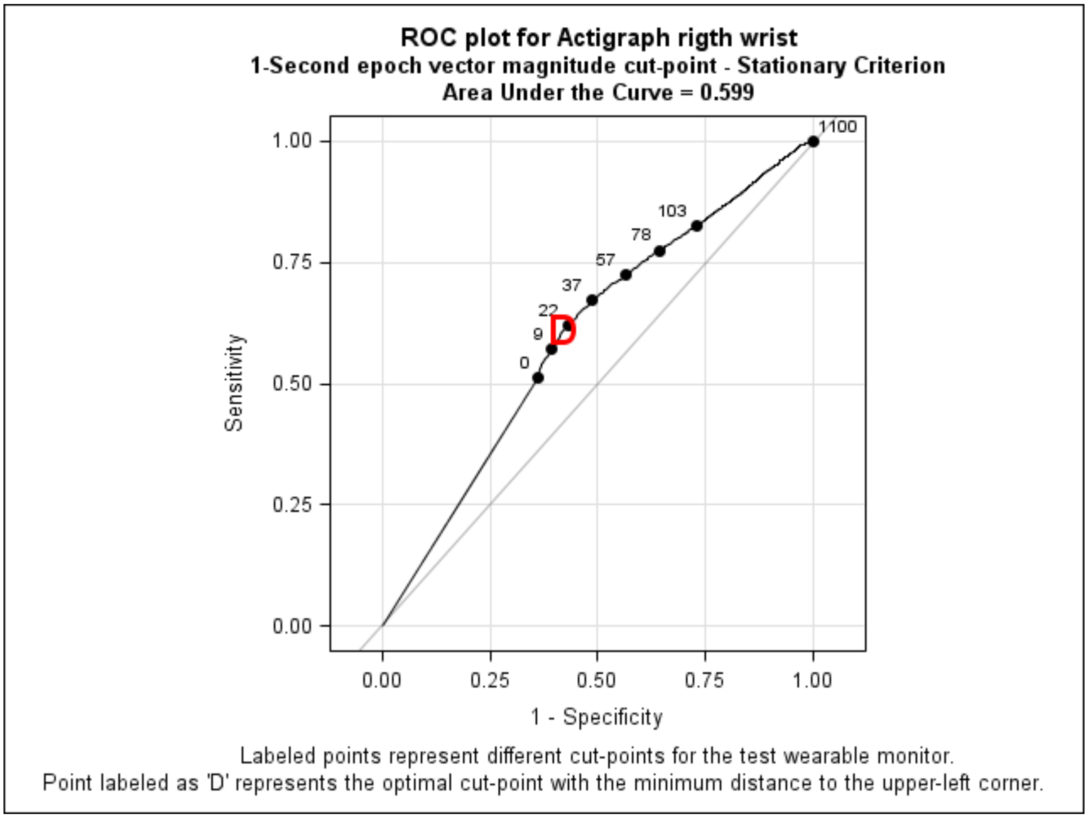
Supplemental material 20 ROC Plot for GENEActiv Left Wrist 15-seconds Epoch Vector Magnitude Cut-point - Stationary Criterion



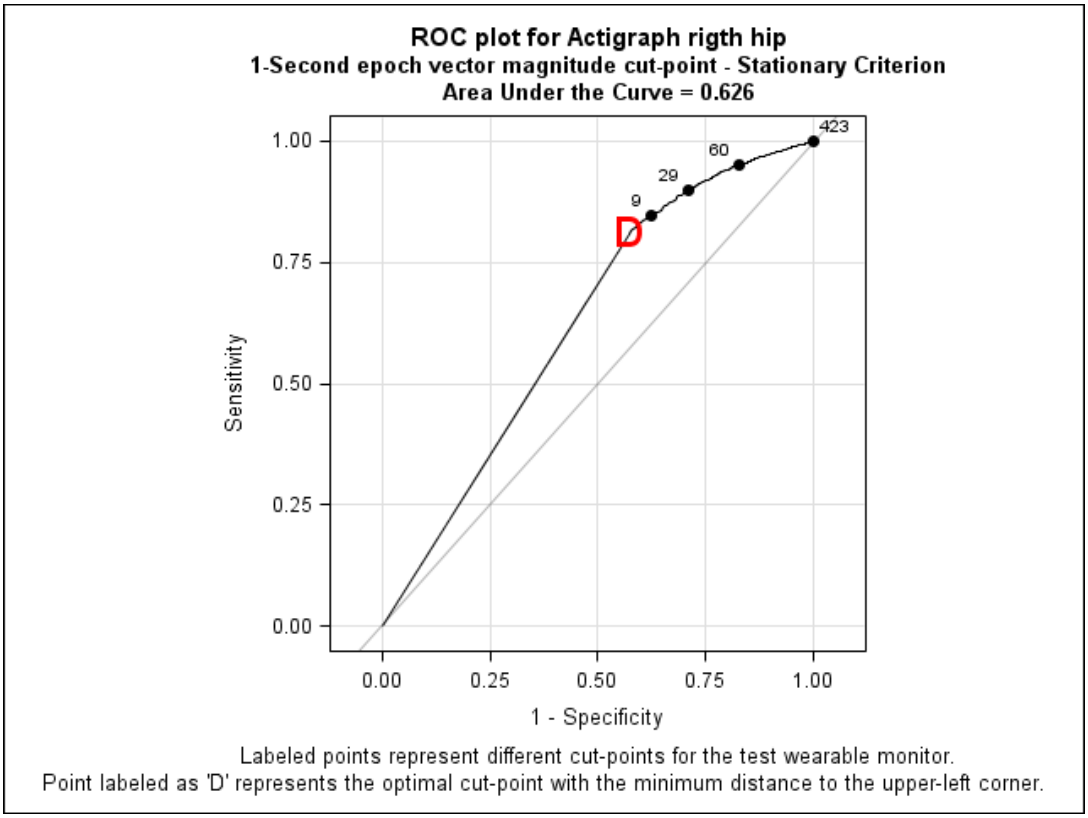
Supplemental material 21 ROC Plot for GENEActiv Right Wrist 15-seconds Epoch Vector Magnitude Cut-point - Stationary Criterion



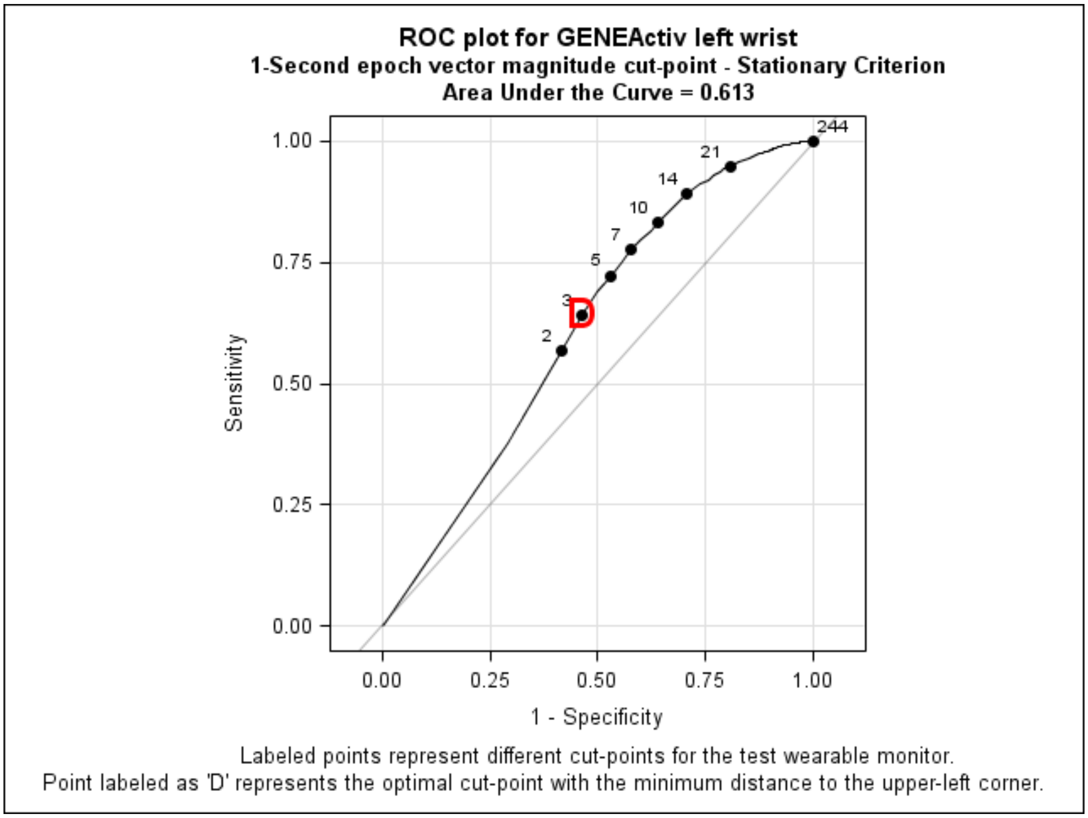
Supplemental material 22 ROC Plot for ActiGraph Left Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion



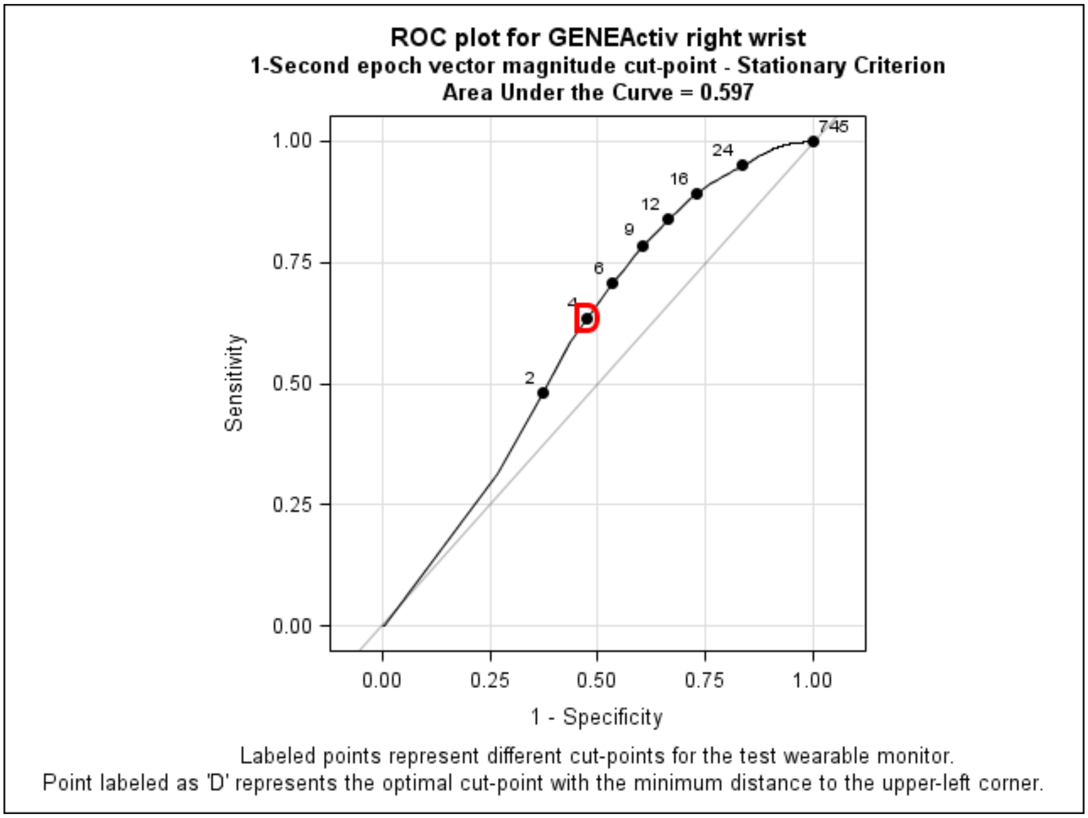
Supplemental material 23 ROC Plot for ActiGraph Right Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion



Supplemental material 24 ROC Plot for ActiGraph Right hip 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion



Supplemental material 25 ROC Plot for GENEActiv Left Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion



Supplemental material 26 ROC Plot for GENEActiv Right Wrist 1-second Epoch Vector Magnitude Cut-point - Stationary Criterion

Chapter 6

ACCURACY OF POSTURE-BASED SEDENTARY BEHAVIOR ESTIMATES MADE BY THE SEDENTARY SPHERE METHOD IN FREE-LIVING SETTINGS

Abstract

Background. The sedentary sphere (SS) is a new method for the assessment of sedentary behaviors (SB) by posture classifications derived from the angle of a wrist-worn triaxial wearable monitor in relation to the horizontal plane. The SS has had little testing in free-living settings, across monitor brands, and only in the non-dominant wrist. The primary aim of this study was to test the accuracy of ST estimates made by the SS with GENEActiv and ActiGraph GT3X+ data during free-living conditions on the dominant and non-dominant wrists. The secondary aim was to test the accuracy of the SS method with different angle configurations.

Methods. Twenty participants (mean age = 30.25 ± 6.43 years) wore four monitors, one ActiGraph GT3X+ (each wrist) and one GENEActiv (each wrist). The sedentary criterion measure was established from participants' direct observation including sitting and lying down. Data were analyzed using equivalence plots, mean percent error (MPE), Bland-Altman plots (BA), kappa coefficient (k), sensitivity (S), and specificity (SP).

Results. None of the SS estimates fell within the equivalency range of ±10% of the criterion mean value. BA showed no trends in error distribution regardless of the wrist placement and monitor used; however, the overall range for the limits of agreement between the criterion and the SS estimates were considerably wider (-238 to 179 minutes). The most accurate estimates of the SS for the GENEActiv were observed on the dominant wrist with the original configuration (MPE=2.25 minutes; k=0.30, 95% CI=0.30 to 0.31; S=0.61, 95% CI=0,61 to 0.62; SP=0.69, 95% CI=0,68 to 0.69). The most accurate estimates of the SS for the ActiGraph worn on the non-dominant wrist with 5° wrist angle and sedentary cut-point <489 counts per 15-second epoch (MPE=-0.49 minutes; k=0.31, 95% CI=0.30 to 0.31; S=0.63, 95% CI=0.62 to 0.63; SP=0.68, 95% CI=0,68 to 0.69).

Conclusion. The SS was not equivalent to the criterion measure of SB but showed moderate accuracy to classify SB from the GENEActiv dominant wrist data and from an alternative configuration of the SS using ActiGraph worn on the non-dominant wrist.

Key Words: Accelerometers, posture, wrist, sitting, standing.

Introduction

Sedentary behaviors are characterized by prolonged periods of inactivity and have shown to be a risk factor for multiple adverse health outcomes, independent of physical activity.[6–9] Breaking up sedentary behaviors by periods of walking and standing can reduce some of the deleterious effects of continuous sedentary time.[19,74] However, a question exists of how to best measure time spent in sedentary behaviors. Sedentary behaviors are defined as any waking behavior characterized by an energy expenditure of ≤1.5 METs while in a sitting or reclining posture.[10] Profiles of sedentary behavior types can be measured using self-report questionnaires while time spent in sedentary behaviors is usually measured with wearable monitors. The two most common types of wearable monitors used to measure sedentary time are the GENEActiv (ActivInsights, Cambs, United Kingdom) and ActiGraph (ActiGraph LLC, Pensacola, FL, USA). Challenges in measuring sedentary time with wearable monitors are considerations that can affect the accuracy; namely, the type of wearable monitor used, wearable monitor placement, compliance in wearing the wearable monitor, and the scoring method used to calculate sedentary time.[147]

The most common method to score wearable monitors data is in the use of cut-points. Cut-points are derived from prediction equations used to classify movement into different intensity levels (sedentary, light, moderate, vigorous) based upon the wearable monitors outputs (activity counts).[147] The cut-points approach is satisfactory for locomotion, but poses several limitations in measuring time spent in sedentary behaviors. As cut-points rely on the magnitude of acceleration, the time spent in sitting and standing behaviors is similar as when there is no movement. Hence, misclassification can occur between activities occurring without movement, regardless of postural differences. For example, the most common cut-point of 100 counts per minute has been shown to misclassify light-intensity physical activities as sedentary behaviors.[37,120,148] A second limitation of the cut-point approach is that data are averaged over a specified period of time, usually one-minute. This eliminates rich features of the accelerometer's signal that can aid in identifying movement and sedentary behaviors. For example, features of the accelerometer's signal not used with the cut-points approach are standard deviation, percentiles, correlation between axes, total signal power, and frequency of the signal with the most power.[92] Such features have the potential to refine wearable monitors measures of sedentary time. Lastly, the cut-point method relies on the principle that accelerations are linearly related to energy expenditure during motion; however, the relationship between sedentary behaviors and energy expenditure is not linear.[99] Collectively, these limitations can increase the chance for misclassifications of time spent in specific types of sedentary behaviors.

Compliance with wearing hip-mounted wearable monitors is low in both children and adults.[13] Low compliance can reduce the accuracy of sedentary behavior estimates by excluding segments of the day. Such errors can result in underestimates of time spent in true sedentary behaviors and reflect time spent in sedentary behaviors only while wearing the wearable monitors. Placement on the wrist is known to increase compliance with wearing a wearable monitor as compared when worn on the waist. Accordingly, the U.S. National Health and Nutrition Examination Survey accelerometer 2011-2012 sub-study has participants wear wrist-mounted wearable monitors in an attempt to increase wear-time compliance. Preliminary reports from the 2011-2012 sub-study cycle shows wear-time with wrist-mounted wearable monitors has increased to 70%-80% (>6 days of data and median wear time of 21–22 hours per day) as compared to the NHANES 2003-2006 cycle in which wear-time was 40%-70% (> 6 days of data and >10 hours per day) with waist-mounted monitors.[149] Thus, wrist-mounted wearable monitors are recommended when assessing sedentary behaviors.

The tri-axial GENEActiv and ActiGraph wearable monitors have an inclinometer feature that provides the possibility of adding posture allocations to the cut-points method when assessing sedentary behaviors. In 2014, Rowlands et al.[41] presented a method for classifying sedentary behaviors based on posture and activity counts from the GENEActiv. This method, referred to as the sedentary sphere, has been described in detail by Rowlands et al.[41] Briefly, by using the gravitational component of the wearable monitor acceleration signal it is possible to determine the orientation of the monitor using the wrist position. In combination with activity counts, the sedentary sphere allows for estimates of a likely posture such as sitting, standing, or lying. The sedentary sphere uses the following directions to determine a sedentary posture: (1) if the arm is elevated to >15 degrees above the horizontal plane and the activity counts are less than 489 counts per each 15-second epoch (light-to-moderate intensity), the posture is classified as siting and/or lying (sedentary); (2) if the arm is hanging to <15 degrees below the horizontal plane and the activity counts are less than 489 counts per each 15-second epoch, posture is classified as standing (non-sedentary); and (3) if the activity counts are greater than 489 counts per each 15-second epoch regardless of wrist elevation, posture is classified as standing (non-sedentary). The sedentary sphere has been examined in a few studies deemed promising as a method to measure time spent in sedentary behaviors.[41,44,102]

The value of the sedentary sphere is that it avoids the limitations of using cut-points solely to determine time spent in sedentary behaviors. The sedentary sphere has shown to be a valid method to determine sedentary time in free-living environments and laboratory settings and across brands (i.e., GENEActiv data and ActiGraph) when wore on the non-dominant wrist. However, the validity of the sedentary sphere has not been determined when the wearable monitors are worn on the dominant wrist and with different configurations of arm elevation angles and activity count thresholds. Identifying the validity of such differences provides flexibility for researchers and may improve the accuracy of identifying sedentary behaviors during free-living conditions.

Thus, the primary aim of this study was to test the accuracy of posture-based sedentary time estimates made using the sedentary sphere method with data obtained from the GENEActiv and the ActiGraph GT3X+ wearable monitors during free-living conditions on the dominant and non-dominant wrists. The secondary aim was to test the accuracy of the sedentary sphere method with different angle configurations of the wrist held below the horizontal plane.

Materials and methods

Participants

A convenience sample of 20 healthy adults was recruited for the study. Eligibility criteria were (1) adults 18-65 years of age; (b) normal to overweight body mass index (18.5 to 29.9 kg/m2); and (c) negative responses to all questions of the Physical Activity Readiness Questionnaire - PAR-Q;[125] Participants were recruited through e-mail and fliers placed on the Arizona State University campus. All participants signed an informed consent before enrollment into the study. The study protocol was approved by the

Arizona State University Institutional Review Board.

Wearable Monitors

The GENEActiv and the ActiGraph GT3X+ wearable monitors were used in this study. Technical specifications of these wearable monitors are in Table 10. Participants wore four monitors simultaneously, two on each wrist. One GENEActiv accelerometer was attached by a strap in the most distal position of the wrist and oriented in a manner that allowed the monitor serial number to be read by the participant. One ActiGraph GT3X+ accelerometer was attached by an adjustable wrist band in the most proximal position of the wrist oriented in a manner that allowed the ActiGraph logo to be read by the participant.

Table 10 - Technical specifications for the GENEActiv and ActiGraph GT3X+ wearable monitors

	GENEActiv	ActiGraph GT3X+
Number of axes	Three	Three
Size	43mm x 40mm x 13mm	46mm x 33mm x 15mm
Weight	16g (without strap)	19g
Acceleration range	+/- 8g	+/- 8g
Sample rate	Selectable 10-100 Hz in 10-	Selectable 30–100 Hz in 10-
Resolution	12 bit	12-bit
Water resistance	10 meters, 24 hours	1 meter, 30 minutes

The inter-monitor reliability was tested before field data collection with the intraclass coefficient (ICC) ($ICC_{GENEActiv}$= 0.96 and $ICC_{ActiGraph}$= 0.95). Methods used to obtain the ICCs have been previously reported.[150]

Data Management and Processing

The GENEActiv software 2.9 and ActiLife software 6.11.5 were used to initialize and download data from the GENEActiv and the ActiGraph, respectively. The wearable monitors were initialized to collect data at 100Hz. Data from the wearable monitors were downloaded to .csv files in 15-second epochs for the GENEActiv and in raw format for the ActiGraph. To compute the posture-based sedentary time estimates, a SAS program was created (available upon request) to replicate the data process made by the sedentary sphere custom built Excel spreadsheets.[41,44]

Criterion Measure

The criterion variable of sedentary behavior during free-living time was obtained from direct observation with focal sampling and duration coding. Six different activity categories (walking, running, sports/exercise, household chores, standing, and sitting/lying down) were observed and independently coded by two researchers as they were performed in free-living conditions. An iPad tablet and a commercially available software which allowing for timestamped annotations over customized observation categories were used to record the behaviors.[118]

Researchers completed extensive training and testing before field observations. A detailed description of the training and testing procedures can be found elsewhere (See project 2). Briefly, researchers completed 24 hours of one-to-one supervised training consisting of familiarization with study protocols and tablet use, techniques to avoid disrupting, disturbing or modifying participant's natural behavior, direct observation practice using the tablet to record observations while watching a set of videos, and direct observation practice using the tablet as persons performed fee-living behaviors. Upon completion of training, researchers completed a video testing session in which their observations were compared to observations previously coded by two senior researchers.

Researchers were required to achieve an ICC > 0.80 before collecting field data.

To observe the participant's behaviors, two researchers accompanied participants in their free-living environment for 6-hours, two days a week (one weekday and one weekend day). Pre-defined activity categories for direct observation notation are described in detail elsewhere (See project 2). Briefly, the categories used for field data collection are defined below:

- Walking. Walking for all locomotion purposes.
- Running. Continuous and short bouts of running and jogging.
- Sports and conditioning exercise. Playing sports or performing continuous or intermittent conditioning exercises.
- Household chores. Performing housekeeping activities.
- Standing. Standing while bearing the body weight in one or both lower limbs.
- Sitting/lying down. Having a body positions in which the body weight is supported by the buttocks, thighs or back; this includes sitting and lying down.

Additional observation categories were designed as follow:

- Private. When a participant required private time (e.g., restrooms use).
- Unobserved. When the participant was available to be observed but out of the sight of the researchers.
- Error. When researchers made an error or were unable to determine an accurate coding for a given activity.

Sedentary behaviors were coded as sedentary (sitting or lying = 1) or non-sedentary (all other activities = 0) based on the predominant behavior during a15-second epoch. If the 15-second epoch included sitting or standing for ≥8 seconds, the epoch was recorded as sedentary (0). If the time was <8 seconds of sitting or standing, the epoch was recorded as non-sedentary (1).

Data Analysis

Descriptive statistics were computed to characterize the sample by sex, age, and body mass index. Several analyses were used to compare the sedentary sphere estimates obtained with the GENEActiv and ActiGraph for the dominant and non-dominant wrist (herein referred to as the wearable monitors under assessment) and the criterion direct observation.

Equivalency testing was used to examine if the sedentary sphere estimates obtained from the wearable monitors under assessment were statistically equivalent to the criterion. As a brief overview, equivalency testing is used to assess the equivalence of two mean values as an alternative to testing for significant differences.[129] Equivalency testing requires identification of a meaningful equivalence range (referred to as the equivalence zone) and to calculate 90% confidence intervals for independent measure scores. In the current study, the independent variables were the sedentary sphere estimated minutes for each wearable monitor under assessment. If the full 90% confidence interval of a sedentary sphere estimate falls within the equivalence zone, it is concluded with 95% confidence that the sedentary sphere value is equivalent to the criterion value. The equivalence zone was set at ±10% of the criterion sedentary minutes;

this value, while arbitrary, is consistent with other wearable monitors validation studies.[130,151]

Percent Error (PE) was calculated to assess the proportion of error for the sedentary and non-sedentary minutes for each wearable monitor under assessment relative to the criterion measure.

$$PE = [(\text{Wearable Monitor Score} - \text{Criterion Score})/\text{Criterion Score}] \times 100.$$

The criterion score was the sum of the sedentary minutes recorded by direct observation. The wearable monitor score was the sum of sedentary sphere estimated minutes for each wearable monitor. A positive PE indicated an overestimate of sedentary time by the sedentary sphere and a negative PE indicated an underestimation of sedentary time.[128]

Bland-Altman plots[131] were used to display the error distribution and systematic variation between total sedentary minutes recorded by the direct observation and total sedentary minutes as created by the sedentary sphere for each wearable monitor under assessment. In the Bland-Altman plots, the difference score (bias) between direct observation sedentary time and the sedentary sphere time was plotted against the averages of the two measures. The error distribution is observed within three horizontal reference lines: the mean difference (zero deviation line), upper limit of agreement (+1.96 standard deviation of the differences), and lower limit of agreement (-1.96 standard deviation of the differences). Bland-Altman plots were enhanced by regressing the difference score against the average of the two scores. The regression line provides a statistical reference for systematic variation between the direct observation and sedentary sphere estimates for each of the wearable monitors. A flat regression line in the Bland-Altman plot indicates no measurement differences between the two methods for each wearable monitor, a positive slope indicates that the sedentary sphere is positively biased when compared to direct observation, and a negative slope indicates that the sedentary sphere is negatively biased.

The kappa statistic was used to observe epoch-by-epoch agreement between the sedentary sphere estimates for each wearable monitor under assessment and the criterion measure. Kappa scores are used to compare agreement between nominal and categorical variables while taking into account the agreement occurring by chance.[133] Kappa values close to 1 indicate perfect agreement (high accuracy) and kappa values close to 0 indicate no agreement (low accuracy). Kappa values are interpreted as follows: 0–0.2 = slight agreement, 0.2–0.4 = fair agreement, 0.4–0.6 = moderate agreement 0.6–0.8 = substantial agreement, and 0.8–1.0 = almost perfect agreement.[134]

Epoch-by-epoch sensitivity and specificity were calculated to measure the accuracy of the sedentary sphere to classify a behavior as sitting/lying for each wearable monitors under assessment. When a sensitivity is close to 1, it shows that the sedentary sphere accurately classified a high proportion of sitting/lying as compared with direct observation. A sensitivity value close to 0 indicates that the sedentary sphere failed to classify the behaviors as sitting/lying. Sensitivity was calculated using the formula,

Sensitivity = True positives / (True positives + False negatives)

Specificity measures the ability of the sedentary sphere to classify activities that are not sitting/lying. Specificity was calculated using the formula,

Specificity = True negatives / (False positives + True negatives)

When specificity is close to 1, the sedentary sphere accurately classifies non-sitting/lying activities as movement (not sitting/lying). Specificity close to 0 indicates that the sedentary sphere fails to exclude movement activities from being classified as sitting/lying.

Equivalence testing, PE, Bland-Altman plots, kappa, sensitivity, and specificity were calculated for each wearable monitor on both wrists for six different configurations of the sedentary sphere as follows.

- Configuration 1 – the original sedentary sphere configuration with an arm elevation threshold at 15 degrees below the horizontal plane and with a light-to-moderate intensity threshold at <489 counts per 15-second epoch.
- Configurations 2-5 – varying arm elevation thresholds (5, 10, 20, 25 degrees below the horizontal plane, respectively) and with the intensity classified as light-to-moderate (<489 counts per 15-second epoch).
- Configuration 6 – the arm elevation threshold is constant at 15 degrees below the horizontal plane and applied vector magnitude sedentary cut-points for 15-second epoch developed previously (GENEActiv non-dominant 65 counts per 15-second epoch, GENEActiv dominant 61 counts per 15-second epoch, ActiGraph non-dominant 455 counts per 15-second epoch, and ActiGraph dominant 495 counts per 15-second epoch).[150]

All analyses were performed using SAS version 9.4. Graphics for the equivalence testing were made using a custom-built Excel spreadsheet.

Results

A total of 20 adults completed the study protocol. Participants were 50% female, 30.25 ± 6.43 years of age (range: 21-46 years), and body mass index = 22.7 ± 3.1 kg/m^2 (range: 18.51-29.76 kg/m^2). All participants were right-handed. A total of 40 sessions and 241.32 hours of free-living direct observation were observed. The average length of free-living observation sessions was 5.97 (± 0.26) hours. Due to a monitor error, 5.99 hours were missing from one GENEActiv worn on a dominant wrist.

Figure 3 presents equivalence plot for each configuration of the sedentary sphere under assessment as compared to the criterion measure. Table 11 presents results from total sedentary time, PE, kappa, sensitivity, and specificity for each configuration of the sedentary sphere under assessment. Supplementary material shows Bland-Altman plots for each configuration of the sedentary sphere under assessment. Total sedentary time as measured by the criterion was 164 ± 89 minutes. None of the sedentary sphere estimates were within the equivalence zone across all configurations, wearable monitors brands, and location (dominant wrist and non-dominant wrist; herein referred to as dominant and non-dominant). There was marginal equivalence for configuration 1 ActiGraph dominant, configuration 2 ActiGraph non-dominant, configuration 3 GENEActiv non-dominant and GENEActiv dominant, configuration 4 ActiGraph dominant, and configuration 6 ActiGraph dominant.

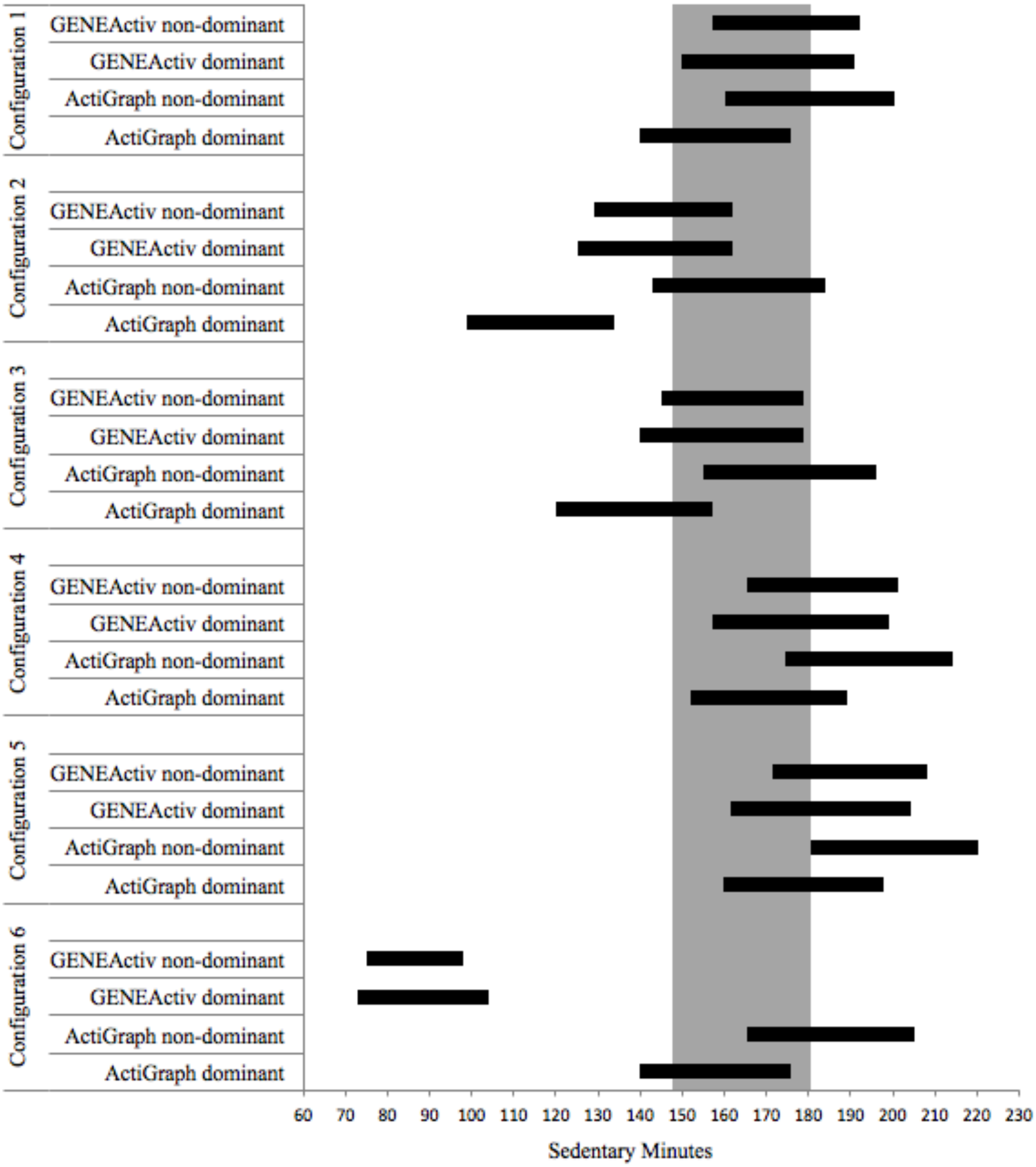


Figure 3 Equivalence plots for each configuration of the sedentary sphere as compared to the criterion measure. Grey area represents +/-10% for the criterion mean (equivalence zone), black bars represents 90% confidence interval for the test sedentary sphere estimates by monitor and location.

Table 11 - Percent Error, kappa, sensitivity, and specificity for each sedentary sphere configuration

		Percent Error	kappa (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
Configuration 1	GENEActiv Non-dominant	6.51	0.30 (0.30, 0.31)	0.61 (0.61, 0.62)	0.69 (0.68, 0.69)
	GENEActiv Dominant	2.25	0.36 (0.35, 0.36)	0.65 (0.64, 0.66)	0.71 (0.70, 0.71)
	Actigraph Non-dominant	13.79	0.34 (0.34, 0.35)	0.62 (0.62, 0.63)	0.72 (0.72, 0.73)
	Actigraph Dominant	-3.46	0.26 (0.25, 0.27)	0.61 (0.60, 0.61)	0.65 (0.65, 0.66)
Configuration 2	GENEActiv Non-dominant	-11.06	0.26 (0.25, 0.27)	0.61 (0.61, 0.62)	0.65 (0.64, 0.65)
	GENEActiv Dominant	-14.03	0.30 (0.29, 0.31)	0.65 (0.64, 0.65)	0.66 (0.66, 0.67)
	ActiGraph Non-dominant	-0.49	0.31 (0.30, 0.31)	0.63 (0.62, 0.63)	0.68 (0.68, 0.69)
	ActiGraph Dominant	-28.89	0.14 (0.13, 0.15)	0.57 (0.56, 0.57)	0.59 (0.58, 0.59)
Configuration 3	GENEActiv Non-dominant	-1.09	0.19 (0.19, 0.20)	0.59 (0.58, 0.59)	0.62 (0.61, 0.62)
	GENEActiv Dominant	-4.36	0.28 (0.28, 0.29)	0.61 (0.61, 0.62)	0.67 (0.67, 0.68)
	Actigraph Non-dominant	7.40	0.33 (0.32, 0.33)	0.62 (0.62, 0.63)	0.70 (0.70, 0.71)
	Actigraph Dominant	-15.47	0.19 (0.19, 0.19)	0.59 (0.58, 0.59)	0.62 (0.61, 0.62)
Configuration 4	GENEActiv Non-dominant	11.8	0.31 (0.30, 0.32)	0.61 (0.60, 0.62)	0.70 (0.70, 0.71)
	GENEActiv Dominant	6.43	0.37 (0.36, 0.38)	0.65 (0.64, 0.65)	0.72 (0.72, 0.73)
	ActiGraph Non-dominant	18.69	0.35 (0.35, 0.36)	0.62 (0.62, 0.63)	0.74 (0.73, 0.74)
	ActiGraph Dominant	4.19	0.29 (0.28, 0.30)	0.61 (0.61, 0.62)	0.68 (0.67, 0.68)
Configuration 5	GENEActiv Non-dominant	15.64	0.32 (0.31, 0.32)	0.61 (0.60, 0.61)	0.71 (0.71, 0.72)
	GENEActiv Dominant	9.36	0.37 (0.36, 0.38)	0.64 (0.64, 0.65)	0.73 (0.72, 0.73)
	ActiGraph Non-dominant	22.24	0.36 (0.35, 0.37)	0.62 (0.61, 0.63)	0.75 (0.74, 0.75)
	ActiGraph Dominant	9.33	0.30 (0.30, 0.31)	0.62 (0.61, 0.62)	0.69 (0.69, 0.70)
Configuration 6	GENEActiv Non-dominant	-47.02	0.18 (0.17, 0.19)	0.64 (0.63, 0.64)	0.60 (0.59, 0.60)
	GENEActiv Dominant	-46.74	0.22 (0.21, 0.23)	0.68 (0.67, 0.68)	0.61 (0.60, 0.61)
	ActiGraph Non-dominant	13.1	0.34 (0.34, 0.35)	0.62 (0.62, 0.63)	0.72 (0.72, 0.73)
	ActiGraph Dominant	-3.38	0.26 (0.25, 0.27)	0.61 (0.60, 0.61)	0.65 (0.65, 0.66)

Configuration 1 Arm elevation threshold 15°, intensity threshold 489 counts per 15-sec epoch
Configuration 2 Arm elevation threshold 5°, intensity threshold 489 counts per 15-sec epoch
Configuration 3 Arm elevation threshold 10°, intensity threshold 489 counts per 15-sec epoch
Configuration 4 Arm elevation threshold 20°, intensity threshold 489 counts per 15-sec epoch
Configuration 5 Arm elevation threshold 25°, intensity threshold 489 counts per 15-sec epoch
Configuration 6 GENEActiv Non-dominant, arm elevation threshold 15°, intensity threshold 65 counts per 15-sec epoch
GENEActiv Dominant, arm elevation threshold 15°, intensity threshold 61 counts per 15-sec epoch
ActiGraph Non-dominant, arm elevation threshold 15°, intensity threshold 455 counts per 15-sec epoch
ActiGraph Dominant, arm elevation threshold 15°, intensity threshold 495 counts per 15-sec epoch.

Sedentary sphere estimates for configuration 1 showed higher PE for the non-dominant wrist than dominant wrist regardless the wearable monitor; however, the ActiGraph had higher values of PE as compared to the GENEActiv in both dominant and non-dominant wrists. Among the alternative tested configurations (2-6), PE tended to be higher as compared to configuration 1. Except for configuration 2 for the ActiGraph non-dominant, configuration 3 GENEActiv non-dominant, and configuration 3 ActiGraph non-dominant showed lower PE (-0.49, -1.09, and 7.40 respectively). The Bland-Altman plots showed no trends in the error distribution regardless of the wrist and wearable monitor. However, the overall range between the 95% limits of agreement were considerably wider (-238 to 179 minutes). The GENEActiv dominant for the configuration 5 showed the narrowest limits of agreement (-111 to 148 minutes), while ActiGraph dominant for configuration 2 showed the widest (-238 to 144 minutes). Regression lines in the Bland-Altman plots had a negative slope regardless of the wrist and wearable monitor. Results for kappa, sensitivity, and specificity were similar; there was slight to fair agreement for kappa values and moderate sensitivity and specificity.

Discussion

The results showed that none of the sedentary sphere estimates obtained with the GENEActiv and the ActiGraph were equivalent to the criterion measure of direct observation. The original configuration of the sedentary sphere[41] indicated moderate accuracy using the GENEActiv and the ActiGraph wearable monitors across all accuracy metrics used to compare the sedentary sphere with the criterion. The sedentary sphere estimates were more accurate using data from the dominant wrist as compared with the non-dominant wrist. The most accurate estimates of sedentary time were observed for the GENEActiv worn on the dominant wrist. With only the exception of configuration 2 (ActiGraph, non-dominant wrist 5° below the horizontal plane and with the light-to-moderate cut-points intensity threshold of <489 counts per 15-second) which was better than the original sedentary sphere configuration proposed by Rowlands et al.,[41] none of the alternative configurations of the sedentary sphere with varying wrist angles and cut-points improved accuracy of estimates made by the sedentary sphere.

Sedentary time estimates from the sedentary sphere revealed relatively small PE and bias (Bland-Altman plots). On the other hand, it showed wide limits of agreement (Bland-Altman plots), slight agreement (kappa) and moderate sensitivity and specificity. Collectively, these metrics indicate high inter-individual variability, which reinforce the utility of the sedentary sphere for group-level estimates of sedentary time.[102] Physical activity measurement studies using wrist-worn wearable monitors on dominant and non-dominant wrist have found no differences between time spent in different intensities of physical activity.[152,153] To our knowledge, no studies have studied whether sedentary time estimates for the dominant wrist are equivalent to the non-dominant wrist. Testing for equivalences of sedentary time of the dominant vs. non-dominant wrists was out of the scope of this study and we suggest this be the focus of future studies of sedentary time measurement.

Previous published research by Rowlands et al. demonstrated the sedentary sphere to be a valid method to measure sedentary time when wore on the non-dominant wrist[41] regardless the wearable monitor brand.[44] In contrast, the current results showed that the dominant wrist was more accurate regardless of the wearable monitor brand and that configuration 2 with ActiGraph non-dominant data was more accurate than the original sedentary sphere configuration of Rowlands et al. These differences may be explained by Rowlands et al. using the activPAL™ (PAL Technologies Ltd., Glasgow, UK) as the criterion instead of direct observation as used in the current study. Both the activPAL™

and direct observation, have shown to be valid measures of sedentary time.[89,154] Direct observation is recognized as a valid posture criterion measure and it has been used by most of the validation studies involving the activPAL™.[89,155] Accordingly, it is possible that the comparisons between the sedentary sphere and direct observation would be more precise than those made to the activPAL™. Another explanation for the differences may be that the current data were collected in free-living environments, while Rowlands et al. collected data in different settings (i.e., laboratory, free-living, and in hospital in-patients). The current sample included adults performing their daily activities in a free-living environment with the nature of the activities carried out by participants differing significantly from those done in other defined settings. Additional studies are needed to show consistency of results for the testing settings and the sedentary sphere configurations to identify the optimal method to estimate sedentary time.

As noted earlier, there are limitations to the cut-point method to estimate time spent in sedentary behaviors and that a more comprehensive approach to scoring wearable monitors data is needed to obtain the most accurate assessment of sedentary time. Human activity recognition techniques based on machine learning have been proposed, but user-friendly methods have not yet been developed as yet. The sedentary sphere method holds promise as it has acceptable validity in controlled and free-living settings. It also overcomes some of the limitations of the uniaxial cut-point method to assess sedentary time. Notably, the sedentary sphere includes posture estimates allowing classification of sedentary time by posture and intensity. This is of substantial importance as allows the measurements to be in agreement with the prevailing conceptual definition of sedentary behaviors. Additionally, the shorter 15-second epoch may identify sporadic non-sedentary behaviors and that can identify non-sedentary epochs that otherwise would be classified as sedentary when using longer epochs, such as 1-minute.

This study has several strengths, including a robust criterion measure of sedentary behaviors obtained by the observations of two independent researchers monitoring participants in free-living settings for two days (weekday and weekend day). This allowed data collection of many behaviors that were not influenced by structured settings, such as the laboratory, where activity intensity and time do not vary considerably. This study is limited by a relatively small convenience sample and of all right-handed healthy adults. The sample was not stratified by handedness and by chance, all participants were right-handed. This may limit generalization of the results to other populations who are left-handed.

Conclusion

The findings of this study indicate that none of the sedentary sphere configurations tested were equivalent to the criterion of direct observation. However, the original configuration of the sedentary sphere method showed moderate accuracy to classify sedentary time in free-living settings from wrist-worn GENEActiv wearable monitors when worn on the dominant wrist as compared with the non-dominant wrist. Among five different configurations of the sedentary sphere, 5° below the horizontal plane and light-to-moderate cut-point intensity threshold of <489 counts per 15-second, showed moderate accuracy to classify sedentary time in free-living settings from wrist-worn ActiGraph wearable monitors when worn on the dominant wrist.

Supplemental Material

Supplemental Material 1 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 1.

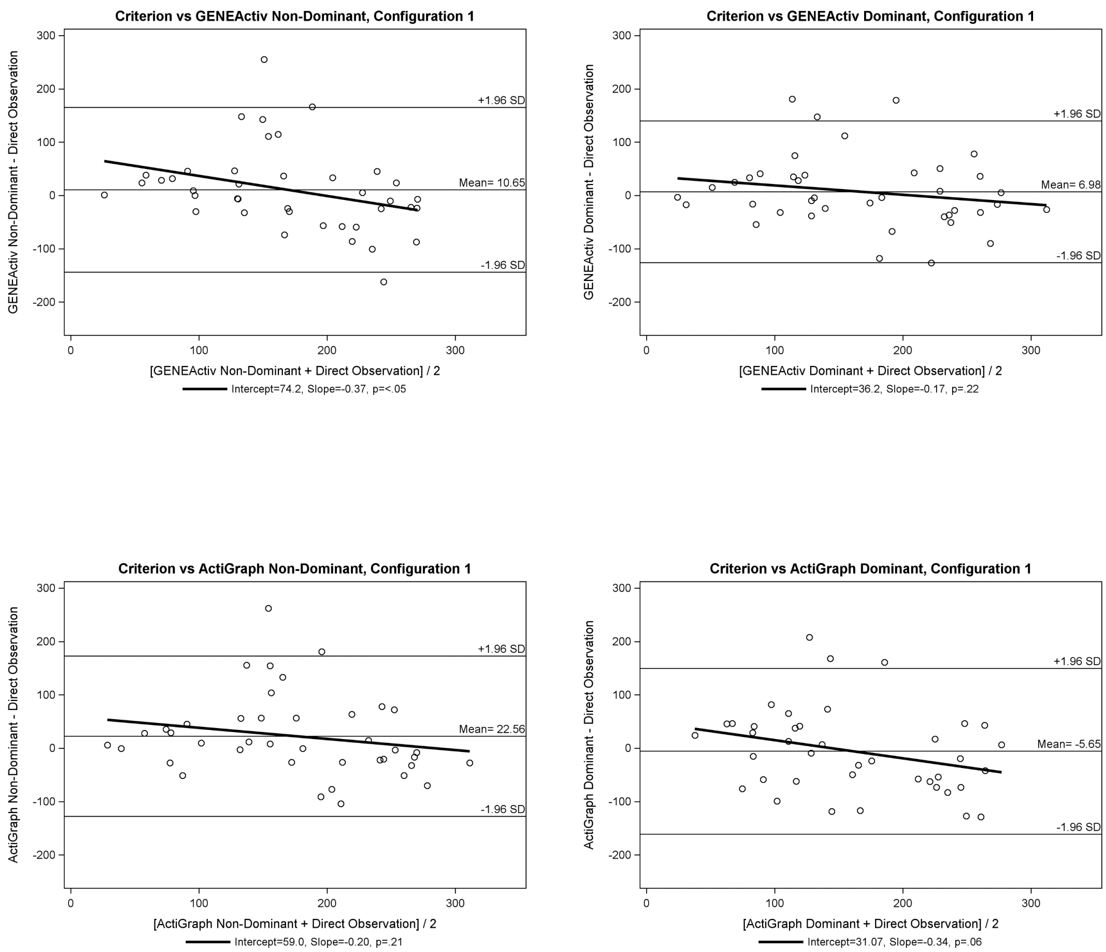
Supplemental Material 2 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 2.

Supplemental Material 3 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 3.

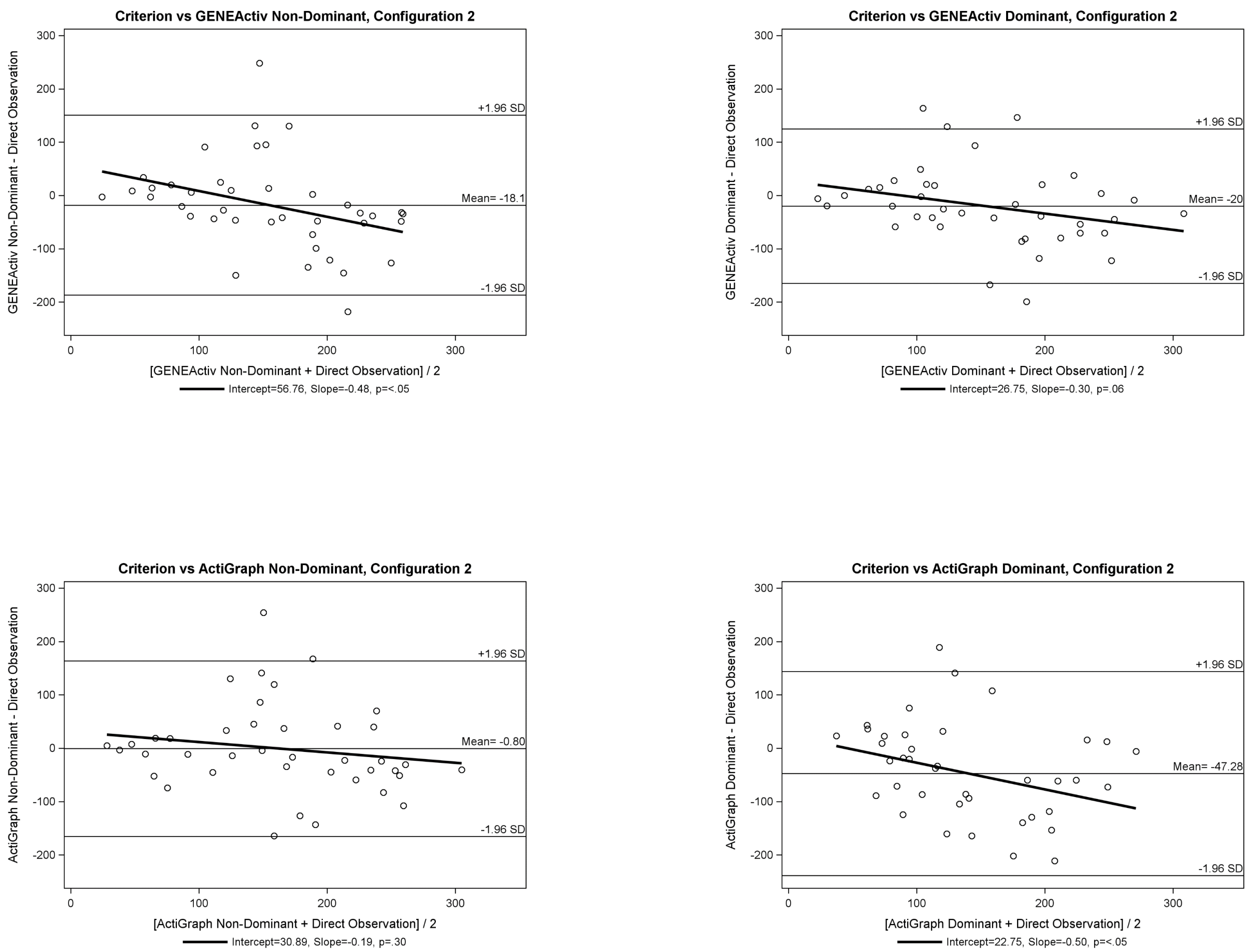
Supplemental Material 4 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 4.

Supplemental Material 5 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 5.

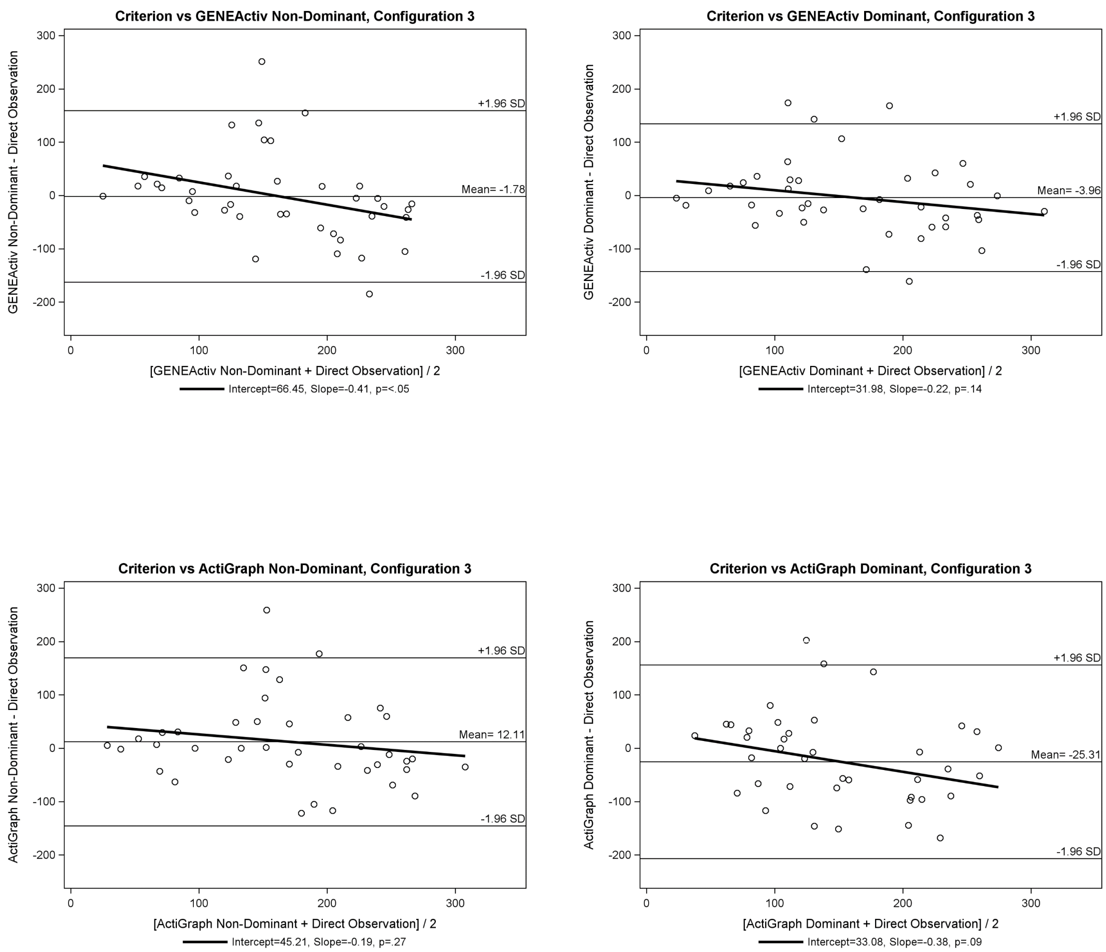
Supplemental Material 6 - Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 6.



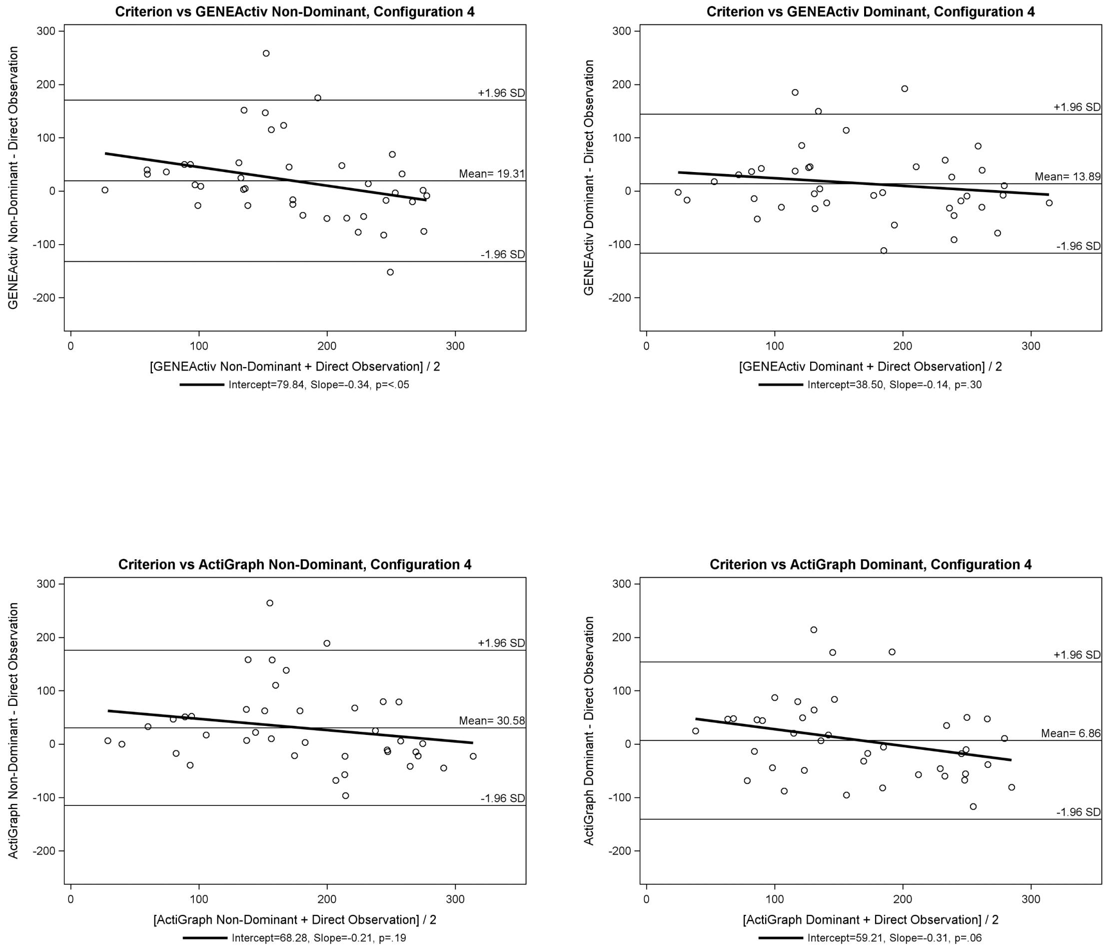
Supplemental Material 1 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 1



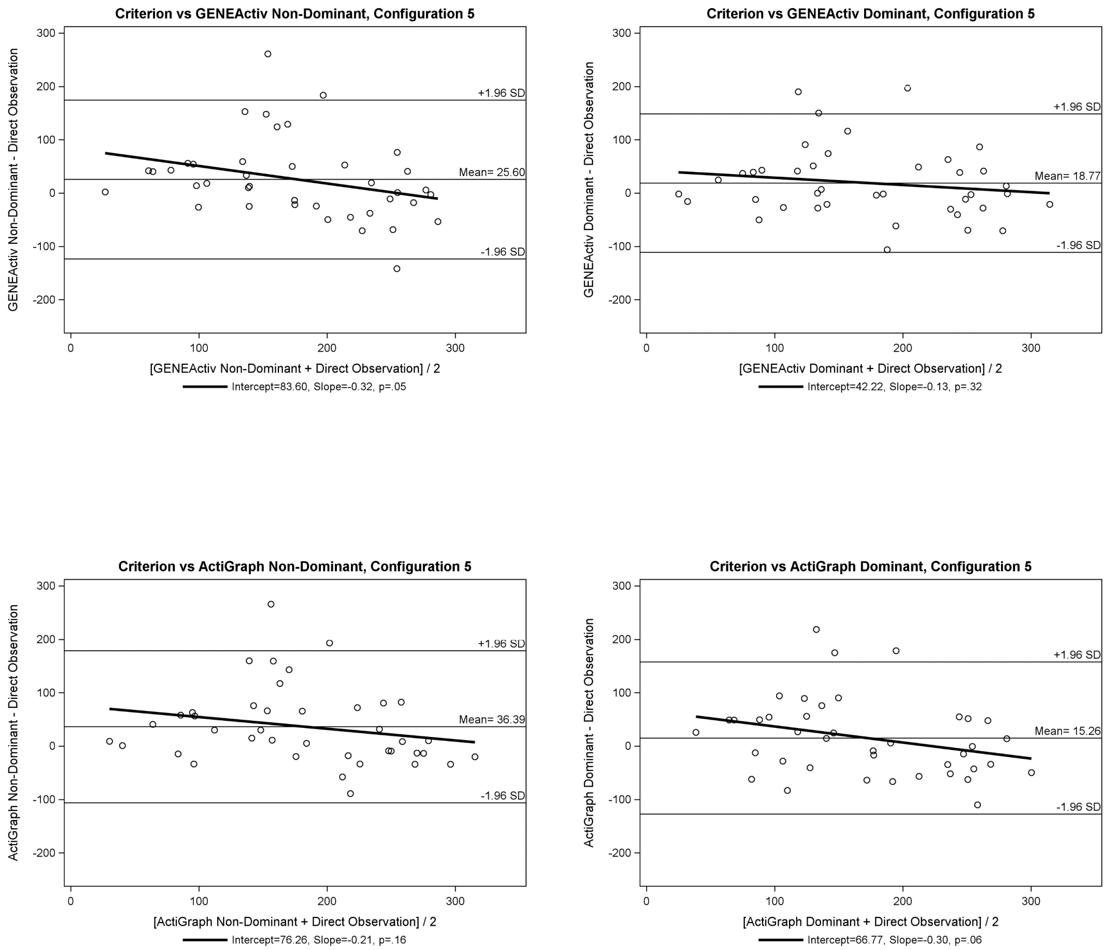
Supplemental Material 2 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 2



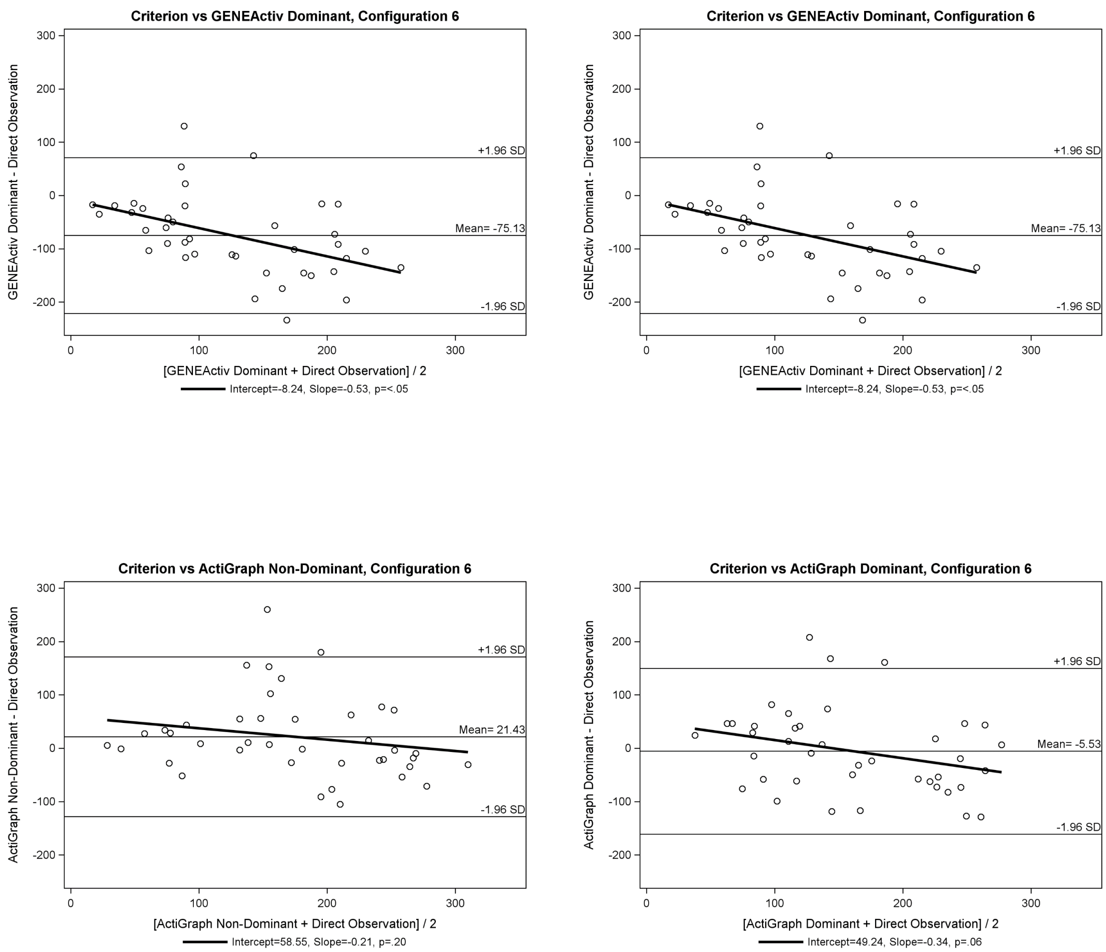
Supplemental Material 3 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 3



Supplemental Material 4 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 4



Supplemental Material 5 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 5



Supplemental Material 6 Bland-Altman Plots for Sedentary Sphere Estimates Compared with the Criterion Value Configuration 6

Chapter 7

DISCUSSION

This dissertation was composed of three distinct research projects with the overall theme of wearable monitors-based measurement of sedentary behaviors. The studies were designed to: A) examine the validity of wearable monitors (ActiGraph GT3X+, activPAL™, and SenseWear 2) to estimate energy expenditure for sedentary-to-light activities; B) test the accuracy wearable monitors (GENEActiv and the ActiGraph GT3X+) to classify sedentary and stationary time in free-living using different cut-points and body locations (wrist and waist) and to develop optimal vector magnitude cut-points to classify sedentary and stationary time based upon data collected under free-living conditions; and C) test the accuracy of posture-based sedentary time estimates made by the sedentary sphere method from GENEActiv and the ActiGraph GT3X+ wearable monitors during free-living conditions in both dominant and non-dominant wrists and with different angle configurations.

The conclusions from project one were that none of the wearable monitors tested (ActiGraph GT3X+, activPAL™, and SenseWear 2) was equivalent with the criterion measure of oxygen uptake to differentiate the energy cost of sedentary behaviors and light-intensity physical activities. Among the wearable monitors tested, the activPAL™ had the highest overall criterion validity to identify sedentary behaviors and light-intensity physical activity as compared with the ActiGraph and SenseWear 2.

Comparing of the ability of different monitors to assess the energy cost of movement with other studies is difficult as most of the existing validation studies have not considered the accuracy of energy expenditure estimates during sedentary-to-light activities as compared to the criterion of indirect calorimetry. Furthermore, there are several equations that can be used to estimate moderate-to-vigorous physical activity METs from the ActiGraph in adults,[137–142] but no prediction equations to estimate energy expenditure during sedentary-to-light physical activities. Only one study by Calabro[40] has validated the Freedson equation[136] to estimate energy expenditure during sedentary-to-light activities. Similar to project 1 in this dissertation, the Freedson equation was used to estimate energy expenditure from the ActiGraph and the study showed poor validity as compared to indirect calorimetry. Similarly, most of the validation studies using the activPAL™ have compared the monitor's accuracy in distinguishing sitting/lying, standing and stepping activities.[25,32,89,103] The validity of the activPAL™ to estimate MET values has not been compared with indirect calorimetry. Calabro[40] also examined the validity of the activPAL™ to assess energy expenditure for sedentary behaviors and light intensity physical activities and found poor validity to estimate the energy cost of sedentary and light-intensity behaviors as compared to indirect calorimetry. This differs from findings observed in project 1. Likewise, the SenseWear 2 has been validated to measure energy expenditure at rest,[156–158] and during exercise.[124,159] Only two studies[40,160] have compared the energy cost of sedentary-to-light intensity physical activities as compared with indirect calorimetry. Findings show considerable measurement error for MET estimates of sedentary-to-light activities as compared to indirect calorimetry (standing still mean percent difference = –8.62 ± 12.47, $p<0.01$; standing while doing office work mean percent difference = –18.64 ± 16.93, $p<0.01$; and sitting while doing office work mean percent difference = –19.09 ± 7.77, $p<0.01$). The results of project 1 conclude that objective monitors have low ability to distinguish between the energy costs of sedentary and light-intensity behaviors using traditional scoring methods. Thus, innovative ways to score accelerometers and other types of wearable monitors is needed to distinguish between sedentary behaviors and light-intensity physical activities.

In projects two and three, innovative methods were applied in scoring wearable monitors to identify sedentary behaviors and to differentiate sedentary behaviors from stationary behaviors. The conclusions from project 2 were that the ActiGraph single axis cut-points of 50, 100, 150, 200, 250, and 500 counts per minute and GENEActiv vector magnitude cut-points of 217 and 386 counts per minute had limited overall accuracy to assess sedentary time in free-living settings. The ActiGraph worn on the right hip using 100 and 150 counts per minute uniaxial cut-points was most accurate in differentiating stationary time (standing, sitting, and lying down) but not sedentary time (sitting and lying down). The estimated vector magnitude cut-points had better accuracy to measure sedentary and stationary time in free living settings. The ActiGraph worn on the left wrist with a vector magnitude cut-point of 2,000 counts per minute and the ActiGraph worn on the right hip with a vector magnitude cut-point of 63 counts per minute had the most accurate thresholds to classify sedentary and stationary time, respectively.

Project 2 was inspired from the findings of Kozey-Keadle et al.,[25] who showed that the ActiGraph worn on the right hip with cut-points of 100 and 150 counts per minute was most accurate in detecting sedentary behaviors. Interestingly, results for project 2 differed using the same cut-points where error magnitudes and directions were similar for measuring stationary time but not for sedentary time. The results may be due to differences in the metrics and methodological procedures used in Kozey-Keadle et al.'s study and project 2. Kozey-Keadle et al. used the low-frequency extension for the

ActiGraph whereas project 2 had no additional filtering applied to the monitors signal. It also is possible that there were differences in the ActiGraph sampling frequency, however Kozey-Keadle et al. did not report the sampling frequency used in their study. While both studies used direct observation as the criterion measure for time spent in sedentary behaviors, Kozey-Keadle et al.'s criterion value was derived from observations by a single researcher while project 2 had two observers. Based on the differences in the study methods, it is difficult to compare results directly between the Kozey-Keadle et al. study and project 2. Accordingly, differences in the validation methodologies may have contributed to the different study findings. It is recommended that a common protocol be used when validating monitor cut-points to assess time spent in sedentary behaviors so study results can be compared. Further, as no other studies have estimated vector magnitude cut-points for sedentary or stationary behaviors, additional studies are needed to confirm the findings observed to date.

As interest in the study of sedentary behaviors increases, advances in measurement methods may increase the precision needed to distinguish sedentary behaviors from other movement types and intensities. The sedentary sphere is a concept created by Rowlands et al.[41] which measures movement intensity and arm positions from a wrist-worn accelerometer to estimate time spent in sedentary behaviors. Project 3 compared the accuracy of different configurations of movement intensities and arm positions with the GENEActiv wearable monitor to estimate sedentary time as compared with sedentary time observed by direct observation. Conclusions from project 3 were that none of the sedentary sphere configurations tested were equivalent to the criterion measure of direct observation and that Rowland et al.'s original configuration of the sedentary sphere method showed moderate accuracy to classify sedentary time in free-living settings when the GENEActiv was worn on the dominant wrist as compared with the non-dominant wrist. Among the five different configurations of the sedentary sphere tested in project 3, the configuration of the wrist at 5° below the horizontal plane with a light-to-moderate cut-point intensity threshold of <489 counts per 15-second showed moderate accuracy to classify sedentary time in free-living settings from wrist-worn ActiGraph wearable monitors when worn on the dominant wrist.

To date, a perfect method has not been identified to measure time spent in sedentary behaviors using wearable monitors. The sedentary sphere is the most recent concept using wrist-worn wearable monitors with Rowlands et al. showing the sedentary sphere as valid in measuring sedentary time when a monitor is worn on the non-dominant wrist[41], regardless the wearable monitor brand.[44] Project 3 showed that the sedentary sphere was more accurate when a monitor was worn on the dominant wrist, regardless of the wearable monitor brand. Further, an alternative configuration of the sedentary sphere for the ActiGraph worn on non-dominant wrist was more accurate than the original sedentary sphere configuration. However, similar to project 2, methodological differences in Rowlands et al.'s study protocol and the one used in project 3 may have contributed to differences in the study findings. Rowlands et al. used an activPAL™ as the criterion measure for sedentary behaviors while project 3 used direct observation as the criterion measure. While, the activPAL™ and direct observation have shown to be valid measures of sedentary time,[89,154] direct observation is recognized as a the preferred criterion measure to assess postural changes. Accordingly, direct observation has been used as the criterion measure validating the activPAL™.[89,155] It is possible that the comparisons between the sedentary sphere and direct observation were more precise in project 3 than those made by Rowlands et al. using the activPAL™. Such comparisons need examination in additional studies. Another explanation for the differences may be that project 3 collected data in free-living environments while Rowlands et al. collected data in laboratory, free-living, and hospital settings. As noted, consistency in methodology used in validation studies is needed to avoid differences in results arising from the protocol used rather than the accuracy of a monitor to assess sedentary behaviors.

The findings from the three projects in this dissertation are relevant since wearable monitors are used more frequently to determine time spent in sedentary behaviors and physical activities in research studies. However, reflection of how methods may have been applied differently in the three projects suggests additional research may expand the scope of the results obtained. In project 1, the use of multiple monitors worn on different body locations would have allowed inter-monitor comparisons. For example, if the activPAL™ and another monitor had been placed on the thigh, it would have been possible to compare if the activPAL™ energy expenditure estimations were due to the location of the monitor or to the estimation equation. Another improvement would have been to include an additional criterion measure to assess the definition of sedentary behavior related to intensity and posture, not just one or the other. In projects 2 and 3, having participants in the study who were left-handed and right-handed (as opposed to having all participants being right-handed as in these studies) would have extended the results to make comparisons between dominant and non-dominant estimations more generalizable to the population.

Collectively, the findings on this dissertation indicate that the tested wearable monitors and methods used have limitations in assessing sedentary behaviors and light-intensity physical activities and that there is considerable room for improvement in the wearable monitors-based measurement of sedentary behaviors and light-intensity physical activities. Additional research is required to show consistency of results and to further understand the scope and limitations of common wearable monitors and approaches to assess sedentary behaviors and light intensity physical activities. Future research topics on sedentary behaviors measurement may include testing alternative locations of monitors on the body to assess sedentary behaviors including the ankle and in pockets. Testing of the technical features of wearable monitors is needed as is testing the accuracy of the equations used to assess sedentary behaviors and light intensity physical activity. Last, in evaluating the sedentary sphere, tests of sedentary time estimations are needed to show that data are equivalent from monitors worn on dominant vs. non-dominant wrists and that the sedentary sphere results are applicable in different settings and populations.

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APPENDIX I

IRB APPROVAL AND CONSENT FORM PROJECT 1

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Barbara Ainsworth School of
From:	Carol Johnston, Chair Biosci IRB
Date:	03/19/2012
Committee Action:	**Amendment to Approved Protocol**
Approval Date:	03/19/2012
Review Type:	Expedited F12
IRB Protocol #:	1105006503
Study Title:	Assessing Activity Using Multiple Measurement Devices
Expiration Date:	06/14/2012

The amendment to the above-referenced protocol has been APPROVED following Expedited Review by the Institutional Review Board. This approval does not replace any departmental or other approvals that may be required. It is the Principal Investigator's responsibility to obtain review and continued approval of ongoing research before the expiration noted above. Please allow sufficient time for reapproval. Research activity of any sort may not continue beyond the expiration date without committee approval. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the approval of this protocol on the expiration date. Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please notify the Committee of the study termination.

This approval by the Biosci IRB does not replace or supersede any departmental or oversight committee review that may be required by institutional policy.

Adverse Reactions: If any untoward incidents or severe reactions should develop as a result of this study, you are required to notify the Biosci IRB immediately. If necessary a member of the IRB will be assigned to look into the matter. If the problem is serious, approval may be withdrawn pending IRB review.

Amendments: If you wish to change any aspect of this study, such as the procedures, the consent forms, or the investigators, please communicate your requested changes to the Biosci IRB. The new procedure is not to be initiated until the IRB approval has been given.

Please retain a copy of this letter with your approved protocol.

CONSENT FORM

Assessing Activity Using Multiple Measurement Devices

INTRODUCTION

The purposes of this form is to provide you (as a prospective research study participant) information that may affect your decision to participate in this research and to record the consent of those who agree to be involved in the study.

RESEARCHERS

Dr. Barbara Ainsworth, Professor, Healthy Lifestyle Research Center and Program of Exercise and Wellness, and Nathanael Meckes have invited your participation in a research study.

STUDY PURPOSE

The purpose of the research is to use determine the activity levels of 7 different activities.

DESCRIPTION OF RESEARCH STUDY

If you decide to participate, you will join a study involving wearing five activity monitoring instruments (Oxycon Mobile, ActiGraph GT3X+, Sensewear Armband, Zephyr Bioharness, and ActivPAL). These instruments will be worn on the arm, waist, thigh, and chest.

The protocol will require a two 1.5 hour sessions with at least 24 hours in between sessions. Upon arrival of the first visit, your height and weight will be assessed. The activity monitoring instruments will be provided to you. Both 1.5 hour sessions will have you engaging in the following activities: typing while seated at a computer, walking at 1.0 mile per hour, walking at 1.5 miles per hour, walking at 2.0 miles per hour, performing kitchen work, reading a book while standing, and playing a seated board game.

If you say YES, then your participation will last for 1.5 hours on two separate days totaling 3.0 hours. The study will be at the Exercise and Wellness Building on the Arizona State University Polytechnic campus.

RISKS

If you decide to participate in this study, then you may face a minimal risk of injury. You may fall off of a treadmill moving slowly. If you have no experience with using a treadmill, then you will be given time to learn how to walk on a treadmill. There are no other significant risks.

BENEFITS

You are furthering the science in the study of sedentary behavior.

NEW INFORMATION

If the researchers find new information during the study that would reasonably change your decision about participating, then they will provide this information to you.

CONFIDENTIALITY

All information obtained in this study is strictly confidential unless disclosure is required by law. The results of this research study may be used in reports, presentations, and publications, but the researchers will not identify you. In order to maintain confidentiality of your records, Nathanael Meckes will assign each subject an ID number for this study. Following initial data collection, all identifying information will be removed from electronic databases used in the study. All information and data collected during this study will be stored in a locked limited access laboratory and all electronic data will be stored on password protected computers. Additionally, only members of the research team will have access to study files or data.

ASU IRB
Approved
Sign SC for Carol Johnston
Date 3/19/12 - 6/14/12

Initials________

WITHDRAWAL PRIVILEGE

It is ok for you to say no. Even if you say yes now, your participation is voluntary and you are free to withdraw from the study at any time. If you are a student nonparticipation or withdrawal from the study will not affect your grades or status as a student. If you withdraw early, you will not receive any financial compensation. However, you will receive a physical activity report from all data collected.

COSTS AND PAYMENTS

There are no costs to you for participation in the study. You will receive $50 cash upon completion of the second visit.

COMPENSATION FOR ILLNESS AND INJURY

If you agree to participate in the study, then your consent does not waive any of your legal rights. However, no funds have been set aside to compensate you in the event of injury.

VOLUNTARY CONSENT

Any questions you have concerning the research study or your participation in the study, before or after your consent, will be answered by Dr. Barbara Ainsworth, Exercise and Wellness Building, ASU Polytechnic campus, 480-727-1924 or Nathanael Meckes at 616-648-1783.

If you have questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Research Compliance Office, at 480-965 6788.

This form explains the nature, demands, benefits and any risk of the project. By signing this form you agree knowingly to assume any risks involved. Remember, your participation is voluntary. You may choose not to participate or to withdraw your consent and discontinue participation at any time without penalty or loss of benefit. In signing this consent form, you are not waiving any legal claims, rights, or remedies. A copy of this consent form will be given (offered) to you.

Your signature below indicates that you consent to participate in the above study.

Participant Signature	Printed Name	Date

INVESTIGATOR'S STATEMENT

"I certify that I have explained to the above individual the nature and purpose, the potential benefits and possible risks associated with participation in this research study, have answered any questions that have been raised, and have witnessed the above signature. These elements of Informed Consent conform to the Assurance given by Arizona State University to the Office for Human Research Protections to protect the rights of human subjects. I have provided (offered) the subject/participant a copy of this signed consent document."

Signature of Investigator	Date

ASU IRB
Approved
Sign Sr for Carol Johnston
Date 03/19/12 - 6/14/12

APPENDIX II

IRB APPROVAL AND CONSENT FORMS PROJECT 2 AND 3

APPROVAL: EXPEDITED REVIEW

Barbara Ainsworth
SNHP - Exercise and Wellness
602/827-2291
Barbara.Ainsworth@asu.edu

Dear Barbara Ainsworth:

On 2/11/2014 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	IDENTIFYING FREE-LIVING PHYSICAL ACTIVITY AND SEDENTARY BEHAVIOR PATTERNS USING A WRIST-MOUNTED ACCELEROMETER: A MACHINE LEARNING ALGORITHM APPLICATION
Investigator:	Barbara Ainsworth
IRB ID:	STUDY00000522
Category of review:	(4) Noninvasive procedures, (7)(a) Behavioral research
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• MLA Consent v3.pdf, Category: Consent Form; • HRP-503b- TEMPLATE PROTOCOLBioscience_v3[2].docx, Category: IRB Protocol; • Visits 2 & 3 collection form.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Visit one data collection form.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Email_v3.pdf, Category: Recruitment Materials; • Flyer_v3.pdf, Category: Recruitment Materials; • not eligible email.pdf, Category: Recruitment

	Materials; • Screening questionnaire[1].pdf, Category: Screening forms;

The IRB approved the protocol from 2/11/2014 to 2/10/2015 inclusive. Three weeks before 2/10/2015 you are to submit a completed "FORM: Continuing Review (HRP-212)" and required attachments to request continuing approval or closure.

If continuing review approval is not granted before the expiration date of 2/10/2015 approval of this protocol expires on that date. When consent is appropriate, you must use final, watermarked versions available under the "Documents" tab in ERA-IRB.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc:

George Runger
Davide Sottara
Argemiro A Florez Pregonero
Matthew Buman
Moinul Chowdhury

ARIZONA STATE UNIVERSITY
INFORMED CONSENT FORM

Project name: Identifying free-living physical activity and sedentary behavior patterns using a wrist-mounted accelerometer: a machine learning algorithm application

Principal Investigator: Barbara Ainsworth, Ph.D., MPH
School of Nutrition and Health Promotion
College of Health Solutions
500 North 3rd Street | Phoenix, AZ 85004
ASU Mail Code 3020
Office Ph: 602.827-2291
Email: Barbara.Ainsworth@asu.edu

Co-Investigators: Matthew Buman, Alberto Flórez Pregonero

INTRODUCTION

The purposes of this form are to provide you (as a prospective research study participant) information that may affect your decision as to whether or not to participate in this research and to record the consent of those who agree to be involved in the study.

RESEARCHERS

Barbara Ainsworth, Ph.D., Professor at the School of Nutrition and Health Promotion at Arizona State University and his co-investigators have invited you to participate in a research study.

STUDY PURPOSE

The purpose of the research is to develop and validate a machine learning algorithm to assess seven different physical activity and sedentary behaviors patterns (walking, running, sitting, standing, conditioning exercise, and lying) based on wrist-mounted motion detectors (accelerometers). You will wear 5 accelerometers (2 on each wrist and one on your waistband) and be observed during your usual activity patterns for two days, at least 6-hours/day.

DESCRIPTION OF RESEARCH STUDY

If you decide to participate, then as a study participant you will join a study involving research to develop and validate a machine learning algorithm to assess different kinds of physical activity and sedentary behaviors based on information collected while observing you in your natural environment. We will use a brief electronic questionnaire to determine if you are eligible for the study. If you qualify for the study and you decide to participate, we will schedule the first of three visits. After that we will give you a brief survey about your socioeconomic status and physical activity habits that will take about 5-10 minutes. Our study personnel will be available to assist if you have any questions or need help filling out the questionnaire.

First visit will be in our study site will be in the Exercise Physiology Laboratory at the Downtown campus of Arizona State University to explain the study in detail to you, allow you to ask questions and address your concerns regarding your participation in the study, allow you to be familiar with the devices to wear during the data collection days, and ask you to sign this informed consent form indicating that you agree to participate in the study. During this first visit to our study site at the Downtown campus of Arizona State University we also will measure your height and weight; in addition to have taken these measurements, we will schedule a time and explain the details for visits two and three. Details for visits two and three include: identification and reporting personal reasons and places in which you think is not confortable to be observed (i.e., family time, leisure time, etc.), also identify additional requirements or aspects to be addressed for the researcher in order to successfully undertake the data collection days (e.g., permits to access work places). To successfully book visits two and three it is necessary that each visit will include at least 6 hours of wearing the monitors and being observed.

During visits two and three you will be followed in your natural environment by two trained researchers while wearing five different PA measurement devices (two on your non-dominant wrist, two on your dominant wrist, and one on your right hip). The researchers will be following you in a silent manner while collecting data with a tablet-based software. During each visit you might need private time (i.e., restrooms use) to that purpose you just need the researchers to know about it and he/she will record this time as 'private' and resume the activity recording when you will have finished the private activity. At the end of each data collection day the researchers will remove the devices from your body and leave you.

If you say YES, then your participation will last for 1 hour during visit 1 and at least 6 hours (between 6:00 am to 10:00 pm) for study visits 2 and 3. Approximately 20 people from the Phoenix area will be participating in this study.

RISKS

If you decide to participate in this study there is low injury risk for you since you will be performing your usual activities. We will not ask you to perform any activity that you do not usually do. We also encourage you to do not modify your habitual activity patterns or engage in an activity that is not usual for you while conducting visits two and three in this study.

Invasion of privacy is a potential risk that encompasses this study. We have developed different strategies to reduce this risk:

- During visit one, researcher and participant will establish times and spaces in which the participant will/won't allow the observation.
- Researchers will be trained on strategies to avoid disrupting or disturbing participants.
- During the days in which observation is conducted, participants will be allowed to have private time when needed (i.e. restrooms use, napping, etc.)
- Two researchers, a male and a female, will perform the observation.

BENEFITS

There is no direct benefit from participation in this study. We do expect an improvement in objective measurement of physical activity, which could have major public health implications, but we cannot predict any health changes for you.

NEW INFORMATION

If the researchers find new information during the study that would reasonably change your decision about participating, then they will provide this information to you.

CONFIDENTIALITY

All information obtained in this study is strictly confidential unless disclosure is required by law. The results of this research study may be used in reports, presentations, and publications, but the researchers will not identify you. In order to maintain confidentiality of your records we will code all the data so that they do not contain any information that could identify you. All confidential information will be kept in a locked filing cabinet in Dr. Barbara Ainsworth Physical Activity Assessment Laboratory and/or in a password-protected computer, and will only be available to members of the research team. All study materials will be destroyed 10 years after the study has been completed or upon your withdrawal from the study. All study-related documents will be shredded.

WITHDRAWAL PRIVILEGE

Taking part in this research study is totally your choice. It is ok for you to say no. Even if you say yes now, you are free to say no later. You can decide to stop taking part in this research study at any time for any reason.

COSTS AND COMPENSATION

The researchers want your decision about participating in the study to be absolutely voluntary. Yet they recognize that your participation may pose some inconvenience due to the time needed to complete the research activities and because we will follow you during your daily activities for two days. In order to compensate for your time and discomfort, you will receive $10 for each observation visits that you participate in for a total of $20.

COMPENSATION FOR ILLNESS AND INJURY

If you agree to participate in the study, then your consent does not waive any of your legal rights. However, no funds have been set aside to compensate you in the event of injury.

VOLUNTARY CONSENT

Any questions you have concerning the research study or your participation in the study, before or after your consent, will be answered by Alberto Flórez Pregonero. You can contact him at 550 North 3rd Street, Phoenix, Arizona, 85004, or alberto.florez.p@gmail.com, or 480-735-8436.

If you have questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at 480-965-6788.

This form explains the nature, demands, benefits and any risk of the project. By signing this form you agree knowingly to assume any risks involved. Remember, your participation is voluntary. You may choose not to participate or to withdraw your consent and discontinue participation at any time without penalty or loss of benefit. In signing this consent form, you are not waiving any legal claims, rights, or remedies. A copy of this consent form will be given (offered) to you.

Your signature below indicates that you consent to participate in the above study.

____________________	____________________	__________
Subject's Signature	Printed Name	Date
____________________	____________________	__________
Other Signature (if appropriate)	Printed Name	Date

INVESTIGATOR'S STATEMENT

"I certify that I have explained to the above individual the nature and purpose, the potential benefits and possible risks associated with participation in this research study, have answered any questions that have been raised, and have witnessed the above signature. These elements of Informed Consent conform to the Assurance given by Arizona State University to the Office for Human Research Protections to protect the rights of human subjects. I have provided (offered) the subject/participant a copy of this signed consent document."

Signature of Investigator______________________________ Date__________

APPENDIX III

PERMISSION STATEMENT

Permission Statement

I hereby attest that Nathanael Meckes, Matthew Buman, and Barbara Ainsworth as co-authors of the paper entitled "Wearable monitors criterion validity for energy expenditure in sedentary and light activities" published in the Journal of Sport and Health Science, have granted their permission to use the article as the fourth chapter in this dissertation.

Sincerely,

Argemiro Alberto Florez Pregonero