The Effect of Study Participant Compliance on the Estimates of Physical Activity: Implications for the Predictions of Health Markers

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Ryan McGrath

Major Professor: David Paul, Ph.D.

Committee Members: Philip Scruggs, Ph.D.; Chantal Vella, Ph.D.; Christopher Williams, Ph.D.

Department Administrator: Philip Scruggs, Ph.D.

Authorization to Submit Dissertation

This dissertation of Ryan McGrath, submitted for the degree of Doctorate of Philosophy with a Major in Education and titled "***The Effect of Study Participant Compliance on the Estimates of Physical Activity: Implications on the Predictions of Health Markers***," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: _____ Date: _____
David Paul, Ph.D.

Committee Members: _____ Date: _____
Philip Scruggs, Ph.D.

_____ Date: _____
Chantal Vella, Ph.D.

_____ Date: _____
Christopher Williams, Ph.D.

Department Administrator: _____ Date: _____
Philip Scruggs, Ph.D.

Abstract

Purpose: To investigate the influence of accelerometer data simulations and adherence on estimates of sedentary behavior and physical activity, and the subsequent application of these data.

Methods: A sample of 50 female (age=25.6±8.6 years) and 50 male (age=25.4±7.2 years) participants wore an accelerometer at least 22 hours/day for 7 consecutive days (raw data) to assess sedentary behavior, light physical activity (LPA), moderate-to-vigorous physical activity (MVPA), and average intensity of daily physical activity (DPA). A series of health markers were also measured. Reductions in accelerometer adherence were simulated by randomly removing 60 minute blocks of time during waking hours until each participant had 17-10 hours of data. Four different accelerometer data simulation techniques were tested by inserting "zeroes" or "dots" in the raw data to simulate accelerometer removals during sleep or waking hours. One-way ANOVA with Bonferroni *post-hoc* tests on mean estimates and absolute percent errors (APE) were used to analyze the differences between each accelerometer data simulation technique and adherence when compared to the raw data. The raw and simulated accelerometer data were then used in univariate regressions to predict each health marker that was measured, and the results were compared.

Results: Participants averaged 23.3 hours/day of accelerometer wear, for a total of 687 days across all participants. Significant differences ($p<0.05$) were detected in the estimates of sedentary behavior, LPA, and DPA when compared to the raw data for some data simulation techniques. APE increased in a stepwise fashion as adherence decreased for LPA and MVPA; however, the data simulation techniques yielded different patterns of error as adherence decreased for sedentary behavior and DPA. Decision changes were found when the simulated data sets were used to predict each health marker, but only in about 7% of analyses.

Conclusions: Generally, accelerometer data simulation techniques and low adherence may negatively influence predictions of sedentary behavior and physical activity when compared to the raw data. However, decision changes resulting from applying spurious accelerometer data in univariate regression models was minimal. These results indicate accelerometer data simulation techniques should be carefully applied and high accelerometer adherence should be a priority for researchers.

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Chapter 1: Introduction

Interrelationships between physical activity, obesity, and disease

Since 2,500 BC, the health aspects of physical activity have been documented, paving the way for present day empirical evidence that has identified sedentary behavior and obesity as risk factors for many preventable diseases and all-cause mortality (Berrington de Gonzalez, et al., 2010; Blair, et al., 1995; Hu, et al., 2004; MacAuley, 1994; Mokdad, Marks, Stroup, & Gerberding, 2004). Historically, obesity levels have continued to climb, but have now plateaued to alarmingly high levels, especially in older and minority populations (Flegal, Carroll, Kitt, & Ogden, 2012; Ogden, Carroll, Kit, & Flegal, 2012; Ogden, Carroll, Kitt, & Flegal, 2014). The high prevalence of obesity is likely related to the amount of time Americans spend being physically inactive, which is estimated to be approximately 7.7 waking hours/day (Matthews, et al., 2008).

Obese patients are also at high risk for comorbid disorders, such as diabetes, cardiovascular disease, and certain cancers (Pi-Sunyer, 2009). Compared to their normal-weight counterparts, obese people have greater medical spending across all payers (Finkelstein, Trogdon, Cohen, & Dietz, 2009). An estimated $40 billion of medical spending and 35% higher inpatient and outpatient costs are associated with obesity annually (Sturm, 2008). Type 2 diabetes alone is responsible for about $132 billion of lost productivity and medical expenditures in the Unites States (Cowie, et al., 2006). Coronary heart disease, osteoarthritis, and hypertension also respectively account for $7 billion, $4 billion, and $3 billion of the direct costs attributed to obesity respectively (Wolf & Colditz, 1998). Overall, obesity is responsible for the highest amount of spending for health care services and the second highest amount for medications (Sturm, 2002).

As a means to mitigate the negative impacts of obesity, the American College of Sports Medicine recommends that people engage in at least 250 minutes/week of moderate physical activity for weight loss or 150-250 minutes/week of moderate physical activity to prevent weight gain (Donnelly, et al., 2009). Interventions designed to achieve these recommendations may take many forms, such as community-wide physical activity programs, infrastructure changes that are conducive to increasing physical activity, and active transportation (Gordon-Larsen, et al., 2009; Marcus, et al., 2006; Saelens, Sallis, Black, & Chen, 2003). However, it remains difficult to assess the impact of these approaches designed to promote physical activity,

not to mention their subsequent impacts on health. Overall, accurately assessing physical activity in free-living populations is an important component of many scientific investigations aimed at determining the effectiveness of strategies to increase physical activity (Bonomi, Goris, Yin, & Westerterp, 2009).

Measurement of physical activity in free-living conditions

There are a number of approaches investigators use to measure physical activity, ranging from devices that study participants wear continuously to self-report questionnaires such as the International Physical Activity Questionnaire (IPAQ) or National Health and Nutrition Examination Survey (NHANES) Physical Activity Questionnaire (Churilla & Fitzhugh, 2012; Shook, et al., 2015). Despite some major limitations, physical activity questionnaires are widely used because they are cost effective, simple to conduct, and easy to complete (Starling, Matthews, Ades, & Poehlman, 1999). Unfortunately, the accuracy of self-report physical activity questionnaires tend to be poor because those completing the questionnaire may inaccurately report their physical activity levels due to poor respondent memory, social desirability recall bias, misinterpretation of a question, incomplete or missing data, or lack of motivation to accurately complete the questionnaire (Dollman, et al., 2009).

Technology has brought a myriad of options to objectively assess physical activity and energy expenditure, such as doubly labeled water, pedometers, heart rate monitors, and accelerometers. Doubly labeled water is an isotope-based method that measures free-living energy expenditure. Studies that have validated doubly labeled water suggest group-level estimates of total energy expenditure are accurate, but individual-level estimates are more problematic (Speakman, 1998). Pedometers are small electronic devices often worn on the hip that objectively assess ambulatory activities throughout the day in the form of step counts (Bravata, et al., 2007). According to Tudor-Locke et al. (2011), pedometers are a valid, accurate measure of assessing physical activity in free-living conditions (Tudor-Locke, Bassett, Shipe, & McClain, 2011). Although these devices are relatively inexpensive, their wide-spread use in research applications are blunted by the amount of variability between different brands of pedometers and their inability to assess non-ambulatory activities. Heart rate monitors are small electronic devices often worn near the chest that can be used for measuring physical activity in free-living conditions (Dollman, et al., 2009). These devices can accurately record heart rate, physical activity intensity, and work threshold; however, data entry is complex

and heart rates are subject to a high degree of variability across individuals due to ambient temperatures, emotions, and fitness levels (Dollman, et al., 2009).

Accelerometers are small electronic devices often worn on the hip, wrist, or ankle that assess physical activity based on either physiological or mechanical responses to bodily movement (Bassett, Rowlands, & Trost, 2012). These devices can estimate the prevalence of meeting physical activity recommendations, the number and length of activity bouts, breaks in sedentary behavior, and transitions between sitting and standing (Matthews, Hagströmer, Pober, & Bowles, 2012). As a result, accelerometers are widely used in physical activity research (Welk, McClain, & Ainsworth, 2012). Accelerometers are a popular instrument used to objectively measure physical activity and energy expenditure in a free-living environment, and their use in research applications continues to increase as the capabilities of accelerometers evolves (Garnier & Bénéfice, 2006; Troiano, 2005).

History and evolution of accelerometers

The use of accelerometers in research dates back to 1922, when they were used for motion and vibration detection in industrial applications (Karcher, 1922). In the 1960's, Cavagna et al. (1961) developed an accelerometer-based device that measured the quantitative force necessary for dynamic movement by the human body (Cavagna, Saibene, & Margaria, 1961). Technology since then has continued to evolve for accelerometers, as Wong et al. (1981) used advanced piezoelectric ceramic sensors to measure physical activity (Wong, Webster, Montoye, & Washburn, 1981). Since this technology was developed, accelerometers have gained prominence for measuring physical activity (John & Freedson, 2012). Accelerometer technologies are also used for other types of research such as detection of falls in elderly populations (Culhane, O'Connor , Lyons, & Lyons, 2005). Mobile accelerometer applications can be easily downloaded on phones for patrons to measure their sedentary behavior and physical activity (Lee & Carlisle, 2011); however, accuracy of the estimates of sedentary behavior and physical activity are limited because the location of the phone on the body is often inconsistent (Antos, Albert, & Kording, 2014). Popular accelerometer manufactures include ActiGraph (Pensacola, FL) and Actical (Phillips Respironics; Bend, OR).

Data acquisition approaches with accelerometers

The fundamental outcome measures from accelerometers are based on speed and acceleration. Speed is defined as the change in position with respect to time; whereas, acceleration is the change in speed with respect to time (Chen & Bassett, 2005). Although an object may not have any acceleration, it is still possible for it to have a constant speed. These physics-based principles cause a piezoelectric device to experience deformation or bending in the beam sensors, creating changes in the displaced charge in one direction to accumulate on one side of the sensor. This produces a voltage signal that is relative to the applied acceleration. Since the piezoelectric element is sensitive to bending direction, it is often referred to as uniaxial. A major limitation of piezoelectric accelerometers is they can only be used to detect dynamic movements. Therefore, recent accelerometer technologies have shifted toward using a capacitive device, which detects changes in acceleration through changes in capacitance of the sensing element, altering the generated peak voltage which is fed to a summing amplifier that processes the final signal (Chau, et al., 1996; John & Freedson, 2012). This allows accelerometers to detect dynamic and static movements through the detected force of gravity when not in motion.

Accelerometers can also detect motion in different planes of movement by positioning sensors orthogonally and in turn, measuring accelerations in multiple directions (Chen & Bassett, 2005). Dual axial accelerometers measure horizontal and vertical accelerations, while triaxial accelerometers measure accelerations occurring in the anteroposterior (x-axis), medial-lateral (y-axis), and vertical axes (z-axis) (Buchowski, Acra, Majchrzak, Sun, & Chen, 2004). Omnidirectional accelerometers measure changes in accelerations from all directions, but tend to be most sensitive in one plane, usually the vertical. Because the accuracy of sedentary behavior and physical activity measurements generally increase when using accelerometers with more axes (Chen & Bassett, 2005), triaxial accelerometers have emerged as popular accelerometer types in research (Cain, Conway, Adams, Husak, & Sallis, 2013; Mitchell, Ziviani, & Boyd, 2015; Rowlands , et al., 2015; Zhang, Rowlands, Murray, & Hurst, 2012); however, uniaxial accelerometers have also been used in studies (Healy, et al., 2007; Mark & Janssen, 2009; Vallance, et al., 2011). As accelerometer technologies continue to evolve, the use of triaxial accelerometers will grow and likely phase out older, uniaxial accelerometers. Other recent improvements in accelerometer technologies have emerged

such as expanded onboard memory that allows for data collection at higher resolutions and increased battery duration that allows accelerometers to be worn for consecutive days without charge (Chen, Janz, Zhu, & Brychta, 2012).

The rate in which accelerometer data acquisition occurs is determined by the sampling frequency of the accelerometer's computer. It is important to confirm that all ranges of human motion are captured independently by utilizing a sampling frequency that is at least twice that of the highest frequency of movement in order to allow for the signal to be completely represented (Chen, Janz, Zhu, & Brychta, 2012). Failure to meet this criterion may result in measurement distortion (Chen & Bassett, 2005). After these data have been sampled, they are run through a band-pass filter that allows frequencies between a pre-determined low- and high-frequency limit to pass while other frequencies are mollified. Band-pass filtering increases the linearity of the output with regards to the true signal, while reducing the influence from wear or temperature drifts, which have a lower frequency.

This voltage signal is often filtered and amplified in order for data to be converted from an analog voltage signal to a digital series of numbers referred to as raw counts (Chen & Bassett, 2005). These raw counts are not often used in current physical activity monitoring studies. Typically, there are three approaches one can take when analyzing raw counts. One approach allows the use of a digital counter to accrue the number of times a signal goes beyond a predetermined threshold. Another approach is to use an algorithm that has the ability to determine the maximum value for a selected time segment (epoch) to represent the counts for that time period.

The third and perhaps most commonly used technique applies the use of an area under the average (integration) algorithm (Chen & Bassett, 2005). Although there are several strengths to using this technique, such as the ease of data simulation, data interpretation can be impacted simply by the choice of epoch duration (because bursts of physical activity are averaged). An epoch is a user-defined time interval over which the accelerometer information is summarized (Heil, Brage, & Rothney, 2012). Choosing long epoch lengths can minimize the influence of intense physical activity occurring in short bouts. Therefore, it has been suggested that short epoch lengths (1-30 seconds) should be used when assessing multiple short bouts of physical activity

(often in children); whereas, 60 second epoch lengths are generally considered to be an appropriate duration that compromises the limitations of short and long epoch lengths (Heil, Brage, & Rothney, 2012).

Another consideration is the location on the body where participants wear accelerometers. Studies have placed accelerometers on the waist (Carter, et al., 2008; Macfarlane, Chan, Chan, Ho, & Lee, 2008; Sasaki, John, & Freedson, 2011; Webber, et al., 2008; Yoshioka, et al., 2005), lower back (Hagströmer, Oja, & Sjöström, 2007; Hoos, Kuipers, Gerver, & Westerterp, 2004; Levine, Melanson, Westerterp, & Hill, 2003), arm (King, Torres, Potter, Brooks, & Coleman, 2004; Lopez-Alarcon, et al., 2004; Swartz, et al., 2000), and ankle (Crouter, Churilla, & Bassett, 2006; Rousham, Clarke, & Gross, 2006). The more proximal accelerometer locations (waist and lower back) allow for the recording of true body movement near the participant's center of mass. However, the more distal locations (wrist and ankle) can measure movements of the upper and lower extremities. It has been suggested that researchers consider having study participants wear accelerometers at proximal and distal locations concurrently as a means for better detecting physical activity through inter-monitor comparisons (Freedson, Bowles, Troiano, & Haskell, 2012).

Challenges of using accelerometers to measure physical activity

Current accelerometer technologies allow researchers to estimate sleep and awake time, predict total and physical activity energy expenditure, classify mode of activity, posture, walking (i.e., number of steps), and detect the frequency, intensity, and duration of physical activity (Butte, Ekelund, & Westerterp, 2012). One challenge of using accelerometers to assess physical activity or energy expenditure is their removal by study participants for sleep, activities involving water, and non-compliance (Healy, et al., 2007; Jerome, Young, Laferriere, Chen, & Vollmer, 2009). Low levels of accelerometer wear time may be associated with a higher percentage of error when measuring sedentary behavior and physical activity (Herrmann, Barreira, Kang, & Ainsworth, 2013). A fundamental problem is that when accelerometers are removed and placed in a stationary position, they produce a zero count, indicating non-movement. When these strings of zeroes appear in a data set, investigators will likely not understand what activities the study participant was engaged in at the time. If a person is physically active but not adherent with the accelerometer, the presence of zeroes in the data set will artificially decrease the estimates of total physical activity (Paul, et al., 2008).

Methods for the determination of accelerometer adherence

Although accelerometer adherence appears to be an important issue, the approaches used for the estimation of non-wear time vary greatly. A number of different non-wear algorithms exist, which are based on detecting strings of consecutive zero counts appearing in the data set, and subsequently assuming the accelerometer was not being worn at that time. A search of the literature reveals the number of consecutive zeroes used to determine non-wear varies considerably, including 10 minutes (Brage, et al., 2004), 15 minutes (Rousham, Clarke, & Gross, 2006), and 60 minutes (Troiano, et al., 2008). Other commonly used non-wear algorithms include ≥ 20 minutes of consecutive zero counts (Buchowski, et al., 2009; Hagströmer, Oja, & Sjöström, 2007; Savitz, et al., 2006), ≥ 30 minutes of consecutive zero counts (van Hees, et al., 2011), and ≥ 60 minutes of consecutive zero counts (Matthews, et al., 2008; Rowlands, Pilgrim, & Eston, 2009). The majority of studies utilizing NHANES data use a non-wear algorithm of ≥ 60 minutes of consecutive zero counts with allowance for up to 2 minutes of data less than 100 counts/minute (Tudor-Locke, Camhi, & Troiano, 2012).

An alternative approach to estimating accelerometer adherence has been proposed by Choi et al. (2011). This approach to non-wear detection recommends implementing: 1) a zero-count threshold during a non-wear time interval, 2) 90-minutes of consecutive zero counts should be defined as non-wear time, and 3) allowance of 2-minute intervals on non-zero counts with 30 minutes of consecutive zero counts (Choi, Liu, Matthews, & Buchowski, 2011). This algorithm was subsequently tested in an elderly population (29 adults, aged 76-96 years) and demonstrated that 90 minutes of consecutive zero counts more accurately defined non-wear time when compared to 60 minutes of consecutive zero counts (Choi, Ward, Schnelle, & Buchowski, 2012). These investigators suggested this non-wear algorithm is equally accurate in younger populations, because older populations are typically the most sedentary (Matthews, et al., 2008). However, the accuracy of Choi et al. (2012) in a younger, more active population remains unknown.

Establishing appropriate adherence standards for accepting accelerometer data are very important for reducing measurement error during an assessment of free-living sedentary behavior and physical activity, because higher levels of accelerometer wear time better predict average intensity of daily physical activity (DPA) (Paul, et al., 2008). Although researchers most often cite at least 10 hours as a minimum wear time for defining a valid day (Tudor-Locke, Camhi, & Troiano, 2012), other studies have used at least 4 hours

(Keyserling, et al., 2002), 6 hours (Jilcott, Evenson, Laraia, & Ammerman, 2007), 8 hours (Buchowski, et al., 2009), 12 hours (Matthews, Ainsworth, Thompson, & Bassett, 2002), or 22 hours (Hoos, Kuipers, Gerver, & Westerterp, 2004). Being that habitual physical activity levels can vary by day of week, it is important for researchers to establish a minimum number of valid days in order to be included in statistical analyses (Paul, Kramer, Stote, & Baer, 2015). The majority of NHANES studies use a 4 day minimum to be included in the analyses (Tudor-Locke, Camhi, & Troiano, 2012). Other studies have used 1 day (Troiano, et al., 2008), 2-3 days (Cain, Conway, Adams, Husak, & Sallis, 2013), 4 days including 1 weekend day (Green, et al., 2014), and 5-7 days (Glazer, et al., 2013). Researchers are generally advised to have participants wear accelerometers for at least 4 days including 1 weekend day, due to changes in activity levels that occur from weekdays to weekend days (Lee, Sesso, Oguma, & Paffenbarger, 2004; Tudor-Locke, Camhi, & Troiano, 2012).

What is the significance of missing data due to low adherent study participants?

If a valid day of accelerometer wear is just 10 hours, the remaining 14 hours of the day would be explained by accelerometer removals due to sleep and/or lack of participant adherence. Assuming 8 hours of sleep occur, at least 6 hours of data remain unaccounted for. If the participant was physically active during those 6 hours, missing data may have implications on the prediction of sedentary behavior and physical activity.

Sedentary behavior

Sedentary behavior is calculated by counting the number of minutes in a day where the intensity of physical activity is below a particular cut-point or threshold. Cut-points for determining sedentary behavior using an Actigraph GT3X+ accelerometer include 0-99 counts/minute (Joseph, Keller, Adams , & Ainsworth, 2015) and 0-100 counts/minute (Hall, Mansfield, Kay, & McConnell, 2015). Given that zeroes are included in the calculation of sedentary behavior, it is difficult for investigators to know whether some or all of the zero counts observed are due to non-adherence. When strings of zero counts due to non-wear are detected in a data set, they can influence the estimation of sedentary behavior in a number of different ways (Tudor-Locke & Myers, 2001). If strings of zero counts due to low accelerometer adherence are included in the analysis, sedentary behavior will be over-estimated. An option to eliminate this error would be to detect the strings of zeroes due to non-wear with the use of a physical activity log and remove them from the analysis, bringing the

estimation of sedentary behavior closer to the actual state. Although this approach seems intuitive, if the techniques for determining low accelerometer adherence are inaccurate, another possibility may exist; if a physical activity log is not used, strings of zero counts could be removed from the analysis when they should have been included, resulting in an underestimation of sedentary behavior.

Light, moderate, and vigorous physical activity

The estimation of time spent in other intensities of physical activity are calculated by summing the number of minutes within cut-points for light, moderate, and vigorous physical activity. Irrespective of the accelerometer brand and model, cut-points for the estimates of these intensities are also highly variable (Tudor-Locke, Camhi, & Troiano, 2012). The presence of zero counts in a data set due to low accelerometer adherence does not directly impact the estimation of different intensities of physical activity; however, if a study participant engages in physical activity without wearing an accelerometer, time spent in the different intensities of physical activity will be underestimated. Unfortunately, investigators may not know what physical activities participants were engaged in when strings of zeroes are present in the data set due to low accelerometer adherence (unless a physical activity log is used).

Average intensity of daily physical activity

Another use of accelerometer data is to estimate the amount of average intensity accumulated per day (Troiano, et al., 2008), which is calculated by summarizing the accelerometer counts into an "epoch" of time (usually in 60 second intervals), then expressing the data as DPA. Strings of zero counts due to low participant adherence, water activities, and sleep in a data set all have the potential to produce inaccurate estimates of true physical activity levels (Catellier, et al., 2005; Paul, et al., 2008). If zero counts are present in the database due to low accelerometer adherence by a study participant, an underestimate of DPA may occur (Paul, et al., 2008). Removing zero counts may bring DPA estimates closer to actual state; however, removing these zeroes may artificially overestimate DPA if they shouldn't have been removed (accelerometer was being worn but no movement occurred).

Impact of sleep detection

Another important issue that impacts the estimation of sedentary behavior and physical activity is the influence of sleep. Study participants typically remove accelerometers during sleep, but some choose to wear them continuously for several consecutive days (Paul, et al., 2008). It is also common for study participants to take naps periodically during the day with or without wearing an accelerometer. Unfortunately, the zeroes that are produced as a result of sleep will have an impact on estimates of both sedentary behavior and DPA.

When a study participant wears an accelerometer during sleep, the estimation of sedentary behavior is impacted because the accumulation of true counts (often zero counts) resulting from the low physical movement that occurs during sleep contributes to time spent in sedentary behavior. Although including counts from sleep is possible (Jago, Anderson, Baranowski, & Watson, 2005), it is not often practiced. The more common approach is to remove counts that occur during sleep when a participant was wearing an accelerometer (Green, et al., 2014), as a means for adhering to the standard accelerometer wear protocol of removing the accelerometer for sleep.

The estimates of light physical activity (LPA) and DPA have a small potential to be impacted by sleep, in large part because low levels of physical activity may occur during sleeping hours, especially in restless sleepers. Some researchers leave these counts in the data set (Janney, et al., 2008), while other investigators remove the counts from the data set that occur during sleep, effectively treating the day as if it is less than 24 hours (Dinger & Behrens, 2006). If accelerometer data are removed during sleep when LPA is registered by the accelerometer or if an accelerometer is removed for sleep when a study participant is restlessly sleeping, an underestimation of LPA and DPA will occur.

The imputation technique

From the discussions above, it can be assumed that when strings of zero counts due to low accelerometer adherence and/or sleeping times are included in statistical analyses, estimates of time spent in sedentary behavior, different intensities of physical activity, and DPA are negatively impacted. In order to differentiate between accelerometer removals, sleeping time, and physical activity, self-report logs are often used. Another approach to developing accelerometer adherence standards is to adjust the physical activity

estimates by imputation (replacing the missing data with a reasonable estimate). Imputation of missing accelerometer data has been shown to improve the estimates of MVPA (MET/minutes) and DPA when compared to including the consecutive zero counts in the analysis (Catellier, et al., 2005; Paul, et al., 2008). Furthermore, imputation may allow researchers to minimize the loss of daily data on study participants (due to accelerometer removals), potentially increasing sample size. Although imputation may improve an estimation of physical activity, collecting true accelerometer data will yield the most accurate estimates of physical activity.

The fundamental principle of imputation is to use observed data values to assist in predicting missing values (Catellier, et al., 2005; Paul, et al., 2008). The accuracy of an imputation estimate depends on the number of predictors being used and their correlation with the missing variable. Typically, the more consistent an individual is with their sedentary behavior or physical activity, the more accurate an imputation technique will be, particularly when other predictors are used in an analysis.

There are a range of imputation procedures a researcher may choose from when imputing data. Three basic approaches of data imputation include: 1) not imputing any data and remove missing data or categorize non-wear times as sedentary, 2) imputing non-wear time by taking the mean activity during wear time for that participant, and 3) imputing non-wear time using the available wear time data at similar times on other days for each participant (van Hees, et al., 2011). Although these single imputation techniques are relatively simple to implement, single imputation techniques treat imputed values as though they were actual values recorded from a participant (Catellier, et al., 2005). Therefore, some uncertainty could remain about the correct value to impute for the missing data.

Unfortunately, a similar application of accelerometer algorithms for the estimates of time spent in sedentary behaviors and the different intensities of physical activity produced no single imputation technique that has been widely applied in the literature. Further investigations are warranted to determine if imputing accelerometer data improves the estimates of the different intensities of physical activity (Ward, Evenson, Vaugh, Rodgers, & Troiano, 2005).

Determination of the significance of missing data in research

Missing data due to non-wear, low participant adherence, and/or sleep have the potential to negatively impact the estimates of sedentary behavior and physical activity. Accordingly, Herrmann et al. (2013) studied a sample of 124 adults that wore a uniaxial accelerometer for 7 days (Herrmann, Barreira, Kang, & Ainsworth, 2013). After identifying a sub-sample of 40 participants that wore an accelerometer for 14 hours/day in a particular day, non-wear times were estimated down to 13, 12, 11, and 10 hours/day. Absolute percent error was used to compare the semi-simulated data sets (13-10 hours/day) to the 14 hour criterion measure for inactivity time, light activity, moderate activity, and vigorous activity. Regardless of activity level, absolute percent error increased as simulated wear time decreased in a stepwise fashion. However, Herrmann et al. (2013) acknowledges limitations such as not using a log to identify non-wear time and primarily having a middle-aged population. It is also unknown how much absolute percent error low adherent study participants would have if these comparisons were made to a highly adherent criterion (24 hours) or how measurement error by low accelerometer adherence impacts the subsequent statistical analyses.

There are three different types of studies where poor estimates of sedentary behavior and physical activity could have a profound impact: 1) studies where estimates of sedentary behavior or physical activity are independent variables utilized in correlation or regression analyses to estimate the strength of relationships with dependent variables associated with disease (Carter et al., 2008; Chen & Son, 1997), 2) epidemiological studies where one population is compared to another (Healy, et al., 2007; Matthews, et al., 2008), and 3) clinical studies that use accelerometers to detect the impact of increasing physical activity in a sedentary population (Helmerhorst, Wijndaele, Brage, Wareham, & Ekelund, 2009; Levine, et al., 2008).

Correlational studies

Correlations are used to determine the strength of a relationship between two variables. In physical activity research, estimated physical activity (independent variable) is often used in a correlation with a health marker (dependent variable). When a correlation between the variables is established, the explained and unexplained variance in the relationship between variables can then be determined. These studies determine how strongly correlated sedentary behavior or physical activity is with markers of health.

The relationships between the patterns of physical activity, body fatness, and age were studied in 120 heterogeneous free-living adults aged 19-62 years that wore a triaxial accelerometer for 1 week (Buchowski, Acra, Majchrzak, Sun, & Chen, 2004). Average weekday total physical activity (TPA) ($p<0.05$, $r=-0.53$), physical activity counts daily variability ($p<0.05$, $r=-0.52$), daily maximum physical activity counts ($p<0.05$, $r=-0.56$), minute-to-minute variability on weekdays ($p<0.05$, $r=-0.60$), and the difference between maximum and minimum daily physical activity counts ($p<0.05$, $r=-0.48$) were significantly and negatively correlated with body fatness.

Hemmingsson and Ekelund (2006) investigated the relationship between body mass index (BMI) and TPA by comparing six different physical activity intensities stratified by BMI (Hemmingsson & Ekelund, 2006). TPA was measured in the free-living environment of 85 obese and 193 non-obese participants for 7 consecutive days. The association between BMI and TPA in non-obese participants was significant for activity counts/day ($p<0.05$, $r=-0.16$) and vigorous intensity physical activity ($p<0.05$, $r=-0.15$). After adjusting for age, vigorous physical activity remained significantly associated with BMI in participants that were not obese ($p<0.05$, $r=-0.17$). In obese participants, significant associations between BMI and physical activity were found for all physical activity categories; sedentary behavior ($p<0.05$, $r=0.26$), light ($p<0.05$, $r=-0.30$), moderate ($p<0.05$, $r=-0.35$), vigorous ($p<0.05$, $r=-0.39$), TPA ($p<0.05$, $r=-0.50$), and steps/day ($p<0.05$, $r=-0.54$). It was concluded that participants with higher BMI engaged in less physical activity.

Buchowski et al. (2009) studied seasonal variability in the patterns of free-living physical activity in 57 healthy women aged 20-54 years (Buchowski, et al., 2009). Physical activity was measured by having the participants wear a triaxial accelerometer for 7 consecutive days in 3 different seasons (summer, winter, and spring or fall). The association between TPA and VO_2 max was lower during winter than during spring/fall ($p<0.05$, $r=-0.37$ and $p<0.05$, $r=-0.53$, respectively). The relationship between TPA and percentage body fat was lower in winter than summer and spring/fall ($p<0.05$, $r=-0.33$ and $p<0.05$, $r=-0.38$, respectively). Overall, the study participants had lower physical activity levels in the winter than any other season.

Hagströmer et al. (2007) assessed the relationships between patterns of physical activity and BMI by having 1,114 adults wear accelerometers for 7 consecutive days (Hagströmer, Oja, & Sjöström, 2007). The results of a 3-way ANOVA suggested that participants with higher BMI and age engaged in lower amounts of

moderate-to-vigorous physical activity (MVPA; $p<0.05$), and men participated in more MVPA than women ($p<0.05$). For vigorous activity, a small but significant gender, age, and BMI effect was seen ($p<0.05$, $R^2=0.14\%$). DPA was significantly related to age and BMI ($p<0.05$, $R^2=0.08\%$).

Healy et al. (2007) examined the associations between physical activity (sedentary behavior, light-intensity physical activity, and MVPA) and plasma glucose (fasting and 2 hour post-challenge) in 173 Australian adults without diabetes that wore a uniaxial accelerometer for all waking hours for 7 consecutive days (Healy, et al., 2007). Sedentary behavior was positively associated with 2 hour plasma glucose ($p<0.05$, $\beta=0.29$), while light intensity activity ($p<0.05$, $\beta=-0.25$), and MVPA time ($p<0.05$, $\beta=-1.07$) were negatively associated with plasma glucose. Light intensity activity remained significantly associated with 2 hour plasma glucose following further adjustment for MVPA ($p<0.05$, $\beta=-0.22$). This study suggested light intensity activity improves blood glucose levels.

Epidemiological studies

Physical activity epidemiology studies often compare the amounts of sedentary behavior or physical activity between different populations. These studies often have a large number of study participants and have a great degree of generalizability to the population being studied. The results of epidemiological studies often have a direct impact on practitioners.

Lovejoy et al. (2001) compared dietary intakes and energy expenditure between middle-aged, African-American and Caucasian women participating in a longitudinal study of the menopausal transition (Lovejoy, Champagne, Smith, de Jonge, & Xie, 2001). A sample of 52 African-American and 97 Caucasian women wore triaxial accelerometers for 4 consecutive days, including 1 weekend day. A general linear model detected significant differences between African-American and Caucasian women for leisure time physical activity, sleeping energy expenditure, and time spent standing ($p<0.05$). The results suggested that Caucasian women were more active and had higher energy expenditures than African-American women.

Two studies demonstrated a number of population-specific trends from NHANES data that monitored 6,329 participants aged greater than 5 years from 2003-2004 (Matthews, et al., 2008; Troiano, et al., 2008). Matthews et al. (2008) suggested that adults over 60 years of age were the most sedentary age cohort. African-

Americans and Caucasians were also more sedentary than Mexican-Americans. Troiano et al. (2008) suggested adult males were engaged in higher amounts of MVPA than adult females, but MVPA declined as age increased. Overall, as children began to age, they were less likely to meet minimum physical activity recommendations, and physical activity continued to decline with age in adults.

Clinical studies

Clinical studies are often designed to determine if changes in physical activity occur when a physical activity intervention or strategy is implemented. These studies are very applied, as practitioners can employ them in a variety of settings.

In order to determine whether a 4 month culturally-appropriate clinic and community-based intervention for African-American women with type 2 diabetes will increase MVPA, Keyserling et al. (2002) conducted a randomized controlled trial of 200 African-American women with type 2 diabetes (Keyserling, et al., 2002). Participants were randomized to 3 treatment conditions: 1) clinical and community intervention, 2) clinical intervention only, and 3) minimal intervention. Accelerometers were worn for a week as a means for assessing physical activity levels. A follow-up occurred at 6 and 12 months post-physical activity intervention. Those who were allocated to the clinical and community-based intervention had higher levels of physical activity than the minimal intervention group at the 12 month follow-up ($p<0.05$). Furthermore, those who were allocated to the clinical-only based intervention had higher levels of TPA at 6 months than those in the minimal intervention group ($p<0.05$).

Marcus et al. (2013) investigated the efficacy of a culturally-adapted physical activity intervention in a Latin-American population (Marcus, et al., 2013). Participants were asked to wear an accelerometer for 7 consecutive days at baseline and 6 months. Those who participated in the intervention had higher levels of MVPA at 6 months when compared to the control group ($p<0.05$). Specifically, the intervention group engaged in approximately 70 more minutes of TPA per week than the control group.

In order to show the effectiveness of a walking intervention in adults, Mitchell et al. (2013) randomly placed participants in a walking intervention or control group for 12 weeks (Mitchell, et al., 2013). Participants

wore an accelerometer for 7 consecutive days at baseline, 6 weeks, and 12 weeks. Those who participated in the intervention engaged in more TPA when compared to the control group ($p<0.05$).

Similarly, a 12 week physical activity intervention was administered in 189 adults with Multiple Sclerosis (Plow, Finlayson, Motl, & Bethoux, 2012). Participants wore an accelerometer for 7 consecutive days, at 3 different periods during the study (baseline, 6 weeks, and 12 weeks). It was concluded that participants allocated to the physical activity intervention group had higher levels of TPA at 6 and 12 months than at baseline when compared to the control group ($p<0.05$).

As a means to evaluate the effectiveness of a worksite vitality intervention on vigorous physical activity, participants wore accelerometers at baseline and 6 months for 7 consecutive days (Strijk, Proper, van der Beek, & van Mechelen, 2012). The results from the linear regression analyses suggested that participants in the physical activity intervention group engaged in 40.4 more minutes/week of sport activities than the control group, and those in the intervention group exercised 67.4 more minutes/week compared to the control group ($p<0.05$).

All of the correlational, epidemiological, and clinical studies listed above used accelerometers to estimate sedentary behavior or physical activity. If study participants were not adherent with the accelerometer, their estimates of sedentary behavior or physical activity were inaccurate, potentially impacting the subsequent application of these data in statistical analyses. This is problematic because results that had measurement error in their analyses may only be generalizable to those who met the minimum accelerometer wear requirements, not to the population (Pedisic & Bauman, 2014).

Summary

Based on the evidence presented above, it is likely that missing data due to low accelerometer adherence, water activities, and sleep may result in imprecise estimates of sedentary behavior and physical activity. The literature also lacks an understanding of how different accelerometer data simulation techniques influence the significance of missing data. Accordingly, the purposes and hypotheses of this study were:

1. To determine the amount of error associated with different accelerometer data simulation techniques.
    - Hypothesis: Errors in the prediction of sedentary behavior and physical activity will be larger in some accelerometer data simulation techniques than others.
2. To determine the amount of error in accelerometer data as accelerometer wear declines.
    - Hypothesis: Errors in the prediction of sedentary behavior and physical activity will increase in a stepwise fashion as accelerometer wear time decreases.
3. To determine if imputing data for sleep is effective in improving the estimates of sedentary behavior and physical activity.
    - Hypothesis: Imputing data for sleep will improve the estimates of sedentary behavior and physical activity.
4. To investigate whether different accelerometer data simulation techniques influence the predictions of health markers.
    - Hypothesis: When accelerometer data are applied in subsequent regression analyses, type I (raw data shows no statistical significance; whereas, other analyses show statistical significance) or II decision changes (raw data shows statistical significance; whereas, other analyses so not show statistical significance) may be produced by some of the data simulation techniques.
5. To investigate if low accelerometer adherence influences the predictions of health markers.
    - Hypothesis: When accelerometer data are applied in subsequent regression analyses, the presence of a type I or II decision change will increase as accelerometer wear time decreases.
6. To determine if imputing data for sleep is effective in improving the predictions of health markers.
    - Hypothesis: Imputing data for sleep will decrease the occurrence of type I or II decision change when accelerometer data are applied in subsequent regression analyses.

Preliminary work

As a means to demonstrate the significance of missing accelerometer data, a series of simulations were conducted from previously collected data (Paul, et al., 2008). The fundamental premise was to test the

impact of utilizing the criteria that a minimum of 10 hours of accelerometer wear time influences the estimates of sedentary behavior and physical activity.

In this experiment, a total of 523 participants wore an accelerometer for up to 2 weeks. Accelerometer wear times of the participants were estimated based on the criteria of a minimum of 60 minutes of non-wear with allowance for 1-2 minutes of low intensity activity (Troiano, et al., 2008). The participants were then categorized into two groups: 1) those wearing the accelerometer for 23-24 hours/day (n=83; 232 days), and 2) participants wearing the accelerometer for 10-11 hours/day (n=79; 103 days).

The next step was to determine the times of day when participants that wore the accelerometer 10-11 hours/day tended to remove them. Although study participants are most likely to remove accelerometers for sleeping (missing data late at night and in the morning), low accelerometer adherence may occur during daylight hours also. Therefore, days for these participants were broken down into early (12:00 am to 7:59 am), middle (8:00 am to 3:59 pm), and late (4:00 pm to 11:59 pm) sections. The times when periods of non-wear began and ended were then identified, as observed in Table 1. For example, the median start of accelerometer removal (median used because of the high variability) was at minute 1 (12:00 am) and ended at minute 536.5 (approximately 9:00 am).

Table 1

Start and end times for accelerometer removals in participants that wore accelerometers for 10-11 hours/day (time of day in minutes).

		Mean	**Median**	**SD**
Early	Start	38.9	1	102.7
	End	541.2	536.5	180.3
Middle	Start*	736.6	757	138.8
	End	959.6	942	212.7
Late	Start	1208.3	1246	111.6
	End	1400.4	1440	86.5

Notes. *840 chosen for the analyses to bring the total removal for the day to approximately 14 hours.

Certain trends emerged from the individuals that wore the accelerometers for 10-11 hours/day. Table 2 represents the number of times participants removed the accelerometer, while still maintaining 10-11 hours of wear time. For example, it is possible for an individual to remove an accelerometer multiple times during

the day. Based on the information from Table 2, a participant could have removed the accelerometer during both the "early" and "late" portions of their day. The highest percentage of daily removals (49.5%) occurred twice per day.

Table 2

Number of accelerometer removals per day in participants that wore accelerometers 10-11 hours/day.

Number of Removals	Number of Days	Percentage of Total
1	18 days	17.5%
2	51 days	49.5%
3	27 days	26.2%
4	7 days	6.8%
Total=	103 days	100.0%

The next step in the simulations was to utilize the median removal times from the 10-11 hours/day participants and apply them to the participants that wore the accelerometers 23-24 hours/day. Therefore, the simulations were carried out to estimate what the data would look like if these participants wore the accelerometers only for the minimal acceptable amount of time. Two different data "treatments" were carried out: 1) inserting a "0" during estimated non-wear times (to simulate removal of the monitor), or 2) deletion of the data (to simulate removing those data due to non-wear).

The effect of non-wear time on predicting physical activity

The effect of simulating accelerometer removals in a group of highly adherent participants can be observed in Table 3. When zero counts were introduced into the data set, the errors in the estimates of time spent in different intensities of physical activity and DPA resulted in both a bias (usually underestimate) and a variance ranging from 18 to 170% when compared to the raw values.

Table 3

Effect of data treatment (simulating a day with 10 hours of wear time) on estimates of average intensity of daily physical activity, moderate-to-vigorous physical activity, sedentary behavior, and light physical activity.

Physical Activity	Data Treatment	Mean (SD)	Percent Difference
DPA (counts/minute)	Raw	220.8 (105.0)	-
	0's	129.8 (74.7)	41.7
MVPA (minutes/day)	Raw	29.1 (25.4)	-
	0's	18.3 (17.9)	37.1
Sedentary (minutes/day)	Raw	1020.9 (119.6)	-
	0's	1201.4 (82.6)	18.5
LPA (minutes/day)	Raw	390.0 (112.8)	-
	0's	220.4 (77.4)	169.6

Notes. DPA: Average intensity daily physical activity
MVPA: Moderate-to-vigorous physical activity
Sedentary: Time spent in sedentary behavior
LPA: Light physical activity
Raw: Raw data from 24 hour physical activity from an accelerometer
0's: Substituting 0's in accelerometer data to simulate 10 hours of accelerometer wear time
Delete 0's: Simulating the effect of deleting 0's that appear due to 14 hours of non-wear time (simulate 10 hours of accelerometer wear time)
Percent Difference: Absolute percent difference vs. raw data

The effect of accelerometer removals when utilizing data for regression analyses

As already demonstrated in the literature review, physical activity is often used to determine the relationship between a dependent variable (e.g., body fat percentage, BMI, waist circumference) and an independent variable (e.g. sedentary behavior, LPA, MVPA, DPA). Given the amount of error in the estimates of average physical activity introduced by accelerometer non-wear (Table 3), it is possible these estimates may also introduce error in regression analyses. What is not well understood is whether these errors result in an over- or under-estimate (attenuation) of the relationships between a dependent variable and physical activity (independent variable). Figure 1 demonstrates a series of simulations estimating the effect of introducing measurement error due to accelerometer removals into a univariate regression model. These simulations demonstrate that introducing errors in an independent variable may artificially inflate residuals and attenuate the actual r-value closer to zero.

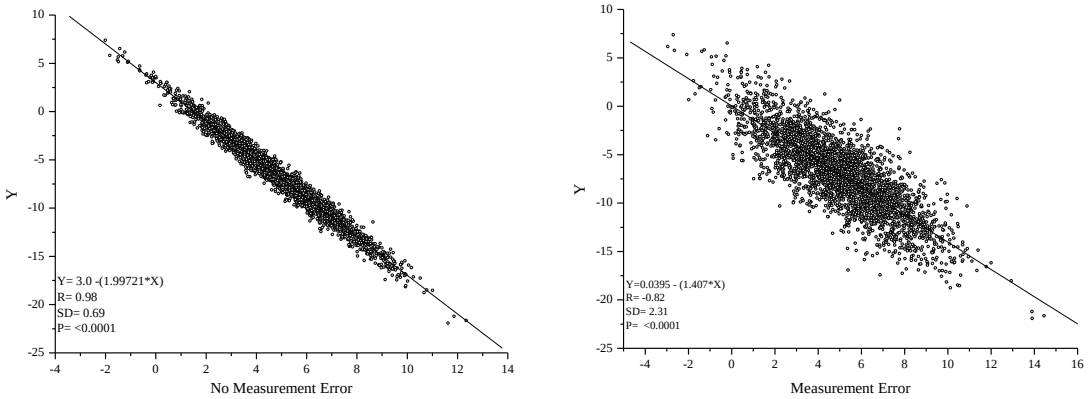

Figure 1. Simulation of the effect of introducing measurement error in an independent variable on the relationship between a dependent and independent variable.

As a result of the information presented in Figure 1, it is clear when measurement error is introduced into a regression model, both the slope and residuals are impacted. Returning to the data sets created in Table 3, a series of regression analysis simulations were conducted using anthropometric characteristics as dependent variables and the different measures of physical activity as independent variables (Table 4).

Interestingly, the results of the simulations from Table 4 are at odds with the simulations from Figure 1. While the simulations from Figure 1 indicate an underestimate of the slope and an over-estimate of the residual values, the opposite effects occurred when utilizing simulated accelerometer removals (Table 4 and Figure 2). For instance, the true relationship between DPA and BMI was not statistically significant (p=0.08) with a residual value of 24.8; however, when zeroes were introduced due to accelerometer removals, the relationship was incorrectly identified as being significant (p=0.03) and the residual value was artificially reduced (24.2). This demonstrates the potential for missing accelerometer data to result in a type I decision change.

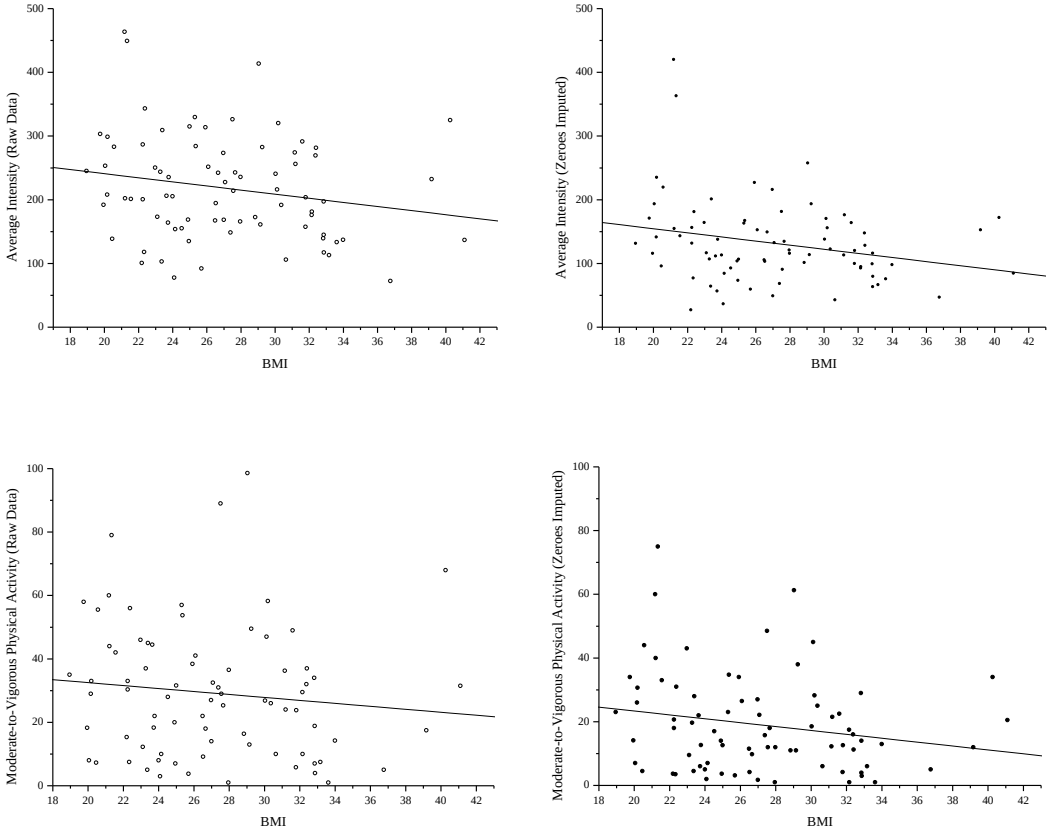

Figure 2. Effect of data treatment (simulating a day with 10 hours of wear time) on the relationship between physical activity (DPA and MVPA) and BMI.

Table 4

Effect of data treatment (simulating a day with 10 hours of wear time) on the predictions of health markers.

Physical Activity	Data Treatment	Body Mass Index			Body Fat Percentage			Waist Circumference		
		Residual	Slope	p	Residual	Slope	p	Residual	Slope	p
DPA	Raw	24.8	-0.012	0.08	53.1	-0.045	<.0001	154.7	0.022	0.09
	0's	24.2	-0.020	0.03	54.2	-0.055	<.0001	153.9	0.035	0.07
MVPA	Raw	25.5	-0.028	0.32	55.8	-0.162	0.0002	158.1	-0.075	0.28
	0's	24.8	-0.067	0.08	54.8	-0.228	<.0001	155.8	-0.142	0.13
Sedentary	Raw	25.6	0.005	0.38	65.8	0.011	0.21	154.7	0.022	0.09
	0's	25.3	0.009	0.23	65.8	0.016	0.21	153.9	0.035	0.07
Light	Raw	25.7	-0.004	0.47	66.8	-0.005	0.57	155.7	-0.021	0.13
	0's	25.6	-0.007	0.38	66.9	-0.007	0.62	155.5	-0.032	0.12

Notes. DPA: Average intensity of daily physical activity
MVPA: Moderate-to-vigorous physical activity
Sedentary: Time spent in sedentary activities
Light: Time spent in light intensity activities
Raw: Raw data from 24 hour physical activity from an accelerometer
0's: Substituting 0's to accelerometer data to simulate 10 hours of accelerometer wear time

Significance of accelerometer non-wear on statistical analyses

Although these data simulations do not necessarily represent actual accelerometer removals, they demonstrate two important problems. First, when accelerometers are only worn to the minimum acceptable standard, the estimates of sedentary behavior and physical activity are greatly impacted. Second, the errors introduced by accelerometer non-wear have implications for accurately detecting the true relationships between dependent and independent variables in regression analyses.

Chapter 2: Methods

Participants

A priori power analyses were conducted using previously collected data (Paul, et al., 2008). These data were entered into a two-tailed, univariate regression model. Assuming a beta value of 0.80 and an alpha value of 0.05, a sample size of at least 84 participants was required to detect a significant relationship between DPA and waist circumference, DPA and BMI, DPA and body fat percentage, MVPA and BMI, MVPA and body fat percentage, and MVPA and waist circumference.

Participant recruitment occurred in the Department of Movement Sciences classrooms at the University of Idaho, and by word-of-mouth and through flyers in the university and Moscow community. The target population was adults, so those less than 18 years of age were not eligible to participate in the study. Those older than 69 years of age were excluded from the study because their estimates of time spent in different physical activity intensity categories are considered a poor representation of the general population (Bassett, Rowlands, & Trost, 2012). This study protocol was approved by the University of Idaho Institutional Review Board.

Procedures

Initial screening

Participants interested in the study reported to the University of Idaho Human Performance Laboratory. After completing the informed consent, participants completed a Physical Activity Readiness Questionnaire (PAR-Q) (Thomas, Reading, & Shephard, 1992). Those who were deemed unfit to participate in physical activity as determined by the PAR-Q were excluded from the study. Furthermore, participants who were at high risk for cardiovascular, pulmonary, or metabolic disease as determined by the AHA/ACSM Health/Fitness Facility Pre-Participation Screening Questionnaire were excluded from the study (Balady, et al., 1998).

A Health Status Questionnaire was then given to participants (Appendix B). This 18-item self-report questionnaire asked participants for some of their personal information (e.g., ethnicity, level of education, income) and health-related behaviors (e.g., smoking, physical activity, alcohol consumption).

Accelerometer, activity log, and sequence of tests

Participants were asked to wear an ActiGraph GT3X+ accelerometer (ActiGraph, Pensacola, FL), which has been demonstrated to be a valid device for measuring physical activity in free-living environments (Cain, Conway, Adams, Husak, & Sallis, 2013). The test-retest reliability of this brand of accelerometer has been previously assessed in adults and was shown to have an intra-class correlation coefficient of 0.70-0.90 (Green, et al., 2014; Sirard, Forsyth, Oakes, & Schmitz, 2011). Participants wore the accelerometer on their right anterior axillary line, on a snuggly-fitted elastic belt over or under clothing, at the waist with the "button" facing up (Feito, Bassett, & Thompson, 2012; Keadle, Libertine, Lynden, Staudenmayer, & Freedson, 2011; Sasaki, John, & Freedson, 2011). Although the accelerometers are water-resistant, participants were asked to not engage in water activities for the duration of the study (e.g., swimming). During sleep, participants were allowed to adjust the position of the accelerometer at the hip in a manner that was most comfortable to them.

In addition to wearing the accelerometer, participants maintained a "physical activity log" that recorded their daily activities, times when the accelerometer was removed, and sleep. Participants were asked to wear the accelerometer for 7 consecutive days, only allowing removal for "grooming" activities (e.g., showering).

After completing the required paperwork, a series of blood pressure measurements were taken on each participant using an automated blood pressure cuff (Omron HEM-907XL; Kyoto, Japan). Cuff size was checked before measuring blood pressure, in order to maintain accuracy of the measurement. Participants rested their arm while staying seated, still, and silent until a blood pressure measurement was completed. A minimum of two blood pressure measurements were taken, each separated by about 2 minutes. If the first two blood pressure measurements differed by more than 5 mmHg, additional blood pressure measurements were taken until two readings were within 5 mmHg. Blood pressure was only taken on the left arm.

Each participant then completed a height and weight measurement using standard techniques in order to determine BMI (Ogden, Carroll, Kitt, & Flegal, 2014). Height was recorded to the nearest 0.1 cm and weight was recorded to the nearest 0.1 kg (Seca 220; Hamburg, Germany). Waist circumference was taken at the most superior level of the iliac crest using anthropometric tape (Alimed; Dedham, MA). Waist

circumference was measured twice and the average of the measurements was taken. The values from each participant's waist circumference and height were used to determine waist-to-height ratio. Research has suggested that waist-to-height ratio is a better measure of centralized obesity, especially over BMI, for detecting cardiovascular risk factors in men and women (Lee, Huxley, Wildman, & Woodward, 2008). Participants were then given an accelerometer and physical activity log, and were provided with detailed instructions for their use (Appendix A).

The second visit to the Human Performance Laboratory occurred approximately 2-3 days after the first visit. During the second visit, participants completed a body composition measurement via Bod Pod (COSMED; Rome, Italy). The Bod Pod has an intra-class correlation coefficient of 0.99 (Noreen & Peter, 2006). Participants were asked to abstain from eating and physical activity at least 2 hours prior to the visit in order to maintain the accuracy of the test. After the Bod Pod was warmed-up and calibrated, participants removed any jewelry, changed into tight fitting clothing (e.g., swimsuit, compression shorts), and wore a swim cap before entering the chamber. Participants sat quietly and still during the measurements. Thoracic gas volume was measured using a filter and breathing tube while participants were seated in the chamber. If the Bod Pod could not detect an accurate thoracic gas volume measurement after three attempts, an estimated measure was taken. The Siri equation was used for all participants (Vescovi, et al., 2001).

After participants completed the Bod Pod measurements, a member of the research team reviewed the participant's accelerometer data and physical activity log for adherence and accuracy. A non-compliant day was defined as a participant wearing the accelerometer for <22 hours/day, unless accelerometer wear could be confirmed by the physical activity log (Hoos, Kuipers, Gerver, & Westerterp, 2004). These instances often occurred when study participants slept without triggering movement in the accelerometer. Investigators asked participants to re-wear the accelerometer for a replacement day if there were study days that involved prolonged intense physical activity that was unaccounted for and could not be confirmed by the physical activity log, and/or adherence with the <22 hours/day criteria.

On the final visit to the Human Performance Laboratory, a member of the research team completed a final review of the accelerometer data and physical activity log for adherence and accuracy. If the participant successfully completed all components of the study, they received a $20 gift card.

Accelerometer data analyses and simulations

Accelerometers were initialized at 30 Hz and epoch length was set for 60 seconds prior to the analyses (Troiano, et al., 2008). Participants were required to have a minimum of 4 valid days of accelerometer data, including a weekend day, to be included in the analyses (Tudor-Locke, Camhi, & Troiano, 2012). Detection of non-wear events was defined as less than or equal to 60 minutes of consecutive zero counts with allowance for up to 2 minutes of activity 100 counts/minute or less (Troiano, et al., 2008). Sedentary behavior was defined as <150 counts/minute (Keadle, Libertine, Lynden, Staudenmayer, & Freedson, 2011), LPA was defined as 150-2689 counts/minute, and MVPA was defined as ≥ 2690 counts/minute (Sasaki, John, & Freedson, 2011).

Four different categories of simulated data sets were then created from the raw accelerometer data, demonstrating a range of possible approaches for taking missing data due to sleep and removals during waking hours into account (Figure 3). Sleep and waking times for each day were identified by the participants in their daily physical activity logs, then confirmed by participant interviews and visual inspection of the accelerometer data. Accelerometer data removals during waking hours were estimated by randomly imputing 60 minute blocks of time from the raw data for each data simulation technique until simulated wear times ranged from 17-10 hours/day. The first type of data simulation (Figure 3, B: "zero/zero") consisted of inserting zeroes during sleep times and simulated removals during waking times (Paul, et al., 2008). The next simulated data set (Figure 3, C: "dot/dot") inserted a missing response (".") in the place of sleeping times and removals during waking times (Hagströmer, Oja, & Sjöström, 2007). In turn, another simulated data set (Figure 3, D: "dot/zero") was generated by inserting a missing response during sleep times and zeroes for non-wear events during waking hours (Paul, et al., 2008). Finally, the last simulated data set (Figure 3, E: "sleep imputation") represents the approach whereby an estimate of the physical activity that occurred during sleep (60 counts/minute in this case) was imputed during sleep times, then zeroes were inserted for the non-wear events during waking hours (Paul, et al., 2008).

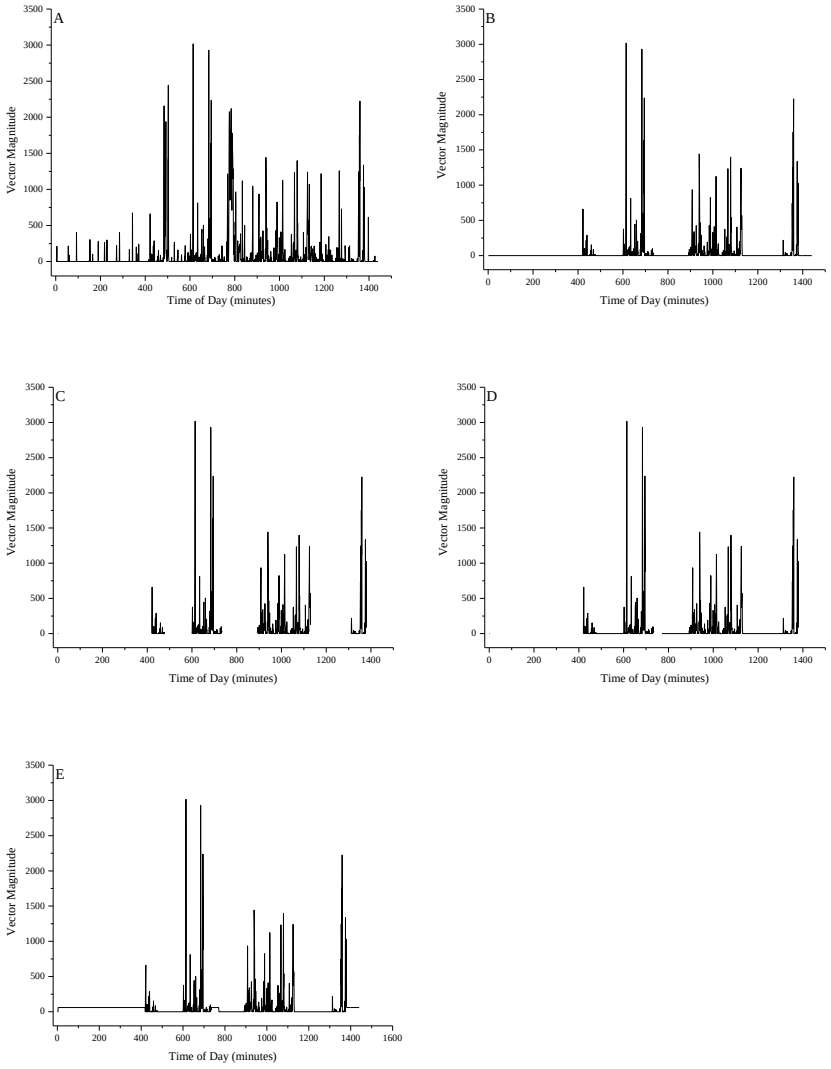

Figure 3. A visual representation of each data simulation technique.

Raw Data (A): Raw 24 hour data
Zero/Zero (B): Zeroes inserted for sleep and simulating when accelerometer is not being worn
Dot/Dot (C): "." inserted for sleep and simulating when accelerometer is not being not worn
Dot/Zero (D): "." inserted for sleep and zeroes inserted for simulating when accelerometer is not being worn
Sleep Imputation/Zero (E): A constant (60 counts/minute; the average observed during sleep times in this sample) imputed for sleep and zeroes inserted for simulating when the accelerometer is not being worn

Statistical analyses

Actilife 6 (ActiGraph, Pensacola, FL) was used to initialize and process the accelerometer data, while SAS 9.3 (SAS; Cary, NC) was used to perform data simulations and statistical analyses. A series of independent t-tests were conducted to compare participant demographics and the differences between each data set for sedentary behavior and physical activity (Table 5). Absolute percent errors were calculated by taking

the absolute value of subtracting raw accelerometer data from simulated data sets and dividing by the raw data (then multiplied 100) for each simulated data set and intensity (sedentary behavior, LPA, MVPA, DPA). One-way ANOVA with Bonferroni post hoc tests were used to compare the mean estimates of each simulated data set with the raw data (Table 5).

To determine the impact of the simulated data on each outcome, univariate regressions were performed independently using each health marker (systolic and diastolic blood pressures, BMI, waist-to-height ratio, waist circumference, age, and body composition) as the dependent variable and each simulated data set as the independent variable. Multiple regression analyses were also conducted on various combinations of these variables. Sex was not utilized as an independent variable in any of the analyses because the sample size calculations were based on a population of both women and men. Statistical significance was set at an alpha level of 0.05 for all analyses.

Chapter 3: Results

Descriptive characteristics of the participants

Of the 101 participants that completed the study, only 1 was excluded from the analyses due to low adherence with the accelerometer wear time. Table 5 and Appendix C show the demographic characteristics of the participants. Most participants were young adults that engaged in over 60 minutes of MVPA/day.

Table 5

Demographic characteristics of the participants

	Women (n=50) Mean (SD)	**Men (n=50) Mean (SD)**
Age (years)	25.6 (8.6)	25.4 (7.2)
BMI (kg/m^2)	23.5 (2.7)*	26.0 (3.2)
Body Fat (%)	27.5 (6.5)*	15.8 (7.0)
Sedentary (minutes/day)	941.0 (84.8)*	929.0 (116.1)
LPA (minutes/day)	431.4 (76.8)	427.7 (98.9)
MVPA (minutes/day)	67.6 (24.6)*	83.3 (33.4)
DPA (counts/minute)	495.5 (115.8)	545.1 (157.8)

Note. *significant difference between sexes ($p<0.05$)
BMI: Body mass index
Sedentary: Sedentary behavior
LPA: Light physical activity
MVPA: Moderate-to-vigorous physical activity
DPA: Average intensity of daily physical activity

Based on the Troiano et al. (2008) non-wear criteria, the 100 participants had 687 compliant days of accelerometer wear, averaging 23.3 hours/day (Table 6; "Raw data"). After taking sleeping hours into account (Table 6; "Sleep adjustment"), the participants were awake for an average of 15.9 hours/day. The ranges of awake times can be observed in the "Hourly Break-Down" section of Table 6; for example, 142 of 687 days of data were comprised of those who were awake between 15 and 16 hours/day.

Table 6

Estimates of wear time for the raw data, adjustments for sleep, and breakdown of hourly wear times

		Mean (SD)	Minimum	Maximum	Days	Percentage of Days
	Raw data	23.3 (1.0)	17.9	24	687	100
	Sleep adjustment	15.9 (1.6)	10.0	20.5	687	100
Hourly Break-Down	≥18	18.7 (0.7)	18.0	20.5	61	8.9
	17-18	17.3 (0.3)	17.0	17.9	119	17.3
	16-17	16.3 (0.3)	16.0	16.9	176	25.6
	15-16	15.5 (0.3)	15.0	15.9	142	20.7
	14-15	14.5 (0.3)	14.0	14.9	109	15.9
	13-14	13.5 (0.3)	13.0	13.9	53	7.7
	12-13	12.4 (0.3)	12.0	12.9	18	2.6
	11-12	11.6 (0.3)	11.4	11.8	8	1.2
	10-11	10.0 (-)	10.0	10.0	1	0.1

Note. Mean (SD), Minimum, and Maximum are presented in hours
Percentage of days are presented in %
Raw data: full participant accelerometer wear
Sleep adjustment: Amount of accelerometer wear after zeroes were inserted during sleeping time

How different accelerometer data simulations affect estimates of sedentary behavior, LPA, MVPA, and DPA

Table 7 shows how simulating data differently during sleeping times impact daily estimates of sedentary behavior, LPA, MVPA, and DPA when compared to the raw data. It should be recognized that MVPA in this sample was 44.3 minutes/day greater than the general health physical activity recommendations, regardless of how data were simulated for sleep (Garber, et al., 2011).

Table 7

The effect of data simulation on estimates of sedentary behavior and physical activity for sleeping time only

Sleep	Sedentary		LPA		MVPA		DPA	
	Mean (SD)	**%**	**Mean (SD)**	**%**	**Mean (SD)**	**%**	**Mean (SD)**	**%**
Raw Data	935.0 (101.3)[a]	-	429.5 (88.1)[a]	-	75.4 (30.3)[a]	-	520.3 (139.9)[a]	-
Sleep Imputation/Zero	973.2 (100.3)[b]	4.2	392.5 (87.1)[b]	9.1	74.3 (30.1)[a]	2.0	520.0 (138.7)[a]	2.5
Zero/Zero	973.2 (100.3)[b]	4.2	392.5 (87.1)[b]	9.1	74.3 (30.1)[a]	2.0	499.8 (139.5)[a]	4.5
Dot/Dot	488.7 (87.8)[c]	48.2	392.5 (87.1)[b]	9.1	74.3 (30.1)[a]	2.0	752.1 (195.3)[b]	45.3
Dot/Zero	488.7 (87.8)[c]	48.2	392.5 (87.1)[b]	9.1	74.3 (30.1)[a]	2.0	752.1 (195.3)[b]	45.3

Note. %: Absolute percent error vs. raw data
Sedentary: Sedentary behavior (minutes/day)
LPA: Light physical activity (minutes/day)
MVPA: Moderate-to-vigorous physical activity (minutes/day)
DPA: Average intensity of daily physical activity (counts/minute)
Results are only for simulation technique left of slash (sleep only)
Different superscripts in the same column indicate statistical significance at $p<0.05$

Simulating the effect of accelerometer adherence during sleeping and waking times on the estimates of sedentary behavior, LPA, MVPA, and DPA

In addition to the impacts of accelerometer data simulations on estimates of sedentary behavior, LPA, MVPA, and DPA when compared to the raw data, the effects of accelerometer wear time (ranging from adjustments for sleep to 10 hours of simulated removals during waking hours) are shown in Figure 4 and Appendix D. Both accelerometer data simulations and adherence impact sedentary behavior and DPA. In the case of sedentary behavior, the estimated means were artificially increased when zeroes were inserted into the data set during waking hours for sleep imputation/zero, zero/zero, and dot/zero; because the means for dot/zero were artificially lower after the sleep adjustment, the means actually increased closer to the raw data (reducing the APE). However, when dots were inserted during waking hours (for dot/dot), the means artificially decreased (increasing APE) (Appendix D). For DPA, the insertion of zeroes for waking hours increased APE for sleep imputation/zero and zero/zero because the additional zeroes decreases estimates of DPA. For dot/zero, the insertion of zeroes improved estimates of DPA because the estimates from the sleep adjustment artificially increased DPA and the additional insertion of zeroes brought the estimates closer to the raw data. When dots were inserted in the data set during waking hours for DPA (dot/dot), absolute percent error did not increase. The lowest absolute percent error for sedentary behavior was observed for "zero/zero" and sleep imputation techniques (estimates are the same because removals during the waking times are both counted as sedentary), although the error associated with only wearing the accelerometer for 10 hours/day reached 23.3%.

Figure 4 demonstrates that although simulated adherence impacts estimates of LPA and MVPA, there were no difference between the different data simulation techniques. LPA and MVPA showed a stepwise increase in absolute percent error as simulated adherence decreased, which reached 40.7 and 36.5% at 10 hours/day for LPA and MVPA, respectively. However, inserting dots or zeroes to simulate the impact of implementing the different data simulation techniques had no impact.

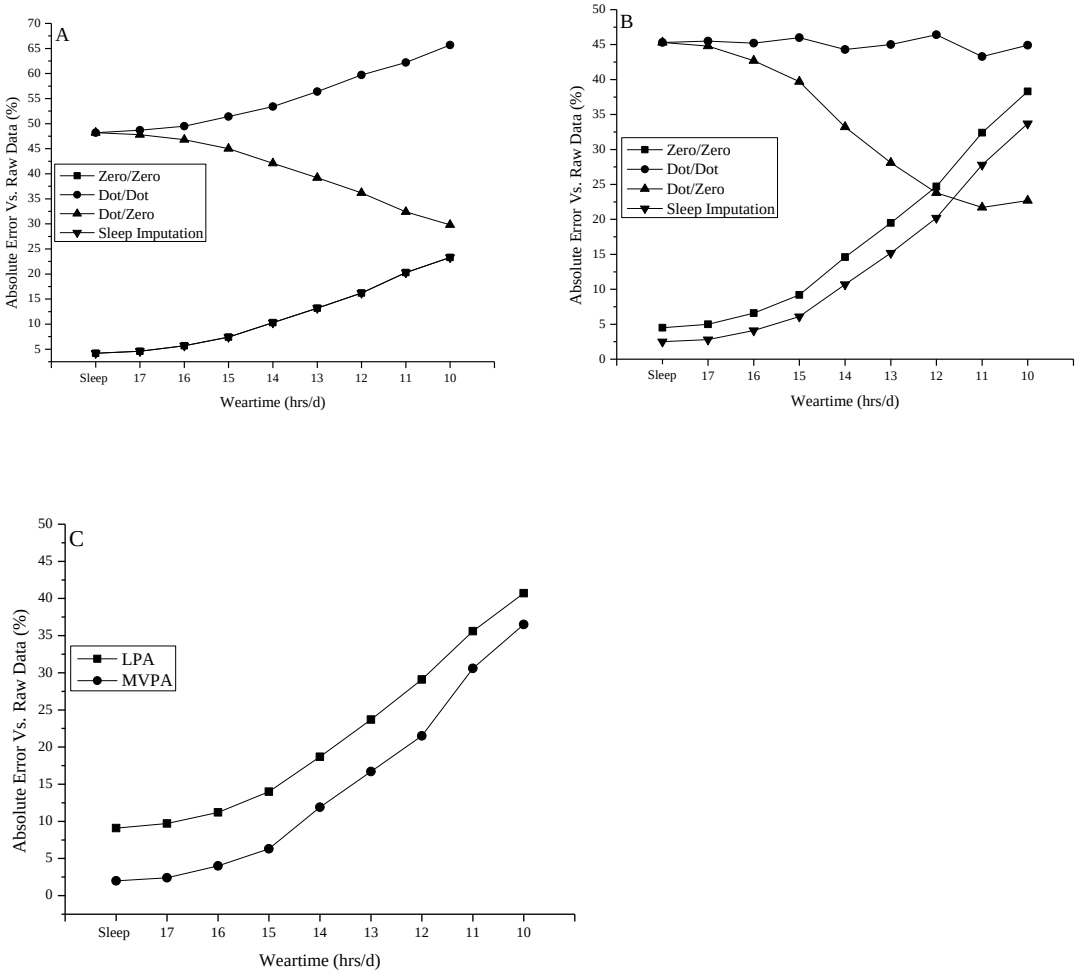

Figure 4. Effect of accelerometer data simulations and accelerometer wear time on absolute percent error for sedentary behavior, average intensity of daily physical activity, light physical activity, and moderate-to-vigorous physical activity

A: Sedentary behavior
B: Average intensity of daily physical activity (DPA)
C: Light physical activity (LPA) and moderate-to-vigorous physical activity (MVPA)

Effect of accelerometer data simulations and adherence when applying the data to regression analyses

Although different data simulation techniques and accelerometer adherence have the potential to introduce some considerable prediction errors for sedentary behavior, LPA, MVPA, and DPA the impacts of prediction errors in the application of these data in a range of regression analyses were minimal (Appendix E). Of the 1,008 univariate regression comparisons, there were no clear patterns of attenuated p-values, but there were 28 examples of type I decision change and 39 examples of type II decision change. In the multiple

regression analyses (multiple independent variables and one dependent variable), there was also no clear pattern of attenuation, and only 8 type II decision changes minimally present (Appendix F).

Chapter 4: Discussion

The results of this investigation demonstrate that both different accelerometer data simulation techniques and poor adherence have the potential to negatively impact predictions of sedentary behavior, LPA, MVPA, and DPA. Despite the presence of imprecise estimates of sedentary behavior, LPA, MVPA, and DPA, the impact of the application of these data in univariate and multiple regression models was minimal.

Given the wide array of accelerometer data simulation techniques available to researchers (Paul, et al., 2008), it is intuitive that estimates of sedentary behavior, LPA, MVPA, and DPA may be highly variable across different studies. In the present study, when data simulations were used during sleeping times (Table 7), there were differences in the estimates of sedentary behavior, LPA, MVPA, and DPA when compared to the raw data. However, more consistency and accuracy existed in the estimates of LPA and MVPA, as each data simulation technique demonstrated an absolute percent error of 9.1% and 2.0%, respectively. There was less consistency and accuracy amongst the estimates of sedentary behavior and DPA. The "dot/dot" and "dot/zero" simulation techniques yielded higher levels of mean absolute percent error for sedentary behavior (48.2%) and DPA (45.3%); whereas, the "zero/zero" simulation technique only showed a mean absolute percent error of 4.2% and 4.5% for sedentary behavior and DPA, respectively. Thus, it is interesting to note that errors associated with accelerometer removals for sleep (what study participants generally do) were actually minimized when the data were not manipulated at all ("zero/zero" simulation technique).

These results support our hypothesis that when data simulations are applied during sleeping times, differences in the estimates of sedentary behavior, LPA, and DPA are greater in some simulation techniques than others. These results are corroborated by other studies reporting that data simulations are more likely to impact the estimates of sedentary behavior than MVPA (Keadle, Shiroma, Freedson, & Lee, 2014), which is not surprising given that time spent being sedentary is much greater than time spent in MVPA (Matthews, et al., 2008). Researchers should consider how using different data simulations during sleeping times may impact the accuracy of their measurements, especially for studies that are measuring sedentary behavior or DPA (Buchowski 2004; Buchowski 2009; Hemmingsson and Ekelund 2006; Hagströmer 2007; Healy 2007; Lovejoy 2001; Matthews 2008; Troiano 2008; Keyserling 2002; Marcus 2013; Mitchell 2013; Plow 2012).

This investigation provides further evidence that accelerometer adherence impacts estimates of sedentary behavior, LPA, MVPA, and DPA. Previous studies (Catellier, et al., 2005; Paul, et al., 2008) have demonstrated that estimates of MVPA (MET-minutes/day) and DPA are negatively impacted by poor adherence, but less evidence demonstrates how adherence impacts LPA and MVPA (minutes/day). Herrmann et al. (2013) demonstrated that absolute percent error increased as accelerometer wear time decreased for sedentary behavior, light, moderate, and vigorous physical activity (Herrmann, Barreira, Kang, & Ainsworth, 2013). Our results mostly concur with Hermann et al. (2013), demonstrating that absolute percent error generally increases as accelerometer wear time decreases. However, the absolute percent errors observed with some of the simulations were not consistent between the two studies. For example, Herrmann et al. (2013) reported that sedentary behavior for 13, 12, 11, and 10 hours/day of wear time were associated with 7.0, 14.2, 20.3, and 28.2% errors, respectively; the corresponding values for the present study were 13.2, 16.2, 20.3, and 23.2% error ("zero/zero"), respectively. Unfortunately, comparisons between the two studies are difficult because the reference database from Hermann et al. (2013) only included 14 hours/day of accelerometer wear for a single day in 40 participants (compared to an average of 23.3 hours/day for 687 days in 100 participants in the present investigation). Furthermore, comparisons are confounded because the data simulation technique chosen by Hermann et al. (2013) was not described.

Accelerometer adherence and choice of data simulation have implications for the estimates of sedentary behavior, LPA, MVPA, and DPA. With the exception of the "dot/zero" simulation technique in sedentary behavior and DPA, and the "dot/dot" simulation technique in DPA, a stepwise increase in absolute percent error occurred as accelerometer adherence declined, supporting what was hypothesized. Implementing the "dot/dot" data simulation technique for DPA produced large absolute percent error (43-46%), but these values showed little change as wear time decreased. For the "zero/zero" simulation technique, the absolute percent error increased from 4.5 to 38.3% in a reasonably stepwise fashion as wear time decreased to 10 hours/day. Curiously, the errors in estimates of sedentary behavior and DPA for the "dot/zero" technique were actually reduced as wear time decreased; removing data during sleep artificially decreased the mean estimates of sedentary behavior and DPA, then inserting zero counts for waking hours increased the estimates so they were closer to the raw data values. However, this simulation technique should not be recommended because it would require that data collected when participants are actually wearing an accelerometer be removed (i.e.,

dots inserted for the actual data). Although estimates of LPA or MVPA were negatively impacted by poor adherence, data simulations had no impact because similar effects occur when data were inserted with a zero or dot into the raw data during waking times. Overall, increasing the minimum wear time criteria appears to be the best approach for minimizing absolute percent errors, but our results suggest that performing no edits to the data (i.e., "zero/zero" data simulation technique) are generally superior to removing data.

Although collecting true accelerometer data in highly adherent participants should be a priority for researchers, imputing a constant value (average amount of movement that occurred during sleep) has been shown to be fruitful in improving the estimates of MVPA and DPA (Catellier, et al., 2005; Paul, et al., 2008). Paul et al. (2008) demonstrated that both imputing a constant value for sleep and performing a statistical imputation for missing data during waking times improved estimates of DPA. The present investigation imputed a constant of 60 counts/minute during sleep, which was the average amount of physical movement detected by the accelerometer in this sample during sleeping time. When these data were imputed for sleep, there was a reduction in the absolute percent error for DPA; however, no improvements occurred in absolute percent error for sedentary behavior, LPA and MVPA. These results do not support the hypothesis that imputing a constant during sleeping times will improve the estimates of sedentary behavior, LPA, and MVPA. Imputing a constant during sleep will not improve the estimates of sedentary behavior because 60 counts/minute is still categorized as sedentary behavior according to the cut points used to define sedentary behavior. Likewise, there were no changes in LPA and MVPA because 60 counts/minute was not within the cut points used for each of those intensities. There was only a small improvement in the predictions of DPA because imputing the average counts/minute value during sleep improved the DPA estimation compared to the other simulation techniques (inserting a zero or dot during sleep).

Another objective of this study was to not only determine if accelerometer data simulations and adherence influence predictions of sedentary behavior, LPA, MVPA, and DPA, but whether applying these estimates in statistical analyses where accelerometer data are used to predict markers of health. It is possible that errors in the estimates of sedentary behavior, LPA, MVPA, and DPA could result in either a type I or type II decision change. For example, when raw MVPA data were used to predict body fat percentage in a univariate regression analysis, there was no statistically significant relationship between the two variables;

however, significant relationships were detected when the 12, 11, and 10 hour data sets were used independently for all data simulation techniques (demonstrating the presence of a type I decision change). Despite the presence of type I and II decision change in the univariate regression analyses, the occurrence of these statistical errors was minimal in regard to the number of comparisons that were made (67 type I or II decision changes in 1,008 comparisons). Therefore, our hypothesis that absolute percent errors are produced by the different data simulation techniques and/or low adherence would have a considerable impact the results of statistical analyses by producing type I or II decision change was not confirmed.

In addition to investigating how accelerometer data simulations and adherence influence predictions of health markers in univariate regression analyses, a range of multiple regression analyses were also investigated (e.g., sedentary behavior as one of several independent variables used to predict health markers as the dependent variable). In one case, fat free mass and sedentary behavior (raw data) significantly predicted systolic blood pressure; however, when the "dot/zero" data simulation technique was applied for 10 hours of wear time, this prediction was no longer significant (type II decision change). However, similar to what was observed for univariate regression analyses, the presence of type I and II decision changes were minimal, which again did not support what was hypothesized in this study.

When the sleep imputed data sets were subsequently used in the univariate and multiple regression analyses, there were little or no changes in p-values. This suggests that imputing for sleep only helps reduce absolute percent error in the estimates of DPA, but has minimal impacts on the predictions of health markers in both univariate and multiple regression analyses. These results did not support the hypothesis that imputing data during sleeping times would improve the predictions of health markers.

One of the important implications of accelerometer adherence is determining how long a participant must wear the accelerometer to capture an accurate picture of daily sedentary behavior, LPA, MVPA, and DPA, which is commonly defined as 10 hours per day (Tudor-Locke, Camhi, & Troiano, 2012). The current study indicates that defining a valid day as 10 hours can potentially result in errors in the estimates of sedentary behavior, LPA, MVPA, and DPA, which can be further exacerbated by the choice of data simulation technique. For example, the absolute percent error for sedentary behavior when wearing an accelerometer for only 10 hours/day ranged from 23.3% ("zero/zero") to 65.5% ("dot/dot"). For MVPA, the absolute percent

errors for 10 hours/day of wear time was 36.5% for all data simulation techniques. This is especially problematic because if absolute percent error from low accelerometer adherence is high in the estimates of MVPA, there may also be inaccuracies in determining if study participants are meeting minimum recommendations for daily physical activity (Garber, et al., 2011). Therefore, investigators should decide how much measurement error can be tolerated and which data simulation technique is most appropriate for their study. NHANES publications, which are often cited for accelerometer methods, describe criteria used for determining wear time and times the device was worn, but little justification is provided for their approach and a lack of alternative criteria is reported in the literature (Miller, et al., 2013). It is safe to suggest that studies should consider increasing minimum accelerometer adherence criteria to a value greater than 10 hours/day as a means for reducing spurious predictions of sedentary behavior, LPA, MVPA, and DPA.

The present study has a number of strengths that extend the current literature on developing accelerometer methods. First, the analyses were conducted on a relatively large number of participants (n=100) that were highly adherent (23.3 hours/day on average) for a full week (687 days of data). Second, although other studies have investigated the impact of poor adherence, to our knowledge none have studied the independent impacts of accelerometer data simulations and adherence. Third, this is the first study to investigate the subsequent application of these data in statistical analyses.

Despite these strengths, some limitations of the present study may have influenced the generalizability of these results. First, the study participants were relatively young, physically active, and healthy volunteers. Furthermore, the limited presence of type I and II decision changes may be related to the fact that participants were relatively active and free from disease. Therefore, the results from this population may not be applicable to others. Finally, the data simulations were conducted in a randomized manner, which may not necessarily represent removals in real life (Herrmann, Barreira, Kang, & Ainsworth, 2013).

Future researchers could utilize a similar study design to investigate a number of important questions. For example, this investigation demonstrates that imputation for sleep has the potential to improve estimates of sedentary behavior and DPA (but not LPA or MVPA), but no studies to date have investigated the impacts of imputation for both sleep and wake times. The results of the present investigation indicate that poor estimates of sedentary behavior and physical activity have little impact on predictions of health markers, but future

studies could apply a different range of dependent variables in other populations where independent variables (e.g., sedentary behavior and physical activity) may explain more of the variance. Since Loprinzi et al. (2013) concluded that activity cut-points may influence the relationship between DPA and various health outcomes, investigating if different activity cut-points for determining sedentary behavior, LPA, MVPA, and DPA in high and low adherent accelerometer data sets should be pursued (Loprinzi, et al., 2013).

Conclusions

Despite how the present investigation demonstrates that accelerometer data simulation techniques and adherence impact estimates of sedentary behavior, LPA, MVPA, and DPA, their influence on the subsequent application of these data was minimal when using the presence of type I and II decision change as the criteria. These results indicate that epidemiological studies (Lovejoy, Champagne, Smith, de Jonge, & Xie, 2001; Matthews, et al., 2008; Troiano, et al., 2008) that rely on accurate estimates of sedentary behavior, LPA, MVPA, and DPA in certain populations may be influenced by accelerometer data simulations and adherence. The same could potentially be suggested for clinical studies (Keyserling, et al., 2002; Marcus, et al., 2013; Mitchell, et al., 2013; Plow, Finlayson, Motl, & Bethoux, 2012; Strijk, Proper, van der Beek, & van Mechelen, 2012) that may be looking to detect small changes in sedentary behavior, LPA, MVPA, and DPA in response to a physical activity intervention. However, correlational studies (Healy, et al., 2007) may be less vulnerable to type I and II decision changes if accelerometer data have measurement error as a result of data simulations and/or adherence.

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Appendix A: Physical Activity Log

Participant Activity Record- Accel Study

Participant # _____

- You will wear the accelerometer for 7 consecutive days starting on _____ and ending on _____
- Your next visit to the laboratory is scheduled for_____
- If you have any questions, contact Ryan McGrath via e-mail at mcgr0583@vandals.uidaho.edu or by phone at 651-895-7570

Directions

1. Wear the accelerometer each day (during all hours) for at least 23 hours/day.
   - Please make sure the black button on the accelerometer is facing upwards and is on the anterior midaxillary line of the hip.
   - When you sleep with the accelerometer, please indicate the times you went to sleep and woke up.
2. For each day you wear the accelerometer, please record in the log if you remove the accelerometer and when it is put back on.
3. Next, record on the log:
   a. Activities you were performing while the accelerometer was not being worn.
      - Showering/Grooming (code "G").
      - Record the activities and time spent on each in the spaces included based on the codes at the end of this log. Use the activity description that most closely represents the activity you engaged in.
      - If the activity is not mentioned in the activity lists, please enter the activity in the "Comment:" section.
   b. Record any structured exercise, errands, and/or machinery work completed during the day.
      - Running, cycling, weed eater, etc.

ID														
Date						**DAY 1**								
		Code						Code					Accelerometer Removal	
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45		Time	Activity
	12 midnt						12 noon						On:	
	1:00						1:00						Off:	
	2:00						2:00						On:	
	3:00						3:00						Off:	
	4:00						4:00						On:	
AM	5:00					PM	5:00						Off:	
	6:00						6:00						On:	
	7:00						7:00						Off:	
	8:00						8:00						On:	
	9:00						9:00						Off:	
	10:00						10:00						On:	
	11:00						11:00						Off:	
Comment:														
Structured Exercise (type, duration, time of day):														

ID

Date

DAY 2

		Code						Code				Accelerometer Removal	
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity
	12 midnt						12 noon					On:	
	1:00						1:00					Off:	
	2:00						2:00					On:	
	3:00						3:00					Off:	
	4:00						4:00					On:	
AM	5:00					PM	5:00					Off:	
	6:00						6:00					On:	
	7:00						7:00					Off:	
	8:00						8:00					On:	
	9:00						9:00					Off:	
	10:00						10:00					On:	
	11:00						11:00					Off:	

Comment:

Structured Exercise (type, duration, time of day):

ID

Date

DAY 3

		Code						Code				Accelerometer Removal	
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity
	12 midnt						12 noon					On:	
	1:00						1:00					Off:	
	2:00						2:00					On:	
	3:00						3:00					Off:	
	4:00						4:00					On:	
AM	5:00					PM	5:00					Off:	
	6:00						6:00					On:	
	7:00						7:00					Off:	
	8:00						8:00					On:	
	9:00						9:00					Off:	
	10:00						10:00					On:	
	11:00						11:00					Off:	

Comment:

Structured Exercise (type, duration, time of day):

ID														
Date														
		Code					Code					Accelerometer Removal		
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity	
	12 midnt						12 noon					On:		
	1:00						1:00					Off:		
	2:00						2:00					On:		
	3:00						3:00					Off:		
	4:00						4:00					On:		
AM	5:00					PM	5:00					Off:		
	6:00						6:00					On:		
	7:00						7:00					Off:		
	8:00						8:00					On:		
	9:00						9:00					Off:		
	10:00						10:00					On:		
	11:00						11:00					Off:		
Comment:														
Structured Exercise (type, duration, time of day):														

ID														
Date														
		Code					Code					Accelerometer Removal		
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity	
	12 midnt						12 noon					On:		
	1:00						1:00					Off:		
	2:00						2:00					On:		
	3:00						3:00					Off:		
	4:00						4:00					On:		
AM	5:00					PM	5:00					Off:		
	6:00						6:00					On:		
	7:00						7:00					Off:		
	8:00						8:00					On:		
	9:00						9:00					Off:		
	10:00						10:00					On:		
	11:00						11:00					Off:		
Comment:														
Structured Exercise (type, duration, time of day):														

ID														
Date												**DAY 6**		
		Code						Code				Accelerometer Removal		
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity	
	12 midnt						12 noon					On:		
	1:00						1:00					Off:		
	2:00						2:00					On:		
	3:00						3:00					Off:		
	4:00						4:00					On:		
AM	5:00					PM	5:00					Off:		
	6:00						6:00					On:		
	7:00						7:00					Off:		
	8:00						8:00					On:		
	9:00						9:00					Off:		
	10:00						10:00					On:		
	11:00						11:00					Off:		
Comment:														
Structured Exercise (type, duration, time of day):														

ID														
Date												**DAY 7**		
		Code						Code				Accelerometer Removal		
	Time	:00	:15	:30	:45		Time	:00	:15	:30	:45	Time	Activity	
	12 midnt						12 noon					On:		
	1:00						1:00					Off:		
	2:00						2:00					On:		
	3:00						3:00					Off:		
	4:00						4:00					On:		
AM	5:00					PM	5:00					Off:		
	6:00						6:00					On:		
	7:00						7:00					Off:		
	8:00						8:00					On:		
	9:00						9:00					Off:		
	10:00						10:00					On:		
	11:00						11:00					Off:		
Comment:														
Structured Exercise (type, duration, time of day):														

Code	Activities	Code	Activities
S	sleeping	20	fishing (river bank)
G	grooming (washing,shaving,make-up)	21	fishing (stream, in waders)
1	aerobics class (land)	22	football
2	aerobics class (teaching)	23	frisbee (easy)
4	aerobics class (water)	24	frisbee (ultimate)
3	automobile repair	25	gardening
5	backpacking	26	golf (carrying clubs)
6	badminton	27	golf (power cart)
3	ballroom dancing	28	golf (walking/pulling clubs)
7	basketball	29	grass cutting (hand mower)
8	bed (getting ready for)	30	grass cutting (riding)
2	bicycling (indoors)	31	hockey (ice)
9	bicycling (outside)	32	horseback riding
10	calisthenics (easy)	33	hunting (large game)
11	calisthenics (light or moderate)	34	hunting (small game)
12	canoeing	35	kayaking
13	carpentry	36	lying (quietly)
14	circuit training, with aerobic movement	37	painting
15	cleaning (light)	38	painting (outside)
16	cooking or food preparation	39	ping pong
17	driving (tractor)	40	pistol shooting/ trap shooting (standing)
18	electrical work, plumbing	41	pneumatic tools (heavy)
19	fishing (boat, sitting)	42	racquetball

Code	Activities	Code	Activities
43	reading	65	swimming (easy)
44	rock climbing	66	swimming (hard)
45	roller blading	67	swimming (moderate)
46	rowing (outdoors)	68	tai chi
47	rowing, (indoors)	69	tennis (doubles)
48	running (easy jog)	70	tennis (singles)
49	running (hard)	71	vacuuming
50	running (moderate)	72	volleyball (competitive)
51	sailing (competitive)	73	volleyball (leisure)
52	sailing (leisure)	74	walking (brisk)
53	shoveling, digging ditches	75	walking (for exercise)
54	skating (ice)	76	walking (hiking, cross country)
55	ski machine	77	walking (with dog)
56	skiing (downhill)	78	watching TV
57	soccer (competitive)	79	weed eater
58	soccer (leisure)	80	weight lifting (light)
59	softball/baseball	81	weight lifting (vigorous effort)
60	softball/baseball (officiating)	82	yoga
61	softball/baseball (pitching)	83	
62	squash	84	
63	stairmaster	85	
64	stretching (mild)	86	

Appendix B: Health Status Questionnaire

Subnum: _____

Health Status Questionnaire

Please complete the following questions as accurately as possible.

Personal Information

Please circle the ethnic group that you most identify with:

A. American Indian
B. Alaskan Native
C. Asian or Pacific Islander
D. African American, not of Hispanic Origin
E. African American, of Hispanic Origin
F. Caucasian
G. Mexican American
H. Latino or Latina
I. Other, please detail: _____

What is your date of birth? _____/_____/_____ What is your age? _____

Please circle marital status:

A. Single
B. Married
C. Common Law
D. Other, please detail: _____

Please circle the highest level of education you have completed:

A. Less than Junior High/Secondary School
B. Some Junior High/Secondary School
C. Some High School
D. GED
E. Completed High School
F. Some college or vocational training
G. Completed Associate Degree
H. Completed Bachelor Degree
I. Completed Graduate Degree

What is your status of employment?

A. Full-time
B. Part-time
C. Unemployed

If you are a student, what is the status of your schooling?

A. Full-time
B. Part-time

What is the average number of hours you typically work in a week?

A. Less than 20
B. 20-40
C. 41-60
D. Over 60

More than 25% of time spent at school/work is (circle all that apply):

A. Sitting at a desk or on a chair
B. Lifting or carrying loads
C. Standing
D. Walking
E. Driving

Circle the approximate combined monthly income for all sources of your income:

A. Less than $850/month
B. $851-$1,650/month
C. $1,651-$2,500/month
D. $2,501-$3,350/month
E. $3,351-$4,150/month
F. $4,151-$5,000/month
G. $5,001-$5,850/month
H. $5,851-$6,650/month
I. $6,651-$7,500/month
J. $7,501-$8,350/month
K. Over $8,351/month

Health-Related Behaviors

Do you smoke?

A. Yes
B. No
C. Socially

If you smoke, how often do you smoke?

A. 1-9 times/day
B. 10-19 times/day
C. 20-39 times/day
D. 40 or more times/day

Do you currently exercise regularly?

A. Yes
B. No

How many hours per week do you engage in exercise? _____ days/week

How many days per week do you engage in exercise? _____ days/week

Do you drink alcohol?

A. Yes
B. No
C. Socially

If you drink alcohol, how often do you drink?

A. 1-2 times/week
B. 3-4 times/week
C. 5 or more times/week

How many hours of sleep do you typically get? _____ hours/night

Appendix C: Extended Descriptive Statistics of the Participants

	Women (n=50)	Men (n=50)
Systolic blood pressure (mm/Hg)	113.22 (13.55)*	122.58 (10.69)
Diastolic blood pressure (mm/Hg)	71.48 (11.83)	69.46 (9.58)
BMI (kg/m^2)	23.55 (2.72)*	25.97 (3.16)
Waist circumference (cm)	78.78 (7.32)*	85.86 (8.76)
Waist-to-height ratio	0.47 (0.04)	0.48 (0.04)
Age (years)	25.62 (8.63)	25.42 (7.20)
Body fat percentage	27.48 (6.54)*	15.82 (7.00)
Ethnicity (%)		
Asian or Pacific Islander	2	2
Caucasian	88	82
Mexican-American	6	10
Latino/Latina	4	6
Marital status (%)		
Married	16	20
Single	84	80
Education (%)		
Completed high school	4	2
Some college	48	58
Completed associate degree	6	4
Completed bachelor degree	26	20
Completed graduate degree	16	16
Employment status (%)		
Full-time	26	40
Part-time	48	42
Unemployed	26	18
Income/month (%)		
≤$850	46	48
$851-$1,650	38	20
$1,651-$2,500	8	16
$2,501-$3,350	0	2
$3,351-$4,150	0	4
$4,151-$5,000	0	4
$5,001-$5,850	0	2
$5,851-$6,650	2	0
$6,651-$7,500	4	2
$7,501-$8,350	0	2
No response	2	0
Smoking status (%)		
Smoker	2	0
Non-smoker	96	92
Social smoking	2	8
Alcohol use (%)		
Drinks alcohol	24	38
No alcohol	14	26
Social drinking	62	36
Self-reported sleep status (hours/day)	7.31 (1.09)	7.24 (0.96)
Self-reported physical activity (hours/week)	4.07 (1.69)	4.78 (1.65)
Sedentary Behavior-Accelerometer (minutes/day)	941.0 (84.8)*	929.0 (116.1)
LPA-Accelerometer (minutes/day)	431.4 (76.8)	427.7 (98.9)
MVPA-Accelerometer (minutes/day)	67.6 (24.6)*	83.3 (33.4)
DPA-Accelerometer (counts/minutes)	495.5 (115.8)	545.1 (157.8)

*Significant differences between sexes
Values are mean (standard deviation) or percentage as indicated.

Appendix D: Absolute Percent Error Tables

Average Intensity of Daily Physical Activity (520.3 +/- 139.9 counts/minute)

	Zero/Zero		Dot/Dot		Dot/Zero		Sleep Imputation	
	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%
Sleep	499.8 (139.5)	4.5	752.1 (195.3)[a]	45.3	752.1 (195.3)[a]	45.3	520.0 (138.7)	2.5
17	497.0 (137.1)	5.0	753.8 (196.7)[a]	45.5	748.6 (193.1)[a]	44.8	517.2 (136.3)	2.8
16	487.6 (131.9)	6.6	752.0 (197.0)[a]	45.2	735.8 (188.9)[a]	42.7	507.7 (131.2)	4.1
15	472.7 (127.1)	9.2	755.2 (200.5)[a]	46.0	714.8 (184.8)[a]	39.7	492.9 (126.6)	6.1
14	444.2 (118.5)[a]	14.6	746.2 (199.0)[a]	44.3	673.7 (176.3)[a]	33.2	464.3 (118.1)	10.7
13	418.6 (112.0)[a]	19.5	750.3 (201.2)[a]	45.0	635.4 (167.7)[a]	28.1	438.8 (111.7)[a]	15.2
12	390.6 (104.5)[a]	24.7	754.6 (203.3)[a]	46.4	592.8 (155.6)	23.8	410.8 (104.2)[a]	20.2
11	348.9 (89.0)[a]	32.4	733.3 (188.2)[a]	43.3	530.8 (136.3)	21.7	369.0 (88.8)[a]	27.8
10	318.5 (84.2)[a]	38.3	733.3 (194.3)[a]	44.9	485.0 (130.0)	22.7	338.7 (84.1)[a]	33.7

Sedentary Time (935 +/- 101.3 minutes/day)

	Zero/Zero		Dot/Dot		Dot/Zero		Sleep Imputation	
	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%
Sleep	973.2 (100.3)	4.2	488.7 (87.8)[a]	48.2	488.7 (87.8)[a]	48.2	973.2 (100.3)	4.2
17	976.2 (97.6)[a]	4.6	484.6 (87.3)[a]	48.7	491.7 (87.2)[a]	47.8	976.2 (97.6)[a]	4.6
16	984.9 (92.6)[a]	5.7	477.7 (86.9)[a]	49.5	500.6 (86.5)[a]	46.8	984.9 (92.6)[a]	5.7
15	999.7 (87.0)[a]	7.4	460.8 (85.3)[a]	51.4	515.4 (85.9)[a]	45.0	999.7 (87.0)[a]	7.4
14	1024.8 (79.7)[a]	10.3	441.7 (80.2)[a]	53.4	540.6 (85.1)[a]	42.1	1024.8 (79.7)[a]	10.3
13	1049.9 (75.0)[a]	13.2	413.6 (76.4)[a]	56.4	566.0 (83.2)[a]	39.2	1049.9 (75.0)[a]	13.2
12	1076.9 (69.3)[a]	16.2	383.0 (71.6)[a]	59.7	593.1 (80.2)[a]	36.2	1076.9 (69.3)[a]	16.2
11	1112.3 (62.0)[a]	20.3	358.0 (64.1)[a]	62.2	628.5 (76.3)[a]	32.4	1112.3 (62.0)[a]	20.3
10	1138.9 (56.3)[a]	23.3	325.2 (58.1)[a]	65.7	655.1 (74.8)[a]	29.8	1138.9 (56.3)[a]	23.3

Light PA (429.5 +/- 88.1 minutes/day)

	Zero/Zero		Dot/Dot		Dot/Zero		Sleep Imputation	
	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%	Mean (SD)	%
Sleep	392.5 (87.1)[a]	9.1	392.5 (87.1)[a]	9.1	392.5 (87.1)[a]	9.1	392.5 (87.1)[a]	9.1
17	389.8 (84.8)[a]	9.7	389.8 (84.8)[a]	9.7	389.8 (84.8)[a]	9.7	389.8 (84.8)[a]	9.7
16	382.5 (81.1)[a]	11.2	382.5 (81.1)[a]	11.2	382.5 (81.1)[a]	11.2	382.5 (81.1)[a]	11.2
15	369.7 (76.0)[a]	14.0	369.7 (76.0)[a]	14.0	369.7 (76.0)[a]	14.0	369.7 (76.0)[a]	14.0
14	349.1 (69.9)[a]	18.7	349.1 (69.9)[a]	18.7	349.1 (69.9)[a]	18.7	349.1 (69.9)[a]	18.7
13	327.6 (65.4)[a]	23.7	327.6 (65.4)[a]	23.7	327.6 (65.4)[a]	23.7	327.6 (65.4)[a]	23.7
12	304.2 (60.2)[a]	29.1	304.2 (60.2)[a]	29.1	304.2 (60.2)[a]	29.1	304.2 (60.2)[a]	29.1

11	276.2 (54.5)[a]	35.6	276.2 (54.5)[a]	35.6	276.2 (54.5)[a]	35.6	276.2 (54.5)[a]	35.6
10	254.1 (49.2)[a]	40.7	254.1 (49.2)[a]	40.7	254.1 (49.2)[a]	40.7	254.1 (49.2)[a]	40.7

MVPA (75.4 +/- 30.3 minutes/day)

	Zero/Zero		**Dot/Dot**		**Dot/Zero**		**Sleep Imputation**	
	Mean (SD)	**%**	**Mean (SD)**	*****	**Mean (SD)**	**%**	**Mean (SD)**	**%**
Sleep	74.3 (30.1)	2.0	74.3 (30.1)	2.0	74.3 (30.1)	2.0	74.3 (30.1)	2.0
17	73.9 (29.8)	2.4	73.9 (29.8)	2.4	73.9 (29.8)	2.4	73.9 (29.8)	2.4
16	72.6 (29.0)	4.0	72.6 (29.0)	4.0	72.6 (29.0)	4.0	72.6 (29.0)	4.0
15	70.5 (28.2)	6.3	70.5 (28.2)	6.3	70.5 (28.2)	6.3	70.5 (28.2)	6.3
14	66.0 (26.6)	11.9	66.0 (26.6)	11.9	66.0 (26.6)	11.9	66.0 (26.6)	11.9
13	62.5 (25.3)[a]	16.7	62.5 (25.3)[a]	16.7	62.5 (25.3)[a]	16.7	62.5 (25.3)[a]	16.7
12	58.9 (23.9)[a]	21.5	58.9 (23.9)[a]	21.5	58.9 (23.9)[a]	21.5	58.9 (23.9)[a]	21.5
11	51.5 (19.9)[a]	30.6	51.5 (19.9)[a]	30.6	51.5 (19.9)[a]	30.6	51.5 (19.9)[a]	30.6
10	47.0 (19.2)[a]	36.5	47.0 (19.2)[a]	36.5	47.0 (19.2)[a]	36.5	47.0 (19.2)[a]	36.5

Appendix E: Univariate Regression Analyses Tables

Body Mass Index

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero Raw	10.12	-0.003	0.29	10.20	0.002	0.56
Dot Raw	10.18	-0.002	0.47	10.20	0.002	0.56
Dot/zero Raw	10.18	-0.002	0.47	10.20	0.002	0.56
Sleep Imp Raw	10.12	-0.003	0.29	10.20	0.002	0.56
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 10 hr.	10.20	-0.003	0.57	10.23	<0.001	0.96
Dot 10 hr.	10.19	-0.003	0.53	10.23	<0.001	0.96
Dot/zero 10 hr.	10.23	<0.001	0.89	10.23	<0.001	0.96
Sleep Imp 10 hr.	10.20	-0.003	0.57	10.23	<0.001	0.96
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 11 hr.	10.18	-0.003	0.48	10.22	0.001	0.79
Dot 11 hr.	10.17	-0.003	0.45	10.22	0.001	0.79
Dot/zero 11 hr.	10.23	-0.001	0.98	10.22	0.001	0.79
Sleep Imp 11 hr.	10.18	-0.003	0.48	10.22	0.001	0.79
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 12 hr.	10.19	-0.003	0.51	10.23	<0.001	0.96
Dot 12 hr.	10.18	-0.003	0.48	10.23	<0.001	0.96
Dot/zero 12 hr.	10.23	-0.001	0.96	10.23	<0.001	0.96
Sleep Imp 12 hr.	10.19	-0.003	0.51	10.23	<0.001	0.96
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 13 hr.	10.17	-0.003	0.43	10.22	0.001	0.76
Dot 13 hr.	10.15	-0.003	0.39	10.22	0.001	0.76
Dot/zero 13 hr.	10.23	-0.001	0.83	10.22	0.001	0.76
Sleep Imp 13 hr.	10.17	-0.003	0.43	10.22	0.001	0.75
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 14 hr.	10.16	-0.003	0.41	10.22	0.001	0.75
Dot 14 hr.	10.15	-0.003	0.37	10.22	0.001	0.75
Dot/zero 14 hr.	10.22	-0.001	0.78	10.22	0.001	0.75
Sleep Imp 14 hr.	10.16	-0.003	0.41	10.22	0.001	0.75
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 15 hr.	10.15	-0.003	0.39	10.22	0.001	0.73
Dot 15 hr.	10.15	-0.003	0.37	10.22	0.001	0.73
Dot/zero 15 hr.	10.21	-0.001	0.70	10.22	0.001	0.73
Sleep Imp 15 hr.	10.15	-0.003	0.39	10.22	0.001	0.73
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 16 hr.	10.15	-0.003	0.37	10.21	0.001	0.69

Dot 16 hr.	10.15	-0.003	0.37	10.21	0.001	0.69
Dot/zero 16 hr.	10.21	-0.001	0.63	10.21	0.001	0.69
Sleep Imp 16 hr.	10.15	-0.003	0.37	10.21	0.001	0.69
Raw	10.15	-0.002	0.37	10.21	0.001	0.66
Zero 17 hr.	10.13	-0.003	0.33	10.20	0.001	0.61
Dot 17 hr.	10.15	-0.003	0.39	10.20	0.001	0.61
Dot/zero 17 hr.	10.19	-0.002	0.54	10.20	0.001	0.61
Sleep Imp 17 hr.	10.13	-0.003	0.33	10.20	0.001	0.61

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**P**
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero Raw	9.90	0.018	0.07	10.06	0.002	0.20
Dot Raw	9.90	0.018	0.07	10.11	0.001	0.28
Dot/zero Raw	9.90	0.018	0.07	10.11	0.001	0.28
Sleep Imp Raw	9.90	0.018	0.07	10.06	0.002	0.20
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 10 hr.	10.00	0.025	0.13	10.14	0.003	0.34
Dot 10 hr.	10.00	0.005	0.13	10.13	0.001	0.33
Dot/zero 10 hr.	10.00	0.025	0.13	10.18	0.001	0.50
Sleep Imp 10 hr.	10.10	0.025	0.13	10.14	0.003	0.35
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 11 hr.	10.01	0.023	0.14	10.13	0.003	0.32
Dot 11 hr.	10.01	0.023	0.14	10.12	0.001	0.30
Dot/zero 11 hr.	10.01	0.023	0.14	10.18	0.001	0.47
Sleep Imp 11 hr.	10.01	0.023	0.14	10.13	0.003	0.33
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 12 hr.	9.90	0.024	0.07	10.10	0.003	0.26
Dot 12 hr.	9.90	0.024	0.07	10.10	0.001	0.25
Dot/zero 12 hr.	9.90	0.024	0.07	10.15	0.001	0.37
Sleep Imp 12 hr.	9.90	0.024	0.07	10.10	0.003	0.26
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 13 hr.	9.99	0.019	0.12	10.11	0.003	0.28
Dot 13 hr.	9.99	0.019	0.12	10.11	0.001	0.27
Dot/zero 13 hr.	9.99	0.019	0.12	10.16	0.001	0.42
Sleep Imp 13 hr.	9.99	0.019	0.12	10.11	0.003	0.29
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 14 hr.	9.97	0.019	0.10	10.12	0.002	0.30
Dot 14 hr.	9.97	0.019	0.10	10.12	0.001	0.29
Dot/zero 14 hr.	9.97	0.019	0.10	10.17	0.001	0.43
Sleep Imp 14 hr.	9.97	0.019	0.10	10.12	0.002	0.30
Raw	9.92	0.018	0.08	10.09	0.002	0.23

Zero 15 hr.	9.92	0.019	0.08	10.09	0.002	0.23
Dot 15 hr.	9.92	0.019	0.08	10.09	0.001	0.24
Dot/zero 15 hr.	9.92	0.019	0.08	10.14	0.001	0.34
Sleep Imp 15 hr.	9.92	0.019	0.08	10.09	0.002	0.24
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 16 hr.	9.91	0.019	0.07	10.08	0.002	0.22
Dot 16 hr.	9.91	0.019	0.07	10.09	0.001	0.25
Dot/zero 16 hr.	9.91	0.019	0.07	10.13	0.001	0.32
Sleep Imp 16 hr.	9.91	0.019	0.07	10.08	0.002	0.23
Raw	9.92	0.018	0.08	10.09	0.002	0.23
Zero 17 hr.	9.92	0.018	0.08	10.08	0.002	0.22
Dot 17 hr.	9.92	0.018	0.08	10.11	0.001	0.27
Dot/zero 17 hr.	9.92	0.018	0.08	10.12	0.001	0.31
Sleep Imp 17 hr.	9.92	0.018	0.08	10.08	0.002	0.22

Systolic Blood Pressure

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero Raw	159.42	-0.034	<0.01	165.35	0.028	0.06
Dot Raw	162.67	-0.033	0.02	165.35	0.028	0.06
Dot/zero Raw	162.67	-0.033	0.02	165.35	0.028	0.06
Sleep Imp Raw	156.30	0.020	<0.01	165.35	0.028	0.06
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 10 hr.	158.63	-0.063	<0.01	165.31	0.050	0.05
Dot 10 hr.	160.44	-0.056	0.01	165.31	0.050	0.05
Dot/zero 10 hr.	169.11	-0.020	0.24	165.31	0.050	0.05
Sleep Imp 10 hr.	158.63	-0.063	<0.01	165.31	0.050	0.05
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 11 hr.	158.29	-0.058	<0.01	164.43	0.048	0.04
Dot 11 hr.	160.15	-0.052	0.01	164.43	0.048	0.04
Dot/zero 11 hr.	168.20	-0.023	0.17	164.43	0.048	0.04
Sleep Imp 11 hr.	158.29	-0.058	<0.01	164.43	0.048	0.04
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 12 hr.	160.05	-0.048	<0.01	166.93	0.035	0.10
Dot 12 hr.	161.25	-0.044	0.01	166.93	0.035	0.10
Dot/zero 12 hr.	168.10	-0.022	0.16	166.93	0.035	0.10
Sleep Imp 12 hr.	160.05	-0.048	<0.01	166.93	0.035	0.10
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 13 hr.	159.38	-0.046	<0.01	165.98	0.035	0.07
Dot 13 hr.	160.17	-0.043	0.01	165.98	0.035	0.07

Dot/zero 13 hr.	167.12	-0.024	0.11	165.98	0.035	0.07
Sleep Imp 13 hr.	159.38	-0.046	<0.01	165.98	0.035	0.07
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 14 hr.	159.00	-0.044	<0.01	165.64	0.034	0.06
Dot 14 hr.	159.62	-0.042	<0.01	165.64	0.034	0.06
Dot/zero 14 hr.	166.28	-0.026	0.08	165.64	0.034	0.06
Sleep Imp 14 hr.	159.00	-0.044	<0.01	165.64	0.034	0.06
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 15 hr.	160.05	-0.038	<0.01	166.54	0.028	0.09
Dot 15 hr.	160.54	-0.038	0.01	166.54	0.028	0.09
Dot/zero 15 hr.	165.70	-0.027	0.06	166.54	0.028	0.09
Sleep Imp 15 hr.	160.05	-0.038	<0.01	166.54	0.028	0.09
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 16 hr.	160.32	-0.035	0.01	166.28	0.027	0.08
Dot 16 hr.	160.87	-0.037	0.01	166.28	0.027	0.08
Dot/zero 16 hr.	164.91	-0.029	0.05	166.28	0.027	0.08
Sleep Imp 16 hr.	160.32	-0.035	0.01	166.28	0.027	0.08
Raw	157.20	-0.037	<0.01	163.55	0.031	0.03
Zero 17 hr.	159.96	-0.034	<0.01	165.90	0.027	0.07
Dot 17 hr.	161.38	-0.036	0.01	165.90	0.027	0.07
Dot/zero 17 hr.	163.68	-0.031	0.03	165.90	0.027	0.07
Sleep Imp 17 hr.	159.96	-0.034	<0.01	165.90	0.027	0.07

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**P**
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero Raw	151.94	0.146	<0.01	156.02	0.028	<0.01
Dot Raw	151.94	0.156	<0.01	155.85	0.020	<0.01
Dot/zero Raw	151.94	0.146	<0.01	155.85	0.020	<0.01
Sleep Imp Raw	151.94	0.146	<0.01	165.04	0.028	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 10 hr.	154.27	0.214	<0.01	157.68	0.043	<0.01
Dot 10 hr.	154.27	0.214	<0.01	158.01	0.018	<0.01
Dot/zero 10 hr.	154.27	0.214	<0.01	158.94	0.027	<0.01
Sleep Imp 10 hr.	154.27	0.214	<0.01	157.98	0.043	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 11 hr.	155.17	0.201	<0.01	157.64	0.041	<0.01
Dot 11 hr.	155.17	0.021	<0.01	157.87	0.019	<0.01
Dot/zero 11 hr.	155.17	0.021	<0.01	158.82	0.025	<0.01
Sleep Imp 11 hr.	155.17	0.201	<0.01	157.89	0.041	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 12 hr.	151.78	0.184	<0.01	156.05	0.037	<0.01

Dot 12 hr.	151.78	0.184	<0.01	156.30	0.019	<0.01
Dot/zero 12 hr.	151.78	0.184	<0.01	157.11	0.024	<0.01
Sleep Imp 12 hr.	151.78	0.184	<0.01	156.22	0.037	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 13 hr.	153.35	0.167	<0.01	156.89	0.033	<0.01
Dot 13 hr.	153.35	0.167	<0.01	156.66	0.019	<0.01
Dot/zero 13 hr.	153.35	0.167	<0.01	157.95	0.021	<0.01
Sleep Imp 13 hr.	153.35	0.167	<0.01	157.06	0.033	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 14 hr.	153.38	0.159	<0.01	156.89	0.032	<0.01
Dot 14 hr.	153.38	0.159	<0.01	156.56	0.019	<0.01
Dot/zero 14 hr.	153.38	0.159	<0.01	157.96	0.020	<0.01
Sleep Imp 14 hr.	153.38	0.159	<0.01	157.04	0.031	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 15 hr.	151.64	0.157	<0.01	156.13	0.030	<0.01
Dot 15 hr.	151.64	0.157	<0.01	155.61	0.019	<0.01
Dot/zero 15 hr.	151.64	0.157	<0.01	156.78	0.020	<0.01
Sleep Imp 15 hr.	151.64	0.157	<0.01	156.23	0.030	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 16 hr.	152.89	0.147	<0.01	156.92	0.028	<0.01
Dot 16 hr.	152.89	0.147	<0.01	156.00	0.019	<0.01
Dot/zero 16 hr.	152.89	0.147	<0.01	157.20	0.019	<0.01
Sleep Imp 16 hr.	152.89	0.147	<0.01	156.99	0.028	<0.01
Raw	151.55	0.146	<0.01	154.72	0.029	<0.01
Zero 17 hr.	152.14	0.146	<0.01	156.37	0.028	<0.01
Dot 17 hr.	152.14	0.146	<0.01	155.53	0.020	<0.01
Dot/zero 17 hr.	152.14	0.146	<0.01	156.30	0.020	<0.01
Sleep Imp 17 hr.	152.14	0.146	<0.01	156.40	0.028	<0.01

Diastolic blood pressure

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero Raw	116.50	-0.007	0.49	117.01	0.002	0.85
Dot Raw	116.62	-0.007	0.55	117.01	0.002	0.85
Dot/zero Raw	116.62	-0.007	0.55	117.01	0.002	0.85
Sleep Imp Raw	116.50	-0.007	0.49	117.01	0.002	0.85
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 10 hr.	116.82	-0.008	0.66	117.05	-0.000	0.97
Dot 10 hr.	116.82	-0.008	0.66	117.05	-0.000	0.97
Dot/zero 10 hr.	117.03	-0.001	0.90	117.05	-0.000	0.97

Sleep Imp 10 hr.	116.82	-0.008	0.66	117.05	-0.000	0.97
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 11 hr.	116.90	-0.006	0.72	117.05	-0.001	0.95
Dot 11 hr.	116.90	-0.005	0.72	117.05	-0.001	0.95
Dot/zero 11 hr.	117.04	-0.001	0.93	117.05	-0.001	0.95
Sleep Imp 11 hr.	116.90	-0.006	0.72	117.05	-0.001	0.95
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 12 hr.	116.90	-0.005	0.72	117.03	-0.002	0.89
Dot 12 hr.	116.86	-0.006	0.69	117.03	-0.002	0.89
Dot/zero 12 hr.	117.04	-0.001	0.91	117.03	-0.002	0.89
Sleep Imp 12 hr.	116.90	-0.005	0.72	117.03	-0.002	0.89
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 13 hr.	116.83	-0.006	0.66	117.05	-0.000	0.98
Dot 13 hr.	116.66	-0.008	0.56	117.05	-0.000	0.98
Dot/zero 13 hr.	117.00	-0.002	0.84	117.03	-0.002	0.89
Sleep Imp 13 hr.	116.83	-0.006	0.66	117.05	-0.000	0.98
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 14 hr.	116.66	-0.007	0.56	117.04	0.001	0.94
Dot 14 hr.	116.37	-0.010	0.45	117.04	0.001	0.94
Dot/zero 14 hr.	116.90	-0.004	0.72	117.04	0.001	0.94
Sleep Imp 14 hr.	116.66	-0.007	0.56	117.04	0.001	0.94
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 15 hr.	116.68	-0.006	0.58	117.05	0.000	0.96
Dot 15 hr.	116.40	-0.009	0.45	117.05	0.000	0.96
Dot/zero 15 hr.	116.88	-0.004	0.70	117.05	<0.001	0.96
Sleep Imp 15 hr.	116.68	-0.006	0.58	117.05	<0.001	0.96
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 16 hr.	116.63	-0.006	0.55	117.04	0.001	0.93
Dot 16 hr.	116.49	-0.008	0.49	117.04	0.001	0.93
Dot/zero 16 hr.	116.80	-0.005	0.65	117.04	0.001	0.93
Sleep Imp 16 hr.	116.63	-0.006	0.55	117.04	0.001	0.93
Raw	116.51	-0.007	0.50	117.01	0.002	0.85
Zero 17 hr.	116.55	-0.007	0.51	117.02	0.001	0.88
Dot 17 hr.	116.56	-0.008	0.52	117.02	0.001	0.88
Dot/zero 17 hr.	116.70	-0.006	0.58	117.02	0.001	0.88
Sleep Imp 17 hr.	116.55	-0.007	0.51	117.02	0.001	0.88

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero Raw	113.46	0.062	0.08	115.69	0.008	0.28
Dot Raw	133.46	0.062	0.08	113.46	0.062	0.08

Dot/zero Raw	113.46	0.062	0.08	115.48	0.006	0.25
Sleep Imp Raw	113.46	0.062	0.08	115.68	0.008	0.28
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 10 hr.	114.81	0.077	0.17	116.44	0.009	0.47
Dot 10 hr.	114.81	0.077	0.17	114.81	0.077	0.17
Dot/zero 10 hr.	114.81	0.077	0.17	116.38	0.006	0.45
Sleep Imp 10 hr.	114.81	0.077	0.17	116.46	0.009	0.48
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 11 hr.	115.08	0.070	0.19	116.50	0.008	0.49
Dot 11 hr.	115.08	0.070	0.19	115.08	0.070	0.19
Dot/zero 11 hr.	115.08	0.070	0.19	116.37	0.005	0.45
Sleep Imp 11 hr.	115.08	0.070	0.19	116.51	0.008	0.50
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 12 hr.	114.85	0.061	0.17	116.45	0.007	0.48
Dot 12 hr.	114.85	0.061	0.17	114.85	0.061	0.17
Dot/zero 12 hr.	114.85	0.061	0.17	116.37	0.005	0.44
Sleep Imp 12 hr.	114.85	0.061	0.17	116.46	0.007	0.48
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 13 hr.	114.93	0.057	0.18	116.50	0.006	0.49
Dot 13 hr.	114.93	0.057	0.18	114.93	0.057	0.18
Dot/zero 13 hr.	114.93	0.057	0.18	116.36	0.004	0.44
Sleep Imp 13 hr.	114.93	0.057	0.18	116.51	0.006	0.50
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 14 hr.	114.26	0.062	0.12	116.10	0.008	0.37
Dot 14 hr.	114.26	0.062	0.12	114.26	0.062	0.12
Dot/zero 14 hr.	114.26	0.062	0.12	115.98	0.005	0.34
Sleep Imp 14 hr.	114.26	0.062	0.12	116.10	0.008	0.37
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 15 hr.	113.99	0.061	0.10	116.03	0.007	0.35
Dot 15 hr.	113.99	0.061	0.10	113.99	0.061	0.10
Dot/zero 15 hr.	113.99	0.061	0.10	115.89	0.005	0.32
Sleep Imp 15 hr.	113.99	0.061	0.10	116.03	0.007	0.35
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 16 hr.	113.80	0.061	0.09	115.91	0.008	0.32
Dot 16 hr.	113.80	0.061	0.09	113.80	0.061	0.09
Dot/zero 16 hr.	113.80	0.061	0.09	115.74	0.006	0.29
Sleep Imp 16 hr.	113.80	0.061	0.09	115.91	0.008	0.32
Raw	113.49	0.062	0.08	115.62	0.008	0.27
Zero 17 hr.	113.61	0.061	0.08	115.80	0.008	0.30
Dot 17 hr.	113.61	0.061	0.08	113.61	0.061	0.08
Dot/zero 17 hr.	113.61	0.06	0.08	115.60	0.006	0.27
Sleep Imp 17 hr.	113.61	0.061	0.08	115.80	0.008	0.30

Waist circumference

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero Raw	77.90	-0.004	0.62	78.08	-0.000	0.94
Dot Raw	77.92	0.004	0.65	78.08	-0.000	0.94
Dot/zero Raw	77.92	0.004	0.65	78.08	-0.000	0.94
Sleep Imp Raw	78.03	-0.004	0.62	78.08	-0.000	0.94
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 10 hr.	78.01	0.004	0.75	77.37	-0.017	0.34
Dot 10 hr.	77.98	0.005	0.71	77.37	-0.017	0.34
Dot/zero 10 hr.	76.49	0.016	0.15	77.37	-0.017	0.34
Sleep Imp 10 hr.	78.01	0.004	0.75	77.37	-0.017	0.34
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 11 hr.	78.02	0.003	0.78	77.59	-0.012	0.43
Dot 11 hr.	78.00	0.004	0.74	77.59	-0.012	0.43
Dot/zero 11 hr.	76.57	0.016	0.16	77.59	-0.012	0.43
Sleep Imp 11 hr.	78.02	0.003	0.78	77.59	-0.012	0.43
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 12 hr.	78.08	0.000	0.95	77.58	-0.011	0.42
Dot 12 hr.	78.07	0.001	0.90	77.58	-0.011	0.42
Dot/zero 12 hr.	77.03	0.012	0.24	77.58	-0.011	0.42
Sleep Imp 12 hr.	78.08	<0.001	0.95	77.58	-0.011	0.42
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 13 hr.	78.08	0.000	0.97	77.74	-0.008	0.51
Dot 13 hr.	78.06	0.001	0.88	77.74	-0.008	0.51
Dot/zero 13 hr.	77.13	0.011	0.27	77.74	-0.008	0.51
Sleep Imp 13 hr.	78.08	<0.001	0.97	77.74	-0.008	0.51
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 14 hr.	78.08	-0.000	0.97	77.80	-0.007	0.55
Dot 14 hr.	78.07	0.001	0.88	77.80	-0.007	0.55
Dot/zero 14 hr.	77.26	0.010	0.31	77.80	-0.007	0.55
Sleep Imp 14 hr.	78.08	-0.000	0.97	77.80	-0.007	0.55
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 15 hr.	78.05	-0.001	0.85	77.93	-0.005	0.66
Dot 15 hr.	78.07	0.001	0.90	77.93	-0.005	0.66
Dot/zero 15 hr.	77.52	0.008	0.40	77.93	-0.005	0.66
Sleep Imp 15 hr.	78.05	-0.001	0.85	77.93	-0.005	0.66
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 16 hr.	78.03	-0.002	0.80	77.99	-0.003	0.73
Dot 16 hr.	78.04	0.002	0.80	77.99	-0.003	0.73
Dot/zero 16 hr.	77.63	0.007	0.45	77.99	-0.003	0.73

Sleep Imp 16 hr.	78.03	-0.002	0.80	77.99	-0.003	0.73
Raw	78.03	-0.002	0.79	78.01	-0.003	0.76
Zero 17 hr.	77.94	-0.003	0.67	78.07	-0.001	0.88
Dot 17 hr.	78.01	0.003	0.76	78.07	-0.001	0.88
Dot/zero 17 hr.	77.85	0.005	0.58	78.07	-0.001	0.88
Sleep Imp 17 hr.	77.94	-0.003	0.67	78.07	-0.001	0.88

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero Raw	75.46	0.053	0.06	77.48	0.005	0.38
Dot Raw	75.46	0.053	0.06	77.87	0.002	0.60
Dot/zero Raw	75.46	0.053	0.06	77.87	0.002	0.60
Sleep Imp Raw	75.46	0.053	0.06	77.51	0.005	0.39
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 10 hr.	76.26	0.069	0.12	77.95	0.004	0.68
Dot 10 hr.	76.26	0.069	0.12	77.96	0.001	0.69
Dot/zero 10 hr.	76.26	0.069	0.12	78.08	-0.000	0.99
Sleep Imp 10 hr.	76.26	0.069	0.12	77.98	0.003	0.71
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 11 hr.	76.75	0.057	0.19	116.50	0.008	0.49
Dot 11 hr.	76.75	0.057	0.19	78.02	0.001	0.78
Dot/zero 11 hr.	76.75	0.057	0.19	78.07	-0.000	0.90
Sleep Imp 11 hr.	76.75	0.057	0.19	78.04	0.002	0.81
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 12 hr.	114.85	0.061	0.17	116.45	0.007	0.48
Dot 12 hr.	75.34	0.068	0.06	77.66	0.003	0.46
Dot/zero 12 hr.	75.34	0.068	0.06	77.98	0.002	0.72
Sleep Imp 12 hr.	75.34	0.068	0.06	77.68	0.006	0.47
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 13 hr.	114.93	0.057	0.18	116.50	0.006	0.49
Dot 13 hr.	76.10	0.055	0.11	77.85	0.002	0.59
Dot/zero 13 hr.	76.10	0.055	0.11	78.06	<0.001	0.85
Sleep Imp 13 hr.	76.10	0.055	0.11	77.85	0.004	0.58
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 14 hr.	114.26	0.062	0.12	116.10	0.008	0.37
Dot 14 hr.	75.92	0.055	0.09	77.88	0.002	0.61
Dot/zero 14 hr.	75.92	0.055	0.09	78.06	<0.001	0.85
Sleep Imp 14 hr.	75.92	0.055	0.09	77.85	0.004	0.59
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 15 hr.	113.99	0.061	0.10	116.03	0.007	0.35
Dot 15 hr.	75.66	0.054	0.07	77.81	0.002	0.55

Dot/zero 15 hr.	75.66	0.054	0.07	77.99	0.001	0.73
Sleep Imp 15 hr.	75.66	0.054	0.07	77.71	0.004	0.49
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 16 hr.	113.80	0.061	0.09	115.91	0.008	0.32
Dot 16 hr.	75.65	0.053	0.07	77.85	0.002	0.59
Dot/zero 16 hr.	75.65	0.053	0.07	77.97	0.001	0.71
Sleep Imp 16 hr.	75.65	0..053	0.07	77.68	0.004	0.47
Raw	75.66	0.051	0.07	77.63	0.004	0.45
Zero 17 hr.	113.61	0.061	0.08	115.80	0.008	0.30
Dot 17 hr.	75.59	0.052	0.07	77.85	0.002	0.58
Dot/zero 17 hr.	75.59	0.052	0.07	77.91	0.002	0.64
Sleep Imp 17 hr.	75.59	0.052	0.07	77.57	0.005	0.42

Waist-height ratio

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero Raw	0.002	<0.001	0.87	0.002	-0.001	0.70
Dot Raw	0.002	<0.001	0.43	0.002	<0.001	0.25
Dot/zero Raw	0.002	<0.001	0.43	0.002	-0.001	0.70
Sleep Imp Raw	0.002	<0.001	0.87	0.002	-0.001	0.70
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 10 hr.	0.002	<0.001	0.36	0.002	-0.001	0.25
Dot 10 hr.	0.002	<0.001	0.43	0.002	<0.001	0.25
Dot/zero 10 hr.	0.002	<0.001	0.16	0.002	-0.001	0.25
Sleep Imp 10 hr.	0.002	<0.001	0.36	0.002	-0.001	0.25
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 11 hr.	0.002	<0.001	0.28	0.002	-0.001	0.22
Dot 11 hr.	0.002	<0.001	0.33	0.002	<0.001	0.22
Dot/zero 11 hr.	0.001	<0.001	0.11	0.002	-0.001	0.22
Sleep Imp 11 hr.	0.002	<0.001	0.28	0.002	-0.001	0.22
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 12 hr.	0.002	<0.001	0.48	0.002	-0.001	0.33
Dot 12 hr.	0.002	<0.001	0.55	0.002	<0.001	0.33
Dot/zero 12 hr.	0.002	<0.001	0.20	0.002	-0.001	0.33
Sleep Imp 12 hr.	0.002	<0.001	0.48	0.002	-0.001	0.33
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 13 hr.	0.002	<0.001	0.45	0.002	-0.001	0.35
Dot 13 hr.	0.002	<0.001	0.51	0.002	<0.001	0.35
Dot/zero 13 hr.	0.002	<0.001	0.18	0.002	-0.001	0.35
Sleep Imp 13 hr.	0.002	<0.001	0.45	0.002	-0.001	0.35

Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 14 hr.	0.002	<0.001	0.55	0.002	-0.001	0.42
Dot 14 hr.	0.002	<0.001	0.57	0.002	<0.001	0.42
Dot/zero 14 hr.	0.002	<0.001	0.23	0.002	<0.001	0.76
Sleep Imp 14 hr.	0.002	<0.001	0.55	0.002	-0.001	0.42
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 15 hr.	0.002	<0.001	0.70	0.002	-0.001	0.54
Dot 15 hr.	0.002	<0.001	0.60	0.002	<0.001	0.54
Dot/zero 15 hr.	0.002	<0.001	0.31	0.002	-0.001	0.54
Sleep Imp 15 hr.	0.002	<0.001	0.70	0.002	-0.001	0.54
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 16 hr.	0.002	<0.001	0.73	0.002	-0.001	0.56
Dot 16 hr.	0.002	<0.001	0.53	0.002	<0.001	0.56
Dot/zero 16 hr.	0.002	<0.001	0.32	0.002	-0.001	0.56
Sleep Imp 16 hr.	0.002	<0.001	0.73	0.002	-0.001	0.56
Raw	0.002	<0.001	0.68	0.002	-0.001	0.52
Zero 17 hr.	0.002	<0.001	0.83	0.002	-0.001	0.67
Dot 17 hr.	0.002	<0.001	0.52	0.002	<0.001	0.67
Dot/zero 17 hr.	0.002	<0.001	0.40	0.002	-0.001	0.67
Sleep Imp 17 hr.	0.002	<0.001	0.83	0.002	-0.001	0.67

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero Raw	0.002	<0.001	0.56	0.002	-0.001	0.90
Dot Raw	0.002	<0.001	0.56	0.002	-0.001	0.69
Dot/zero Raw	0.002	<0.001	0.56	0.002	-0.001	0.69
Sleep Imp Raw	0.002	<0.001	0.56	0.002	-0.001	0.89
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 10 hr.	0.002	<0.001	0.82	0.002	-0.001	0.55
Dot 10 hr.	0.002	<0.001	0.82	0.002	-0.001	0.58
Dot/zero 10 hr.	0.002	<0.001	0.82	0.002	-0.001	0.39
Sleep Imp 10 hr.	0.002	<0.001	0.82	0.002	-0.001	0.53
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 11 hr.	0.002	-0.000	0.96	0.002	-0.001	0.39
Dot 11 hr.	0.002	<0.001	0.96	0.002	<0.001	0.43
Dot/zero 11 hr.	0.002	<0.000	0.96	0.002	-0.001	0.27
Sleep Imp 11 hr.	0.002	-0.001	0.96	0.002	-0.001	0.38
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 12 hr.	0.002	<0.001	0.69	0.002	-0.001	0.67
Dot 12 hr.	0.002	<0.001	0.69	0.002	-0.001	0.70
Dot/zero 12 hr.	0.002	<0.001	0.69	0.002	-0.001	0.49

Sleep Imp 12 hr.	0.002	<0.001	0.69	0.002	-0.001	0.65
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 13 hr.	0.002	<0.001	0.85	0.002	-0.001	0.58
Dot 13 hr.	0.002	<0.001	0.85	0.002	<0.001	0.61
Dot/zero 13 hr.	0.002	<0.001	0.85	0.002	-0.001	0.42
Sleep Imp 13 hr.	0.002	<0.001	0.85	0.002	-0.001	0.56
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 14 hr.	0.002	<0.001	0.76	0.002	-0.001	0.60
Dot 14 hr.	0.002	<0.001	0.76	0.022	<0.001	0.60
Dot/zero 14 hr.	0.002	<0.001	0.76	0.002	-0.001	0.43
Sleep Imp 14 hr.	0.002	<0.001	0.76	0.002	-0.001	0.58
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 15 hr.	0.002	<0.001	0.65	0.002	-0.001	0.76
Dot 15 hr.	0.002	<0.001	0.65	0.002	-0.001	0.71
Dot/zero 15 hr.	0.002	<0.001	0.65	0.002	-0.001	0.56
Sleep Imp 15 hr.	0.002	<0.001	0.65	0.002	-0.001	0.75
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 16 hr.	0.002	<0.001	0.58	0.002	-0.001	0.82
Dot 16 hr.	0.002	<0.001	0.58	0.002	-0.001	0.72
Dot/zero 16 hr.	0.002	<0.001	0.58	0.002	-0.001	0.62
Sleep Imp 16 hr.	0.002	<0.001	0.58	0.002	-0.001	0.81
Raw	0.002	<0.001	0.61	0.002	-0.001	0.81
Zero 17 hr.	0.002	<0.001	0.59	0.002	-0.001	0.86
Dot 17 hr.	0.002	<0.001	0.59	0.002	-0.001	0.70
Dot/zero 17 hr.	0.002	<0.001	0.59	0.002	-0.001	0.65
Sleep Imp 17 hr.	0.002	<0.001	0.59	0.002	-0.001	0.84

Age

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero Raw	61.26	-0.013	0.08	60.27	0.019	0.03
Dot Raw	61.96	-0.012	0.16	60.27	0.019	0.03
Dot/zero Raw	61.96	-0.012	0.16	60.27	0.019	0.03
Sleep Imp Raw	61.26	-0.013	0.08	60.27	0.019	0.03
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 10 hr.	62.49	-0.014	0.29	61.66	0.025	0.12
Dot 10 hr.	61.95	-0.019	0.16	61.66	0.025	0.12
Dot/zero 10 hr.	63.20	-0.001	0.91	61.66	0.025	0.12
Sleep Imp 10 hr.	62.49	-0.014	0.29	61.66	0.025	0.12
Raw	61.61	-0.012	0.11	60.78	0.017	0.05

Zero 11 hr.	62.51	-0.013	0.29	61.85	0.021	0.14
Dot 11 hr.	62.04	-0.016	0.17	61.85	0.021	0.14
Dot/zero 11 hr.	63.19	-0.001	0.86	61.85	0.021	0.14
Sleep Imp 11 hr.	62.51	-0.013	0.29	61.85	0.021	0.14
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 12 hr.	61.91	-0.016	0.15	61.04	0.024	0.06
Dot 12 hr.	61.38	-0.018	0.09	61.04	0.024	0.06
Dot/zero 12 hr.	63.00	-0.005	0.56	61.04	0.024	0.06
Sleep Imp 12 hr.	61.91	-0.016	0.15	61.04	0.024	0.06
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 13 hr.	62.01	-0.014	0.17	61.06	0.022	0.06
Dot 13 hr.	61.42	-0.017	0.09	61.06	0.022	0.06
Dot/zero 13 hr.	62.98	-0.005	0.55	61.06	0.022	0.06
Sleep Imp 13 hr.	62.01	-0.014	0.17	61.06	0.022	0.06
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 14 hr.	62.11	0.013	0.19	61.28	0.019	0.08
Dot 14 hr.	61.58	-0.015	0.11	61.28	0.019	0.08
Dot/zero 14 hr.	62.96	-0.005	0.53	61.28	0.019	0.08
Sleep Imp 14 hr.	62.11	-0.013	0.19	61.28	0.019	0.08
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 15 hr.	61.64	-0.014	0.11	60.62	0.021	0.04
Dot 15 hr.	61.32	-0.016	0.08	60.62	0.021	0.04
Dot/zero 15 hr.	62.61	-0.008	0.33	60.62	0.021	0.04
Sleep Imp 15 hr.	61.64	-0.014	0.11	60.62	0.021	0.04
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 16 hr.	61.40	-0.014	0.09	60.46	0.020	0.03
Dot 16 hr.	61.76	-0.013	0.13	60.46	0.020	0.03
Dot/zero 16 hr.	62.31	-0.010	0.23	60.46	0.020	0.03
Sleep Imp 16 hr.	61.40	-0.014	0.09	60.46	0.020	0.03
Raw	61.61	-0.012	0.11	60.78	0.017	0.05
Zero 17 hr.	61.09	-0.148	0.06	60.03	0.020	0.02
Dot 17 hr.	61.99	-0.012	0.16	60.03	0.020	0.02
Dot/zero 17 hr.	61.88	-0.013	0.15	60.03	0.020	0.02
Sleep Imp 17 hr.	61.09	-0.014	0.06	60.03	0.020	0.02

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero Raw	63.12	-0.010	0.70	62.96	0.003	0.53
Dot Raw	63.12	-0.010	0.70	63.05	0.001	0.62
Dot/zero Raw	63.12	-0.010	0.70	63.05	0.001	0.62
Sleep Imp Raw	63.12	-0.010	0.70	62.97	0.003	0.54

Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 10 hr.	62.72	-0.036	0.38	63.19	-0.001	0.87
Dot 10 hr.	62.72	-0.036	0.38	63.21	<0.001	0.96
Dot/zero 10 hr.	62.72	-0.036	0.38	63.15	-0.001	0.75
Sleep Imp 10 hr.	62.72	-0.036	0.38	63.19	-0.001	0.85
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 11 hr.	62.86	-0.029	0.46	63.21	0.000	0.94
Dot 11 hr.	62.86	-0.029	0.46	63.19	<0.001	0.86
Dot/zero 11 hr.	62.86	-0.029	0.46	63.20	-0.000	0.93
Sleep Imp 11 hr.	62.86	-0.029	0.46	63.21	<0.001	0.96
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 12 hr.	63.04	-0.017	0.60	63.15	0.002	0.76
Dot 12 hr.	63.04	-0.017	0.60	63.10	0.001	0.68
Dot/zero 12 hr.	63.04	-0.017	0.60	63.19	<0.001	0.87
Sleep Imp 12 hr.	63.04	-0.017	0.60	63.16	0.002	0.77
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 13 hr.	62.91	-0.021	0.49	63.20	0.000	0.89
Dot 13 hr.	62.91	-0.021	0.49	63.17	0.001	0.79
Dot/zero 13 hr.	62.91	-0.021	0.49	63.21	-0.000	0.98
Sleep Imp 13 hr.	62.91	-0.021	0.49	63.20	<0.001	0.90
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 14 hr.	62.96	-0.018	0.53	63.18	0.001	0.81
Dot 14 hr.	62.96	-0.018	0.53	63.14	0.001	0.73
Dot/zero 14 hr.	62.96	-0.018	0.53	63.21	<0.001	0.94
Sleep Imp 14 hr.	62.96	-0.018	0.53	63.18	0.001	0.83
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 15 hr.	62.99	-0.016	0.55	63.14	0.002	0.74
Dot 15 hr.	62.99	-0.016	0.55	63.12	0.001	0.70
Dot/zero 15 hr.	62.99	-0.016	0.55	63.19	<0.001	0.86
Sleep Imp 15 hr.	62.99	-0.016	0.55	63.15	0.001	0.75
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 16 hr.	63.09	-0.011	0.67	63.05	0.003	0.61
Dot 16 hr.	63.09	-0.011	0.67	63.09	0.001	0.66
Dot/zero 16 hr.	63.09	-0.011	0.67	63.13	0.001	0.73
Sleep Imp 16 hr.	63.09	-0.011	0.67	63.06	0.002	0.62
Raw	63.12	-0.009	0.70	62.96	0.003	0.53
Zero 17 hr.	63.12	-0.010	0.70	62.94	0.003	0.52
Dot 17 hr.	63.12	-0.010	0.70	63.06	0.001	0.63
Dot/zero 17 hr.	63.12	-0.010	0.70	63.04	0.002	0.61
Sleep Imp 17 hr.	63.12	-0.010	0.70	62.95	0.003	0.53

Body fat percentage

Data Treatment	Sedentary (minutes/day)			Light (minutes/day)		
	Residual	Slope	p	Residual	Slope	p
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero Raw	79.92	0.008	0.33	80.44	-0.005	0.59
Dot Raw	80.46	0.005	0.60	80.44	<0.001	0.59
Dot/zero Raw	80.46	0.005	0.60	80.44	-0.005	0.59
Sleep Imp Raw	79.92	0.008	0.33	80.44	-0.005	0.59
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 10 hr.	79.89	0.015	0.32	80.58	-0.006	0.72
Dot 10 hr.	80.17	0.012	0.43	80.58	<0.001	0.72
Dot/zero 10 hr.	80.68	<0.001	0.95	80.58	-0.006	0.72
Sleep Imp 10 hr.	79.89	0.015	0.32	80.58	-0.006	0.72
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 11 hr.	79.32	0.018	0.19	80.25	-0.012	0.46
Dot 11 hr.	79.68	0.015	0.26	80.25	-0.012	0.46
Dot/zero 11 hr.	80.56	0.004	0.70	80.25	-0.012	0.46
Sleep Imp 11 hr.	79.32	0.018	0.19	80.25	-0.012	0.46
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 12 hr.	79.66	0.014	0.26	80.51	-0.006	0.64
Dot 12 hr.	79.97	0.011	0.35	80.51	-0.006	0.64
Dot/zero 12 hr.	80.59	0.003	0.74	80.51	-0.006	0.64
Sleep Imp 12 hr.	79.66	0.014	0.26	80.51	-0.006	0.64
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 13 hr.	79.79	0.012	0.29	80.47	-0.007	0.61
Dot 13 hr.	80.14	0.009	0.42	80.47	-0.007	0.61
Dot/zero 13 hr.	80.59	0.003	0.74	80.47	-0.007	0.61
Sleep Imp 13 hr.	79.79	0.012	0.29	80.47	-0.007	0.61
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 14 hr.	79.92	0.010	0.33	80.55	-0.005	0.68
Dot 14 hr.	80.34	0.007	0.52	80.55	-0.005	0.68
Dot/zero 14 hr.	80.61	0.003	0.76	80.55	-0.005	0.68
Sleep Imp 14 hr.	79.92	0.010	0.33	80.55	-0.005	0.68
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 15 hr.	80.03	0.009	0.37	80.55	-0.004	0.69
Dot 15 hr.	80.39	0.006	0.55	80.55	-0.004	0.69
Dot/zero 15 hr.	80.60	0.003	0.75	80.55	-0.004	0.69
Sleep Imp 15 hr.	80.03	0.009	0.37	80.55	-0.004	0.69
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 16 hr.	80.00	0.008	0.36	80.50	-0.005	0.64
Dot 16 hr.	80.35	0.006	0.52	80.50	-0.005	0.64
Dot/zero 16 hr.	80.56	0.003	0.70	80.50	-0.005	0.64

Sleep Imp 16 hr.	80.00	0.008	0.36	80.50	-0.005	0.64
Raw	79.91	0.008	0.33	80.44	-0.005	0.59
Zero 17 hr.	80.01	0.008	0.36	80.51	-0.004	0.65
Dot 17 hr.	80.42	0.005	0.57	80.51	-0.004	0.65
Dot/zero 17 hr.	80.53	0.004	0.67	80.51	-0.004	0.65
Sleep Imp 17 hr.	80.01	0.008	0.36	80.51	-0.004	0.65

Data Treatment	**MVPA (minutes/day)**			**DPA (counts/minute)**		
	Residual	**Slope**	**p**	**Residual**	**Slope**	**p**
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero Raw	78.45	-0.049	0.09	78.89	-0.009	0.13
Dot Raw	78.45	-0.049	0.09	79.22	-0.006	0.18
Dot/zero Raw	78.45	-0.049	0.09	79.22	-0.006	0.18
Sleep Imp Raw	78.45	-0.049	0.09	78.91	-0.009	0.14
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 10 hr.	77.50	-0.092	0.04	78.09	-0.019	0.07
Dot 10 hr.	77.50	-0.092	0.04	78.26	-0.007	0.08
Dot/zero 10 hr.	77.50	-0.092	0.04	78.73	-0.010	0.12
Sleep Imp 10 hr.	77.50	-0.092	0.04	78.16	-0.018	0.07
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 11 hr.	77.35	-0.091	0.04	78.05	-0.018	0.07
Dot 11 hr.	77.35	-0.091	0.04	78.25	-0.008	0.08
Dot/zero 11 hr.	77.35	-0.091	0.04	78.81	-0.009	0.13
Sleep Imp 11 hr.	77.35	-0.091	0.04	78.11	-0.017	0.07
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 12 hr.	77.15	-0.078	0.03	77.77	-0.016	0.05
Dot 12 hr.	77.15	-0.078	0.03	77.98	-0.008	0.06
Dot/zero 12 hr.	77.15	-0.078	0.03	78.42	-0.009	0.09
Sleep Imp 12 hr.	77.15	-0.078	0.03	77.82	-0.016	0.06
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 13 hr.	78.11	-0.062	0.07	78.63	-0.012	0.11
Dot 13 hr.	78.11	-0.062	0.07	78.82	-0.006	0.13
Dot/zero 13 hr.	78.11	-0.062	0.07	79.22	-0.007	0.18
Sleep Imp 13 hr.	78.11	-0.062	0.07	78.67	-0.012	0.11
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 14 hr.	77.94	-0.061	0.06	78.49	-0.012	0.10
Dot 14 hr.	77.94	-0.061	0.06	78.77	-0.006	0.12
Dot/zero 14 hr.	77.94	-0.061	0.06	79.04	-0.007	0.15
Sleep Imp 14 hr.	77.94	-0.061	0.06	78.52	-0.012	0.10
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 15 hr.	78.30	-0.054	0.08	78.83	-0.010	0.13
Dot 15 hr.	78.30	-0.054	0.08	79.08	-0.006	0.16

Dot/zero 15 hr.	78.30	-0.054	0.08	79.26	-0.006	0.18
Sleep Imp 15 hr.	78.30	-0.054	0.08	78.85	-0.010	0.13
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 16 hr.	78.57	-0.049	0.10	78.99	-0.009	0.15
Dot 16 hr.	78.57	-0.049	0.10	79.20	-0.006	0.17
Dot/zero 16 hr.	78.57	-0.049	0.10	79.36	-0.006	0.20
Sleep Imp 16 hr.	78.57	-0.049	0.10	79.01	-0.009	0.15
Raw	78.35	-0.050	0.09	78.87	-0.009	0.13
Zero 17 hr.	78.36	-0.050	0.09	78.86	-0.009	0.13
Dot 17 hr.	78.36	-0.050	0.09	79.11	-0.006	0.16
Dot/zero 17 hr.	78.36	-0.050	0.09	79.20	-0.006	0.17
Sleep Imp 17 hr.	78.36	-0.050	0.09	78.88	-0.009	0.13

Appendix F: Multivariate Regression Analyses Tables

P-values associated with using PA in the model: Systolic Blood Pressure=Fat Free Mass + Sedentary behavior/MVPA/DPA

		Hours Removed								
		Sleep	17	16	15	14	13	12	11	10
Sedentary	Raw	0.02								
	Zero	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.02
	Dot	0.04	0.03	0.03	0.03	0.02	0.03	0.04	0.03	0.02
	Dot/Zero	0.04	0.05	0.07	0.08	0.09	0.13	0.17	0.19	0.2
	Sleep	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.02
MVPA	Raw	0.02								
	Zero	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.03
DPA	Raw	0.02								
	Zero	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04
	Dot	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.04
	Dot/Zero	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.04
	Sleep	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04

P-values associated with using Sedentary time in the model: Fat-Free Mass=Fat Mass + Sex + Sedentary time

		Hours Removed								
		Sleep	17	16	15	14	13	12	11	10
Sedentary	Raw	0.06								
	Zero	0.05	0.06	0.06	0.07	0.07	0.07	0.11	0.05	0.12
	Dot	0.2	0.2	0.17	0.17	0.16	0.15	0.19	0.08	0.18
	Z/D	0.2	0.22	0.27	0.4	0.5	0.54	0.73	0.59	0.95
	Sleep	0.05	0.06	0.06	0.07	0.07	0.07	0.11	0.05	0.29

Appendix G: University of Idaho Institutional Review Board Acceptance

University *of* Idaho
Office of Research Assurances
Institutional Review Board
875 Perimeter Drive, MS 3010
Moscow ID 83844-3010
Phone: 208-885-6162
Fax: 208-885-5752
irb@uidaho.edu

To: David Paul

From: Traci Craig, Ph.D.,
Chair, University of Idaho Institutional Review Board
University Research Office
Moscow, ID 83844-3010

Date: 4/15/2014 5:51:55 PM

Title: Effect of Study Participant Compliance on Estimates of Physical Activity: Implications for the Prediction of Health Markers

Project: 14-63
Approved: April 15, 2014
Renewal: April 14, 2015

On behalf of the Institutional Review Board at the University of Idaho, I am pleased to inform you that the protocol for the above-named research project is approved as offering no significant risk to human subjects. This study may be conducted according to the protocol described in the application without further review by the IRB. As specific instruments are developed, each should be forwarded to the ORA, in order to allow the IRB to maintain current records. Every effort should be made to ensure that the project is conducted in a manner consistent with the three fundamental principles identified in the Belmont Report: respect for persons; beneficence; and justice.

This IRB approval is not to be construed as authorization to recruit participants or conduct research in schools or other institutions, including on Native Reserved lands or within Native Institutions, which have their own policies that require approvals before Human Participants Research Projects can begin. This authorization must be obtained from the appropriate Tribal Government (or equivalent) and/or Institutional Administration. This may include independent review by a tribal or institutional IRB or equivalent. It is the investigator's responsibility to obtain all such necessary approvals and provide copies of these approvals to ORA, in order to allow the IRB to maintain current records.

As Principal Investigator, you are responsible for ensuring compliance with all applicable FERPA regulations, University of Idaho policies, state and federal regulations.

This approval is valid until April 14, 2015.

Should there be significant changes in the protocol for this project, it will be necessary for you to submit an amendment to this protocol for review by the Committee using the Portal. If you have any additional questions about this process, please contact me through the portal's messaging system by clicking the 'Reply' button at the top of this message.

Traci Craig, Ph.D.