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Discretionary self-monitoring of physical activity: A mixed-methods study of behavior change technique use and historical physical activity

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Public Health (Health Behavior)

by

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The Dissertation of Ernesto Raul Ramirez is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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DEDICATION

To Laura.

You're the best.

EPIGRAPH

The time will come when diligent research over long periods will bring to light things which now lie hidden. A single lifetime, even though entirely devoted to the sky, would not be enough for the investigation of so vast a subject... And so this knowledge will be unfolded only through long successive ages. There will come a time when our descendants will be amazed that we did not know things that are so plain to them... Many discoveries are reserved for ages still to come, when memory of us will have been effaced.

Seneca

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LIST OF ABBREVIATIONS

API	Application Programming Interface
BCT	Behavior Change Technique
BCTTv1	Behavior Change Technique Taxonomy Version 1
MVPA	Moderate-to-Vigorous Physical Activity

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ABSTRACT OF THE DISSERTATION

Discretionary self-monitoring of physical activity: A mixed-methods study of behavior change technique use and historical physical activity

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In the last decade there has been a rise in the availability of consumer focused physical activity and fitness tracking devices. Recently there has been interest in using these devices from the research community for data collection and as part of health behavior interventions. With millions of adults using activity trackers it is necessary to develop an understanding of how they are used, and to what extent different factors may affect physical activity outcomes.

The current study sought to explore the relationship between behavior change techniques (BCTs) used by long-term users of Fitbit activity tracking devices and change in physical activity over time. In-depth interviews were conducted with participants in order to obtain information about behavior change techniques connected to the use of the Fitbit system. Historical Fitbit data (steps and activity intensity) were also collected.

Thirty participants were recruited to take part in the study. Based on coding of the in-depth interviews, individuals who are long-term users of physical activity tracking devices were found to use a variety of techniques associated with their engagement with the devices and it's connected applications. On average participants took 9,695 steps (*SD* = 5,309) and participated in 33.90 minutes of MVPA (*SD* = 42.90) per day. An exploration of the relationship between technique use and physical activity outcomes using multi-level modeling indicated that there was limited support for the relationship between use of techniques included in the design the Fitbit system and positive change in physical activity over time. No support was found for a positive relationship between the use of additional BCTs not included in the design of the Fitbit system and physical activity outcomes. Additional qualitative analysis demonstrated that individuals think about and use the same techniques in different ways and apply them in different contexts.

This exploratory study is the first examination of BCT use by individuals who freely choose to use physical activity tracking devices, and provided a proof of concept for a systematic mixed methods approach. Results of the study highlight the importance of understanding context of behavior change technique use in relation to physical activity behavior change.

INTRODUCTION

Any casual observer of technological trends has seen the rise of personal physical activity monitors. Since Fitbit introduced the first advanced wearable activity tracker in 2009, Fitbit has inspired a range of activity tracking devices and applications such as the Jawbone UP, Nike Fuelband, and Garmin Vivofit, and over 60 additional devices, with annual sales of over $350 million (Dolan, 2014, Ramirez, 2014). Smartphone manufactures have also taken notice and have built dedicated measurement and processing systems into their devices. Public health and research institutions as well as funding agencies have begun to see the value in the vast amounts of data that are being collected by individuals tracking their own physical activity. However, there is a lack of understanding of how individuals use these devices during the normal course of their lives, how they understand and develop relationships with the device's explicit behavioral design characteristics, and the relationship between device use and behavior change.

This study was designed to build on prior work across the fields of health behavior research and human computer interaction using a four-phase mixed-methods approach. Phase one examined the currently available behavior change techniques available in the Fitbit system (device, mobile applications, and website). Phase two explored the use of self-directed and device-directed behavior change techniques in individuals who use physical activity self-tracking devices through in-depth interviews and qualitative analysis. Phase three analyzed the relationship between behavior change technique use and change in physical activity over time using a linear mixed model approach. Finally, phase four explored contextual similarities and differences in behavior change technique use across participants.

Primary Aims

1. Determine what behavior change techniques (BCT)s are used by a group of long-term discretionary users of physical activity self-trackers.
2. Determine the relationship between BCT use and:
    - Change in daily total steps over time.
    - Change in daily time spent in moderate-to-vigorous physical activity (MVPA) over time.

BACKGROUND & SIGNIFICANCE

Physical Activity & Public Health

Since the seminal work of Morris and colleagues in the early 1950's that examined the relationship between work-related physical activity and coronary heart disease, public health officials and researchers have extolled the benefits of leading an active lifestyle (Morris, Heady, Raffle, Roberts, & Parks, 1953). Over the last six decades, numerous studies have examined the link between physical activity and health. At one end, a number of prospective studies have indicated that there is a significant increase in the relative risk of all cause and specific cause mortality associated with living a physically inactive lifestyle for adult men and women (e.g., Nocon et al., 2008; Oguma, 2002; Paffenbarger, Hyde, Wing, & Hsieh, 1986; Simonsick et al., 1993). The first Surgeon General's report on Physical Activity and Health, released in 1996, emphasized the role of physical activity as a preventative health behavior, especially the importance of including moderate levels of activity (U.S. Department of Health and Human Services, 1996). This report, along with many systematic and narrative reviews, have concluded that there is compelling evidence that participating in regular physical activity is related to reductions in the risk of cardiovascular diseases (including coronary heart disease and hypertension), obesity, osteoporosis, type 2 diabetes, and certain types of cancer (Bauman, 2004; Kokkinos, Sheriff, & Kheirbek, 2011; Warburton, Nicol, & Bredin, 2006). Physical activity has also been shown to have protective effects for mental health (Bauman, 2004; Penedo & Dahn, 2005).

Furthermore, there is an abundance of evidence indicating that an inverse dose-response relationship exists between physical activity and cardiovascular health, among other health conditions, and that significant improvements in health occur when individuals move from being inactive (and least fit) to being active (and improving physical fitness) (Blair et al., 1989; Lee & Skerrett, 2001; Li et al., 2016; Thune & Furberg, 2001; Warburton et al., 2006). The 1996 Surgeon General's report found that participating in a moderate amount of activity, equivalent to 30 minutes of brisk walking per day (150 kcal/day), was associated with "substantial health benefits", and that for those already meeting this threshold, additional physical activity may experience additional health benefits (U.S. Department of Health and Human Services, 1996). These findings were echoed in the release of the 2008 Physical Activity Guidelines for Americans.

Physical Activity Guidelines - United States

In 2008 the U.S. Department of Health and Human Services published the Physical Activity Guidelines for Americans based on the available literature and insight from the 13-member Physical Activity Guidelines Advisory Committee. These guidelines offer separate recommendations based on age (youth, adults, and elderly), and on the type (strength vs. aerobic) and intensity of exercise (moderate vs. vigorous) (U.S. Department of Health and Human Services, 2008). For adults, the guidelines recommend:

- At least two days a week of muscle-strengthening activities

Plus one of the following:

- 150 minutes per week of moderate-intensity physical activity,
- 75 minutes per week of vigorous-intensity physical activity
- Or any equivalent combination of moderate-to-vigorous physical activity

The guidelines also state that additional health benefits are observed for individuals who increase moderate-intensity activity to 300 minutes per week, and/or increase vigorous-intensity activity to 150 minutes per week. The guidelines further elaborate on how an individual may acquire the weekly amount of activity, stating that moderate or vigorous activity must occur for at least 10 consecutive minutes and that total activity should be spread throughout the week.

These guidelines are based on the recommendations of the Physical Activity Guidelines Advisory Committee who found in their research that "a range of 500 to 1,000 MET-minutes of activity per week provides substantial benefit" and sought to translate this into something "useful for the public." (U.S. Department of Health and Human Services, 2008, Appendix 1). The 150 minutes of moderate-intensity activity is a translation of 500 MET-minutes, where moderate activity is classified as 3.0 to 5.9 METs. Specifically, a brisk walk at 3.0 MPH requires 3.3 METs and 150 minutes of walking at 3.0 MPH is approximately equal to 500 MET-minutes. This same rationale was used to create the lower limit for vigorous activity, where vigorous-intensity activity is classified as greater than or equal to 6.0 METs.

Prevalence of Physical Activity - United States

While the above-mentioned guidelines give the general public concrete goals to reach for weekly physical activity, a large proportion of the population is physically inactive. According to objective accelerometer data from the 2003-04 National Health and Nutrition Examination Survey (NHANES) approximately 95% of adults (over 19 yrs.) did not achieve at least 30 minutes of moderate-intensity activity on five of seven days (Troiano et al., 2008). Tucker, Welk, and Beyler (2011) conducted a similar analysis based on 2005-06 NHANES accelerometer data and the 2008 Physical Activity Guidelines for Americans. They found that only 9.5% of men and 7.0% of women were meeting the guidelines. Data from the National Health Interview Survey, found that among adults self-reporting their physical activity behavior, 21.4% met the physical activity guidelines (U.S. Department of Health and Human Services, 2014). Low levels of physical activity have also been directly associated with a significant financial burden on the Unites States healthcare system. Carlson and colleagues (2015) found that even after adjusting for individuals who could have difficulty participating in regular physical activity, low levels of physical activity was associated with approximately 9% of aggregate healthcare expenditures.

Current estimates of the type of physical activity that adults most engage in are derived from self-report. Data from the 2011 Behavioral Risk Factor Surveillance System was analyzed and walking was the most commonly reported, with 47% of adults reporting walking for aerobic physical activity (Watson, Frederick, Harris, Carlson, & Fulton, 2015). Walking remained consistently high when compared to other activities across age groups, with only 19-29 year olds reporting walking as the second most popular activity to running/jogging. For all age groups, running/jogging was reported as the second most common (13%) followed by lawn and garden activities (10%), sports (9%), and conditioning exercises (9%). The findings are important as they may help public health official create tailored messages that "meet people where they are" as well as guide the use of measurement tools that accurately capture the most common activities.

Measuring Physical Activity

The measurement of movement can be understood through two dimensions as demonstrated by LaMonte and Ainsworth (2001): physical activity expressed as an observable behavior, and energy expenditure expressed as the observable energy cost of the behavior. Although these two dimensions are not synonymous, the methods employed when measuring movement often use one dimension to infer the other. The methods described below are primarily used to collect information about physical activity through direct or indirect means in population and public health research.

Direct Observation

The systematic recoding of what people do, how they do it, and the context(s) in which the behaviors occur can provide rich data for behavioral researchers. Using various measurement systems, direct observation allows the observer to collect data about the physical activity an individual or group of individuals are participating in, including the type, duration, intensity, and frequency of the behavior. Additionally, contextual information such as where the activity occurs, with whom it occurs, and other social and/or environmental information like behavioral stimuli (T L McKenzie, 1991, 2002) can be recorded. A number of direct observation data collection instruments have been designed and validated. These instruments, such as the System for Observing Fitness Instruction Time (SOFIT), System for Observing Play and Leisure Activity in Youth (SOPLAY), and the Children's Activity Rating Scale (CARS), are primarily used to assess younger populations, primarily school-age children (McKenzie, Marshall, Sallis, & Conway, 2000; McKenzie, Sallis, & Nader, 1991; Puhl, Greaves, Hoyt, & Baranowski, 1990). Tools like the System for Observing Play and Recreation in Communities (SOPARC) can be used to assess physical activity in a wide range of age groups from children to seniors (Thomas L McKenzie, Cohen, Sehgal, Williamson, & Golinelli, 2006). Direct observation, while offering detailed information about physical activity, requires extensive effort from research staff, namely the time to adequately train observers and conduct observations (T L McKenzie, 2002; T L McKenzie et al., 2000). In addition, direct observation requires access to locations in which physical activity is occurring, making it prohibitively difficult to collect information regarding the full range of physical activity that happens throughout the course of a day.

Indirect Observation

Self-Report. Researchers have also deployed a variety of instruments that allow individuals to report on their behavior. In the late 1960's researchers began including questions about occupational and leisure time physical activity in studies of mortality and heart disease (Hammond 1964; Frank,1966). This marked a new direction in physical activity measurement, which had previously been inferred through occupational information (Haskell, 2012). In the half-century since that innovation numerous questionnaires, guided interviews, and survey instruments have been used to assess physical activity. A recent systematic review found 85 unique questionnaires (different versions of the same instrument were considered unique; Poppel, Chinapaw, Mokkink, Mechelen, & Terwee, 2010). The authors found that construct validity (the degree to which the instrument measures actual physical activity behavior) was evaluated for 77 questionnaires through comparisons with objective measures such as accelerometers, heart rate monitors, pedometers, or doubly labeled water. Correlations between questionnaire outcomes and objective measures were overwhelmingly low, typically less than 0.50. Numerous factors on the part of the respondent and the measure may impact the reliability and validity of a self-report measure. For example, the complexity and overall length of a measure, the type of scale or response required, and length of time a respondent is asked to recall can all impact the accuracy of a measure. Individual and social factors, such as the ability to remember or recall behaviors or the social desirability of appropriate behavior, may also influence an individual's ability to accurately report their behavior (Sallis & Saelens, 2000; Shephard, 2003).

Pedometers. The pedometer is relatively simple and typically inexpensive tool for measuring human locomotion. The invention of the pedometer can be traced back to Leonardo de Vinci and includes a tale of invention and re-invention by, among others, Thomas Jefferson (Jefferson, Wilson, & Stanton, 1999). The first mention of the pedometer in scientific literature is a letter to the editor in the December 13, 1912 edition of Science, wherein the author (identified only as T.C.M.) describes the pedometer as,

> A most useful addition to the outfit of a traveler and an especially delightful and comforting companion to those who know the joy of seeing the world à piede. (T.C.M., 1912)

He further explains the difference between the wrong kind of pedometer (which only counts steps) and the right kind (which counts distance). Type aside, the pedometer as a measurement device became part of the public consciousness as a result of the widespread popularity of walking clubs in

Japan. Tudor-Locke and Bassett (2004) describe a 2001 presentation at the annual meeting of the American College of Sports Medicine during which Dr. Yoshiro Hatano explained the rise in popularity of the pedometer and the now widely adopted 10,000 steps per day guideline. In the 1960's the pedometer company Yamasa Corportaion, which sells pedometers under the Yamax brand in the U.S., sold a pedometer under their nickname manpo-kei, which translated means "ten thousand step meter."

The pedometer has been widely use a measurement tool and intervention component in physical activity and public health research. As a measurement tool, pedometers have been used to measure and track steps as a representation of daily physical activity in children and adults beginning in the early 1990s (Bassett et al., 1996; Tryon, Pinto, & Morrison, 1991). Different types of pedometers have been used as various models and brands have been shown to be accurate and reliable. As an intervention tool, pedometers have been described as:

> A tracking device (continuously collecting current activity), a feedback tool (providing immediate information on activity level), and as an environmental cue (reminder to be active). Used in combination with record keeping (e.g., calendars or diaries of daily progress), pedometers may be used in an effective way to increase daily physical activity. (Tudor-Locke, 2002, pg. 5)

According to a systematic review, the use of pedometers was associated with an increase of 2,491 steps per day for adults engaged in randomized controlled trials, and 2,183 steps per day for adults enrolled in observational studies. Across all study types the authors also found that pedometer use was associated with significant reductions in body mass index (Bravata, Smith-Spangler, Sundaram, & al., 2007).

Accelerometers. Accelerometers are small microchips that contain systems for measuring the gravitational forces (g-force) on a given axis. Accelerometers are used in combination with microprocessors and digital memory storage. These microprocessors use algorithms to interpret the g-force readings supplied by the accelerometer and save it to the digital memory. In 1983, researchers tested a uni-axial accelerometer intended to measure vertical displacement during human movement when worn on the hip and found the accelerometer output to be highly correlated ($r = 0.74$) with oxygen uptake during a variety of exercises (Montoye et al., 1983). Since then accelerometers have become one of, if not the most, commonly used objective measurement tool for assessing physical activity, with over 600 research articles mentioning accelerometery and physical activity in 2012 and 2013 (Troiano, McClain, Brychta, & Chen, 2014). Accelerometers now feature sensors that can measure acceleration along three axes to better interpret and classify the frequency and intensity of physical activity, as well as improved memory storage and battery life.

Accelerometers typically produce outputs in activity counts per epoch, and software applications translate these counts into more understandable outputs such as time spent in different physical activity intensity categories (some accelerometers also generate behavioral data such as step counts).

Numerous equations exist for translating the outputs from different accelerometer models into energy expenditure values and time spent at different activity intensities (Matthew, 2005). Overall, accelerometers and the various methods for interpreting their outputs are reliable and valid for measuring physical activity in children, adults, and older adults (Berlin, Storti, & Brach, 2006). New technological advances and statistical methods have improved activity recognition and energy expenditure estimation. It should be noted that accelerometers are not without limitations. For example, obtaining an appropriate measurement period in free-living conditions can be problematic as participants may object to wearing the device on a belt or waist clip due to discomfort (Troiano et al., 2014).

Behavioral Self-Monitoring

> People cannot influence their own motivations and actions very well if they cannot pay adequate attention to their own performance, the consequences under which they occur, and the immediate and distal effects they produce."(Bandura, 1991, p. 250)

Behavioral self-monitoring, observing and recording one's own behavior(s), was originally designed as a method for obtaining data and insight about behavior that was only observable by the individual. It has also been identified as worthwhile technique for clinical, therapy, and health behavior intervention research applications. Self-monitoring is an effective method of engaging individuals in their health behavior because of reactive effects, evaluative effects, and it's influence on self-regulatory mechanisms.

Self-monitoring has a rich history in the therapeutic and behavioral psychology literature. Self-monitoring is effective for prompting behavior change and is used by over 80% of cognitive and behavioral therapists (Elliott, Miltenberger, Kaster-Bundgaard, & Lumley, 1996; Korotitsch & Nelson-Gray, 1999; Olson & Winchester, 2008). Dating back to the 1970's researchers and clinicians have been debating about how self-monitoring interacts with changes in human behavior. In the 1970s, Kanfer described self-monitoring as being composed of three distinct and ordered processes related to self-directed behavior change: self-monitoring, self-evaluation, and self-reinforcement or punishment. Self-monitoring is simply the act of observation and recording of the behavior of interest. Self-evaluation is the act of comparing the observed and recorded information against a self-selected criterion or goal. Lastly, self-reinforcement or punishment is the "motivational" component during which self-selected internal or external rewards are introduced (when observed behavior meets or exceed the criterion) or internal or external negative consequences are realized (i.e. punishment), when observed behavior does not meet the criterion (Kanfer, 1970).

In his Social Cognitive Theory of Self-Regulation, Albert Bandura emphasized the role of self-monitoring as a primary generator of self-regulatory processes. In contrast to the earlier characterization by Kanfer, Bandura describes self-monitoring as "not simply a mechanical audit of one's performances." In addition to the regulatory actions of criterion formation and evaluation, Bandura proposed additional processes through which we can understand how behavioral self-monitoring impacts behavior. These processes include self-diagnostic and self-motivating functions, the temporal proximity of self-monitoring to the target behavior, informativeness, motivational level, behavior valence, and orientation to self-monitoring (Bandura, 1991, p. 250). Bandura describes the cognitive self-regulatory processes of self-observation, judgment, and self-reaction, suggesting that interactions between these processes create the locus of self-regulated motivation. Bandura proposed that the locus of self-regulated motivation is observed discrepancies between current behavior and personal or social standards. Bandura also suggests that self-efficacy predicts cognitive self-regulation, and that reducing the discrepancies between current behaviors and personal or social standards can enhance self-efficacy.

As with any measurement method, a premium is placed on accuracy. Korotitsch and Nelson-Gray (1999) identified nine variables that may affect the accuracy of the self-monitored data: 1) Awareness of accuracy checks, 2) Topography of the target behavior 3) Training, 4) Compliance, 5) Reinforcement, 6) Nature of the recording device, 7) Concurrent response requirements, 8) Valence of the target behavior, and 9) Timing of recordings. Furthermore, Korotitsch and Nelson-Gray identified several techniques that can increase compliance, such as verbal commitments, frequent prompts or reminders, and monetary incentives. Both compliance and accuracy affect the degree to which self-monitoring is effective for inducing behavior change. Olson et al. (2011) found that offering individuals a choice in target behavior, as opposed to prescribing a specific behavior, resulted in increased compliance with self-monitoring activities and self-reported levels of behavior change. Foster et al. (1999) also indicated that issues related to compliance with data collection, data quality, and the burden or participation in self-monitoring research are important areas of exploration in this field of study.

Self-monitoring has been shown to have an impact on behavior even when additional intervention methods or tools do not accompany it. For example, self-monitoring is an effective method for improving diet and weight, physical activity, and diabetes control. In fact, self-monitoring has been described as a “key strategy” for long-term weight loss by researches examining the behaviors of participants in the National Weight Control Registry. A meta-analysis of behavior change techniques for healthy eating and physical activity identified self-monitoring as the technique that explains the greatest amount of heterogeneity in the included studies, indicating it’s value and importance for improving effectiveness of health behavior interventions (Michie, Abraham, Whittington, McAteer, & Gupta, 2009).

The New Age of Self-Monitoring

In 2008, Gary Wolf and Kevin Kelly held the first Quantified Self meetup where approximately 30 individuals gathered to share stories about how they were using technological methods and tools to track, measure, analyze, and understand their lives (Ferris, n.d.). In 2010 Wolf wrote what is consider the definite account of the creation and rationale behind the Quantified Self phenomenon. In his article, he describes the historical and present context of self-monitoring, noting that prior to recent changes most self-monitoring was done by hand and required using laborious methods to infer meaning.

> Then four things changed. First, electronic sensors got smaller and better. Second, people started carrying powerful computing devices, typically disguised as mobile phones. Third, social media made it seem normal to share everything. And fourth, we began to get an inkling of the rise of a global superintelligence known as the cloud. (Wolf, 2010)

These four changes to our personal interactions with technology have caused a widespread increase the availability and use of devices, applications, and tools that have quickly overtaken the paper and pencil methods of self-monitoring and self-collected data gathering. For instance, there are over 60 wrist-worn devices that can track physical activity data including heart rate, skin temperature, and skin conductivity (Ramirez, 2014). Individuals can use their smart phones to track their location and activity at high fidelity by using applications that gather and process signals from the many onboard sensors (i.e. accelerometer, gyroscope, GPS). The popularity of self-monitoring in and outside of the physical activity domain has been increasing over time. In the 2013 report, Tracking for Health, the Pew Research Center’s Internet and Life Project found that nearly 70% of adults track at least one health indicator for themselves or others. Of those who track, 21% use technology (Fox & Duggan, 2013).

Who's Using Wearables?

In addition to behavioral self-monitoring with smartphones, advances in technology have also spawned numerous additional devices. Estimates of the prevalence of wearable device use show that 10% of Americans own an activity tracker of some kind, that 50% of individuals who have owned an activity tracker no longer use it, and one third stopped using it within six months (Ledger & McCaffrey, 2014). An update to these findings found that the percentage of adult consumers that still wore and used their activity tracker had improved, with 88% still wearing it after three months, 77% after 3–6 months, 66% after 6–13 months, and 65% after a year (Ledger, 2014). A global survey found that 8% of individuals aged 11 to 55 owned a wearable fitness monitor and 6% owned a wearable health device (Björnsjö, Viglino, & Lovati, 2014). Another survey of 2,245 US adults found that 16% of US consumers use wearable health and fitness tracking devices (Fuel, 2014). A more recent survey of 8,000 consumers across seven countries (2,225 in the US) found that wearable device use had more than doubled, to 21% (Safavi, Ratli, Webb, & MacCracken, 2016). The findings of these surveys, while encouraging to those who make and market wearable devices, must be taken with caution. In nearly all cases, the survey methodology, questions, and even the participant characteristics are excluded from the reports.

Fitbit Physical Activity Trackers

The first version of the Fitbit activity tracker was unveiled in September 2008. At the time it was described as "a small, wireless device, the size of a thumb" that used a tri-axial accelerometer to measure and track steps, distance, energy expenditure, and sleep (Miller, 2008). The first Fitbit devices were distributed on year later and cost $99. The initial device included a "base station" that combined wireless data transfer and battery charging when the device was connected to the base station. The battery lasted for approximately seven days, and the device would sync with the user's online account whenever it was in range of a base station that was connected to an internet-connected computer. The device included an LED screen and one physical button. By pushing the button a user was able to cycle through the data the device had captured for the current day including: steps, distance traveled, energy expenditure (kcal), and a flower icon representing physical activity over the last three hours (“Fitbit Tracker Product Manual,” n.d.).

Since 2009 Fitbit, Inc. has released an additional ten tracking devices, 8 of which are currently available for purchase (see Table 1 for a description of all devices). Each of these devices, whether worn as a clip or on the wrist, is based on a tri-axial accelerometer and proprietary data processing algorithms.

Table 1. Fitbit devices.

Fitbit Device	Release Date	Design	Activity Features	Price
Fitbit (Original)	Sep. 2009	Clip - LED Display	Steps, Distance, Calories Burned, Sleep, Flower	$99
Fitbit Ultra	Oct. 2011	Clip - LED Display	Steps, Distance, Calories Burned, Sleep, Flower, Floors	$99
Zip	Se. 2012	Clip - LCD Display	Steps, Distance, Calories Burned,	$60
One	Sep. 2012	Clip - OLED Display	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible)	$100
Flex	Mar. 2013	Wrist - No Display (Five LEDs)	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible).	$100
Force	Oct. 2013	Wrist - OLED Display	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm	$150
Charge	Oct. 2014	Wrist - OLED Display	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm	$130
Charge HR	Jan. 2015	Wrist - OLED Display	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm, Heart Rate	$150
Surge	Jan. 2015	Wrist - LCD Touchscreen	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm, Heart Rate, GPS	$250
Alta	Feb. 2016	Wrist - OLED Display	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm	$130
Blaze	Feb. 2016	Wrist – LCD Touchscreen	Steps, Distance, Calories Burned, Sleep, Floors, Bluetooth (smartphone app compatible), Time, Alarm, Heart Rate, Smartphone notifications	$200

Fitbit Market Estimation

Fitbit is the market leader in the activity tracker space with an estimated 26.9% market share for wearables worldwide (IDC, 2016). More specifically, the NPD Group found that Fitbit accounted for 79% of the sales for connected activity trackers in 2015 (The NPD Group, 2016). In May 2015 Fitbit registered with the Security and Exchange Commission (SEC) for an initial public offering. In their filing documentation they disclosed the volume of their sales since 2009, when the original Fitbit tracker was released. Yearly sales have risen steady, from almost six thousand devices in 2009 to 21.4 million in 2015 (Fitbit, 2015; Fitbit, 2016a). It is important to note that the number of devices sold may not accurately reflect the number of individuals using a device. In their SEC filing Fitbit released the number of "paid active users":

> We define a paid active user as a registered Fitbit user who, within the three months prior to the date of measurement, has (a) an active Fitbit Premium or FitStar subscription, (b) paired a health and fitness tracker or Aria scale with his or her Fitbit account, or (c) logged at least 100 steps with a health and fitness tracker or a weight measurement using an Aria scale. The number of paid active users is based on subscription and device activity associated with each Fitbit user account and, accordingly, a user with multiple devices synced to his or her Fitbit account is counted as only one paid active user regardless of the number of devices that such user syncs to the account. (Fitbit, 2015, pg. 57)

Paid active users increased each year it has been reported, from 558,000 in 2012 to 16.9 million in 2015. Overall, the United States is currently the largest consumer of Fitbit devices, comprising 74% of Fitbit's 2015 revenue (Fitbit, 2016a). As Fitbit devices have been widely adopted as a method for personal physical activity measurement, there has been considerable interest from the research community for understanding their utility as a measurement tool and intervention component.

Validity & Reliability of Fitbit Devices

To date, Fitbit has not publicly released any information related to the accuracy of their devices. They indicate, on a webpage addressing accuracy concerns, that they have "performed multiple internal studies to rigorously test the accuracy of Fitbit trackers." and that their testing has "confirmed that our trackers are some of the most accurate wireless tracking devices", however none of these studies are available to the general public or research community (Fitbit, n.d.).

A number of studies that are available to the public have examined the validity and reliability of various Fitbit devices. A study of 17 adults found evidence indicating the Fitbit Ultra performs adequately for structured activities in outdoor and laboratory environments. The magnitude of the difference between the Fitbit and direct observation of step counts (*M* (*SD*); range) was small across all activities when worn on the waist (2.0% (4.7%); -6 – 23%) and the bra (0.8% (4.3%); -11 – 15%). A significant effect for speed was found indicating that at higher locomotor speeds (e.g. jogging) the Fitbit underestimates the number of steps taken (Ramirez, Peterson, Wu, & Norman, 2012). In addition, Everson, Goto, and Furberg (2015) recently published a systematic review of the validity and reliability of activity trackers, including Fitbit. They identified 22 studies published since 2012 that examined the validity and/or reliability of the data captured by one or several of the six following Fitbit devices: the Fitbit Classic (original), Fitbit Ultra, Fitbit One, Fitbit Zip, and Fitbit Flex. Overall, steps reported by Fitbits worn at the waist (Classic, Ultra, One, and Zip) were highly correlated ($r >= .80$) with direct observation and validated measurement tools such as the Yamax CW-700 pedometer and Actigraph GT3X accelerometer. The Fitbit Flex, which is worn at the wrist, was slightly less accurate. One study examined the validity of the reported distance by the Fitbit One, and it was found to underestimate distance at slow speeds and overestimate at fast speeds. It should be noted that Fitbit recommends calibrating the user's actual stride length to achieve optimal distance measurement for walking and running (Fitbit, 2016b). Fitbit also reports minutes in four activity intensity categories (sedentary, lightly active, fairly active, very activity). When compared to established cutpoints for research accelerometers, there does not appear to be a consensus on how accurate these measurements are. One study reported a very high correlation for the Fitbit Zip, while a second study reported low agreement for both the Zip and One. Lastly, for energy expenditure, across seven studies the Classic, Ultra, Zip, One, and Flex tended to underreport total energy expenditure.

Everson and colleagues (2015) located seven studies that examined interdevice reliability of Fitbit devices. That is, studies examining reliability only examined multiple similar devices and/or location placement, but did not test whether a single device remained reliable under consistent conditions. For steps, the Classic, Ultra, One, and Flex showed high reliability for walking and running. Reliability was also very high for different trackers (of the same type) and wearing in different locations (hip vs. pocket or different wrists) for both distance (one study) and energy expenditure (two studies).

Overall the authors concluded that for the tested devices there is high validity for steps, and high interdevice reliability for steps and energy expenditure. It should be noted that to-date no validity or reliability studies have been published for the physical activity tracking abilities of the Fitbit Force (recalled), Fitbit Charge, Fitbit Charge HR, or Fitbit Surge.

Interventions using Fitbit Devices

Fitbits have been deployed as a measurement device, as an active component of the intervention, or a combination of the two. As a measurement device, the Fitbit has been used in a series of studies to examine the impact of different feedback and reinforcement schedules on daily steps counts in adults (Kurti & Dallery, 2013; Washington, Banna, & Gibson, 2014]. These studies restricted participant's use of the full Fitbit platform (which also includes a website and mobile applications) in order to reduce the potential influence of additional behavioral components. More recently, Cadmus-Bertram and colleagues (2015) examined the feasibility of using a Fitbit One for continuous physical activity monitoring and found that adult women adhered to wearing the Fitbit with a median weartime of 10hrs per day during a 16-week physical activity intervention. This finding was similar to what was observed in an intervention trial with 29 inactive pregnant women using the Fitbit Ultra who wore it approximately 80% of the time during a 12-week study (Choi, Lee, Vittinghoff, & Fukuoka, 2015).

There is some evidence that a Fitbit alone can be used to improve physical activity behavior. In a randomized control trial, women using the Fitbit platform (Fitbit One and the Fitbit website) had significant increases weekly MVPA, MVPA bouts, and steps per day when compared to the control group who used a simple pedometer (Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015). However, Thorndike et al. (2014) found that a Fitbit alone was not sufficient to improve physical activity behavior among medical residents in a randomized controlled trial.

Researchers have also have deployed additional behavior change strategies with Fitbit devices and/or the full Fitbit platform in order to understand what complementary intervention techniques might be useful for improving physical activity. Fitbits, along with mechanisms for feedback, goal setting, and reinforcement, were found to improve physical activity during recess in small trial of six elementary students (Hayes & Van Camp, 2015). In adults, the addition of text-messaging prompts did not have an impact on physical activity behavior of those using and wearing Fitbit One devices (Wang et al., 2015). In older adults (65 - 95 years old), a combination of the Fitbit and phone-based and in-person physical activity counseling did not improve physical activity in a randomized controlled crossover study (Thompson, Kuhle, Koepp, McCrady-Spitzer, & Levine, 2014). A small study of seven overweight adults found partial support for the Fitbit One as a positive influencer of physical activity behavior. The addition of behavioral coaching, which included tailored feedback, personalized goal-setting, behavioral recommendations, and social support, further improved activity outcomes (Valbuena, Miltenberger, & Solley, 2015). In a trial of cardiac telerehabiliation adults were asked to use a Fitbit Zip for a minimum of three months and maximum of one year. Across the 64 participants the average Fitbit use was 160 days, with a trend for improved walking behavior (steps per day) associated with longer device use (Thorup et al., 2016).

These interventions represent a small piece of the growing interest in using commercial physical activity monitors in clinical research. A recent search of the ClincalTrials.gov database by journalists at MobiHealthNews.com uncovered 21 registered clinical trials that include a Fitbit device in their research design (Comstock, n.d.), and the number of trials using Fitbit devices is likely to grow as Fitbit, Inc. introduces new devices and improvements in software.

Behavior Change Techniques

Interventions that positively impact health behaviors, especially physical activity and weight loss associated behaviors, are more efficacious when they employ theoretically driven approaches. Recently, there has been a shift toward more specifically identifying the individual components in interventions in a trans-theoretical approach (Abraham & Michie, 2008; Michie et al., 2011). This new area of research focuses on the specific techniques employed by behavior change interventions (behavior change techniques, BCTs). Michie and colleagues (2013) have defined BCTs as having the following eight characteristics:

1. They aim to change behavior.
2. They are the "active ingredients" of the intervention.
3. They are smallest components of the active ingredients.
4. Are used by themselves or in combination with each other.
5. Are both observable and replicable.
6. They can have measurable effects on behavior.
7. May or may not be supported by the literature.
8. May be self-delivered, or by another individual (process).

The current version of the Behavior Change Technique Taxonomy (BCTTv1) was developed through an iterative process that involved multiple studies and over 400 behavior change experts and researchers (Michie et al., 2015). This process identified 16 domains that encompass 93 unique techniques that have been employed in health behavior change interventions (see Table 2).

These BCTs can be used for intervention planning and system or program assessment. For instance, a refined BCT taxonomy has been used to assess mobile health applications, wearable physical activity trackers, and internet-based programs for physical activity and weight loss (J. Chen, Cade, & Allman-Farinelli, 2015; Conroy, Yang, & Maher, 2014; Cowan et al., 2013; Dennison, Morrison, Conway, & Yardley, 2013; Lyons, Lewis, Mayrsohn, & Rowland, 2014; Pagoto, Schneider, Jojic, DeBiasse, & Mann, 2013; Yang, Maher, & Conroy, 2015). This assessment work is vital as the use of BCTs has been directly associated with behavioral improvement, and this association follows a dose-response relationship. A review and meta-analysis of internet-based health interventions indicates that interventions that use more BCTs have larger effects on behavior than interventions that used fewer BCTs (Webb, Joseph, Yardley, & Michie, 2010).

The current understanding of the impact of BCTs on health behavior is guided by rigorous reviews and post-hoc evaluations of reported intervention components. For instance, Michie and colleagues (2009) found that physical activity and diet interventions that include behavioral self-monitoring (an identified BCT) and at least one other BCT were more effective than interventions that did not include self-monitoring. As the lay population has rapidly adopted commercial health behavior tracking and behavior change tools, researchers have begun to evaluate these tools through the lens of the BCT taxonomy. These reviews typically explore the design of commercial tools/apps in order to determine if “what works” (BCTs) is included in the design of their tools. However these reviews are based on researcher’s brief experience with the app/tool, sometimes lasting as little as a few days (J. Chen et al., 2015; Conroy et al., 2014; Cowan et al., 2013; Dennison et al., 2013; Lyons et al., 2014; Pagoto et al., 2013; Yang et al., 2015). Additionally, there appears to be an underlying belief being that BCT inclusion, and the volume of the inclusion, will have a direct positive impact on individuals who use those tools/apps.

To date, Lyons et al. (2014) have conducted the only systematic analysis to determine what BCTs are used by the devices, mobile applications, and websites (if available) of commercial physical activity monitoring systems. Trained coders used 13 different tracking devices for one to two weeks. One Fitbit device, the Fitbit Force and its mobile and web-based applications, was included in the analysis. Overall, BCTs within the domains of *Goals and Planning* and *Feedback and Monitoring* were the most commonly used including *Goal Setting (Behavior)*, *Discrepancy Between Current Behavior and Goal*, *Feedback on Behavior*, and *Self-monitoring of Behavior*, which were observed in all systems included in the analysis. Specific to the Fitbit Force, the authors identified 20 BCTs implemented in the design of the device, mobile application (iOS/Apple only), and website. It should be noted although the focus of their analysis was on electronic activity monitors, they included aspects of the system that were not directly related to physical activity data gathering and behavior change such as weight and mood measurement. Since this analysis was published many changes have occurred that may impact these findings. In the intervening two years the Fitbit Force has been recalled and discontinued, Fitbit has released an additional five devices, and the mobile applications have undergone numerous revisions and updates that have introduced new features.

Table 2. BCT domains and techniques included in the BCTTv1.

Domain and Technique	Domain and Technique	Domain and Technique
1. Goals and planning	7. Associations	12. Antecedents
1.1. Goal-setting (behavior)	7.1. Prompts/cues	12.1. Restructuring the physical environment
1.2. Problem-solving	7.2. Cue signaling reward	12.2. Restructuring the social environment
1.3. Goal-setting (outcome)	7.3. Reduce prompts/cues	12.3. Avoidance/reducing exposure to cues for the behavior
1.4. Action planning	7.4. Remove access to the reward	12.4. Distraction
1.5. Review behavior goal(s)	7.5. Remove aversive stimulus	12.5. Adding objects to the environment
1.6. Discrepancy between current behavior and goal	7.6. Satiation	12.6. Body changes
1.7. Review outcome goal(s)	7.7. Exposure	13. Identity
1.8. Behavioral contract	7.8. Associative learning	13.1. Identification of self as role model
1.9. Commitment	8. Repetition and substitution	13.2. Framing/reframing
2. Feedback and monitoring	8.1. Behavioral practice/rehearsal	13.3. Incompatible beliefs
2.1. Monitoring of behavior by others without feedback	8.2. Behavior substitution	13.4. Valued self-identify
2.2. Feedback on behavior	8.3. Habit formation	13.5. Identity associated with changed behavior
2.3. Self-monitoring of behavior	8.4. Habit reversal	14. Scheduled consequences
2.4. Self-monitoring of outcome(s) of behavior	8.5. Overcorrection	14.1. Behavior cost
2.5. Monitoring of outcome(s) of behavior without feedback	8.6. Generalization of target behavior	14.2. Punishment
2.6. Biofeedback	8.7. Graded tasks	14.3. Remove reward
2.7. Feedback on outcome(s) of behavior	9. Comparison of outcomes	14.4. Reward approximation
3. Social support	9.1. Credible source	14.5. Rewarding completion
3.1. Social support (unspecified)	9.2. Pros and cons	14.6. Situation-specific reward
3.2. Social support (practical)	9.3. Comparative imagining of future	14.7. Reward incompatible behavior

outcomes

Table 2. BCT domains and techniques included in the BCTTv1, Continued.

Domain and Technique	Domain and Technique	Domain and Technique
3.3. Social support (emotional)	10. Reward and threat	14.8. Reward alternative behavior
4. Shaping knowledge	10.1. Material incentive (behavior)	14.9. Reduce reward frequency
4.1. Instruction on how to perform the behavior	10.2. Material reward (behavior)	14.10. Remove punishment
4.2. Information about antecedents	10.3. Non-specific reward	15. Self-belief
4.3. Re-attribution	10.4. Social reward	15.1. Verbal persuasion about capability
4.4. Behavioral experiments	10.5. Social incentive	15.2. Mental rehearsal of successful performance
5. Natural consequences	10.6. Non-specific incentive	15.3. Focus on past success
5.1. Information about health consequences	10.7. Self-incentive	15.4. Self-talk
5.2. Salience of consequences	10.8. Incentive (outcome)	16. Covert learning
5.3. Information about social and environmental consequences	10.9. Self-reward	16.1. Imaginary punishment
5.4. Monitoring of emotional consequences	10.10. Reward (outcome)	16.2. Imaginary reward
5.5. Anticipated regret	10.11. Future punishment	16.3. Vicarious consequences
5.6. Information about emotional consequences	11. Regulation	
6. Comparison of behavior	11.1. Pharmacological support	
6.1. Demonstration of the behavior	11.2. Reduce negative emotions	
6.2. Social comparison	11.3. Conserving mental resources	
6.3. Information about others' approval	11.4. Paradoxical instructions	

Current Research

In the last few years a few different disciplines have begun to engage in research on the use of new self-tracking and personal health tools and devices. Across disciplines there is an overwhelming focus on introducing these new types of tools into the lives on participants in order to understand their usability, validity, and ability to serve as intervention tools. To date, there have been few studies that have sought to examine the use of BCTs by users of self-tracking devices. A majority of studies have typically focused on usability testing (testing design characteristics), or recruit individuals to use a device for only a short period of time (Mercer et al., 2016; Rabin & Bock, 2011; Shih, Han, Poole, Rosson, & Carroll, 2015). The few studies that have recruited a sample of individuals who have freely chosen to engage with self-tracking devices and/or apps have focused on a broad range of technology-oriented health behavior change systems (Gowin, Cheney, Gwin, & Franklin Wann, 2015).

As stated previously, there are a large number of individuals who are using these tools to track, engage, and learn about their own behavior in real-time. Currently there is a distinct lack of research that explores how and why people who self-select to use physical activity trackers use their devices. In 2014 Fritz and colleagues (2014) conducted a qualitative inquiry to better understand how individuals use different activity tracking devices. Explaining their rationale for the study they stated,

> Investigating the experiences of people who have adopted these technologies "organically" and continued to use them over time offers the opportunity to study certain contexts and aspects of use not possible in shorter-term experimental deployments. It also affords the opportunity to see how findings of previous shorter studies hold over longer-term use. (pg. 487)

Their research was based on in-person and online audio interviews of 30 participants who had been using different devices (Fitbit, Jawbone, and the Nike Fuelband among others) for at least three months. Their chosen method of identifying and assigning open and closed codes (identified through literature review) focused on observing general themes about device use, changes in use over time, and psychosocial and behavioral aspects of device use. Through the interviewing, transcription, coding, and analysis process they identified six major themes: attachment to the devices and data, awareness of self and behavior, immediate impact of data capture and reflection in real-time, motivation and reflection, meeting goals and "getting credit", using internal and external rewards, and the use of social support and community features. These findings build on the previous qualitative work by Li, Dey, and Forlizzi (2011), who interviewed 15 individuals who identified as self-trackers. These participants represented variety of data collection types including blood glucose, weight, sleep, physical activity, and productivity. The authors were able to identify six common questions that are present when people talk about their data collection and reflection processes. These six themes were: Status ("What is my current state?"), History ("What does my data indicate over a long period of time?"), Goals ("What should my goals be and how do I set them?”), Discrepancies (“How does my current status compare with my goal?”), Context (“What other information is related to my data?”), and Factors (“What changes my status over longer periods of time?”). The authors further break down the act of personal data collection into a two-phase structure: Discovery and Maintenance. The discovery phase includes individuals who are focusing on their history, goals, context, and factors. They are unclear of what they should be focusing on pertaining to goals and/or do not understand what influences their behavior. On the other hand, the maintenance phase unsurprisingly features individuals who ask themselves primarily about status and discrepancies. That is, they are attempting to maintain their behavior by using a system to consistently check themselves against their identified goal(s). These studies, two of the few that explore the real-world behavior of individuals using new digital self-monitoring tools, primarily focus on using their findings to inform the future design of similar tools.

Summary

Engaging in regular physical activity is an important component of living a healthy life and there is overwhelming evidence that physical activity protects against the development of numerous health conditions. Unfortunately, the number of individuals who engage in the amount of physical activity necessary to experience these benefits remains very low. Even eight years after the publication of national guidelines for weekly physical activity, the vast majority (> 90%) of Americans continue to lead primarily inactive lives (Troiano et al., 2008).

However, in the last few years there has been an exponential increase in the number of individuals who are engaging with their own physical activity behavior through various different physical activity tracking devices. Millions of individuals are using Fitbits and other devices to track their daily steps, distance, energy expenditure, and in some cases even their heart rate. These tools are becoming so widespread that they have become the focus of numerous research studies, which seek to understand how best to design these types of devices and their interactive features. Even with this new line of research, we currently know very little about the theoretical basis of what might work for discretionary users of self-trackers. If we can better understand the ways people use activity tracking devices and software, we can better design them to prompt behavior change, which, given the popularity of these devices, has the potential to impact population level physical activity behavior.

The current study was designed to develop an understanding the relationship between BCTs and physical activity behavior change for individuals who freely choose to use physical activity tracking devices. The primary aims of this study were to: 1) determine what BCTs are used by a group of long-term discretionary users of physical activity self-trackers, and 2) determine the relationship between BCT use and change in physical activity over timeIn relation to the second aim, it was hypothesized that the number of BCTs used by individuals would be a significant predictor of change in physical activity (as measured by the device) over time, and that use of BCTs *not* explicitly included in the design of the Fitbit system will be positively associated with change in physical activity over time.

As physical activity tracking devices and applications become ubiquitous it is important for individuals working in preventive medicine and public health to understand how people integrate these devices into their everyday lives. The current study was proposed to be starting point for both the research and commercial communities that are seeking to better understand the role of physical activity devices in the lives of individuals who use them. The mixed methods approach was undertaken in order to construct a rich dataset that could serve to address the aims of this study and serve as a model for future research in this important area.

METHODS

Research Design

This study was designed to elicit qualitative and quantitative information from individuals who had been using a Fitbit physical activity-tracking device. Participants completed informed consent and were asked to connect their Fitbit accounts to the Fitabase analytics system (Small Steps Labs, San Diego, CA, USA). This allowed participants to grant access to their historical data, collected through their Fitbit device, to the author. Participants were then asked to complete a two-stage interview in-person, via phone, or via a web-video conference. Each interview was designed to last between 1.5 and 2 hours. The first stage of the interview assessed of demographic data and psychosocial measures. The second stage was a semi-structured interview and conversation with the participant that covered a variety of topics related to the participants' use of their Fitbit, the participants' relationship with the data the Fitbit collects, and the use of behavior change techniques. A four-phase analytical approach was undertaken to address the aims of the study. First, the currently available Fitbit system was evaluated for the presence of BCTs supported in the design. Second, the in-depth interviews were coded in order to generate a dataset of BCTs used by participants in relation to their Fitbit experience. Third, a linear mixed-model was used to analyze the relationship between BCT use and change in physical activity over time. Lastly, a qualitative contextual analysis was conducted to explore similarities and differences in participants’ use of BCTs. The institutional review board from the University of California, San Diego approved this study.

Setting

As participants were able to complete both phases of the study remotely, this study was open to individuals living in the United States and abroad.

Recruitment

Recruitment materials (see Appendix A) that described the study were posted to the following locations:

- Fitbit subreddit
  - (available at http://reddit.com/r/fitbit)
- Fitbit discussion forums
  - (available at https://community.fitbit.com/t5/Discussions/ct-p/discussions)
- Quantifiedself.com forums
  - (available at https://forum.quantifiedself.com)
- Quantified Self Facebook group
  - (available at https://www.facebook.com/groups/quantifiedself/)

These websites are open to anyone and are used to announce events and opportunities, engage in open discussion, and coordinate group activities. The author posted under his own account or an account labeled "UCSDFitbitStudy". Snowball sampling was also used to recruit additional participants. At the conclusion of the interview participants were asked to recommend study participation to individuals who are listed in their Fitbit Friends network along with friends and family who meet the inclusion criteria. Additional copies of recruitment materials were provided to participants who expressed interest in sharing the study with others. All recruitment materials prompted individuals to contact the author via email if they were interested in participating. The author replied to all individuals who expressed interest with additional information about the study and a prompt to schedule a brief (10 to 15 minute) screening phone call. If the individual met the inclusion (described below) they were provided a copy of the informed consent and the study methods were described in detail. If the individual consented he or she scheduled an interview with the author and were given detailed instructions on how to connect their Fitbit account to the Fitabase analytics system. Thirty participants were recruited for this exploratory study.

Inclusion Criteria

Inclusion criteria consisted of: 1) men and women between 18 and 60 years old, 2) current user of a Fitbit activity tracking device, 3) a minimum of 90 days of use of any combination of Fitbit activity tracking devices, 4) the ability to use video teleconferencing systems (e.g. Skype, Google Hangout, Facetime), 5) willing and able authorize the author to access and download a copy of Fitbit data via the Fitabase analytics system, 6) no more than six (20% of total sample size) participants who identify as early adopters of self-tracking practices as derived from their membership in Quantified Self meetup groups or online communities. Participants were not excluded based on ethnic background, location, or health status.

Primary and Secondary Outcome Measures

Fitbit Data Collection

In addition to the user-centered components of the Fitbit platform (device, application, and website), Fitbit has developed and provides access to an application programming interface (API) that allows outside entities to build tools and services to enhance the user experience. The API allows a third party to access and add to the data currently gathered and stored in the Fitbit database. These read/write privileges allow an application developer to build feedback visualizations, reminder tools, and additional services to existing behavioral or data storage platforms.

Fitabase, a company that uses the Fitbit API to collect user data for research purposes, was used to access Fitbit data from research participants. Fitabase provides a simple platform for authenticating participants and accessing the data gathered while using a Fitbit device. Fitabase was chosen because all data is stored on a secure server, and its history of collaboration with research institutions (Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015; Choi, Lee, Vittinghoff, & Fukuoka, 2015; Diaz et al., 2015; Hartman et al., 2015; Schaefer, Ching, Breen, & German, 2016). Participants were asked to authorize the Fitabase system to access their Fitbit data and make it available for download via an online portal.

Participants were asked for a valid email address to send the authorization link. The author then created a profile for the participant that included a unique study identifier. A link to a Fitabase Authorization Page was then emailed to the participant (see Appendix B). At the bottom of the online Fitabase Authorization page a “connect your device” button was presented. The participant was asked to read the authorization page and if they agreed, to connect their Fitbit and authorize Fitabase to read and access their Fitbit data. It important to note that the personal Fitbit login information for each participant was entered outside of the view of the author and is not passed to the Fitabase system by using the OAuth protocol established for API authentication. When the participant entered their information and connected their Fitbit account to Fitabase, the online authorization was completed. This completion also signaled an acceptance of the Fitabase Terms of Use and Privacy Policy (Fitabase, 2016).

Fitbit Data

For each participant interday (aggregate daily) level data and intraday (minute-by-minute values) level data was available. At the interday level the following data were downloaded: Steps, Distance Traveled, Very Active Minutes, Fairly Active Minutes, Lightly Active Minutes, Sedentary Minutes, and Estimated Energy Expenditure. At the intraday level, the following data were downloaded: Steps, Intensity Classification, MET Values, and Estimated Energy Expenditure. All Fitabase data files were downloaded in CSV format. The current study did not examine sleep, weight, or dietary data. If that data was available for a participant via the Fitabase interface it was not viewed, downloaded, or saved as part of the research protocol. All participant data files were checked for completeness. In rare cases a participant's daily and/or intraday data files were missing data. In these cases the author requested that Fitabase re-run the data request from Fitbit in order to generate complete data files.

Interview

A short set of interview questions was prepared prior to recruitment and was refined to reflect emerging knowledge as the research process progressed. Interviews were conducted in order to uncover the narratives and processes that reflect the realty of using a physical activity tracker. An Informed Grounded Theory approach was used to develop the initial questionnaire (Thornberg, 2012). This approach included using knowledge about the design of the Fitbit system, available features and functionality, and behavior change techniques that were identified in prior research (Lyons et al., 2014). The interview was designed with a three-level hierarchical structure: 1) sections of questions based on a general theme, 2) main questions designed to elicit answers related to the section theme, and 3) probing questions that prompted more specific answers or feedback relating to the main question(s). The final interview guide is available in Appendix C.

Interviews were audio-recorded by the author and transcribed using a third-party transcription service (CastingWords, LLC; www.castingwords.com). One interview was plagued by audio issues and was transcribed by the author. All transcripts were checked for accuracy upon receipt.

Demographic Information

Participants completed a demographic questionnaire during the interview that included birth year, sex, race/ethnicity, education, height, weight, marital status, and household income.

Data Processing

BCT Identification

Previous research has identified BCTs that were implemented by Fitbit in one device (Fitbit Force) and the associated mobile and web applications (Lyons et al., 2014). As the device used in that analysis was recalled and there have been numerous updates to available devices and the mobile and web applications, a review of the BCTs available in the Fitbit system was conducted. In addition to a review of the mobile application and website features, the author used personal experience with multiple Fitbit devices (Fitbit, Fitbit Ultra, Fitbit One, Fitbit Charge HR). Additionally, a review of the features of all available Fitbit devices as described on the Fitbit website (www.fitbit.com/compare) was conducted.

Fitbit Data Processing

There was a wide range for the length of time participants had been using a Fitbit device. To simplify understanding, the term "Fitbit user period" is used to describe the total length of time a participant has been in identified as a user in Fitbit platform, from the date of the creation of a Fitbit account until the date of their interview. It is possible that the Fitbit user period does not accurately reflect the total time a participant was using a Fitbit device. As the data are retrospective in nature there is no guarantee that the participants were using their device and collecting physical activity information for each of the days present in their data files. Participants may have lost a device for a period of time, forgotten to wear their device, or even chosen not to wear it for a particular day or period of time. Even if the device is not worn, and it does not move, the data are synced to Fitbit and made available through the API. Typically this results in a day with values equal to zero for physical activity data (steps, active minutes, distance, etc.). These days are included when the historical data is accessed. This complete historical file was used in order to calculate the Fitbit user period. Participants in this study ranged from relatively new to using a Fitbit device to long-term users, with a Fitbit user period range of 98 to 2,014 days. On average, participants had a mean user period of 688 days (SD = 487.54). The initial review of all historical Fitbit data from the 30 participants in this study resulted in a total of 20,637 participant-days of available Fitbit data. To better classify the available data and use data that most accurately reflected actual device wear, a multi-step wear time classification process was conducted.

Weartime Processing

The first step for determining valid wear days was to detect and remove all days with zero steps. This initial pass reduced the full data set from 20,637 to 17,232 person-days.

The second step involved a weartime validation process commonly used when processing physical activity accelerometer data. Initially, minute-level step values were used to approximate the commonly used count measure produced by research accelerometers such as the Actigraph GT3X. However, since accelerometer counts are derived from the intensity of the accelerometer movement in Actigraph models (ActiGraph, n.d.), additional data sources provided by Fitbit were explored. Fitbit states:

> All Fitbit trackers calculate active minutes using metabolic equivalents (METs). METs help measure the energy expenditure of various activities. Because they do so in a comparable way among persons of different weights, METs are widely used as indicators for exercise intensity. For example, a MET of 1 indicates a body at rest. Fitbit trackers >estimate your MET value in any given minute by calculating the intensity of your activity. (Fitbit, n.d.)

Because the minute-level MET value provided by Fitbit are a more appropriate measure for inferring the movement of the actual device, and not a behavioral measure like steps, this was used for wear time analysis. Minute-Level data files containing the date/time stamps and MET values were downloaded from Fitabase for each participant. Data were processed in R and the accelerometery package was used to analyze and flag period of non-wear time (Domelen, 2015; R Core Team, 2015). Data were processed using parameters commonly used for processing accelerometer data in physical activity research (Choi, Liu, Matthews, & Buchowski, 2011; Troiano et al., 2008). These parameters include a minimum non-wear window of 90 minutes, a tolerance of two minutes for non-zero counts within a non-wear window, and a maximal tolerance of two METs for a minute within the non-wear window. Additionally, processing was set to use a moving window to go through every possible 90-minute window in the data. Days were classified as valid if at least 600 minutes within a 24hr day period were classified as valid wear time. Processing the minute-level MET data for each participant for algorithmically determined non-wear time resulted in further reduction to 15,954 valid person-days.

Visual Analysis

A visual analysis of the data was used to further inspect Fitbit data for characteristics that would indicate invalid days. Each participant's minute-level step and MET data were plotted and inspected for uncharacteristic values and patterns. Specifically, this visual analysis of the minute-level data allowed for identification of periods of data that could be attributed to device malfunctions or non-locomotor activity. Figure 1 provides an annotated example of data that were identified as inconsistent with normal activity patterns due to device malfunction.

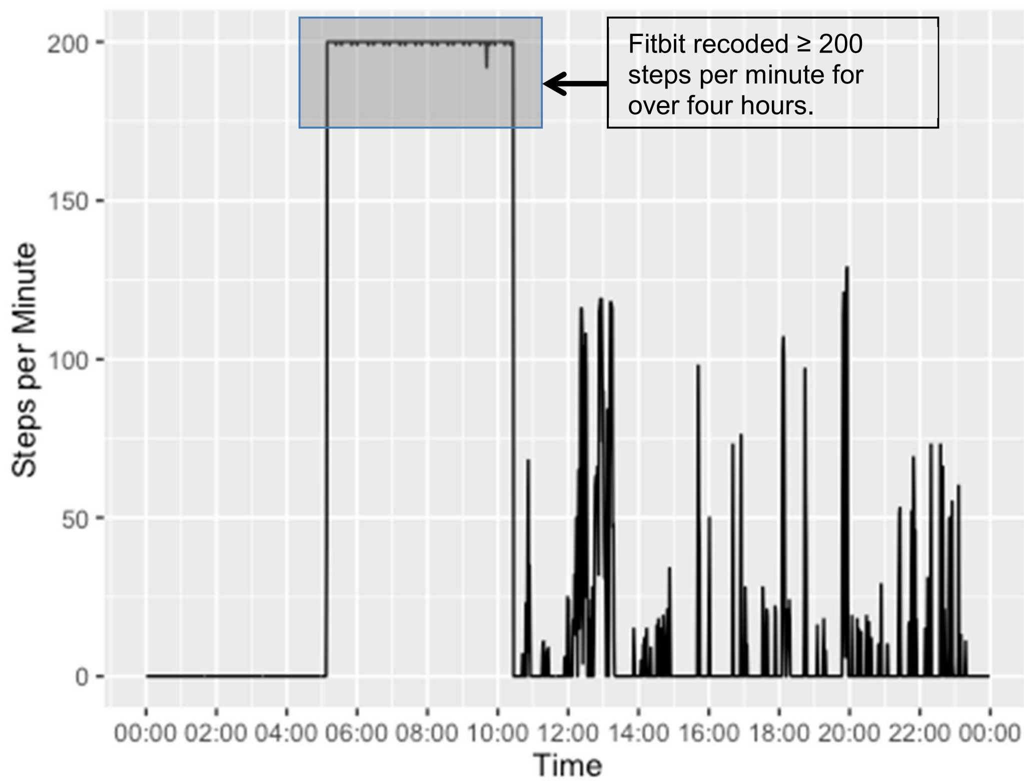

Figure 1. Annotated example of Fitbit malfunction.

Censuring Abnormal Data

After visual analysis it was determined that step values greater than or equal to 200 steps per minute should be classified as abnormal. As the participants could possibly achieve 200 steps per minute a conservative process was used to eliminate valid days that included minutes with values above 200 steps. Days previously marked as valid were only censured if greater than ten percent of the daily step total was attributed to abnormal minutes.

Consistency

Consecutive valid wear days were flagged using the run length encoding function included in the R "accelerometery" package (Domelen, 2015) in order to assess consistency of wearing a Fitbit.

Steps per Day Dataset

A two-step process was used to create participant datasets that included the total steps per day for all valid days. First, the valid days dataset for each participant was merged with the daily data sets procured from Fitabase. Then, if a day was considered invalid according the process described above, the steps per day data field was marked as missing ("NA"). These two steps were repeated for each participant.

MVPA Minutes per Day Dataset

To generate a dataset that included MVPA per day for each participant the minute-level (intraday) datasets for activity intensity were collected for each participant from Fitabase. Then the minute-level dataset was processed in R and the accelerometery package was used to identify and flag bouts of physical activity (Domelen, 2015; R Core Team, 2015). The National Physical Activity Guidelines for adults specify that activity should occur in bouts that last a minimum of 10 minutes (U.S. Department of Health and Human Services, 2008). Therefore 10 minutes was used as the minimum acceptable bout length. Each minute of activity was flagged as an "MVPA bout minute" if it was classified by Fitbit as "fairly active" or "very active" and if 10 of more consecutive minutes were observed in the data set. The sum of minutes classified as an MVPA bout minute was calculated per day per participant to generate a MVPA per day variable. As with steps per day, if a day was considered invalid, the MVPA per day variable was set to missing.

Coding Interviews

An Informed Grounded Theory approach was used to guide the qualitative portion of the study. This approach focuses attention on specific ideas or concepts during the qualitative research process (Thornberg, 2012). By using prior research in the area of behavior change as well as findings from similarly designed studies (i.e. Fritz and colleagues (2014), this process allowed the study to build on the existing knowledge in this area.

Coding was conducted using a multi-step, iterative process that allowed the author to continually refine and revise the application of codes assigned to all available interviews. First, the author read all interview transcripts to become familiar with the content and nature of the material. Next, each participant's answers to the interview questions were coded according to the 16 BCT domains present in the BCTTv1 (Michie et al., 2015). After each participant's interview was coded at the "domain level" the interviews were re-coded at the "technique level." Each answer, quotation, or section that was previously coded as pertaining to one or more BCT domains was reviewed and assigned one or more of the 93 specific BCTs. The identification of BCTs was based on the definitions included with the published BCTTv1, however it should be noted that the locus of control was shifted so that the BCTs identified as being implemented by the participant and not by an intervention. All coding was completed using Atlas.ti for Macintosh systems, version 1.0.44 (ATLAS.ti Scientific Software Development, GmbH).

Statistical Modeling

This study used a two-level design, with repeated observations (days) nested within each participant. A multi-level approach was therefore used to determine the relationship between BCT use and a) change in daily total steps over time, and b) change in daily minutes of MVPA over time. Multi-level modeling allows for the number of observations per participant and the spacing of the observations to vary as individual (per participant) growth trajectories that can be modeled. Additionally, multi-level modeling allows for missing data to be present in the analyzed data set as there is an assumption that data is missing at random. This assumption, coupled with the additional assumption that an individual's data is a true random sample of data from their true growth trajectory, allows for interpretation of model estimates when measurements are missing (Singer & Willett, 2003). However, it should be noted that the multilevel uses full-information maximum likelihood to estimate the model parameters and those parameters are reflective of what would have been observed if the data were complete (Hoffman & Rovine, 2007). In the data gathered for this study, five participants had observed data that were systematically missing for extended periods of time and that their available data represented less than 50% of their Fitbit use period. These participants were not included in the modeling process described below, as it was not reasonable to assume their data was missing at random.

Multi-level modeling allows for estimation of both fixed and random effects. Fixed effects are estimates that remain constant across groups, which in the case of this single-group study is across all participants. Random effects are the effects of variables that are allowed to vary across individuals (Hoffman & Rovine, 2007). Both fixed and random effects were explored in the analysis, specifically, demographic variables and BCT use were retained in the models as fixed effects. Random intercepts and random slopes (the effect of time) were fitted to the model allowing the intercept and slope to vary by individual.

Models & Variables

The statistical analysis included a multi-step approach to produce final model estimates. First, a *demographic model* was produced. This model included only demographic variables (including a "data affinity variable") as predictors in a model. Backwards stepwise deletion was performed. All non-significant effects, starting from the random effects, and then fixed ones, were excluded from the final demographic model, and model fit was evaluated. Next, the use of BCTs within the 16 domains were entered into the model in a two-step procedure. All BCT domains were evaluated as dichotomous variables; if a participant used any techniques within a BCT domain then the domain level variable was coded as being used by the participant. The initial BCT model included all BCT domains that that were identified as containing BCTs available to the participant within the Fitbit platform. Again, backwards stepwise deletion was performed and model fit of the initial BCT model was evaluated. Lastly, the remaining dichotomous variables reflecting the use of BCT domains that were not identified as available in the Fitbit system were included in addition to any variables retained in from the initial BCT model.

In order to address the hypothesis that a dose-response relationship exists between BCT use and the activity outcome variables (described below), another set of models was evaluated. This process mirrored the model building described for the BCT domain models. However, the BCT domain variables were re-structured to reflect the relative percentage of techniques used within the domain. The number of techniques used per domain was identified for each participant and divided by the total number of available techniques for that domain. For example, a participant may use 5 of the 9 (55.56%) *Goals and Planning* techniques, but another participant may use only 2 (22.22%). The BCTTv1 indicates that each domain has between three and eleven techniques (Michie et al., 2015). The percentage of techniques used within each domain was chosen, rather than absolute number of techniques, in order to standardize each domain. The presence of each unique technique was considered, but using 93 separate predictors could easily lead to over-fitting. Additionally, techniques within a domain could be assumed to be inherently correlated, thus allowing for this variable reduction technique. Again, the variables reflecting the BCT domains that were identified as being included in the design of the Fitbit were entered and evaluated first (initial BCT model), and then all other BCTs were entered and evaluated using the same backward stepwise deletion procedure as described above.

This modeling process led to the creation of five models for each of the two primary outcomes, steps per day and minutes of MVPA per day. These outcomes represented the repeated measures nested within participants over time, and each outcome was assessed independently. Steps per day reflected the step total for each valid wear. Daily minutes of MVPA occurring in bouts of at least 10 minutes were used for each valid day. Coefficients and model fit statistics were calculated at each step. All modeling analysis procedures were conducted in R using the lme4 and LmeTest packages (Bates, Mächler, Bolker, & Walker, 2014; Kuznetsova, Brockhoff & Christensen, 2016).

Contextual Analysis

During the course of interviews and the BCT coding process the author collected thematic notes in research memos. This process produced an observation that participants who used the same BCTs were expressing themselves in unique and sometimes very different ways. This observation prompted the author to examine contextual differences in BCT use among participants. First, research memos were thoroughly reviewed in order to create a list of BCTs to focus on. Second, the quotations that were coded to correspond to BCTs observed in step one were collected and re-examined as a group in order to determine if there were contextual differences (or similarities) in how participants operationalized the BCT in reference to their behavior or cognitive processing of their Fitbit experience. Major and minor themes related to these differences were then identified. This contextual analysis was conducted in order to provide a richer understanding of how individuals explore and employ BCTs during discretionary use of self-tracking tools.

RESULTS

Participants

Participants were recruited between June and August 2015. Thirty-seven individuals responded to recruitment postings and expressed an interest in participating. Of the 37 individuals who expressed interest, 33 completed the screening process for inclusion in the study. All 33 met the inclusion criteria and were asked to schedule the interview and connect their Fitbit data to Fitabase. Thirty-two individuals scheduled interviews and connected their Fitbit data to Fitabase, however two participants were not able to complete the interview due to time constraints. The Fitabase data connection was deleted for the two participants who were not able to complete the interview. In total, 30 participants fully participated in the current study.

Table 3 displays the demographic information for the sample that completed the study. The sample consisted of 11 (37%) men and 19 women (63%). Participants were between 23 and 60 years old, with a mean age of 36.60 years (SD = 10.56). The majority of participants reported that they were of Caucasian race/ethnicity (73%), college educated (80% completed college or graduate degree), and worked full time (83%). Half the sample reported being married with another 40% reporting as “Single and Never Married.” Additionally, 33% of the sample reported a household income in excess of $100,000. Median income was $80,000 - $89,000 (one participant abstained from reporting household income information). Height and weight were self-reported and BMI was calculated. Participants had a BMI range of 17.28 to 59.67 kg/m2, with a mean of 25.85 kg/m2 (SD = 8.47). Two participants were classified as “underweight” (6.67%, BMI < 20kg/m2), 24 participants (80%) were classified as “normal weight” (BMI = 20-25kg/m2), two participants were classified as "Obese Level I" (BMI = 30-35kg/m2), and two participants were classified as “Obese Level III" (BMI > 40kg/m2). Four participants reported membership in "Quantified Self" communities.

Fitbit Devices

At the time of this study there were six different Fitbit devices available for purchase. Each of the six available devices was represented in the data set, with an additional device that is no longer available for purchase also represented (Ultra). In total, six participants were using the ChargeHR, six participants were using the Zip, five participants were using the Flex, five were using the One, two participants were using the Surge, and one participant was using the Ultra.

Table 3. Participants' demographic and personal characteristics.

ID	Sex	Age	BMI	Ethnicity	Education	Marital Status	Employment Status	Household Income	Fitbit Type	Data Affinity
1	Female	24	21.58	Caucasian	Completed College or University	Single and Never Married	Part-time	$10,000-$19,000	One	Yes
2	Male	28	21.85	Caucasian	Completed College or University	Married	Full-time	$90,000-$99,000	One	Yes
3	Male	35	59.67	Caucasian	Completed College or University	Single and Never Married	Full-time	$30,000-$39,000	One	Yes
4	Female	25	17.28	Caucasian	Some College or Vocational Training	Single and Never Married	Part-time	$10,000-$19,000	Charge	No
5	Male	34	23.13	Caucasian	Completed Graduate or Professional Degree	Married	Full-time	$80,000-$89,000	Zip	No
6	Female	29	22.39	Caucasian	Completed Graduate or Professional Degree	Single and Never Married	Full-time	$50,000-$59,000	Charge	No

Table 3. Participants' demographic and personal characteristics, Continued

ID	Sex	Age	BMI	Ethnicity	Education	Marital Status	Employment Status	Household Income	Fitbit Type	Data Affinity
7	Female	52	20.30	Caucasian, African American	Completed Graduate or Professional Degree	Married	Full-time	> $100,000	Flex	No
8	Male	26	30.81	Caucasian	Completed Graduate or Professional Degree	Living with Partner	None or Less Than Part-time	$30,000-$39,000	Flex	No
9	Female	23	18.24	Caucasian	Completed College or University	Single and Never Married	Full-time	$40,000-$49,000	Charge HR	No
10	Female	36	23.29	Caucasian, Asian-American	Completed Graduate or Professional Degree	Single and Never Married	Part-time	> $100,000	Surge	Yes
11	Male	48	24.27	Caucasian	Completed Graduate or Professional Degree	Married	Full-time	> $100,000	Ultra	Yes
12	Male	25	21.92	Caucasian	Completed Graduate or Professional Degree	Single and Never Married	Full-time	$30,000-$39,000	One	Yes

Table 3. Participants' demographic and personal characteristics, Continued

ID	Sex	Age	BMI	Ethnicity	Education	Marital Status	Employment Status	Household Income	Fitbit Type	Data Affinity
13	Female	34	27.44	Hispanic	Completed Graduate or Professional Degree	Married	Full-time	$80,000-$89,000	Zip	No
14	Male	31	24.34	Caucasian	Completed College or University	Single and Never Married	Full-time	$60,000-$69,000	Charge HR	No
15	Female	42	23.24	Caucasian	Completed Graduate or Professional Degree	Married	Full-time	> $100,000	Flex	No
16	Female	40	23.69	Caucasian	Completed Graduate or Professional Degree	Married	Full-time	> $100,000	Charge HR	Yes
17	Female	27	28.32	Caucasian	Completed Graduate or Professional Degree	Single and Never Married	Full-time	> $100,000	One	Yes
18	Male	58	24.80	Caucasian	Some College or Vocational Training	Married	Full-time	> $100,000	Flex	Yes
19	Female	60	29.05	Caucasian	Some High School	Married	Part-time	$80,000-$89,000	Zip	No

Table 3. Participants' demographic and personal characteristics, Continued

ID	Sex	Age	BMI	Ethnicity	Education	Marital Status	Employment Status	Household Income	Fitbit Type	Data Affinity
20	Male	34	24.27	Asian-American, Pacific Islander	Completed Graduate or Professional Degree	Married	Full-time	> $100,000	Charge HR	No
21	Female	32	29.53	Caucasian	Completed Graduate or Professional Degree	Single and Never Married	Full-time	$40,000-$49,000	Zip	No
22	Female	38	25.60	Hispanic	Completed College or University	Married	Full-time	$90,000-$99,000	Zip	No
23	Female	50	20.17	Caucasian	Some College or Vocational Training	Married	Full-time	> $100,000	Flex	No
24	Female	25	19.66	Caucasian	Completed College or University	Single and Never Married	Full-time	$30,000-$39,000	Charge	No
25	Female	28	21.30	Caucasian	Completed College or University	Single and Never Married	Full-time	$40,000-$49,000	Charge HR	No

Table 3. Participants' demographic and personal characteristics, Continued

ID	Sex	Age	BMI	Ethnicity	Education	Marital Status	Employ ment Status	Household Income	Fitbit Type	Data Affinity
28	Male	40	47.49	Hispanic	Some College or Vocational Training	Widowed/ Divorced/ Separated	Full-time	$80,000- $89,000	Surge	No
27	Female	49	25.23	Hispanic	Completed College or University	Married	Full-time	NA	Charge	No
29	Male	43	27.12	Caucasian	Some College or Vocational Training	Married	Full-time	$90,000- $99,000	Zip	No
30	Female	32	19.39	Hispanic	Completed College or University	Married	Full-time	> $100,000	Charge HR	No

Fitbit Use, Wear Time, and Consistency

Participants in this study ranged from relatively new to using a Fitbit to long-term users, with a range of 98 to 2,014 days (M = 688.00, SD = 487.54). Initial review of all Fitbit data from the 30 participants in this study resulted in a total of 20,605 participant-days of available data. After completing the weartime processing and validation steps a total of 15,941 valid participant-days of data were observed in the dataset. The ratio of valid days to total available days per participant ranged from 10.22% to 100.00%. The number of days of data at each step in the previously described analysis is presented in Table 4. A visual representation of all valid wear days is also presented in Figure 2.

The average duration of consecutive wear days without a non-wear day was 20.70 days (SD = 48.17). Values for the minimum, maximum, mean, and standard deviation of consecutive day streaks for valid and non-wear days are included in Table 5. The longest consecutive streak of valid wear time lasted nearly two years (714 days, Participant 17). The longest consecutive streak of non-wear time was 597 days (Participant 18)

Table 4. Weartime processing information.

ID	Fitbit Use Period	Valid Days (MET Processing)	Valid Days (Censured)	Valid Days (Final)	Percent Available
1	1,262.00	1,096.00	1,096.00	1,096.00	86.85%
2	1,161.00	1,062.00	1,062.00	1,062.00	91.47%
3	793.00	686.00	686.00	686.00	86.51%
4	203.00	198.00	198.00	198.00	97.54%
5	496.00	472.00	472.00	472.00	95.16%
6	550.00	542.00	542.00	542.00	98.55%
7	186.00	181.00	181.00	181.00	97.31%
8	552.00	538.00	538.00	538.00	97.46%
9	524.00	515.00	515.00	515.00	98.28%
10	631.00	382.00	382.00	382.00	60.54%
11	2,013.00	1,977.00	1,977.00	1,977.00	98.21%
12	1,011.00	992.00	992.00	992.00	98.12%
13	627.00	580.00	580.00	580.00	92.50%
14	647.00	390.00	386.00	386.00	59.66%
15	413.00	411.00	411.00	411.00	99.52%
16	100.00	100.00	100.00	100.00	100.00%
17	1,360.00	1,287.00	1,287.00	1,287.00	94.63%
18	1,051.00	448.00	448.00	448.00	42.63%
19	424.00	171.00	171.00	171.00	40.33%
20	161.00	132.00	132.00	132.00	81.99%
21	424.00	233.00	233.00	233.00	54.95%
22	1,654.00	1,258.00	1,256.00	1,256.00	75.94%
23	431.00	96.00	96.00	96.00	22.27%
24	269.00	214.00	214.00	214.00	79.55%
25	98.00	97.00	97.00	97.00	98.98%
26	465.00	460.00	459.00	459.00	98.71%
27	215.00	179.00	175.00	175.00	81.40%
28	1,154.00	118.00	118.00	118.00	10.23%
29	431.00	163.00	163.00	163.00	37.82%
30	1,299.00	975.00	973.00	973.00	74.90%

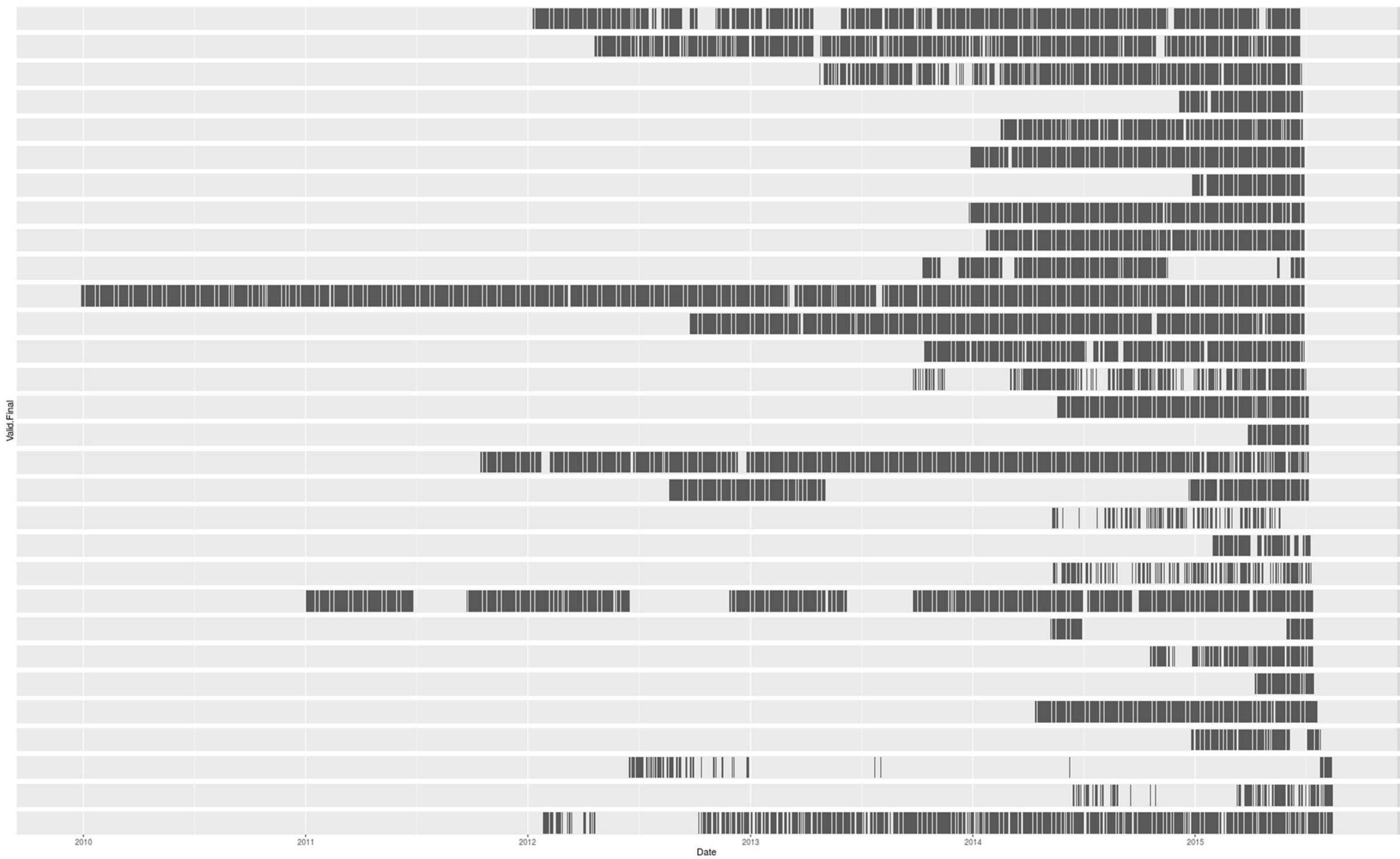

Figure 2. Visualization of valid wear days for each participant.

Note: Vertical black lines indicate a single day of wear time. Blank (non-black) spaces indicate missing or invalid days.

Table 5. Consecutive non-wear and valid wear days per participant.

	Non-Wear Streak Duration (Days)				Valid Wear Streak Duration (Days)			
ID	Min	Max	*M*	*SD*	Min	Max	*M*	*SD*
1	1.00	46.00	5.76	9.57	1.00	155.00	37.79	45.34
2	1.00	12.00	1.52	1.86	1.00	81.00	16.09	18.50
3	1.00	10.00	2.15	1.96	1.00	56.00	12.70	14.60
4	1.00	5.00	3.00	2.83	47.00	151.00	99.00	73.54
5	1.00	2.00	1.09	0.29	2.00	90.00	20.52	20.01
6	1.00	5.00	2.00	2.00	27.00	222.00	108.40	76.35
7	1.00	5.00	3.00	2.83	19.00	162.00	90.50	101.12
8	1.00	3.00	1.25	0.62	1.00	231.00	44.83	61.74
9	1.00	2.00	1.13	0.35	5.00	155.00	57.22	51.82
10	2.00	179.00	41.50	68.18	5.00	174.00	54.57	60.42
11	1.00	9.00	1.95	2.37	4.00	360.00	104.05	104.48
12	1.00	8.00	2.71	2.56	6.00	257.00	124.00	85.45
13	1.00	12.00	2.29	2.88	1.00	121.00	29.00	31.87
14	1.00	108.00	3.40	12.29	1.00	62.00	5.08	9.08
15	1.00	1.00	1.00	0.00	23.00	325.00	137.00	164.04
16	1.00	1.00	1.00	NA	100.00	100.00	100.00	NA
17	1.00	14.00	2.28	3.20	1.00	714.00	39.00	125.39
18	1.00	597.00	120.80	266.21	18.00	207.00	89.60	83.20
19	1.00	49.00	3.97	7.43	1.00	6.00	2.71	1.60
20	2.00	11.00	5.80	3.35	7.00	63.00	22.00	21.97
21	1.00	15.00	2.37	2.36	1.00	12.00	2.88	2.32
22	1.00	163.00	24.88	49.34	3.00	176.00	73.88	53.24
23	4.00	335.00	169.50	234.05	45.00	52.00	48.50	4.95
24	1.00	29.00	2.33	5.69	1.00	29.00	8.92	9.36
25	1.00	1.00	1.00	NA	17.00	80.00	48.50	44.55
26	1.00	3.00	1.75	0.96	21.00	293.00	114.75	121.32
27	1.00	27.00	3.15	7.19	1.00	27.00	13.46	9.07
28	1.00	409.00	39.85	102.39	1.00	23.00	4.37	5.16
29	1.00	131.00	5.49	19.01	1.00	15.00	3.33	2.90
30	1.00	170.00	3.05	16.39	1.00	50.00	9.01	9.92

Physical Activity Outcome Variables

Steps

For all valid days, participants in the current study totaled 154,546,189 steps. The mean across all participants was 9,6945 steps per day (*SD* = 5,309). Steps per valid day ranged from a 109 to 68,565 steps. Descriptive data on steps per valid day for each participant are shown in Table 6.

MVPA Bout Minutes

For all valid days, participants in the current study totaled 529,078 minutes of MVPA that were performed in bouts of at least 10 minutes. The mean amount of MVPA Bout Minutes was 33.19 minutes per day (*SD* = 42.70). Per participant minutes of MVPA, when classified in bouts, ranged from 0 to 474 minutes per day. Half of the sample did not obtain a mean of at least 30 minutes of MVPA per day for observed valid days. Descriptive data on minutes of MVPA (Bouts) per day for each participant are shown in Table 7.

Individual figures for the daily step totals and minutes of MVPA (Bouts) for each participant are available in Appendices D and E, respectively.

Table 6. Summary statistics for steps per day.

ID	Valid Wear Days	Sum	*M*	*SD*	Min	Max	SE
1	1,096	6,117,774	5,581.91	3,742.40	109	26,378	113.04
2	1,062	9,005,887	8,480.12	3,766.05	278	31,516	115.56
3	686	6,670,422	9,723.65	4,501.77	818	29,741	171.88
4	198	3,796,671	19,175.11	3,346.57	10,761	36,110	237.83
5	472	4,032,322	8,543.06	3,562.97	2,080	27,093	164.00
6	542	7,355,677	13,571.36	8,651.76	519	68,565	371.63
7	181	2,166,893	11,971.79	2,435.99	2,114	20,122	181.07
8	538	3,859,680	7,174.13	4,137.36	778	31,615	178.37
9	515	4,463,372	8,666.74	3,567.16	1,402	23,600	157.19
10	382	5,500,498	14,399.21	6,992.03	876	50,510	357.74
11	1,977	22,108,231	11,182.72	4,767.97	892	32,108	107.23
12	992	10,693,439	10,779.68	5,338.67	1,475	34,068	169.50
13	580	4,865,728	8,389.19	3,462.48	1,684	25,778	143.77
14	386	3,463,492	8,972.78	5,470.12	538	36,033	278.42
15	411	3,153,450	7,672.63	3,620.34	943	26,275	178.58
16	100	1,154,266	11,542.66	4,026.60	4,445	22,477	402.66
17	1,287	11,979,724	9,308.26	3,841.64	307	25,363	107.08
18	448	4,264,727	9,519.48	2,764.22	3,075	20,032	130.60
19	171	1,869,418	10,932.27	2,824.67	2,744	30,238	216.01
20	132	454,920	3,446.36	1,797.16	931	13,790	156.42
21	233	1,746,203	7,494.43	3,246.68	3,099	28,333	212.70
22	1,256	9,897,362	7,880.07	2,951.72	955	30,209	83.29
23	97	1,023,434	10,550.87	3,836.69	3,499	19,383	389.56
24	214	1,981,755	9,260.54	4,433.06	630	26,375	303.04
25	97	1,414,063	14,577.97	6,205.59	2,494	31,499	630.08
26	459	8,819,535	19,214.67	7,606.29	2,462	45,415	355.03
27	175	1,672,674	9,558.14	3,645.12	3,259	19,954	275.55
28	118	1,184,513	10,038.25	5,406.23	2,969	25,944	497.68
29	163	1,016,640	6,237.06	3,739.96	2,104	24,574	292.94
30	973	8,813,419	9,057.99	3,924.54	994	32,573	125.81
All	15,941	154,546,189	9,694.89	5,309.45	109	68,565	42.05

Table 7. Summary statistics for MVPA bout minutes per day.

ID	Valid Wear Days	Sum	*M*	*SD*	Min	Max	SE
1	1,096	8,638	7.88	16.49	0.00	153.00	0.50
2	1,062	16,735	15.76	26.70	0.00	260.00	0.82
3	686	25,360	36.97	38.29	0.00	208.00	1.46
4	198	12,179	61.51	41.10	0.00	279.00	2.92
5	472	11,607	24.59	23.62	0.00	180.00	1.09
6	542	24,972	46.07	56.02	0.00	428.00	2.41
7	181	11,118	61.43	26.75	0.00	140.00	1.99
8	538	9,952	18.50	31.23	0.00	272.00	1.35
9	515	9,158	17.78	22.23	0.00	142.00	0.98
10	382	23,741	62.15	62.60	0.00	426.00	3.20
11	1,977	115,979	58.66	48.74	0.00	474.00	1.10
12	992	37,595	37.90	43.05	0.00	288.00	1.37
13	580	9,409	16.22	22.98	0.00	133.00	0.95
14	386	23,085	59.81	71.58	0.00	432.00	3.64
15	411	9,536	23.20	24.38	0.00	148.00	1.20
16	100	3,553	35.53	34.90	0.00	171.00	3.49
17	1,287	48,680	37.82	31.77	0.00	252.00	0.89
18	448	10,320	23.04	37.32	0.00	320.00	1.76
19	171	1,020	5.96	20.11	0.00	230.00	1.54
20	132	402	3.05	13.60	0.00	109.00	1.18
21	233	3,525	15.13	25.25	0.00	213.00	1.65
22	1,256	21,657	17.24	25.95	0.00	180.00	0.73
23	97	3,363	34.67	34.89	0.00	123.00	3.54
24	214	5,549	25.93	34.74	0.00	198.00	2.37
25	97	6,335	65.31	49.11	0.00	311.00	4.99
26	459	38,445	83.76	70.44	0.00	316.00	3.29
27	175	2,247	12.84	20.19	0.00	86.00	1.53
28	118	5,659	47.96	54.02	0.00	300.00	4.97
29	163	2,183	13.39	24.78	0.00	138.00	1.94
30	973	27,076	27.83	27.64	0.00	192.00	0.89
All	15,941	529,078	33.19	42.70	0.00	474.00	0.34

BCT Identification

A review of the Fitbit system (device(s), mobile apps, and website) identified a total of 17 BCTs available to users. The identified techniques were grouped within eight of the sixteen BCT domains in the BCTTv1. The techniques primarily clustered within the domains of *Goals and Planning* and *Feedback and Monitoring*, with five techniques identified in each these two domains. A complete list of all domains and specific techniques identified as being available to Fitbit users is reported in Table 8. A comparison to the findings of similar work by Lyons and colleagues (2014) found that five techniques previously identified as being implemented by Fitbit were not applicable due to their focus on outcomes of behavior, in this case weight tracking and weight loss, and thus were excluded in the current study. An additional two techniques were also not identified as "native" to the design of the currently available Fitbit system at the time of this study. *Monitoring of Emotional Consequences* was previously identified as being available due to a "mood tracking" feature that was built into the Fitbit user's website (dashboard). That feature was removed in 2014, and therefore no longer applicable at the time of this study. *Adding Objects to the Environment* was also no longer considered applicable. The authors explained that this technique was identified because, "activity monitors were considered additions to the environment." (Lyons, Lewis, Mayrsohn, & Rowland, 2014). The Fitbit system is designed to monitor and engage individuals with personal physical activity tracking, not as a "facilitator of performance" as defined in the BCTTv1

(Michie et al., 2015). Therefore this was considered an incorrect classification. One technique, *Prompts/Cues*, was identified that was not included in the previously mentioned analysis. This technique was included due to the availability of push notifications deployed by the Fitbit mobile applications. During the course of a day, the mobile applications may notify an individual of their behavior, specifically attempting to prompt behavior (steps) in order to reach a goal (see Figure 3). This fits within the definition provided by Michie et al. (2015), who defined this technique as "stimulus with the purpose of prompting or cueing the behavior."

Table 8. BCTs incorporated by the Fitbit system and used by participants.

BCT Domain / Technique	Identified by Lyons et al. (2014)	Identified in the Current Study	Used by Participants in the Current Study
1. Goals and planning			
1.1. Goal-setting (behavior)	X	X	X
1.3. Goal-setting (outcome)	X		
1.4. Action planning			X
1.5. Review behavior goal(s)	X	X	X
1.6. Discrepancy between current behavior and goal	X	X	X
1.7. Review outcome goal(s)	X		
1.9. Commitment			X
2. Feedback and monitoring			
2.2. Feedback on behavior	X	X	X
2.3. Self-monitoring of behavior	X	X	X
2.4. Self-monitoring of outcome(s) of behavior	X		
2.6. Biofeedback	X	X	X
2.7. Feedback on outcome(s) of behavior	X		
3. Social support			
3.1. Social support (unspecified)	X	X	X
3.2. Social support (practical)			X
3.3. Social support (emotional)	X	X	X
4. Shaping knowledge			
4.2. Information about antecedents			X
4.4. Behavioral experiments			X
5. Natural consequences			
5.1. Information about health consequences			X
5.4. Monitoring of emotional consequences	X		X
6. Comparison of behavior			
6.2. Social comparison	X	X	X
7. Associations			
7.1. Prompts/cues		X	X
8. Repetition and substitution			
8.2. Behavior substitution			X

Table 8. BCTs incorporated by the Fitbit system and used by participants, Continued

BCT Domain / Technique	Identified by Lyons et al. (2014)	Identified in the Current Study	Used by Participants in the Current Study
8.3. Habit formation			X
8.5. Overcorrection			X
8.6. Generalization of target behavior			X
8.7. Graded tasks	X	X	X
9. Comparison of outcomes			
9.3. Comparative imagining of future outcomes			X
10. Reward and threat			
10.2. Material reward (behavior)			X
10.3. Non-specific reward	X	X	X
10.4. Social reward	X	X	X
10.6. Non-specific incentive			X
10.9. Self-reward			X
10.10. Reward (outcome)	X		
10.11. Future punishment			X
12. Antecedents			
12.1. Restructuring the physical environment			X
12.2. Restructuring the social environment			X
12.5. Adding objects to the environment	X		
13. Identity			
13.1. Identification of self as role model			X
13.2. Framing/reframing			X
13.3. Incompatible beliefs			X
13.4. Valued self-identify			X
13.5. Identity associated with changed behavior			X
15. Self-belief			
15.1. Verbal persuasion about capability			X
15.3. Focus on past success	X	X	X
15.4. Self-talk			X

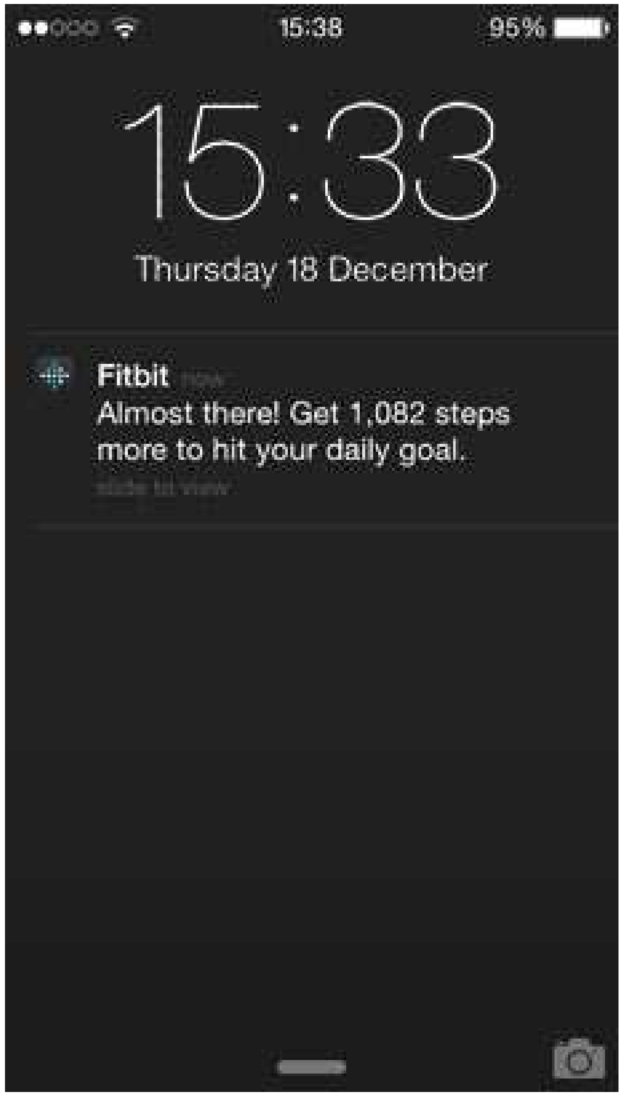

Figure 3. Example of a push notification from the Fitbit mobile application.

Qualitative Results

Data Affinity Variable Creation

Through the interview and the coding process nine participants were determined to have "high data affinity" due to their interactions with their activity data, their choice to connect their Fitbit account to additional services, and/or their previously mentioned association with a "Quantified Self" community. Most common among these activities that represented data affinity was downloading and visualizing activity data in alternative software programs. For example:

> "I was able to download all my data and I've got that all in an Excel spreadsheet from beginning to end. For me it's easier to look at things as a whole on that spreadsheet then it is the Fitbit website." (P3)

> "I've done historically cool things. I have just it in Google sheets, I keep open a quick histogram of my step count to see where I'm at historically, so just a chart" (P2)

> "But of course. [laughs] I do, do that routinely [download data from Fitbit website]. I've had some issues with custom date range exports lately but yeah. It lets me slice and dice data. How did I do in any given time or a given six□month period, look at trends over time. I do all that geeky stuff." (P18)"

Domain Use

Participants in this study used at least one BCT within 14 of the 16 (87.5%) domains identified in the BCTTv1. No responses in the transcripts were attributed and coded as expressing the use of BCTs within the domains of *Scheduled Consequences* or *Covert Learning*. Alternatively, all thirty participants were found to engage with techniques within the domains of *Goals and Planning* and *Feedback and Monitoring*. Table 9 displays the number of participants who described actions that were attributed to the BCTs within each of the 16 domains.

Of the eight BCT domains incorporated into the design of the Fitbit system, participants commonly used seven. Techniques within the *Associations* domain were used by only six participants, compared to the 20 to 30 participants who reported using techniques within the other seven domains available in the Fitbit system design. Of the domains that include techniques not available in the design of the Fitbit system, the most common domain was *Shaping Knowledge* with 22 participants (73.3%) who used techniques within this domain. On average, the eight domains that are included in the design of the Fitbit were used by over three times more participants as those not included in the design (approximately 26 vs. 7 participants, respectively).

Participants used techniques within an average of 8.10 domains (*SD* = 1.52) with a range of 6 to 11 of the 16 domains identified in the BCTTv1. Per participant domain use is visualized in Figure 4.

Table 9. BCT domain use.

BCT Domain	Number of Participants
1. Goals and planning[a]	30
2. Feedback and monitoring[a]	30
3. Social support[a]	24
4. Shaping knowledge	22
5. Natural consequences	15
6. Comparison of behavior[a]	28
7. Associations[a]	6
8. Repetition and substitution[a]	27
9. Comparison of outcomes	3
10. Reward and threat[a]	20
11. Regulation	3
12. Antecedents	5
13. Identity	10
14. Scheduled consequences	0
15. Self-belief[a]	20
16. Covert learning	0

Note. [a] = BCTs within the domain are incorporated into the design of the Fitbit system.

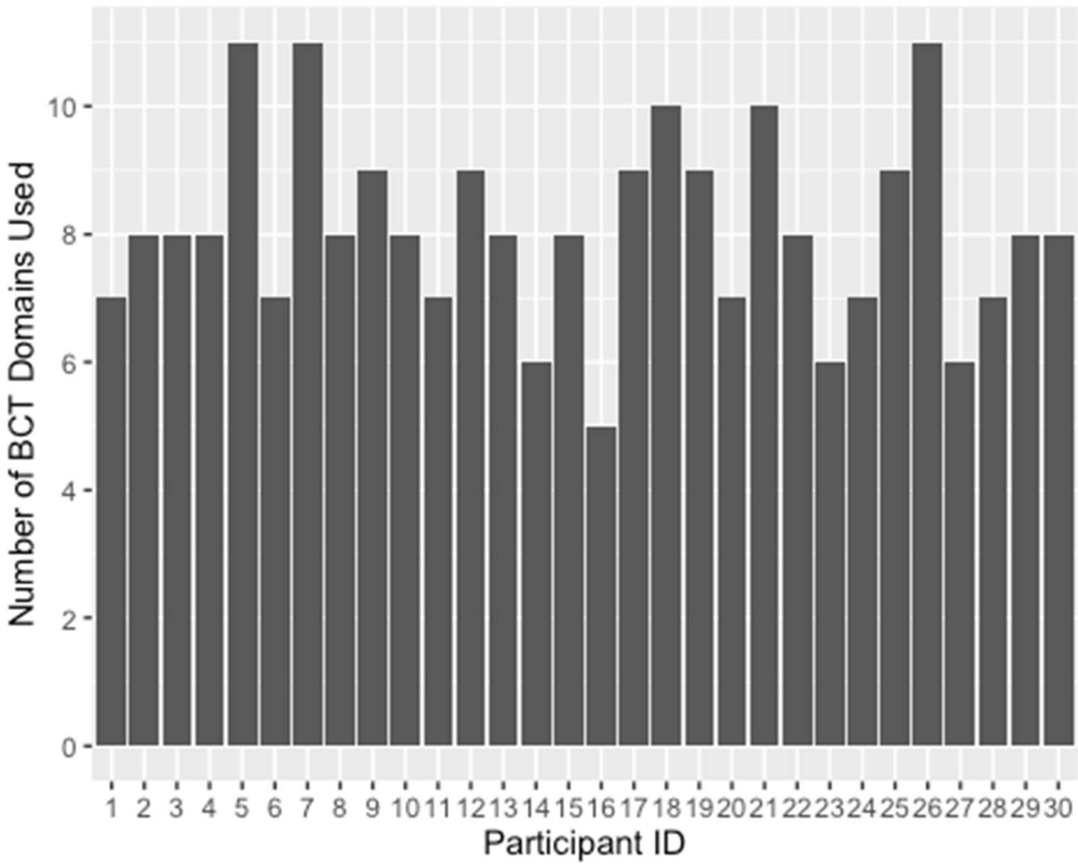

Figure 4. Sum of BCT domains used per Participant.

Technique Use

At the technique level, 40 unique BCTs were identified as being used by participants. The most common techniques were *Goal-setting (behavior)*, *Feedback on Behavior*, and *Self-monitoring of Behavior*, with all thirty participants expressing the use of these techniques during the interview. Other highly used BCTs include *Social Comparison* (*n* = 28), *Review Behavioral Goal(s)* (*n* = 24), and *Action Planning* (*n* = 22). The most infrequently reported BCTs were *Behavioral Experiments*, *Future Punishment*, *Identification of Self as Role Model*, and *Valued Self-identity*. Only one participant in this study used each of these techniques. Participants in the current study used between 8 and 20 unique techniques, with a mean of 14 techniques used per participant (SD = 3.08). Participants used 23 techniques that are not currently included in the design of the Fitbit system. Table 10 displays the number of participants who used each identified BCT and includes example quotations that reflect the technique use.

Table 10. BCTs used by participants and example quotations.

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
1. Goals and planning		
1.1. Goal-setting (behavior)	30	"Take the Fitbit daily step goal, I have it set at 10,000. That works for me. Lately, I've hit that more often than not." (P2)
1.4. Action planning	22	"Doing normal things like on the weekends it's easy for me to get over the 10,000 steps, because of doing normal things. It's like, "Oh, instead of driving to the store, let me walk to the store, and that will get me a couple of thousand steps." (P21)
1.5. Review behavior goal(s)	14	"My goal is only 8,500, and not 10,000, because it did not seem like I was ever hitting that. I have a new job that I started in March. Even my old job was requiring a lot of desk time." (P15)
1.6. Discrepancy between current behavior and goal	24	"I will check it when I'm leaving work, and if I need to either reach my goal or if I want to reach a certain step number, I'll make sure I try to get that before it hits midnight." (P30)
1.9. Commitment	3	"You've done what you said you were going to do." (P7)
2. Feedback and monitoring		
2.2. Feedback on behavior	30	"Maybe I could describe it as a touchstone reinforcement or validation of my own impression for the day. Sometimes, it is helpful to note that there are days where I am far less active than I thought." (P11)
2.3. Self-monitoring of behavior	30	"I sound obsessive. It's got the watch on it now, too, so if I check the time, I check how many steps I have. Probably quite frequently, at least once an hour or so." (P26)
2.6. Biofeedback	14	"I have the resting heart rate. It's so interesting. That, for me, very much varies with the amount of cardio I'm doing." (P16)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
3. Social support		
3.1. Social support (unspecified)	7	“When I hit my thousand-mile goal last year, I took a screen cap and posted it on Twitter and Facebook being like, ‘Oh! New Year's resolutions are easy.’ ” (P14)
3.2. Social support (practical)	20	My boyfriend has a Fitbit also, so usually I can get him to go for a walk at night if he hasn't hit his five miles yet. I can say, ‘Hey, we should go for a walk.’ He'll look at his thing and see he is only at, like, three miles, and he'll say ‘OK.’” (P4)
3.3. Social support (emotional)	21	“On challenges, there's one guy who I've never met, I don't know the guy from Adam, but he sets up challenges and invites me every week. I've thanked him for that. Occasionally, when I see somebody just really kicking it out, I will send them a note complimenting them on that.” (P18)
4. Shaping knowledge		
4.2. Information about antecedents	21	“I've learned, number one, how much weather really affects my motivation to move at all, not just exercise but to see if I can even get up out of my chair. That's a big one, and that one I wish had a solution for, other than moving to Fiji.” (P2)
4.4. Behavioral experiments	1	“I find that when I'm actively doing cardio, like say I say, ‘I'm going to do high□intensity interval training on the bike a couple times a week’ then that's when my resting heart rate is the lowest. If I get out of that habit, then it creeps up, and up, and up. Then, I'll be like, ‘I need to be doing some more cardio’ so I'll ride the bike more or I'll do some more intensity intervals or whatever.” (P16)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
5. Natural consequences		
5.1. Information about health consequences	5	"For me. I'm thinking of trying to get 30 active minutes a day. I know that that's the recommendation for optimal cardiovascular and my aunt's heart attack is definitely still on my mind, from December. Just kind of a consistent thing to do, and that for me it's less about the quantity of the steps, but more the quality of them. I really move it when I'm out there." (P15)
6.2. Social comparison	28	"It's gotten a little bit more competitive, because some of my sorority sisters have decided to do weekend challenges and weekly challenges where we challenge each other to see who can have the most steps. I get a little bit more competitive that way, and if I don't hit my steps I'll be like, 'Oh no, what if I don't win? What if I can't be competitive?' " (P6)
5.4. Monitoring of emotional consequences	15	"I feel better when I'm active. I feel better about myself when I'm active. Yeah, I think those two things, I feel better physically, and I feel better mentally." (P30)
7. Associations		
7.1. Prompts/cues	6	"When you're in a challenge with two or three people, I think it actually is more motivating. You're not getting inundated with alerts, but at the same, time you're getting a few more nudges during the day, than you are otherwise when you're not in a challenge." (P1)
8. Repetition and substitution		
8.2. Behavior substitution	15	"If I have a Skype meeting where I don't have to be typing, I'd pick up the laptop now and walk with it. I would never have done that before I got a Fitbit. If I was Skyping, I was sitting." (P7)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
8.3. Habit formation	13	“I am methodically making sure that I take the long way around to get to the printer, or I take the back parking space in the parking lot, or I get up every hour or so and make a circuit of the office. I do try to take many more breaks than I used to, as far as just to get up and move a little bit within the office.” (P29)
8.5. Overcorrection	7	“I think about how can I get more in tomorrow? Can I make it up? If I'm only going to get 7,000 today, what can I do to get 11,000 tomorrow?” (P29)
8.6. Generalization of target behavior	2	“At first, it was this mental goal of, ‘OK I need to get all the steps.’ Then, it was I want to get all the steps faster. The only way to get the steps faster is to run. It's like, ‘OK, I'll try this Couch to 5K thing’ that a couple of my friends kept talking about.” (P15)
8.7. Graded tasks	16	“I really want to push myself for July and set a goal and you know maybe I feel like I'm setting the bar a little lower to begin with, just to start creating smaller victories, to try and get myself back to where I need to be, I need to do that start having more victories, and start rolling that ball downhill.” (P3)
9. Comparison of outcomes		
9.3. Comparative imagining of future outcomes	3	“That's my biggest thing about losing the weight and so by looking at the app, I'm accomplishing something. It's going to be able to let me go hiking, scuba diving, skiing and not worry about hurting self just by being there.” (P28)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
10. Reward and threat		
10.2. Material reward (behavior)	3	“It is connected to Walgreens because they send me points after so many steps, and that I do use because, I think it's 10,000, every 10,000, you get a dollar or something. So I have redeemed those points for actual gift cards to Walgreens.” (P22)
10.3. Non-specific reward	11	“I love getting the little vibration on my wrist.” (P6)
10.4. Social reward	6	“It would automatically post [to Twitter] every day the previous day's stats, and people would like it like, ‘Great job.’ You get that.” (P26)
10.6 Non-specific incentive	5	“Like Fitbit it [Leap4Life] has challenges between users. You get points and at some point, before I die perhaps, the points will equate to a gift card and things, or financial rewards.” (P18)
10.9. Self-reward	9	“I'll walk through the mall, and I'll look at my Fitbit, and I'll notice the step count, and I'll feel kind of like proud, and sort of accomplished for the day, like ‘Man, like that's a high number, like that's awesome.’ ” (P5)
10.11. Future punishment	1	“I'll look at it and say, my weekly email, that's going to be my least active day. And it's going to give me that frowny face.” (P4)
11. Regulation		
11.3. Conserving mental resources	3	“I don't have to worry about keeping track of it anymore.” (P25)
12. Antecedents		
12.1. Restructuring the physical environment	2	“Yeah. I guess I try and compensate [for the weather]. I know, like last year I would do it a lot more. I remember in the summer, [my son] and I would go to the mall. We'd never go to like buy anything.” (P5)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
12.2. Restructuring the social environment	3	“We've had walking groups' right after school. As soon as we get out we change, we walk. It has encouraged some behaviors to help each other out by walking together. Me and the other guy who's right behind me all the time, we always tease other. We're not going to get let each other walk more than the other during the school day, at least.” (P26)
13. Identity		
13.1. Identification of self as role model	1	“But I have heard from more than a few of my friends that they appreciate my sharing stuff about that.” (P15)
13.2. Framing/reframing	4	“It definitely has helped me to realize that you can be doing normal things that you need to do throughout your day, and still be a little bit more active, rather than sitting on your butt. That's something that I wouldn't have paid attention to before.” (P21)
13.3. Incompatible beliefs	5	“I would say it pointed out crystal-clear to me at the beginning how much of a slob I was [laughs] and that I needed to get moving. I'm still surprised that I'm running a half-marathon this week. [laughs] I mean that is just so incomprehensible to me because I would love going for walks previously, but just didn't think that I could run.” (P15)
13.4. Valued self-identify	1	“One, even when I'm not making an effort to be active, I'm more active than I realized. That helped me get up and go to the next step.” (P18)
13.5. Identity associated with changed behavior	4	“It just makes me think about it more than I would and reminds me, ‘Yes, this is something you care about.’ ” (P9)

Table 10. BCTs used by participants and example quotations, Continued

BCT Domain / Technique	Number of Participants Using Technique	Example of Participant Responses Coded by Technique
15. Self-belief		
15.1. Verbal persuasion about capability	2	"I've learned that I can motivate myself to do unbelievable things for a 450lb dude. You know, I'm trying to think, in August of the last two years I've walked 225 miles and 206 miles, which is an average of 7.27 and 6.66 miles per day, which you don't associate that with a 450lbs guy." (P3)
15.3. Focus on past success	18	"Then sometimes I'll look at the part where it shows you your activity for the last seven days. Give you the stars on the days that you met your goals, so I'll look at that. Then I'll look at what times with the I was active." (P13)
15.4. Self-talk	6	"Even as we were enjoying this very nice walk in the back of my head there was this voice going, 'You must be racking up a lot of steps here. Wow.' " (P7)

Fitbit Device Use

As previously reported, participants in this study used a variety of different Fitbit devices. These devices were determined through the device identification available through the Fitabase service. However, ten participants mentioned that their current Fitbit device was not their first. Some of these participants bought a new device because of new features:

> They gave all of our employees a Zip at corporate, and then I went and bought the One because I wanted to track more. I didn't end up tracking more with it. I feel like it didn't help that well because of sleep and stuff like that. Now I'm using this one [Charge HR]. (P14)

Buying new devices because of loss, or receiving replacement because of malfunctioning devices was also a common theme among those who had experience with multiple devices:

> I actually ruined it three times. I did it every summer for three years. The first of the summer I would jump in the pool with it still on, and I'd just call Fitbit, and they would replace it. After the third time I thought, "I should probably just by one, and stop getting free ones," but work gave me [a Zip], so I didn't have to buy one. (P22)

One participant mentioned that they were use two devices concurrently because of the different features and ability to track additional data during periods of exercise:

> The only time I usually switch it is after the gym. I'll get up, and if I know I'm going to the gym, I'll just put on the Charge HR, and then I'll either just continue wearing it for the rest of the day, or I'll come home after the gym, shower, and I put the Zip on for the

> rest of the day. If I change it, I only change it once a day. I don't change it more than once a day. (P30)

Interacting with the Fitbit System

The Fitbit system is composed of three parts: the Fitbit device, the mobile application, and the Fitbit website. The Fitbit device primarily presents information about current behavioral data (steps, distance, floors, etc.) through its display. The mobile application and website also offer this data (if the device as synced), in addition they provide the ability to explore historical data, change settings, and engage with social components. During the interview participants reported interacting with their device between 2 and 12 times per day (M = 5.35, SD = 3.31). For the mobile application, participants reported interacting with between 0 and 20 times per day (M = 2.94, SD = 3.81). Lastly, for the website, participants reported logging on between 0 and 7 times per week (M = 1.75, SD = 2.33).

Multi-Level Models

Date Reduction & Variable Refinement

Participants who possessed less than 50% valid days to total available days (Valid Days / Fitbit User Period) would not be included in the multi-level model analysis as their data represents inconsistent wear behavior and may not be representative of actual physical activity. Five participants were therefore excluded from the multi-level model analysis. These participants' interviews were retained and included in the qualitative analysis.

Education was reduced to a two-level variable for ease of interpretation. Participants were grouped by whether or not they completed a graduate or professional degree. Additionally, the date variable was transformed to represent *time* and rescaled in order to maximize the likelihood of model convergence. The time variable was calculated as the number of days since the participant began using a Fitbit device, with the first day being represented as *time* = 0. Time was then rescaled to represent the approximate ratio of days per month by dividing the *time* variable by 30. A one-unit change in *time* therefore represents a 30-day increase.

Modeling Individual Activity Trajectories and BCT Use

Prior to developing and testing the multi-level models to explore the relationship between activity outcomes and behavior change technique use individual participant activity trajectories were explored. Each participant's activity outcome data was regressed on the scaled 30-day time variable. Seven of the 25 participants included in this analysis exhibited a non-significant change (non-significant beta coefficient) for steps over time. Of the 19 participants who had a significant slope over time six exhibited a significant decrease over time, with a range of a 17.72 to 835.50 decrease in steps per 30-day period. Twelve participants had a positive increase in steps over time. The magnitude of significant slopes over time ranged from 4.82 to 793.50 steps per 30-day period. For all participants who exhibited a significant trend the mean change over time was 34.43 steps per 30-day period (*SD* = 344.31). The Pearson's product-moment correlation between mean step count and the slope of steps over time was not significant (*r* = 0.09, p = 0.66) for this sample. Additionally, a chi-square test of independence indicated that the there was no relationship between the direction of the slope for change in activity steps over time and tertile classification of mean steps. The relationship between individual activity outcomes and BCT use was also explored. There was no significant relationship between the total number of BCTs used by participants and their mean step count (for valid days).

Modeling Steps per Day

Random Slope Model. The first step in the multi-level model analysis was to assess if fitting a random slope improves the unconditional linear growth model. This was accomplished by evaluating an ANOVA comparing the model fit of the unconditional linear growth models with and without the inclusion of random slopes. A Q-Q plot of the residuals indicated that the data was heavy-tailed. Therefore the outcome variable, daily steps, was log transformed for all remaining analyses. The inclusion of random slope for time significantly improved the model fit (χ^2 (2) = 454.44, $p < .001$). The random slope model indicates that a) there is a small, non-significant decrease in steps over time in this sample, b) participants differ in terms of their initial level of steps per day, and c) the linear individual growth pattern varies among participants. Model estimates (see Table 11) indicate that for this sample there is a 0.1% decrease in steps per day over a 30-day period.

Demographic Model. Next, demographic variables were entered into the model as fixed effects (including interaction terms) and backwards elimination of non-significant effects was performed in order to determine if any participant characteristics were significantly related to the change in step counts over time. Age, Sex, BMI, Household Income, Education Level, Type of Fitbit, and Data Affinity classification were all entered into the initial model. The fixed effect and interaction term for Education Level was retained as a significant predictor of daily step counts. The inclusion of the fixed effect and interaction term for Education Level significantly improved the model fit when compared to the Random Slopes Model (χ^2 (4) = 9.26, p = .01). Model estimates (see Table 11) indicate the growth pattern among participants continues to vary and that there is a small, but significant decrease in steps per day over time. The Time By Education Level interaction is also significant.

Table 11. Random slope and demographic multi-level model coefficient (outcome = steps per day).

Model	Fixed Effect	*Estimate*	SE	df	t *Value*
Random Slope Model	Intercept	9.06	0.09	23.86	104.92[c]
	Time	-0.00	0.00	14.57	-0.30
Final Demographic Model	Intercept	9.12	0.13	22.89	67.93[c]
	Time	-0.01	0.00	17.64	-2.33[a]
	Completed Graduate or Professional Degree	-0.10	0.18	22.89	-0.56
	Time* Completed Graduate or Professional Degree	0.02	0.01	17.94	2.73[a]

Note. a = $p < .05$, b = $p < .01$, c = $p < .001$

Initial BCT Domain Model. Next, the BCT Domains included in the design of the Fitbit were entered into the model and backwards elimination of non-significant effects was performed. Additionally, only BCT Domains with observed variability were entered into the model. BCT Domain 1 (*Goals and Planning*) and Domain 2 (*Feedback and Monitoring*), which were used by all participants, were not included in the model. This resulted in the inclusion of BCT Domains 3, 6, 7, 8, 10, and 15. The fixed effect and interaction term for Education Level was also included per the previous model fit. After the backwards elimination was completed only the fixed effect and interaction term for BCT6, *Comparison of Behavior*, was retained from the initial set of BCTs entered at this stage. The inclusion of the fixed effect and interaction term for Comparison of Behavior significantly improved the model fit when compared to the Demographic Model (χ^2 (2) = 9.10, p =. 01). Again, the model estimates (see Table 12) indicate that there is small, but significant negative effect of time on steps per day corresponding to a 6.8% decrease in steps per day over every 30-day period. The Time by BCT6 (*Comparisons of Behavior*) domain use interaction was also significant.

Final BCT Domain Model. Lastly, the remaining BCT domains were entered into the model and backwards elimination of non-significant effects was performed. Both Education Level and BCT6 were retained (fixed effects and interaction term) per the previous model. After backwards elimination was completed, BCT9, *Comparison of Outcomes*, and BCT12, Antecedents, were retained in the final model (fixed effects and interactions terms). The inclusion of these terms in the final model significantly improved model fit when compared to the Initial BCT Domain Model (χ^2 (4) = 24.43, p < .001). The model estimates in the Final BCT Domain Model (see Table 12) continued to indicate that the growth pattern among participants varies and that there is a small, but significant decrease in steps per day over time. A significant fixed effect for BCT12 (*Antecedents*) indicates that participants who used techniques within the *Antecedents* domain have higher initial values for steps per day when all other variables are set to zero. Interaction terms for each of the included BCT domains are significant. The plots of the interaction effect for Time by BCT6 (*Comparison of Behavior*) and Time by BCT12 (*Antecedents*) show similar trends (see Figures 5 and 6, respectively). Interaction effects indicate that initial values for steps per day were higher for participants who used techniques in the *Antecedents* domain, and steps per day is predicated to decrease over time. Participants who reported using techniques in the *Comparison of Behavior* domain had lower initial steps per day and showed a predicted increase over time. Alternatively, the plot of the Time by BCT9 (*Comparison of Outcomes*) predicted interaction effect indicates an inverse relationship between steps per day and use of the domain (see Figure 7). Lastly, the Time by Education Level interaction was significant as well. Individuals who have a graduate or professional degree start at a lower initial value for steps per day, and have a small increase in steps per day over time (see Figure 8).

Table 12. Initial BCT and final BCT domain multi-level model coefficients (outcome = steps per day).

Model	Fixed Effects	*Estimate*	SE	df	t *Value*
Initial BCT Model	Intercept	9.39	0.33	22.60	28.06[c]
	Time	-0.07	0.02	276.00	-3.39[c]
	BCT6 (Comparison of Behavior)	-0.29	0.36	22.64	-0.88
	Completed Graduate or Professional Degree	-0.10	0.18	21.91	-0.55
	Time*BCT6 (Comparison of Behavior)	0.06	0.02	262.50	2.93[b]
	Time*Completed Graduate or Professional Degree	0.02	0.01	19.78	2.63[a]
Final BCT Model	Intercept	9.40	-0.29	20.89	32.37[c]
	Time	-0.07	0.02	304.34	-3.51[c]
	BCT6 (Comparison of Behavior)	-0.43	0.29	20.84	-1.46
	BCT9 (Comparison of Outcomes)	0.07	0.37	20.33	0.17
	BCT12 (Antecedents)	0.53	0.25	20.75	2.14[a]
	Completed Graduate or Professional Degree	-0.12	0.16	19.96	-0.71
	Time*BCT6 (Comparison of Behavior)	0.06	0.02	287.62	3.12[b]
	Time*BCT9 (Comparison of Outcomes)	-0.06	0.02	76.71	-3.08[b]
	Time*BCT12 (Antecedents)	0.03	0.02	205.39	2.19[a]
	Time*Completed Graduate or Professional Degree	0.02	0.01	18.37	3.11[b]

Note. a = $p < .05$, b = $p < .01$, c = $p < .001$

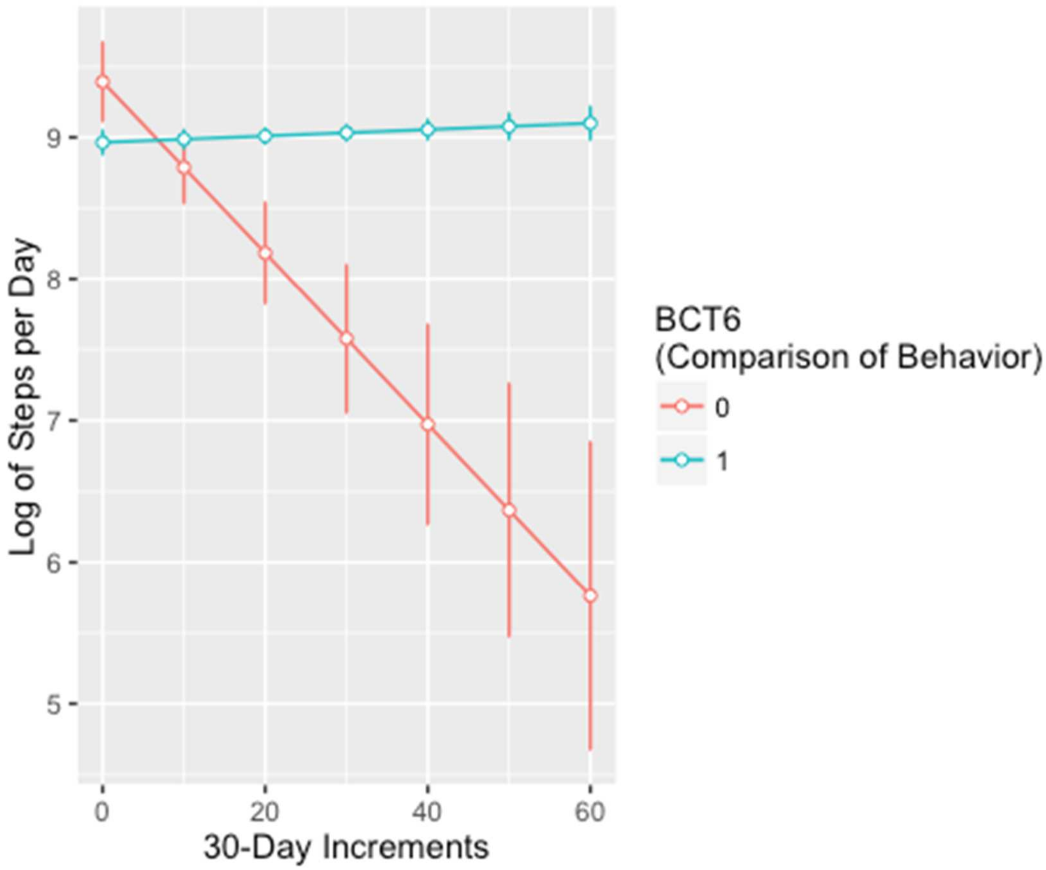

Figure 5. Interaction between BCT6 (Comparison of Behavior) use and steps per day.

Note. 0 = did not use Comparison of Behavior (*n* = 2), 1 = did use Comparison of Behavior (*n* = 23).

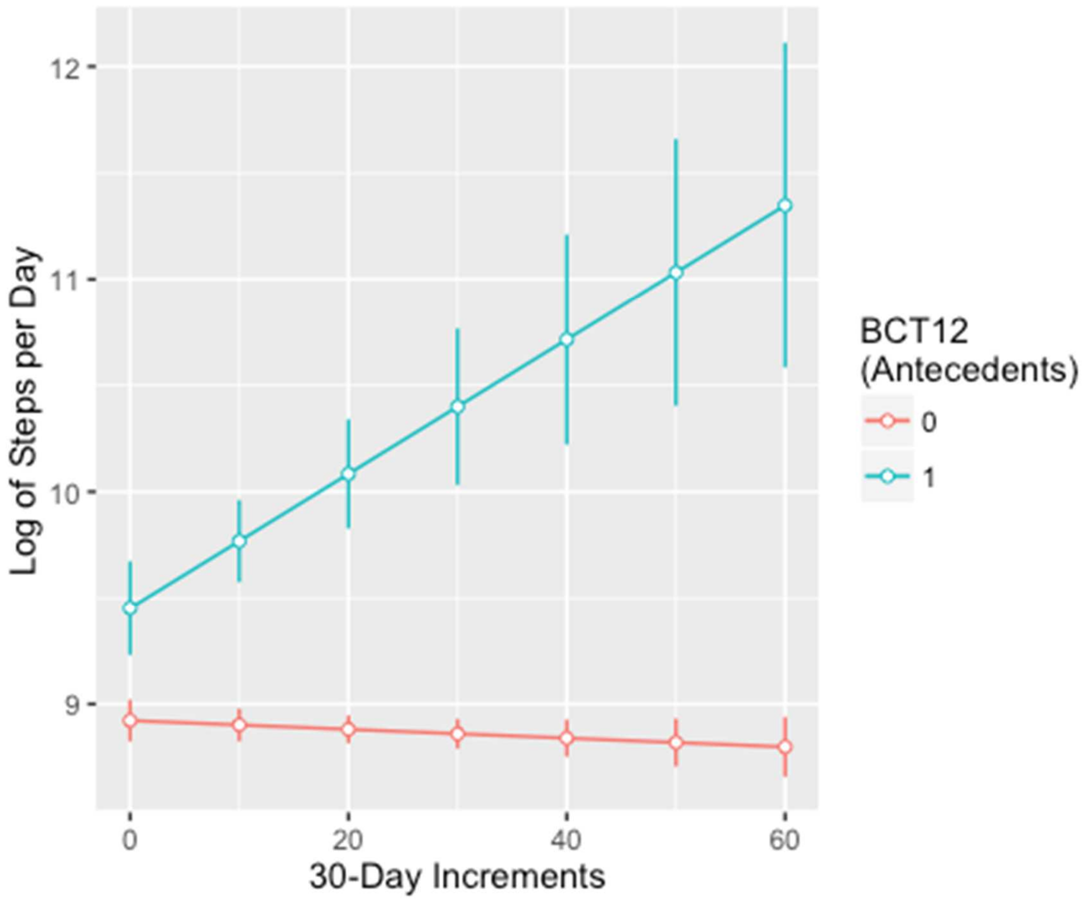

Figure 6. Interaction between BCT12 (Antecedents) use and steps per day.

Note. 0 = did not use Antecedents (*n* = 20), 1 = did use Antecedents (*n* = 5).

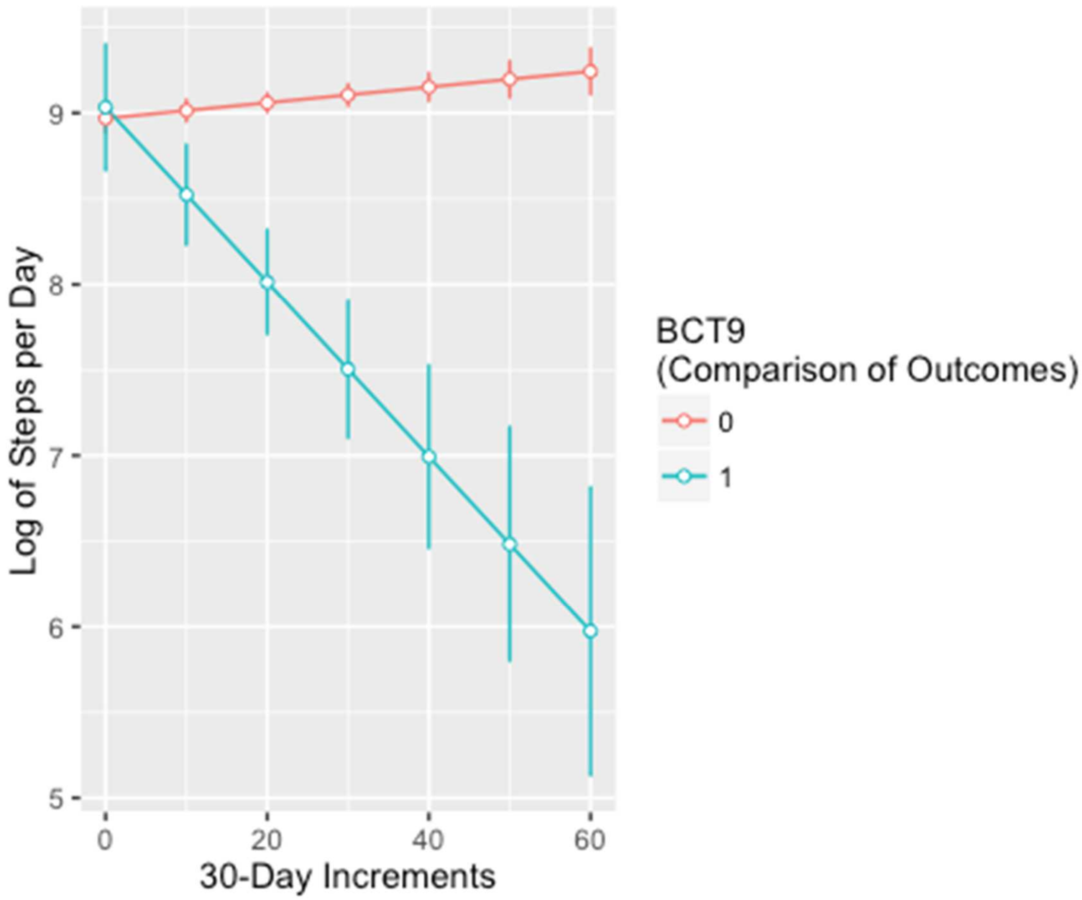

Figure 7. Interaction between BCT9 (Comparison of Outcomes) use and steps per day.

Note. 0 = did not use Comparison of Outcomes (*n* = 23), 1 = did use Comparison of Outcomes (*n* = 2).

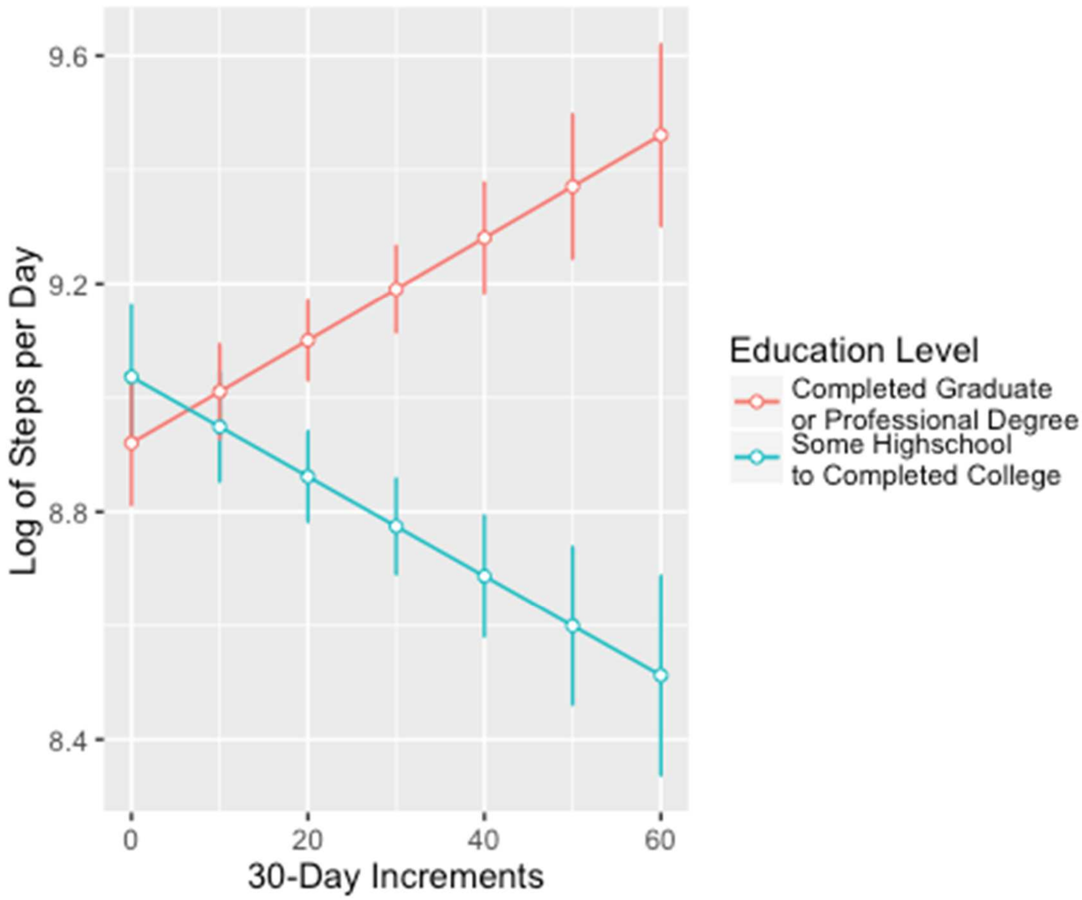

Figure 8. Interaction between education level and steps per day.

Note. Completed Graduate/Professional Degree: *n* = 14, Some High School to Completed College: *n* = 11)

Initial BCT Strength Model. The initial BCT Strength Model introduced the number of techniques used per domain, which reflects the strength of BCT domain use. In the initial BCT Strength Model, domains included in the design of the Fitbit were entered into the model already containing random slopes and significant demographic variables, and backwards elimination of non-significant effects was performed. Similar to the BCT Domain Model, the only domain retained in the initial BCT Strength Model was BCT6 (*Comparison of Behavior*). The inclusion of the fixed effect and interaction term for *Comparison of Behavior* significantly improved the model fit when compared to the Demographic Model (χ^2 (2) = 9.10, p =. 01). Model estimates (see Table 13) indicate that there is small, but significant negative effect of time on steps per day. The Time by BCT6 (*Comparisons of Behavior*) interaction was also significant. The significant Time by Education Level interaction was retained in this model.

Final BCT Strength Model. The remaining BCT variables were entered into the model and backwards elimination of non-significant effects was performed. Both Education Level and BCT6 were retained (fixed effects and interaction term) per the previous model. As was observed in the Final BCT Domain Model, BCT9, *Comparison of Outcomes*, and BCT12, *Antecedents*, were retained in the Final BCT Strength Model (fixed effects and interactions terms). The inclusion of these terms in the final model significantly improved model fit when compared to the Initial BCT Strength Model (χ^2 (4) = 24.43, p < .001). The model estimates the Final BCT Strength Model mimic those of the Final BCT Domain Model. The three retained variables reflecting BCT use were effectively entered as dichotomous variables as participants only used one technique from each of these domains.

Modeling Minutes of MVPA per Day

Random Slope Model. Results from an ANOVA comparing the model fit of the unconditional linear growth models with and without the inclusion of random slopes indicated that the inclusion of random slope for time significantly improved the model fit (χ^2 (2) = 330.34, p < .001). The random slope model estimates (see Table 13) indicate that a) there is a small, but insignificant decrease in minutes of MVPA over time in this sample, b) participants differ in terms of their initial level of minutes of MVPA, and c) the linear individual growth pattern varies among participants.

Demographic Model. All demographic variables were entered into the model and backwards elimination was performed. No demographic variables were significant. Thus, the final demographic model is equal to the unconditional growth model that includes the random effect of time.

Initial BCT Domain Model. Next, the first set of BCTs (those included in the design of the Fitbit system), were entered into the model. After the backwards elimination was completed only the fixed effect and interaction term for BCT6, *Comparison of Behavior*, was retained from the initial set of BCTs entered at this stage. The inclusion of the fixed effect and interaction term for the *Comparison of Behavior* domain significantly improved the model fit when compared to the Demographic Model (χ^2 (4) = 6.95, $p < 0.05$). Model estimates for the Initial BCT Domain Model, with minutes of MVPA defined as the dependent variable, indicate that there is a significant negative effect for Time. The Time By BCT6 (*Comparison of Outcomes*) interaction is also significant.

Final BCT Domain Model. Lastly, the remaining BCTs were entered into the model. BCT6 (fixed effect and interaction term) was retained per the previous model. After backwards elimination was completed, BCT9, Comparison of Outcomes, and BCT12, Antecedents, were retained in the final model. Only the interaction term for BCT9 was retained. The inclusion of these additional terms in the model significantly improved model fit when compared to the Initial BCT Domain Model (χ^2 (3) = 15.00, $p = 0.002$).

The model estimates in the Final BCT Domain Model (see Table 13), with minutes of MVPA defined as the dependent variable, continued to indicate that the growth pattern among participants varies and that there is a small, but significant decrease in minutes of MVPA over time. A significant fixed effect for BCT12 (*Antecedents*) domain indicates that participants who used techniques within the *Antecedents* domain have higher initial values for minutes of MVPA when all other variables are set to zero. Interaction terms for Time by BCT6 (*Comparison of Behavior*) and BCT9 (*Comparison of Outcomes*) are significant. The plots of the predicted interaction effect for Time by BCT6 (*Comparison of Behavior*) indicate that participants who reported using techniques in the *Comparison of Behavior* domain and those who didn't had similar initial values for minutes of MVPA. Those who used techniques in the *Comparison of Behavior* domain had a very small predicted decline in minutes of MVPA over time, while those who did not use any techniques in that domain had a much more pronounced decline (see Figure 9). Alternatively, the plot of the Time by BCT9 (*Comparison of Outcomes*) predicted interaction effect indicates an inverse relationship between the trend for minutes of MVPA and use of the domain (see Figure 10).

Table 13. Random slope, initial BCT domain, and final BCT domain multi-level model coefficients (outcome = minutes of MVPA per day).

Model	Fixed Effects	*Estimate*	SE	df	t *Value*
Random Slope Model	Intercept	36.08	5.31	24.02	6.79[c]
	Time	-0.19	0.23	19.12	-0.81
Initial BCT Model	Intercept	33.04	19.31	24.39	1.71
	Time	-3.70	1.57	226.29	-2.37[a]
	BCT6 (Comparison of Behavior)	3.91	20.11	24.27	0.19
	Time* BCT6 (Comparison of Behavior)	3.55	1.58	204.74	2.24[a]
Final BCT Model	Intercept	33.05	17.14	22.35	1.93
	Time	-3.71	1.53	277.96	-2.43[a]
	BCT6 (Comparison of Behavior)	-4.96	18.02	22.24	−0.24
	BCT9 (Comparison of Outcomes)	0.01	20.93	22.22	0.00
	BCT12 (Antecedents)	39.80	13.28	24.39	3.00[b]
	Time* BCT6 (Comparison of Behavior)	3.83	1.54	246.41	2.48[a]
	Time* BCT9 (Comparison of Outcomes)	-1.87	0.74	18.80	-2.54[a]

Note. a = $p < .05$, b = $p < .01$, c = $p < .001$

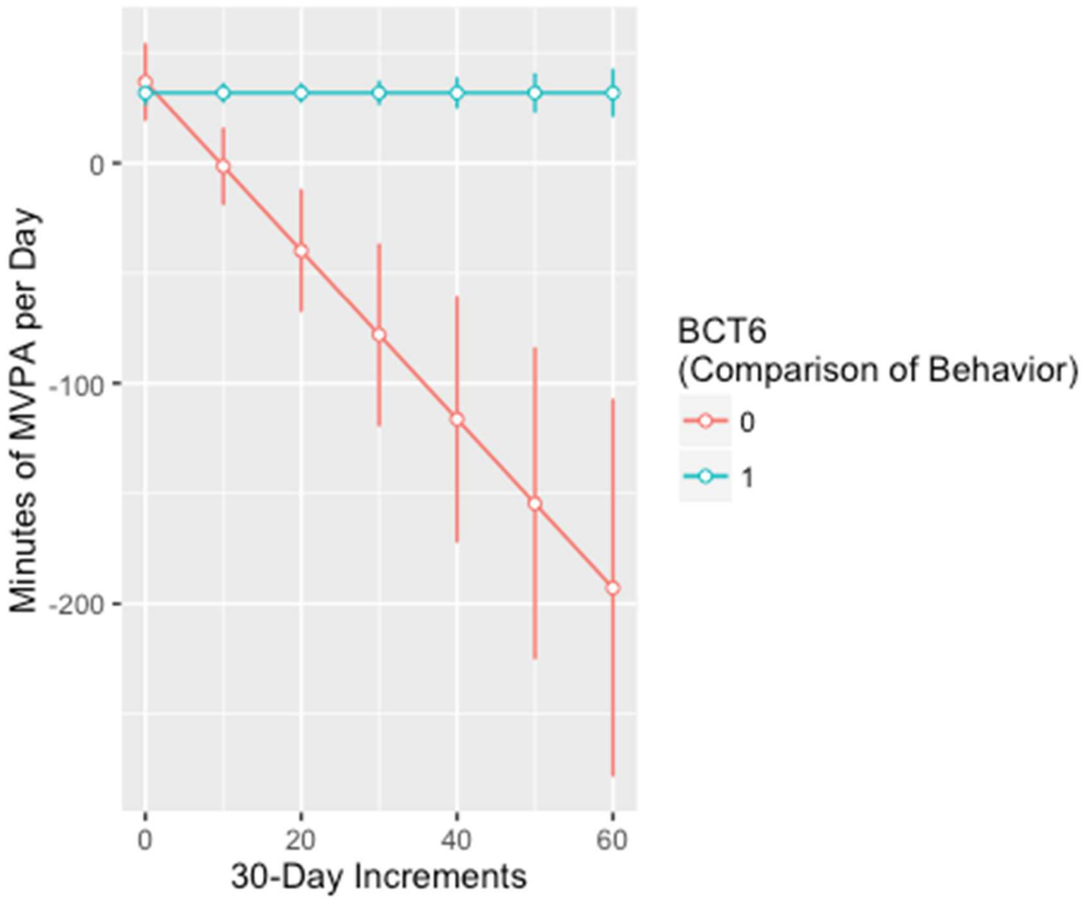

Figure 9. Interaction between BCT6 (Comparison of Behavior) use and minutes of MVPA per day.

Note. 0 = did not use Social Comparison (*n* = 2), 1 = did use Social Comparison (*n* = 23)

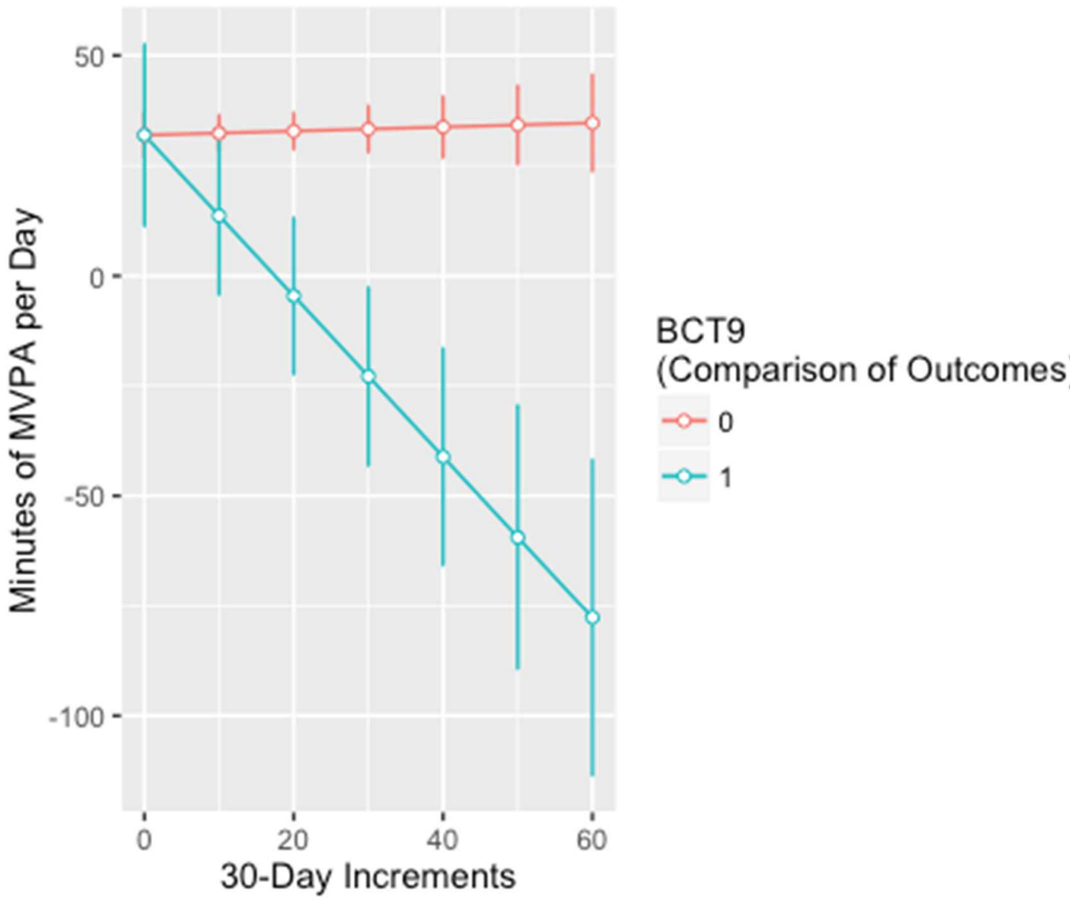

Figure 10. Interaction between BCT9 (Comparison of Outcomes) use and minutes of MVPA per day.

Note. 0 = did not use Comparison of Outcomes (*n* = 23), 1 = did use Comparison of Outcomes (*n* = 2).

Initial BCT Strength Model. A second set of models was produced to examine the relationship between the number of BCTS used per domain and daily minutes of MVPA. The first set of BCTs (those included in the design of the Fitbit system), were entered into the Demographic Model. After the backwards elimination was completed only the fixed effect and interaction term for BCT1, *Goal Setting and Planning*, and BCT6, *Comparison of Behavior*, were retained from the initial set of BCTs entered at this stage. The inclusion of the fixed effect and interaction term for these BCTs significantly improved the model fit when compared to the Demographic Model (χ^2 (4) = 14.91, $p < 0.01$). Model estimates for the Initial BCT Strength Model, with minutes of MVPA defined as the dependent variable, indicate the Time By BCT1 (*Goals and Planning*) and the Time by BCT6 (*Comparison of Behavior*) interaction terms are significant.

Final BCT Strength Model. Lastly, the remaining BCTs were entered into the model. BCT1 and BCT6 (fixed effects and interaction terms) were retained per the previous model fit. After backwards elimination was completed, BCT9, Comparison of Outcomes, and BCT12, Antecedents, were retained in the final model. Only the interaction term for BCT9 was retained. The inclusion of these additional terms in the model significantly improved model fit when compared to the Initial BCT Strength Model (χ^2 (3) = 17.59, $p < 0.001$).

The model estimates in the Final BCT Strength Model (see Table 14), with minutes of MVPA defined as the dependent variable, no longer indicate a significant main effect for time. A significant fixed effect for BCT12 (*Antecedents*) domain indicates that participants who used techniques within the *Antecedents* domain have higher initial values for minutes of MVPA when all other variables are set to zero. Interaction terms for Time By BCT1 (*Goals and Planning*), Time by BCT6 (*Comparison of Behavior*), and Time by BCT9 (*Comparison of Outcomes).* The plots of the predicted interaction effect for Time by BCT1 (*Goals and Planning*) indicate that participants who reported differing numbers of techniques used in the domain had similar initial values for minutes of MVPA. The predicted slope for minutes of MVPA over time for those who used zero, one, or two techniques in the *Goals and Planning* domain was positive. For those who used three or more techniques, a negative slope was predicted (see Figure 11). The plots of the predicted interaction effect for Time by BCT6 (*Comparison of Behavior*) indicate that participants who reported using a technique in the *Comparison of Behavior* domain and those who didn't had similar initial values for minutes of MVPA. Those who used a technique in the *Comparison of Behavior* domain had a very small predicted increase in minutes of MVPA over time, while those who did not use any techniques in that domain had a pronounced decline (see Figure 12). Alternatively, the plot of the Time by BCT9 (*Comparison of Outcomes*) predicted interaction effect indicates an inverse relationship between the trend for minutes of MVPA and use of a technique within the domain (see Figure 13).

Table 14. Initial BCT and final BCT strength multi-level model coefficients (outcome = minutes of MVPA per day).

Model	Fixed Effects	*Estimate*	SE	df	t *Value*
Initial BCT Model	Intercept	22.00	35.87	22.46	0.61
	Time	-1.41	1.86	79.13	-0.76
	BCT1 (Goal Setting and Planning)	2.93	7.46	22.06	0.39
	BCT6 (Comparison of Behavior)	5.86	21.80	23.08	0.27
	Time* BCT1 (Goal Setting and Planning)	-0.69	0.29	20.59	-2.40[a]
	Time* BCT6 (Comparison of Behavior)	3.38	1.54	269.77	2.19[a]
Final BCT Model	Intercept	29.10	32.04	20.20	0.91
	Time	-1.57	1.74	98.50	-0.90
	BCT1 (Goal Setting and Planning)	1.16	6.67	19.80	0.17
	BCT6 (Comparison of Behavior)	-4.94	19.65	21.00	-0.25
	BCT9 (Comparison of Behavior)	-1.07	21.59	21.40	-0.05
	BCT12 (Antecedents)	41.33	13.51	25.00	3.06[b]
	Time* BCT1 (Goal Setting and Planning)	-0.66	0.25	18.60	-2.61[a]
	Time* BCT6 (Comparison of Behavior)	3.73	1.49	378.40	2.50[a]
	Time* BCT9 (Comparison of Behavior)	-1.94	0.66	20.70	-2.94[b]

Note. a = $p < .05$, b = $p < .01$, c = $p < .001$

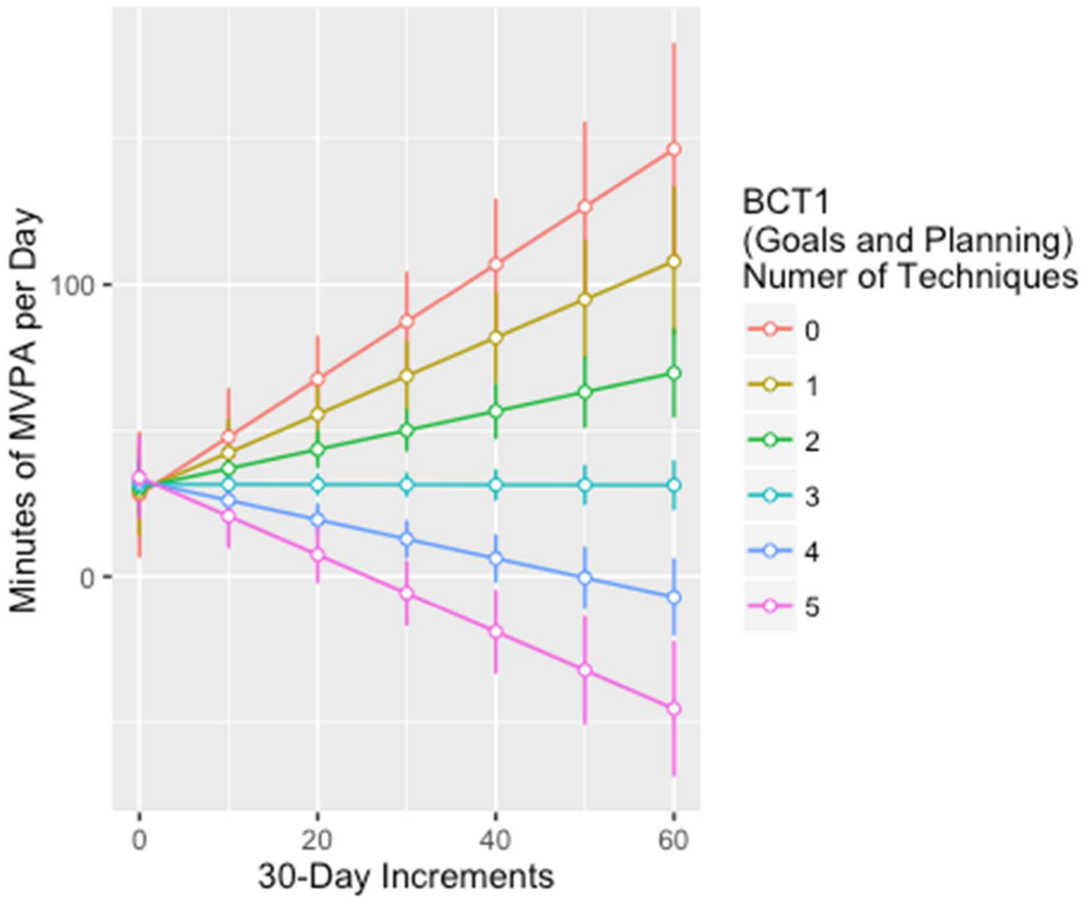

Figure 11. Interaction between BCT1 (Goals and Planning) use and minutes of MVPA per day.

Note. Number of participants using techniques in Goals and Planning domain: 0 techniques: *n* = 0, 1 technique: *n* = 0, 2 techniques: *n* = 5, 3 techniques: *n* = 12, 4 techniques: *n* = 7, 5 techniques: *n* = 1.

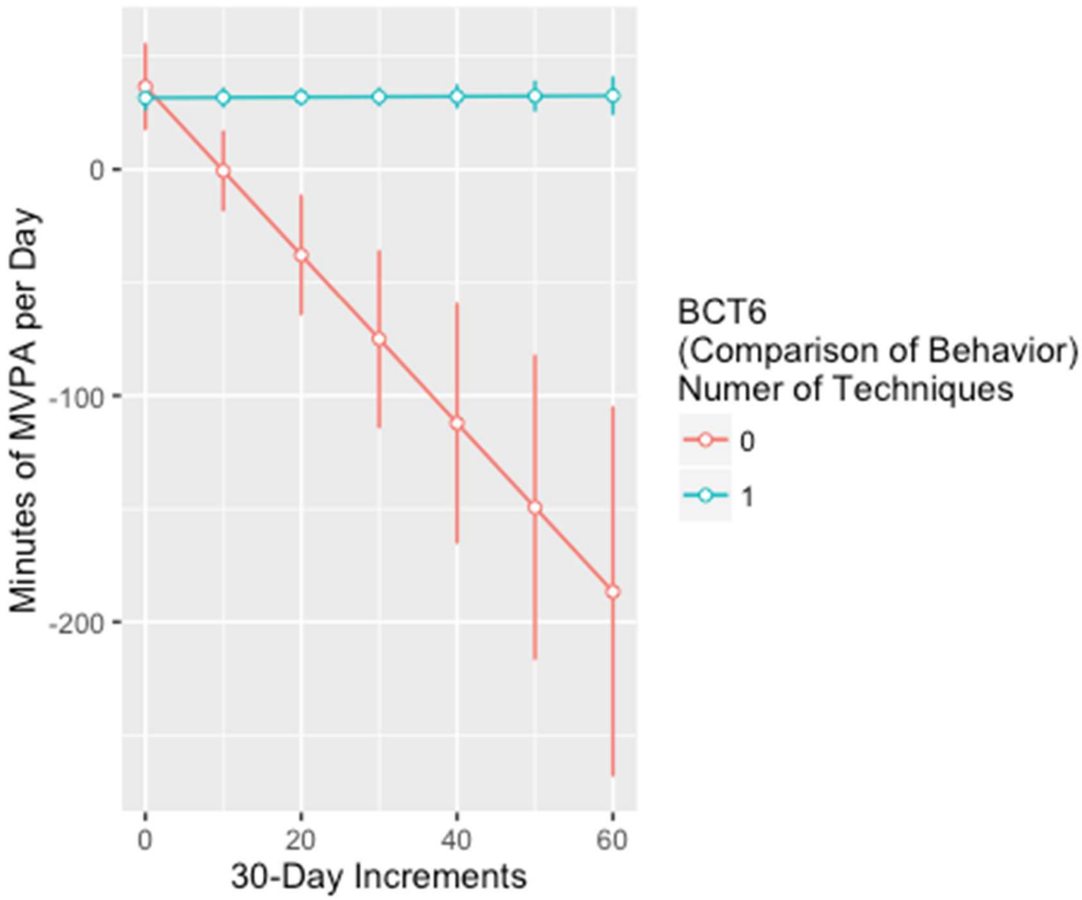

Figure 12. Interaction between BCT6 (Comparison of Behavior) use and minutes of MVPA per day.

Note. 0 = did not use Social Comparison (*n* = 2), 1 = did use Social Comparison (*n* = 23)

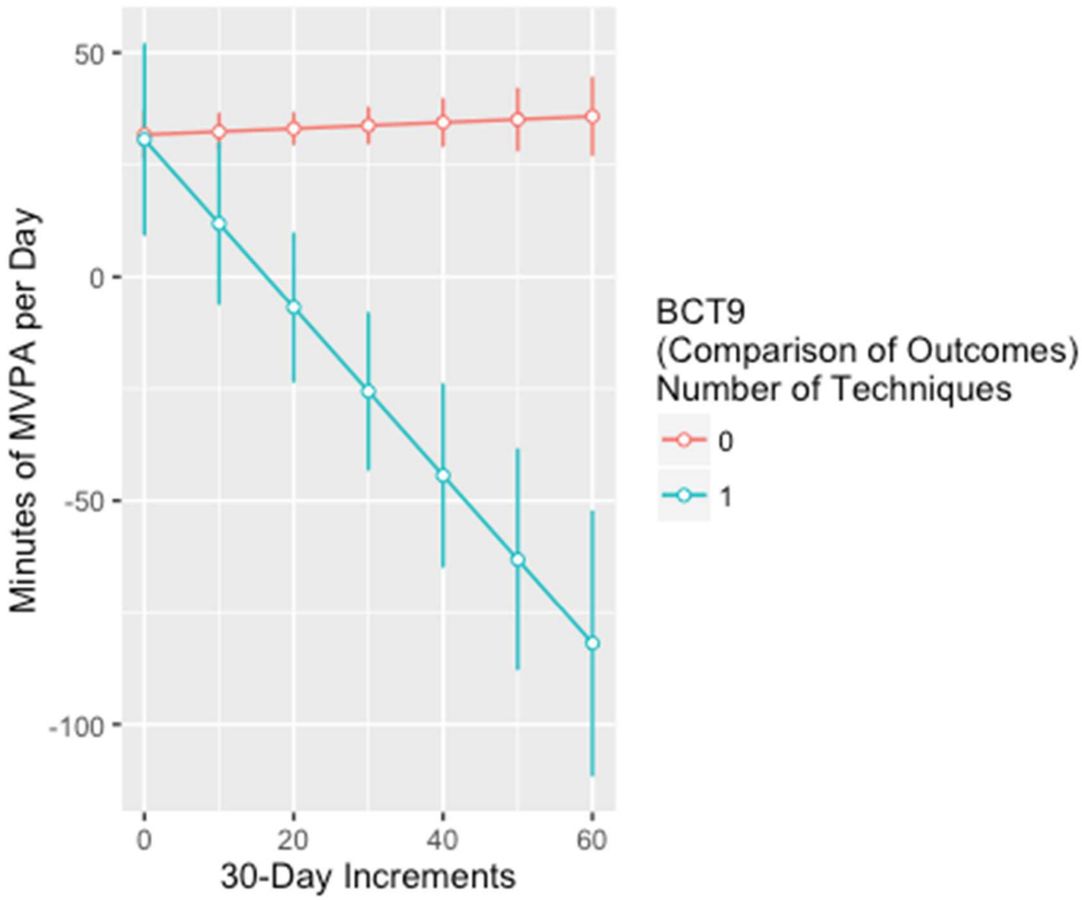

Figure 13. Interaction between BCT9 (Comparison of Outcomes) use and minutes of MVPA per day. Contextual Analysis

Note. 0 = did not use Comparison of Outcomes (*n* = 23), 1 = did use Comparison of Outcomes (*n* = 2).

Contextual Analysis

Through the exploration of quotations, contextual information, and research notes three thematic areas emerged that indicated commonly used techniques and difference in technique application among participants. The outcomes of this process identified the *Goals and Planning* domain as being particularly powerful, while also being the source of different mechanisms of use among participants. Participants' stated experience with *Social Comparison,* provided unique examples of differences in technique use primarily driven by Fitbit features. Lastly, an examination of how participants expressed their use of techniques within the *Social Support* domain provided a number of examples of contextual differences.

Goals and Planning

The impact of the BCTs within the *Goals and Planning* domain was quite clear. Among the specific BCTs within the *Goals and Planning* domain the *Goal-setting (Behavior)* technique was the most apparent. All participants mentioned using the daily step goal (some participants also used the distance goal). Among the themes associated with activity goals, the most common centered on changing the pre-set goal(s), using multiple goal levels, changing behavior in order to meet goals, and using personalized goal setting systems.

Fitbit allows a user to change any of the pre-set activity goals. Nine participants (30%) mentioned changing their daily step goal in order to create a metric that was more appropriate for their level of activity. Six participants found that the 10,000 step per day that Fitbit automatically sets as the step goal was too high relative to their ability to be active and reduced their system goal:

> I actually did recently decrease my step goal, which I hadn't done before. I was just like, “I'm never actually hitting 10,000 steps. Why don't I change it to something that's possibly more attainable?" For steps, I'm at 7,500 now. (P1)

> It started at 10,000. When you first get it, it automates you to 10,000. I adjusted it down to 7,000 and then I adjusted it back up to 8,500. [...] I wasn't meeting my goal, and I thought it was hard to do. I didn't like not meeting it so I was like, “OK. Let me make a more realistic goal.” So I made it a more realistic goal. That was too easy for me, or I was meeting it fairly often, so I decided to jump it up again. I'm contemplating jumping it up again to at least 9,000 or 9,500. (P30)

Three participants had adjusted their goal upwards as they found that reaching 10,000 steps per day was too easy and therefore created a goal that was harder to reach:

> 10,000 was not a stretch goal for me because I was definitely getting that every single day, so I wanted something that would be actually a goal that some days I don't get that, so I shifted it up [to 15,000 steps per day]. I did that probably two months after I got it. (P4)

An interesting phenomenon was observed for goal setting among participants. While each participant had an explicitly stated goal in the Fitbit system, a few also mentioned creating a system of multiple goals that they mentally kept track of and used to reflect on their behavior. For some participants this included a minimum acceptable amount of steps they wanted to reach per day, while others sought to go beyond their stated system goal:

> I have a 14,000-step goal. I don't hit it very often anymore. I frequently hit 10,000, which to me is the cut off goal. It's a secondary goal that's in my mind. (P10)

> The number on my Fitbit is 7,500, but I guess in my mind I'm like, "If you only get 5,000 you'll be OK," which I don't know why I say that, but it's better than not being active at all. I think because I read somewhere that the average person, without even trying, gets in about 3,000 steps a day, so I figure if I do five, then I'm trying a little bit more than the average person. (P22)

> I never set my goal at 10,000. Actually I still don't. I still have it set at 9,000. In my head, I'm trying to get to around 12,000. You know how it buzzes you when you get your goal? I like that buzz to come early enough in the day that I never feel stressed that I'm not going to make it. I know I'm going to hit 10,000, but I still want to feel that buzz at 9,000 to say, "You've done what you said you were going to do. Good going." The rest is just gravy. (P7)

The ability to receive feedback about progress towards an activity goal (*Discrepancy Between Current Behavior and Goal*) was quite impactful for participants in this study. Participants mentioned interacting with their device and the mobile app during the day to see how many steps they had to take in order to reach their daily goal. In some cases, these interactions took the form of receiving push notifications from the Fitbit mobile application. These checks frequently occurred towards the end of the day and influenced participants to engage in activity in order to reach their goals:

> If I'm at home in the evening and it's 30 minutes or an hour before I'm supposed to go to bed and I know I have less than 2,000 steps away from hitting my goal it'll motivate me to walk around the house until I get to that 10,000 before I go to bed (P13)

> There definitely have been days where I'm at like, I don't know, 9,000 steps and that'll make me want to do a couple laps around the building, to get over the 10,000 mark. (P21)

> When I first got the Fitbit I'd do the classic, walk around my apartment until I reached 10,000. Maybe I shouldn't assume that everyone goes through that phase, but I assume I'm not even close to the only person who's done that before. (P12)

Social Comparison

Social Comparison was the only technique within the *Comparison of Behavior* domain observed in this study. Michie and colleagues (2015) define the *Social Comparison* technique as, "Drawing attention to others' performance to allow comparison with the person's own performance." Fitbit has two features that directly incorporate this type comparison. First, one of the main interactive screens in the Fitbit mobile application is the "Friends" leaderboard. Fitbit allow uses to connect with each other and share activity data. If individuals are connected they will show up in the leaderboard under the Friends tab. The leaderboard contains all connected friends and ranks them (and the user) according to their running 7-day total. The second feature that involves comparison of performance is the "Challenges". Challenges are time-bound competitions between "friends and family members" that can be as short as one day, or as long as a workweek (five days). Participants in challenges are ranked according to their cumulative steps for the period of the challenge. When the challenge concludes a winner is determined.

The leaderboard was mentioned numerous times as a motivating feature that can affect their behavior. Individuals also internalize the ranking on the leaderboard as a form of competition. Often this manifested as a focus on their rank. Some places special emphasis on "winning" the leaderboard, while others sought to maintain their ranking and not fall behind.

> I don't know anyone yet who has a Fitbit who doesn't look at the friends tab and see where they stack up for the week. (P2)

> Even though I can be not very active sometimes I can be very competitive, so if I know that I'm being compared to other people, then that definitely motivates me more. I find it motivating. I know I definitely put the extra effort in to walk more, because I knew other people would be checking it. (P21)

> I'll click on my friends and see where I'm at in the list. Because I get six or lower, then that will motivate me to do more steps. I like to be in the top five of my friends. (P13)

> There are different times when I'll pull it [the leaderboard] up and I am number one in my list of friends. I'm like, “Woo, look at me. I beat everyone." (P5)

> Yeah, two days ago was a great day because I actually got home and I had more steps than she did. She always has more steps than I do. It was kind of a little, "Yay, I'm winning today." (P29)

Participants also engaged with the leaderboard in a non-competitive way, often just checking to see how their friends are doing, or to see evaluate themselves in relation to their friends.

> It [the leaderboard] will sometimes prod me to go and look and see where I'm at relative to my friends. (P2)

> It's interesting just to see, especially if I know someone. One of my really good friends, I know he just ran a half marathon, so I'm always interested to see what his steps are compared to everyone else. (P6)

> But when I look at those lists they're almost always the same. The friends in my group are fairly consistent. The numbers are all different each week, but the order is very similar. (P10)

> I'd say I do [the leaderboard] because I'm definitely the middle of the pack of it, and so I can't see who the top five are. I see what they're up to. (P15)

Some participants credited the ability to see their friend's activity for making them consider their own physical activity behavior in a new way, and possibly encouraging them to try new methods for being active.

> When she gets back ahead, it's like, "OK, [my friend] is doing something, that she can figure out how to work activity into her day. That's awesome." I know her job is a desk job. Maybe her office is a little more friendly, but I do research for God's sake. My job is pretty flexible, or could it be. I think the friend thing is an encouragement that people are working. It's people who are working, and driving to work, if they can figure out a way to do it like, I should too. (P9)

> What's interesting is being socially connected to people through these trackers, that on Fitbit you can be connected to a group of 20 friends and unfortunately see how inactive everybody is, but you have some people stand out. It makes you think it's not like competition, but it made me think about how active I am as a person in a different way. (P10)

> I think that's kind of interesting, because I'll see some of my friends...I know that they don't do anything mostly during the day but then they'll go out for a run and still get in a lot. I'm like, “Oh, other people do things different." (P30)

Participating in challenges was also mentioned as being highly motivating. Participants ascribed the competitive aspect of the challenge, where there is a clear winner, to their participation in "extra" activity or going above and beyond their normal activity behavior.

> I've been doing challenges. I think that's something that definitely encourages me too. I never want to finish last on those challenges. (P5)

> I like doing the challenges. I've noticed on the weekends, I'm a little more sedentary than I'd like to be. This weekend, I thought, 'Let's try one of these Weekend Warrior challenges.' I was talking to some of my co-workers, and we decided let's start this, so we did that. They added some of their friends. Just looking at everyone else's step count for that challenge and being super motivated, it made me have one of the most active weekends I can remember. (P25)

> Like I said, I'm a very competitive person, so it's definitely a good motivational tool. If I see that I'm in close competition with someone else in the challenge, I will definitely go take an extra walk, or go and do something extra. (P30)

Social Support

Social Support, both practical and emotional, was a commonly coded BCT for nearly all participants. One of the interesting themes that emerged within the domain of Social Support was the incorporation of physical activity (steps) as a shared social behavior within close-knit social ties, such as romantic partners and family members. When a close social group all had Fitbits and was connected as "Fitbit Friends" there was an ability to check on each other, prompt each other to be active, or offer other forms of support.

> My boyfriend has a Fitbit also, so usually I can get him to go for a walk at night if he hasn't hit his five miles yet. I can say, "Hey, we

> should go for a walk." He'll look at his thing and see he is only at, like, three miles, and he'll say "OK." Then, I just need him to stop watching TV and go with me. (P4)

> I actually got the one for my mom before I got this one and I wasn't wearing one at the time I gave her one. Then I was like now that she has one, I want to have one because I know there's a social dynamic there. I've never had an opportunity to have it with a family member, so that was another reason why at that moment I really wanted it. (P10)

> I would say nine times out of ten, I will always check the website, or the app, right after I get back, to see how I compare with the other people in my family, that day. Which isn't something that I would have done before I got it. I obviously wouldn't have called them and been like, "Hey, what did you do today?" I notice that. They do too. If my dad knows that he got a lot of steps one day, he'll either taunt me on the website, or he'll send me a text message, like, "Oh, I got this many steps today." It definitely has made us more aware. (P21)

> A lot of my co-workers have the Fitbit, too. We all got it together, and so we keep track of each other, too. We'll grab one another and go for a walk or I'll see how many my co-worker Kevin has and I'll be like, “All right, I'm going to beat him, so let's see how I'm going to do this." (P25)

As social connections can share their activity data through the Fitbit system, disruptions in normal patterns of behavior prompted participants to reach out using alternative communications systems (e.g. text messaging, phone calls).

> A friend who'd been really consistent dropped off. I actually sent her a little message saying, “Hey, you know, is everything OK?” She said, “Yeah." She went onto Africa on a safari and just decided not to take it." She said, 'I'm going to be off it for two weeks, and I'll pick it up when I come back.” It's like, “Oh, OK. Now I know." (P7)

> I do sometimes look at my coworkers competitively, but both these guys are animals. One's a very active soccer player, the other one's a trail runner who had routinely been getting well into the 120, 140 thousand steps a week kind of thing. He's dropped off lately. Though, I will say this. I saw him drop off so much that I called him to see if he was OK, because it was counter to his norm. (P18)

> Probably a month ago, or three weeks ago, or something, I had a friend that was always at the top of my list, and then she fell down further. I do it in a joking manner. I'm not doing it to be mean, or anything, but I say like, “What's happening? You're usually at the top of my list, and you fell down.” That type of thing. (P30)

These findings indicate that all individuals who use physical activity trackers may not engage with devices and its associated features and services in the same manner. The same feature, while directly related to a specific BCT, was used by participants in vastly different ways. Technique use, especially when employed as part of a self-directed effort to track and engage with one’s own physical activity was found to be quite nuanced as expressed by the current study’s participants.

DISCUSSION

Current research indicates that the use of behavior change techniques in health behavior interventions is related to positive outcomes. With the introduction of new devices and systems designed to track and engage people with their own health behavior it is important to understand if these same techniques are being applied by the individuals who use them and to what extent they are useful. The first hypothesis of this study was supported. The current study found that individuals who are long-term users of physical activity tracking devices use a variety of techniques connected to their engagement with the devices and it’s connected application(s). Regarding the second aim to determine if there was a relationship between BCT use and change in activity over time, the current study found limited support for the relationship between use of techniques included in the design the Fitbit system and positive change in daily steps or minutes of MVPA over time. Additionally, no support was found for the hypothesized positive relationship between the use of additional BCTs not included in the design of the Fitbit system and physical activity outcomes. Additional qualitative analysis of the use of BCTs indicated that individuals think about and use the same techniques in different ways and apply them in different contexts.

The Fitbit System and BCTs

The review of the Fitbit system (device, mobile application, website) at the time of this study found that it incorporates 17 of the 93 BCTs in the

BCTTv1. This is in contrast to the 20 BCTs found by Lyons and colleagues (2014) for Fitbit in their systematic review. Four techniques that focused on behavioral outcomes were removed, as they were not applicable to the current study. This study focused on the Fitbit system as a tool for tracking physical activity behavior, not a tool for tracking weight or other health outcomes associated with physical activity. One new BCT was identified during the current study's review, *Prompts/Cues* (under the *Associations* domain). This ability of the Fitbit mobile applications to prompt an individual to engage in physical activity through push notifications may not have been available when Lyons and colleagues (2014) conducted their review. The Fitbit system is not a static entity. Fitbit routinely updates features available to users through the mobile application and website. For example, a review of the version history of the Fitbit iOS application found a total of 18 updates for the nine-month period between April and December 2015. During the course of this study, Fitbit released two new tracking devices (Alta, Blaze) that were not evaluated in this study. These new devices may include features that correspond with BCTs that were not identified in the current study. Researchers who wish to conduct similar research on commercial physical activity tracking device systems must keep in mind the rapidly evolving nature of this field.

BCT Use among Users of Physical Activity Tracking Devices

As hypothesized, participants in this study employed a variety of behavior change techniques during the period of time they used the Fitbit system. Of the 93 techniques described in the BCTTv1 by Michie et al. (2015), participants in this study used 40 unique techniques. The three techniques that were coded as being present for all participants were *Goal-setting (behavior)*, *Feedback on Behavior*, and *Self-Monitoring of Behavior*. Each of these is built into the design of the Fitbit. Both the *Feedback on Behavior*, and *Self-Monitoring of Behavior* techniques are implicitly included in the design of any self-monitoring system, including pedometers, and physical activity tracking devices such as a Fitbit. The Fitbit automatically keeps track of a variety of data streams related to physical activity (self-monitoring), and presents that information (feedback) through device displays, the mobile application(s), and the Fitbit website. Additionally, the Fitbit automatically includes goals for physical activity. Upon initialization, a new user is automatically given goal corresponding to Steps (10,000 per day), Distance (5 miles per day), and Activity Minutes (30 minutes per day). A Floors Climbed goal is also set to 10 floors climbed per day if the Fitbit device supports floor tracking. All 30 participants reported interacting with at least one activity goal, most often steps per day.

The Relationship between BCT use and Physical Activity Behavior Change

The results of the multi-level model analysis did not support the hypothesis that there would be a positive relationship between BCT use and change in physical activity behavior over time. The lack of support for this hypothesis was surprising as the literature suggest that the inclusion techniques within the *Feedback and Monitoring* domain are related to successful physical activity change when employed as part of an intervention (Michie et al. 2009). The non-significant effect for most BCTs on activity outcomes may be due in part to the lack of variability in the use domains in the sample. This is especially evident at the domain level where all 30 participants had used at least one technique in two of the fourteen identified domain used by participants.

The models that took into account the number of techniques used by participants found that there was very little support for a positive dose-response relationship between technique use and change in physical activity outcomes over time. One of the final models found a complex interaction between the number of techniques used in the *Goals and Planning* domain and Time for the minutes of MVPA per day outcome. Predicted values indicated a negative dose-response, with the largest slope for minutes of MVPA per day over time when no techniques in the *Goals and Planning* domain are used. However, it may be the case that there are significant differences between the effects BCTs that are deployed as part of an intervention trial and the effects of BCTs that individuals choose to use. For instance, *Action Planning* was associated with significantly higher levels of physical activity in intervention studies (Williams and French, 2011). *Action Planning* is defined as "prompting detailed planning of the behavior that includes at least one of context, frequency, duration, or intensity (Michie et al. 2015). An intervention may include specific materials or employ a coach to provide the "details" for the action plan. In the current study, *Action Planning* was undertaken by the participant, without the presence of an intervention, and thus may not be as clear or detailed as those that are provided during interventions. An example of the use of a coded action plan in the current study is when participant 25 mentioned walking additional steps during their daily trip to the grocery store for lunch: "At lunch I'll go to Trader Joe's to grab a salad. I'll walk up and down the aisles so I can get extra steps."

There was no evidence to support the hypothesis that the use of BCTs that are not explicitly included in the design of the Fitbit system would be positively associated with change in physical activity (daily steps and daily minutes of MVPA) over time. In fact, in both three of the four final multi-level models there was a significant interaction between the use of the *Social Comparison* technique and Time. The interaction terms in these three models indicate that participants who used the *Social Comparison* technique had a predicted increase in activity outcome over time. Fitbit supports *Social Comparison* mainly through the use of leaderboards based on weekly activity and through competitions (challenges) that users can enter with friends. This effect should be interpreted with caution as the overwhelming majority of participants (28 of 30) in the sample reported using this technique.

A lack of support for the relationship between BCT use and change in activity over time may be related to the fact that participants in this study may not have had much room for improvement in the outcomes of interest. The average daily step count for all participants was approximately 9,700 and the average daily minutes of MVPA (occurring in bouts of at least 10 minutes) was 33 minutes. Both of these are higher than published values for adults derived from nationally representative datasets. According to data from the 2005-2006 NHANES US adults took an average of 6540 steps per day (Tudor-Locke, Johnson, and Katzmarzyk, 2010). Data from the 2003-2004 NHANES indicate that US adults participated in an average of 16.2 MVPA bout minutes per day (Metzger et al., 2008).

It is also important to understand the time-independent nature of BCT use observed in this study. This study was not designed to elucidate when, and how often, participants used specific techniques. However, participants may have used some techniques repeatedly while using others only once. For example, when participants engaged with *Social Comparison* actions, such as checking the leaderboard or participating in a challenge, they typically do so frequently throughout the course of a week (or the duration of a challenge). Other techniques may only be employed once or twice, such as *Review Behavior Goal(s)*. The frequency of use for specific techniques may be determined by inherent characteristics of the technique, if and how it is supported by the activity tracker system, or individual choice. It may be possible to design a future study that would gather data on BCT use prospectively throughout the duration of the study. For example, researchers may recruit very new users of activity tracker devices to participate, authenticate the study for prospective data access, and use a low-burden process to survey participants about their technique use. Researchers may also be able to partner directly with Fitbit in order to generate insights on specific feature use and activity over time from internal anonymous data sources.

Comparison & Competition: Two Side of the Same Coin?

Michie and colleagues (2013) state the BCTs are the smallest active ingredients of an intervention that aims to change behavior. Contextual analysis of participants' interview responses coded as being related to the *Social Comparison* technique revealed marked differences in employed behavior change processes that according to the BCTTv1 are the same technique. The act of engaging in comparison of behavior, in this case steps, was not found to always be associated with competitive behavior. Some participants in the sample reported using the activity comparison feature, a 7-day step leaderboard, to check their ranking and/or to see how their friends were doing (activity wise). It's important to not that these participants did not mention that these interactions prompted competitive behavior, such as a desire to "beat" their friends. However, many participants did use the leaderboard as a purely competitive feature, focusing on "winning" by having the highest 7-day step total among their friends or beating specific friends by having a higher step total. Interestingly, the Fitbit friend leaderboard does not a feature commonly associated with behavioral competitions: an end date. The leaderboard continually runs for as long as an individual is actively syncing their device. However, Fitbit has also recently introduced a purely competitive feature - challenges. Fitbit challenges encourage individuals to "see who can get the most steps" for the specific period of time (challenges can include 2 to 10 people). Challenges were described by participants as highly motivating, and in one case led a participant to achieve their highest daily step total. The BCTTv1 was intended to reflect a wide range of techniques that can be applied in behavioral interventions. It may be the case that the interventions that were reviewed in order to generate the taxonomy did not include any competition components, and thus social competition was not included in the BCTTv1. In the current study, competition appeared to be an effective BCT, and should be considered for future versions of the taxonomy.

Applicability of the BCTTv1 for Discretionary Use of Activity Trackers

The current version of the behavior change technique taxonomy is intended to describe the specific ingredients that are being deployed as part of health behavior interventions (Michie et al., 2013). To the author’s knowledge, this is the first study that has attempted to apply this taxonomy to describe what individuals do while they engage with behavior change tools, such as activity tracking devices. It is unclear if the current taxonomy covers all the available techniques that an individual might use during their activity tracker experience. As part of the coding process the author developed a process to redefine each observed BCT in reference to the self-directed nature employed by the participants. As mentioned above, the BCTTv1 may need to evolve to include additional techniques that capture real-world behavior change processes such as *competition*. Using a participants-centric rather than an intervention-centric frame of reference provides the health behavior science research community with an opportunity to more accurately examine what research participants do. Although additional work is needed in order to validate the application of the BCTTv1 for individual’s behavior, this study offers a template for that may help researchers understand what their intervention participants actually do when they take part in interventions that deploy specific techniques.

Communities of Activity

An interesting finding is the effect of having a network of close social ties that also use the Fitbit. Participants who mentioned co-workers, friends, and/or family members that also use Fitbit devices consistently spoke about the positive effect having these close ties who also had on their own behavior. This effect can be attributed to the introduction of practical support for physical activity behavior, as in the case of a couple deciding to start walking together in order to meet their step goals. Participants also reported communicating about activity behavior with their friends and family members, especially those who were connected within the Fitbit system. Communication took form of emotion support such as praise for reaching milestones, and sometimes as good-natured "trash talk" and taunting. Previous research found that there was insufficient evidence to recommend the use of family-based social support to improve physical activity (Task Force on Community Preventive Services, 2002). Since 2002, technically mediated social support has blossomed. As evidenced in the design of the Fitbit system, social connection and communication through the application and website is a key feature. Further investigation is necessary to determine if the use of these features, especially with individuals that have close social ties, impacts physical activity behavior.

Study Limitations

Participant Characteristics

Participants in this study tended to be highly educated and have a high total household income (median household income was $80,000 - $89,000). It is unclear if this sample is reflective of the greater population that is using physical activity tracking devices. To date no study has explored the demographic characteristics of individuals who use activity trackers.

Generalizability to Other Activity Tracking Systems

The current study recruited participants who used a Fitbit device. Even though the Fitbit is the most popular consumer physical activity tracking system (The NPD Group, 2016), there are many other devices currently being used by individuals to track and engage with their physical activity behavior. Individuals who use other devices, such as the Jawbone UP4, Withings Activité, or Apple Watch, may not use the same BCTs or have similar activity outcome trends as was observed in the current study. Different manufacturers may also deploy applications, websites, and/or device characteristics that are significantly different from the Fitbit system. Additional studies are needed to understand if the findings of the current Fitbit-specific study are more broadly applicable.

Weartime Classification

This study employed a rigorous weartime classification process designed to mimic the processes applied to studies using research grade accelerometers. To the author's knowledge, this is the first instance of applying a weartime classification algorithm to Fitbit data. Previous research involving interventions that included Fitbit devices described much simpler methods for classifying a day as valid or invalid. For example, Cadmus-Bertram and colleagues (2015) classified any day with at least 2,000 steps as being a valid day. The current study, using minute-level activity data to determine valid weartime, may have inappropriately classified valid days as invalid due technical limitations inherent in the design of the Fitbit device software. A Fitbit device contains onboard memory to store activity data at a per-minute resolution. However it is designed to only store minute-level data for a maximum of seven days. If an individual does not sync their device at least once every seven days then the minute-level data is deleted and only daily-level information is retained and reported to Fitbit during the next sync (Fitbit, n.d.). An exploration of the final Fitbit dataset used in the analysis uncovered 258 days (1.25% of all observed days) where participants recorded step counts, but no minute-level information was available and thus each of those days were marked invalid.

Coding Process

The author coded all interviews. Typically, multiple individuals undertake coding of qualitative data. When more than one coder is used to code the same material, the coders can discuss disagreements, identify unique themes or information, and provide a check on possible errors. As no additional coders were used, the author conducted multiple reviews of the qualitative data to refine the applied codes. Even after multiple reviews, there is still the possibility that the codes assigned to the qualitative data were misapplied. Future studies examining BCTs related to discretionary activity tracking device use should employ more than one coder to minimize possible error.

CONCLUSION

The current study indicated that individuals who freely choose to use physical activity tracking devices employ a variety of BCTs. The techniques used include those that are supported by the native design of the activity tracking system, as well as techniques that are not natively supported. A small, but significant negative trend was observed for change in daily steps and daily minutes of MVPA over time in the sample. Examination of the relationship between BCT use and change in activity (steps and MVPA) resulted in a complex set of interactions. The main findings of the multi-level-model analysis indicate that individual who engage in *Social Comparison* tend to increase physical activity outcomes over time. Additionally, higher education level was associated with a positive trend in daily steps over time. Analysis of the BCTs identified in this sample indicates that differences exist in how participants contextualize and use the same BCT. This was especially evident for *Goal-setting (Behavior)* and *Social Comparison*. This exploratory study provides the first examination of BCT use by individuals who freely choose to use physical activity tracking devices, and provided a proof of concept for a systematic mixed methods approach. The findings of this study may be used to inform future research on what might work for discretionary users of physical activity trackers as well as interventions that use physical activity trackers as part of a physical activity intervention.

APPENDIX A

Recruitment Material

Attention Men and Women: Do you have a Fitbit? Have you been using it for at least 3 months? Would you like to contribute to research designed to understand how people use commercial physical activity tracking devices?

UCSD researchers are conducting a new study to learn about how people use physical activity devices, like Fitbits, and engage with their activity data to understand their health and behavior.

You may be eligible to participate if you:

- Are between the ages of 19-60
- Own a Fitbit
- Have been using your Fitbit for at least 90 days (3 months)
- Are able to complete a 1 to 1.5 hour phone or web-based interview

Participants who are eligible for this study and consent to participate will be asked to participate in an in-depth interview about their experience with their Fitbit device and the data it collects. Participants will also be asked to authorize researchers to view their historical Fitbit data.

Participants will not be compensated for participating. Upon completion of the study participants will receive a copy of the data they contribute to this study including: interview transcript, survey answers, and Fitbit data. The principle investigator will also be available to describe the results of the research study over the phone or a web-based video conference.

If you are interested in participating, please contact Ernesto Ramirez at (480) 225-0002 or erramirez@ucsd.edu.

This study is being conducted under the direction of Dr. Kevin Patrick, MD, MPH, Principal Investigator, Department of Family and Preventive Medicine, University of California, San Diego 9500 Gilman Drive, Dept. 0811, La Jolla, CA 92093 Phone: 858-663-0531.

This study is partially funded by the Robert Wood Johnson Foundation as part of the Health Data Exploration Project.

University of California, San Diego
Consent to Act as a Research Subject

STUDY TITLE
Self-Directed Physical Activity Tracking (SDPAT): Understanding Use and Implications of Wearable Activity Devices.

Who is conducting the study, why you have been asked to participate, how you were selected, and what is the approximate number of participants in the study?
Ernesto Ramirez, MS, a student in the Department of Family and Preventive Medicine within the School of Medicine, is conducting a research study to find out how people use physical activity tracking devices. You have been asked to participate in this study because you expressed interest in participating and you meet the study criteria. There will be approximately thirty (30) participants in this study.

Why is this study being done?
The purpose of this study is to examine how individuals engage with and use their physical activity tracking device and the data the device gathers in their everyday life. Additionally, this study is seeking to use a combination of subjective and objective data to explore and define the types of individuals who use physical activity tracking devices.

Who is funding this study?
This study is being funded as part of the Health Data Exploration Project in the Center for Wireless and Population Health Systems at the University of California, San Diego. This study is being funded by the Robert Wood Johnson Foundation.

What will happen to you in this study\?
If you agree to be in this study, you will be asked to participate in all of the following activities:

- **Interview (part one)** – During the first part of the interview you will be asked to answer questions about your demographic background, your thoughts and feelings about your physical activity, and about your past physical activity behavior.
- **Interview (part two)** – During the second part of the interview you will be asked about your experiences with your Fitbit device. This will include questions about your daily usage, you thoughts and emotions related to your use of the device and its mobile/web applications, and how you think about the information it collects.
- **Fitbit Data Authorization** – You will be asked to authorize the research staff to access and download your historical Fitbit data. This

authorization will not require you to give your password or other personal information to the research staff. You will be directed to secure system (Fitabase) that will allow you to sign in with your Fitbit login and authorize the research staff to download your data. After you complete the interview described above the research staff will delete your authorization so that any data you collect after you complete the interview will not be collected. Research staff will access and download the following data gathered from your Fitbit account:

- **Daily steps total**
- **Measured steps per minutes**
- **Estimated energy expenditure**
- **Distance moved**
- **Minutes of vigorous activity**
- **Minutes of moderate activity**
- **Minutes of light activity**
- **Minutes of sedentary time**
- **Sleep length, quality, and movement**

What is involved with the Fitabase Authorization?
In order to access your Fitbit data you will be asked to authorize a third party, Fitabase Services, owned and operated by Small Steps Labs LLC, via an online form. Fitabase is a research platform that collects data from internet connected consumer activity devices. In order to authorize Fitabase to collect and store your Fitbit data you will connect Fitabase to your Fitbit account. This is done in order to gather you historical information for quantitative analysis of you physical activity. Fitabase, upon your authorization, will collect:

- Personal details added to your Fitbit user account, such as height, weight, gender, and age.
- Information sent wirelessly from your Fitbit product to the service and that is stored in your Fitbit user account.
- Information that was added manually to the Fitbit service and is stored in your Fitbit user account.
- Accounts of when a you elected to share data from your Fitbit user account with others.
- GPS route and location data for saved activities
- Minute-level data reported by devices including:
    - Number of steps taken
    - Calories burned
    - Intensity of movement metrics
    - Sleep data and times of awakening
    - Weight
    - Body fat percentage
    - Heart rate

- Any manually reported food or exercise information provided to Fitbit.com.
-

Your Fitbit username and password will not be accessed, viewed, or stored by Fitabase, Small Steps Labs, LLC, or any study personnel.

When you authorize Fitabase to access and store your Fitbit data you are agreeing to the Terms of Use and Privacy Policy set by Fitabase. A copy of those Terms of Use and Privacy Policy will be given to you. We ask that you review both the Terms of Use and Privacy Policy before agreeing to participate in this study. If you have any questions about your privacy and the Fitabase system please contact the Principle Investigator, Ernesto Ramirez, at erramirez@ucsd.edu or (480) 225-0002.

If you decide to forgo participation in any of the above activities (Interview Part One, Interview Part Two, or the Fitbit Data Authorization) you will be removed from the study and any data contributed will be deleted or destroyed.

How much time will each study procedure take, what is your total time commitment, and how long will the study last?
The activities will be completed during a phone call or web-based interview session using Skype or another online video-calling system. In total the above procedures will take a total of 1.5 hours. The first part of the interview including survey questions will take approximately 30-45 minutes. The second part of the interview that asks about Fitbit specific thoughts and emotions will last approximately 45 minutes. The Fitbit authorization will take approximately 5 minutes.

What risks are associated with this study?
Participation in this study may involve some added risks or discomforts. These include the following:

1. A potential for the loss of confidentiality. We will attempt to employ the following procedures to maintain confidentiality:
    a. We will not record your name or link identifiable information to the data. After conducting the interview, we will transcribe the audio recording and remove any personally identifiable information from the transcript.
    b. Research data will be stored electronically on a laptop computer in an encrypted file or stored electronically on a secure server in an encrypted file with password protection. The audio recordings will also be stored in a secure location; then transcribed as soon as possible and erased within six (6) months of the end of the study.

c. We will keep your contact information for no more than 6 months after conducting the interview. Your contact information will not be linked to the interview recording or transcript and will be stored separately.
d. The researchers intend to keep the anonymized research data in a repository indefinitely. Other researchers may have access to the data for future research. Any data shared with other researchers will not include your name or other personal identifying information.
e. To ensure the confidentiality of data and participant information, all study participants will be de-identified and will receive a study identification number, which will be used for data tracking. Data collected over the phone, via web-based calls, in-person, and through Fitabase will be transferred to a study database on a secure server at UCSD. All files containing identifiable information, including the linked file with participant's name, contact information, and study ID number will be stored in locked cabinets. Only key study personnel will have access to the password-protected database.

2. Research records may be reviewed by the UCSD Institutional Review Board.

3. The possible risks and/or discomforts associated with the procedures described in this study include anxiety, embarrassment, and invasion of privacy.

4. As we will be conducting interviews to inquire about physical activity behavior and experiences there is a possibility that you will become embarrassed or may not be comfortable answering questions. You may experience shame, remorse, or discomfort due to recalling previous behaviors such as the inability to meat goals or periods of low activity. We will attempt to mitigate potential psychological distress due to boredom, feelings of discomfort, or other psychological discomfort by creating an open and inviting dialogue with you during the survey and interview process. You may stop at any time and resume the interview (if desired) at a future time. You may also refuse to answer any interview or survey question. Doing so will not affect your eligibility to participate in this study.

5. There is a risk that employees of the Fitabase service may access your Fibit data, including information you post or add to your Fitbit account. This data is only associated with your unique study identifier. Additionally your data will be deleted from the Fitabase system (both online and backup servers) at the completion of this study. Fitabase

also employs robust security and encryption. For more details please read the Fitabase Security and Privacy Information sheet provided to you.

Because this is a research study, there may also be some unknown risks that are currently unforeseeable. You will be informed of any significant new findings.

Will my data be shared with others?
Yes, the data you contribute to this study will be retained and made available to other researchers and entities interested in understanding Fitbit data, physical activity measurement device use, or other similar research questions. Only anonymized transcripts, surveys, and matched and anonymized Fitbit data will be retained and made available to others. Any data shared with other researchers and other entities will not include your name or other personal identifying information.

Will I be able to access the data I contribute to this study?
You will be contacted via email after the principal investigator, Ernesto Ramirez, completes the study in order to return a copy of the data you contributed to this research study. This will include a copy of your transcribed interview (parts one and two), and copy of your Fitbit data. Ernesto Ramirez will also make himself available for a phone call or web video conference for at least 30 minutes upon returning a copy of your data in order to answer questions about your data and the study findings. **You are not required to take part in this post-study call if you are not interested**.

Data collected during the course of this study and returned to you are not for treatment or diagnosis, and data findings will only reflect your physical activity levels. Questions regarding your physical activity status should be discussed with a physician.

What are the alternatives to participating in this study?
The alternative to participation in this study is to not participate.

What benefits can be reasonably expected?
There may or may not be any direct benefit to you from participating this study. The investigator, however, may learn more about how individuals use and experience self-directed physical activity measurement and society may benefit from this knowledge. The results of this research have the potential to generate new methods for understanding physical activity behavior and the role of technology for understanding and impacting health behaviors. There is the potential that this research will inform future generations of devices and applications that may positively impact you as well as many future users of similar devices and applications.

Can you choose to not participate or withdraw from the study without penalty or loss of benefits?
Participation in research is entirely voluntary. You may refuse to participate or withdraw or refuse to answer specific questions in an interview or on a questionnaire at any time without penalty or loss of benefits to which you are entitled. If you decide that you no longer wish to continue in this study, you will be required to contact the Principle Investigator, Ernesto Ramirez, at erramirez@ucsd.edu or (480) 225-0002.
You will be told if any important new information is found during the course of this study that may affect your wanting to continue.

Can you be withdrawn from the study without your consent?
The PI may remove you from the study without your consent if the PI feels it is in your best interest or the best interest of the study. You may also be withdrawn from the study if you do not follow the instructions given you by the study personnel.

Will you be compensated for participating in this study?
You will not be compensated for participation.

Are there any costs associated with participating in this study?
There will be no cost to you for participating in this study.

What if you are injured as a direct result of being in this study?
If you are injured as a direct result of participation in this research, the University of California will provide any medical care you need to treat those injuries. The University will not provide any other form of compensation to you if you are injured. You may call the Human Research Protections Program Office at (858) 657-5100 for more information about this, to inquire about your rights as a research subject or to report research-related problems.

Who can you call if you have questions?
Ernesto Ramirez, MS has explained this study to you and answered your questions. If you have other questions or research-related problems, you may reach Ernesto Ramirez at 480-225-0002.

You may call the Human Research Protections Program Office at (858) 657-5100 to inquire about your rights as a research subject or to report research-related problems.

Your Signature and Consent
You have received a copy of this consent document.

You agree to participate.

APPENDIX B

Fitabase Authorization Page
SDAT Study

About
Thank you for agreeing to participate in the UCSD "Self-Directed Physical Activity Tracking" (SDPAT) study.

Ernesto Ramirez, MS, a student in the Department of Family and Preventive Medicine with the School of Medicine, is conducting this research study to find out how people use physical activity tracking devices. You have been asked to participate in this study because you meet the study criteria.

You will be asked to authorize the research staff to access and download your historical Fitbit data. This authorization will not require you to give your password or other personal information to the research staff.

You are being asked here to authorize Fitabase, a product of Small Steps Labs, LLC, to access and store your Fitbit data. This is done in order to gather you historical information for quantitative analysis of you physical activity. Fitabase, upon you authorization will collect:

- personal details added to a Fitbit user account, such as height, weight, gender, and age.
- information sent wirelessly from your Fitbit product to the service and that is stored the Fitbit user account.
- information that was added manually to the Fitbit service and is stored in the Fitbit user account.
- accounts of when a Fitbit user elected to share data from their Fitbit user account with others.
- minute-level data reported by devices including:
    - number of steps taken
    - calories burned
    - intensity of movement metrics
    - sleep data and times of awakening
    - weight
    - body fat percentage
    - heart rate
    - and any manually reported food or exercise information provided to fitbit.com.

For the purposes of this study only the following data will be accessed and downloaded for analysis:

- **Daily steps total**
- **Measured steps per minutes**
- **Estimated energy expenditure**
- **Distance moved**
- **Minutes of vigorous activity**
- **Minutes of moderate activity**
- **Minutes of light activity**
- **Minutes of sedentary time**
- **Sleep length, quality, and movement**

When Fitabase accesses your Fitbit data it will not be associated with your name, email address, or any other identifying information. It will be associated with a unique study identifier.

When the research staff has completed downloading your Fitbit data your authorization will be deleted from the Fitabase system so that research staff will not be able to access your data. Upon completion of the study all Fitbit data associated with the study will be deleted from the Fitabase servers.

You can request your data be removed from analysis at any time. If you would like to do so, or have any questions about this research study please contact the Principle Investigator, Ernesto Ramirez, at erramirez@ucsd.edu or (480) 225-0002.

Terms
By completing this authorization you are agreeing to the Fitabase Terms of Use and Privacy Policy. Both the Terms of Use and Privacy Policy will also be supplied to you as part of your consent documentation.

You can review the Fitabase Terms of Use here:
https://www.fitabase.com/Terms

You can review the Fitabase Privacy Policy here:
https://www.fitabase.com/Privacy

If you have any questions about your privacy and the Fitabase system please contact the Principle Investigator, Ernesto Ramirez, at erramirez@ucsd.edu or (480) 225-0002.

APPENDIX C

Interview Guide

Key:

- I = Intent
- Q = Main Question
- P = Probing Question

I*: Encourage participants to talk freely about their personal experience with physical activity and physical activity tracking in a more open-ended, non-threatening manner.*

Q1: What is your favorite type of exercise?

P1: Reasons why it is their favorite / why they enjoy it

I: *Broad opening to discussing tracking and tracking behavior.*

Q2: Tell me about the kind of things you track for your health?

P2a: How do you track these (what kind of tools or apps do you use)?

P2b: If more than one health metric/outcome tracked - Which of these is most important to you? Why?

I: *Generate information about physical activity behavior.*

Q3: Tell me about your physical activity? What do you do to be active?

P3a: How does tracking play a role in your activity (behavior)?

P3b: Are there activities that you don't track? Why?

I*: Develop understanding of Fitbit use/thoughts.*
Use setup to orient participant: Now we're going to talk specifically about your experience with your Fitbit.

Q4a: How do you use your Fitbit?

Q4b: What does a typical day for your look like in terms of your Fitbit experience?

P4a: How often do you open the app on your phone? Website? Use notifications?

P4b: Do you track anything other than steps?

Q5: What parts of the Fitbit app do you use the most?

P5a: How many Fitbit friends do you have?

P5b: Have you participated in any challenges?

P5c: How often do you message your Fitbit friends?

I: *Understand data and behavior.*

Q6: What do you think about the data Fitbit gives you?

P6a: Do you trust the data? *or* Do you think it's accurate?

P6b: Have you ever done anything with your data like downloaded it or connected it to another app?

I: *To develop understanding of actual activity behavior recall and goals.*
Setup: We're going to get a bit more specific now about your actual data and goals.

Q7: Tell me about your best step/activity day. What happened that day?

Q8: How important are your daily activity goals?

P8a: How often do you think your meet your goals?

P8b: Have you ever changed your goals?

Q9: What does it mean to you when you reach your goal?

P9: What about when you don't?

I: *Generate higher-level perceptions of Fitbit usefulness.*

Q10: If you think about your entire Fitbit experience, what have you learned?

P10a: What have you learned since you started using your Fitbit?

I*: Missing insights and information*

Q11: Is there anything else you'd like to share about your Fitbit experience?

APPENDIX D

Steps per Day Figures

Note: For all figures included in Appendix A the red dashed line indicates the mean value for steps per day.

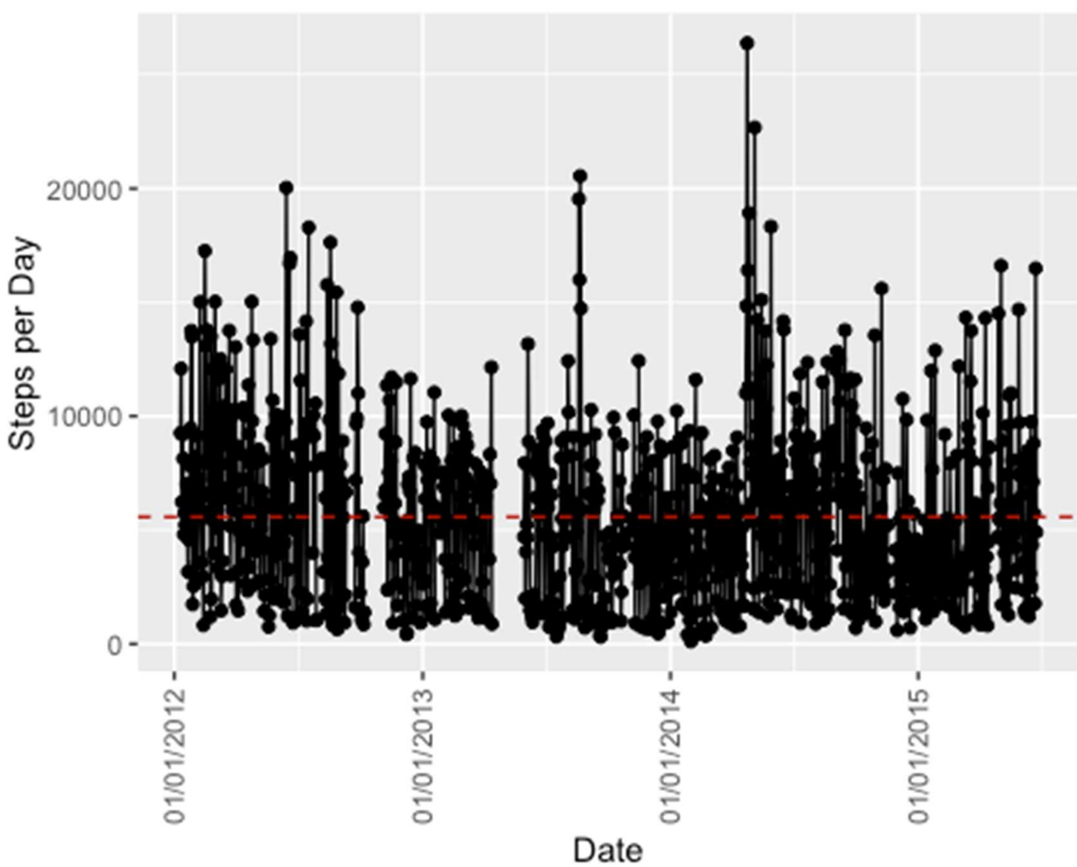

Figure A1. Steps per Valid Day: Participant 1

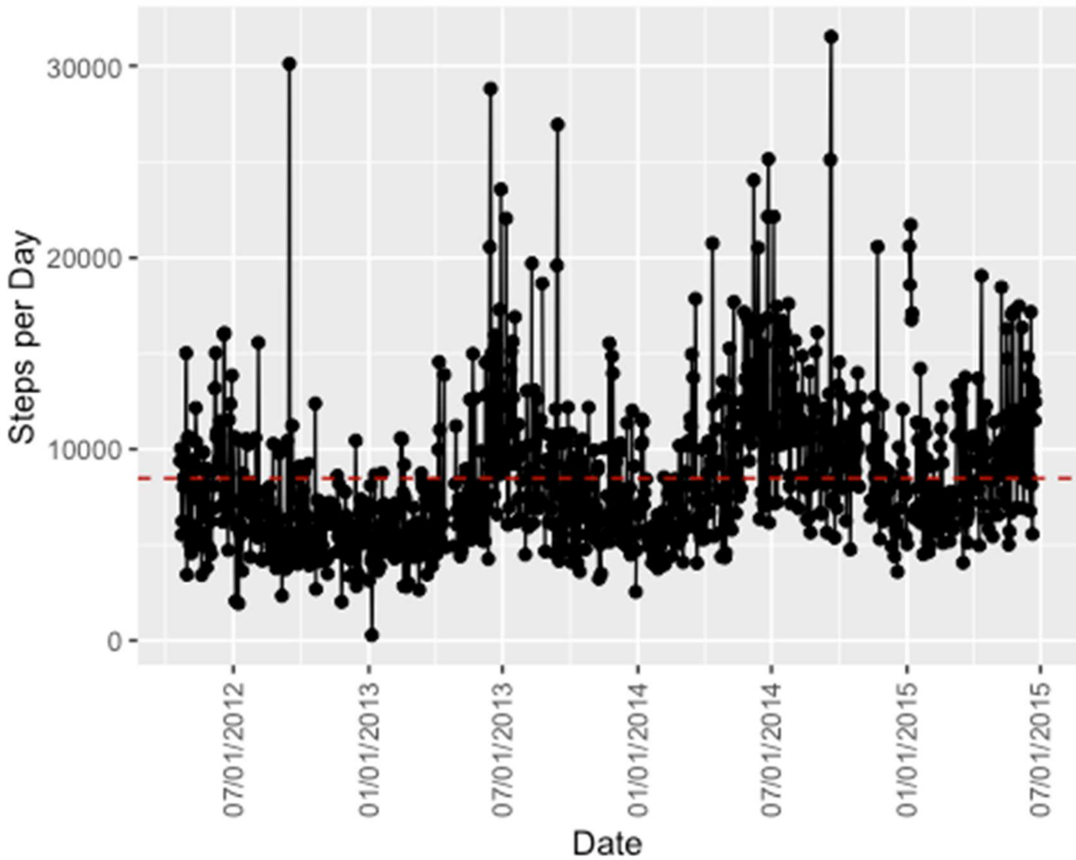

Figure A2. Steps per Valid Day: Participant 2

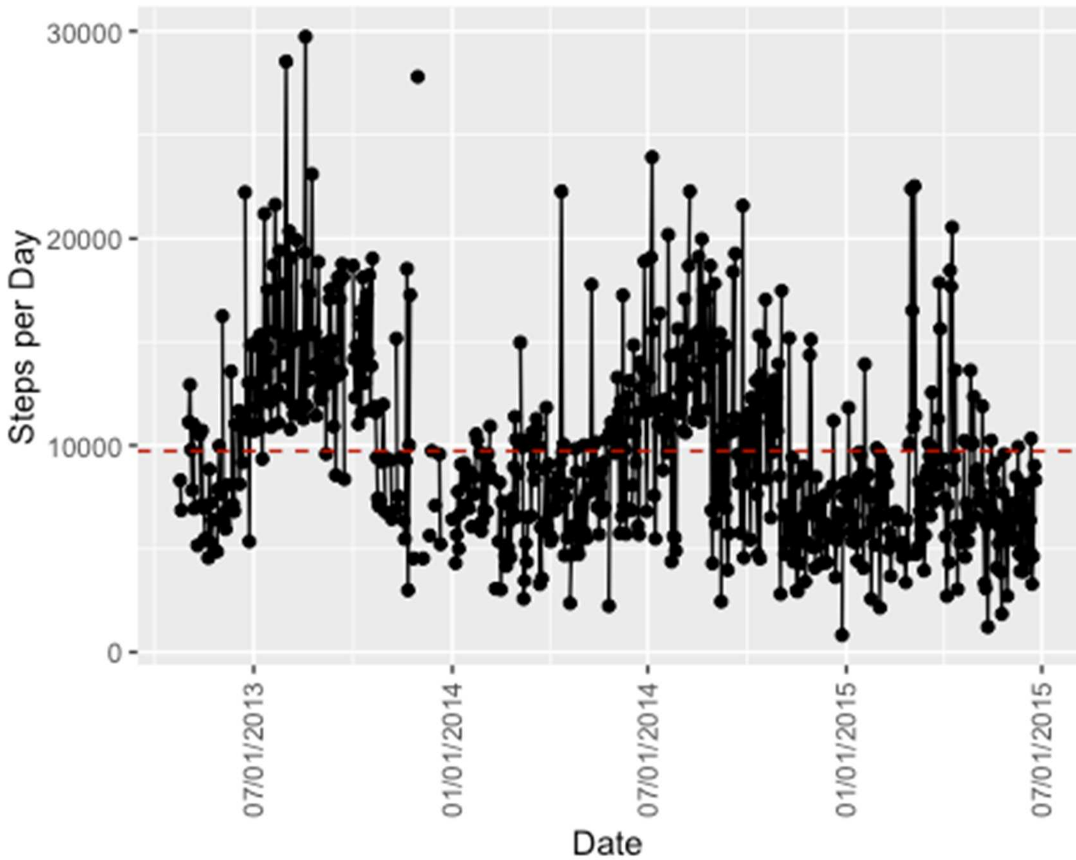

Figure A3. Steps per Valid Day: Participant 3

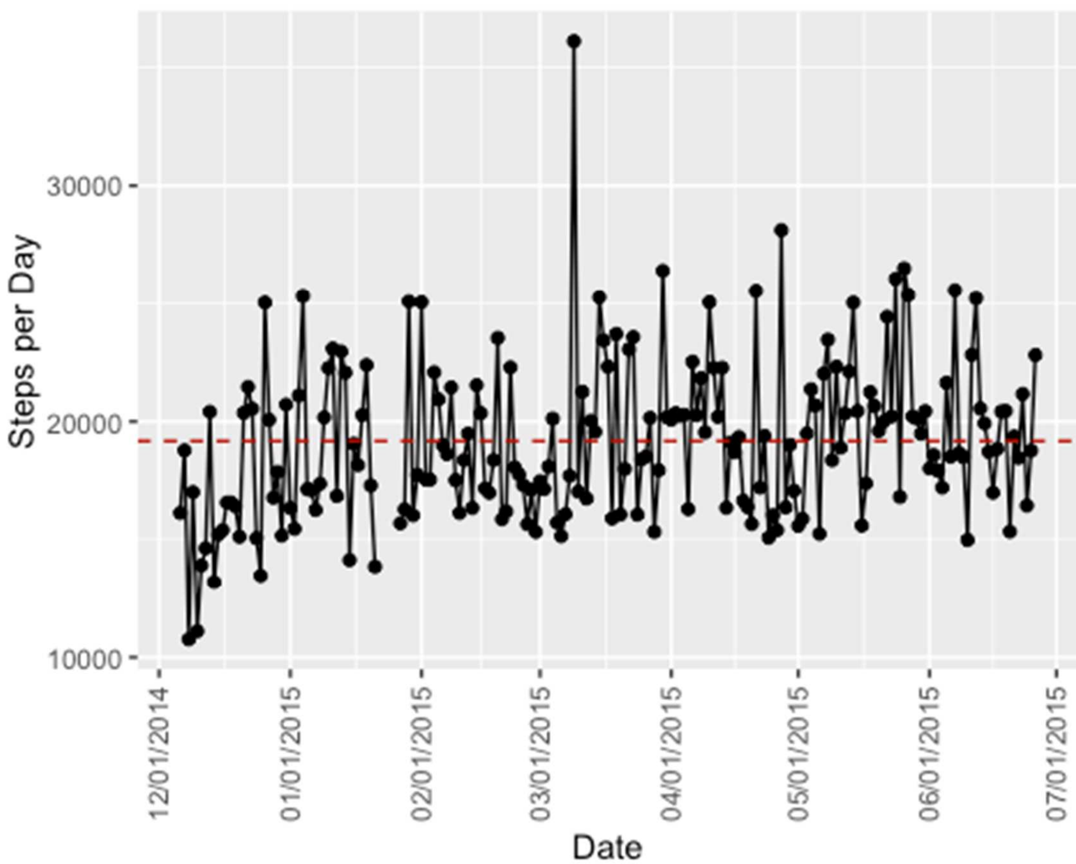

Figure A4. Steps per Valid Day: Participant 4

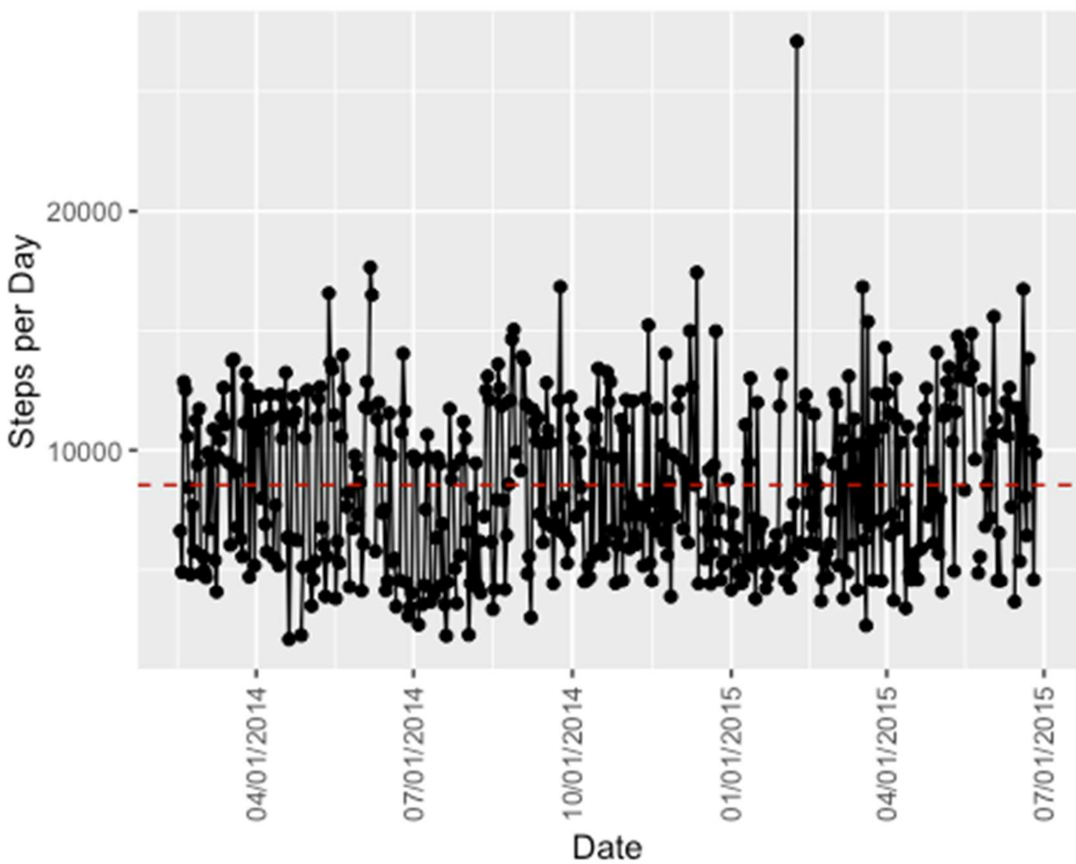

Figure A5. Steps per Valid Day: Participant 5

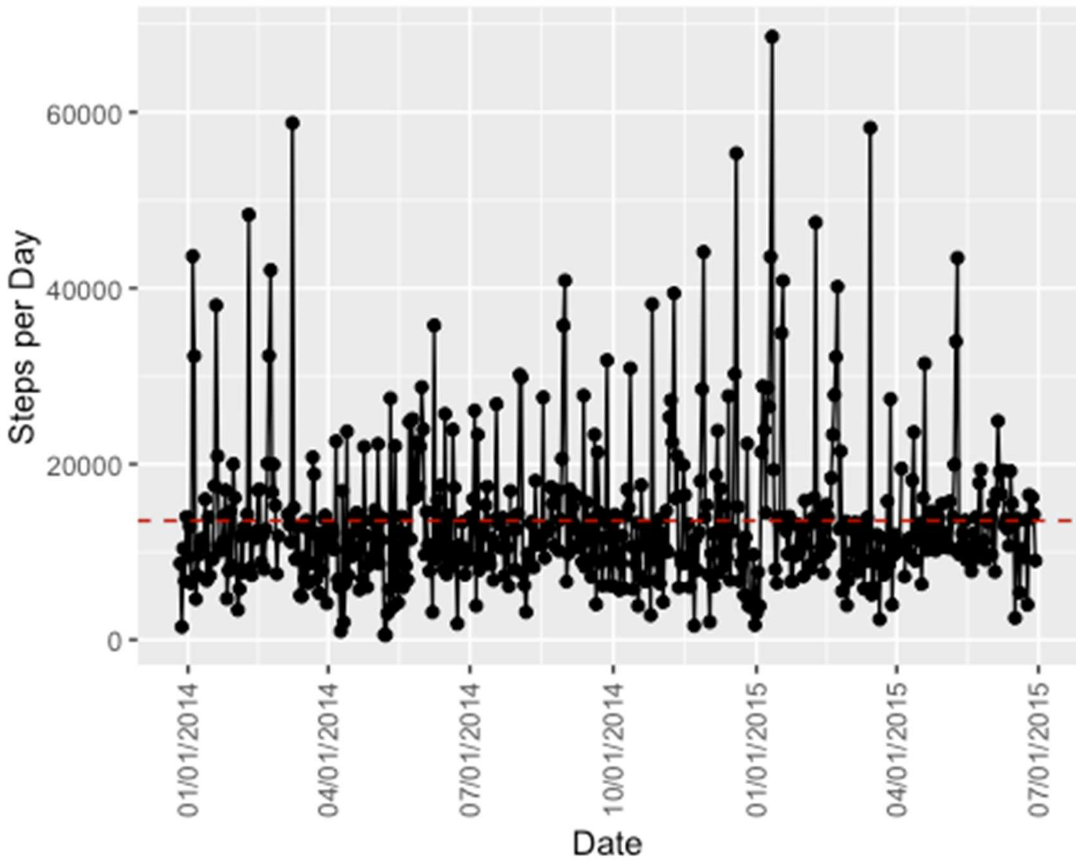

Figure A6. Steps per Valid Day: Participant 6

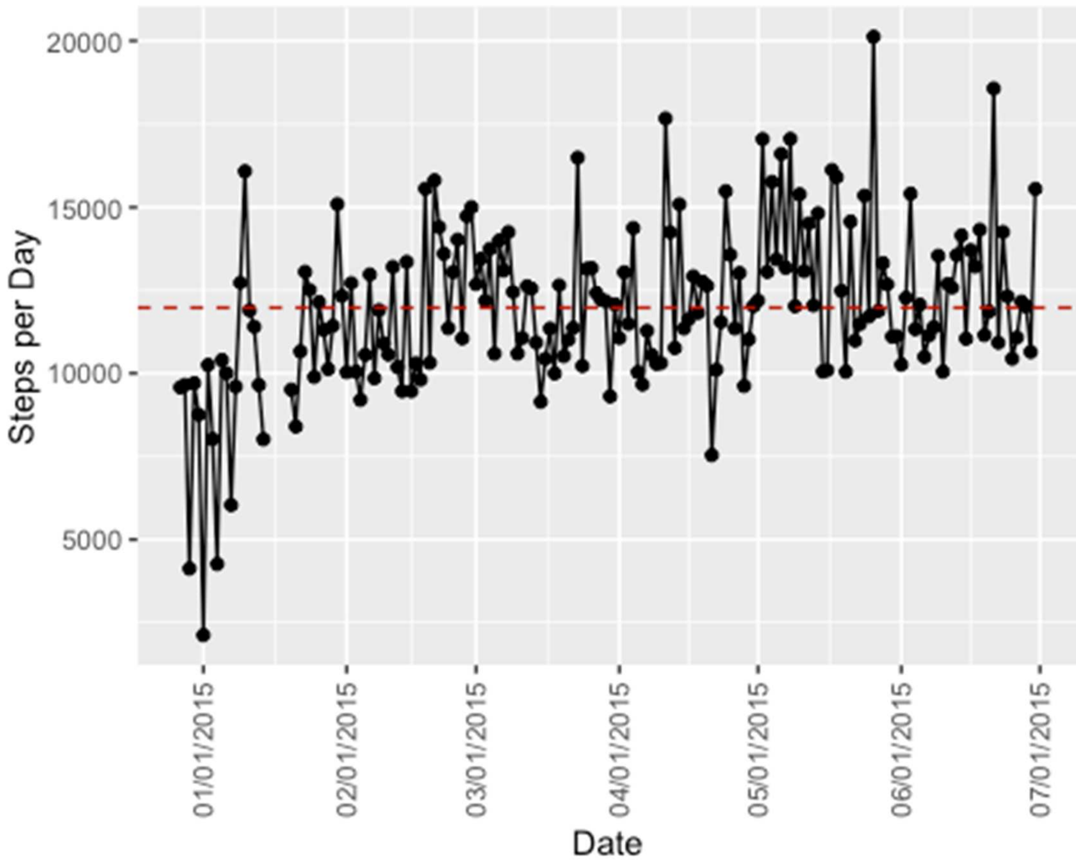

Figure A7. Steps per Valid Day: Participant 7

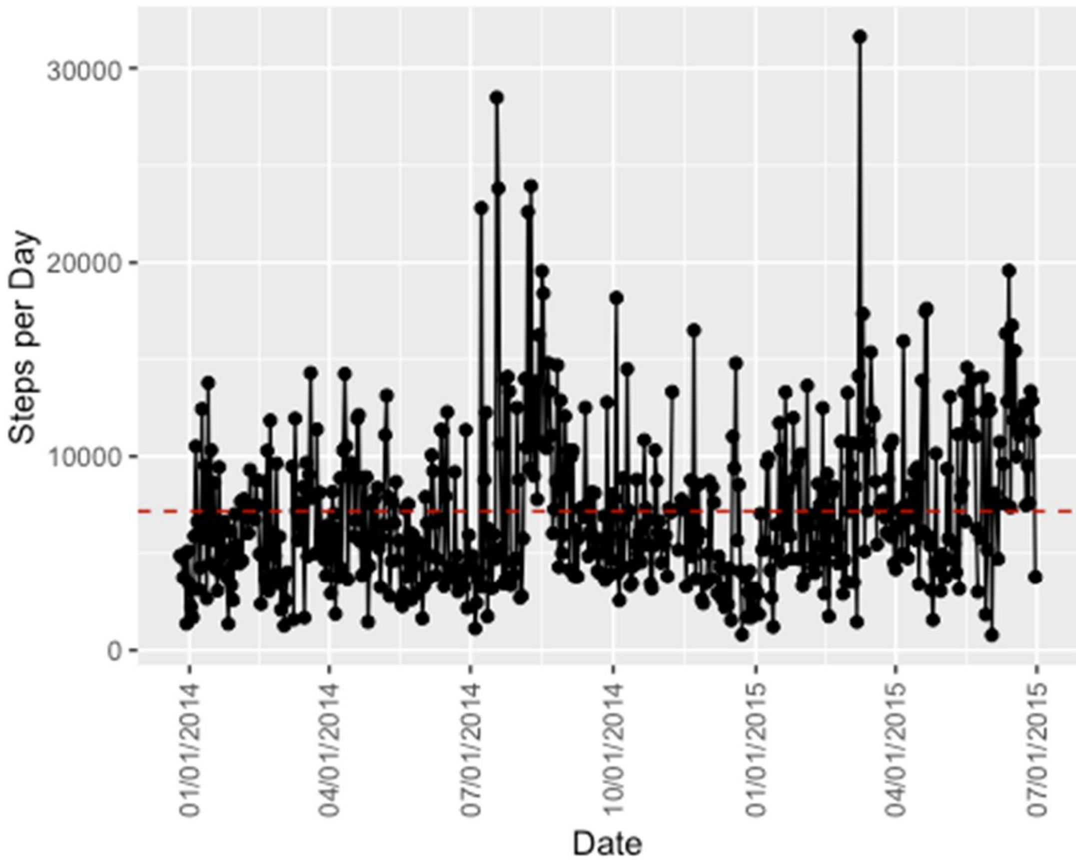

Figure A8. Steps per Valid Day: Participant 8

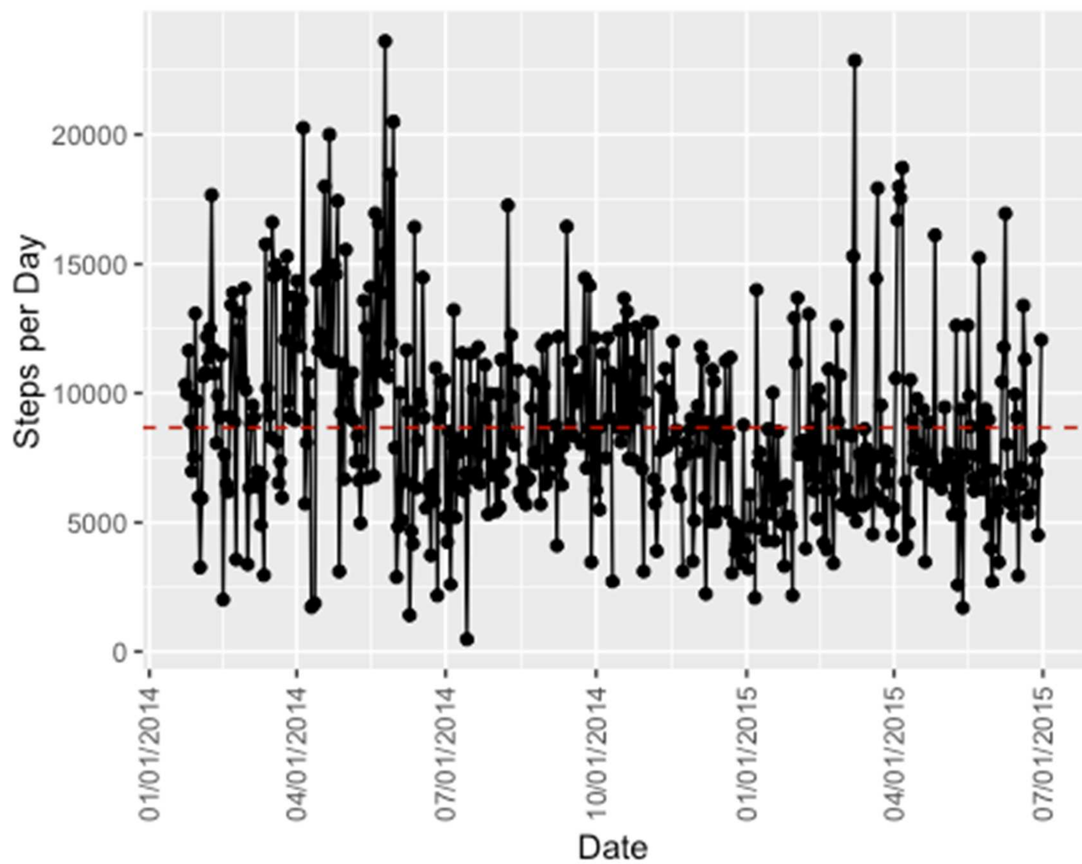

Figure A9. Steps per Valid Day: Participant 9

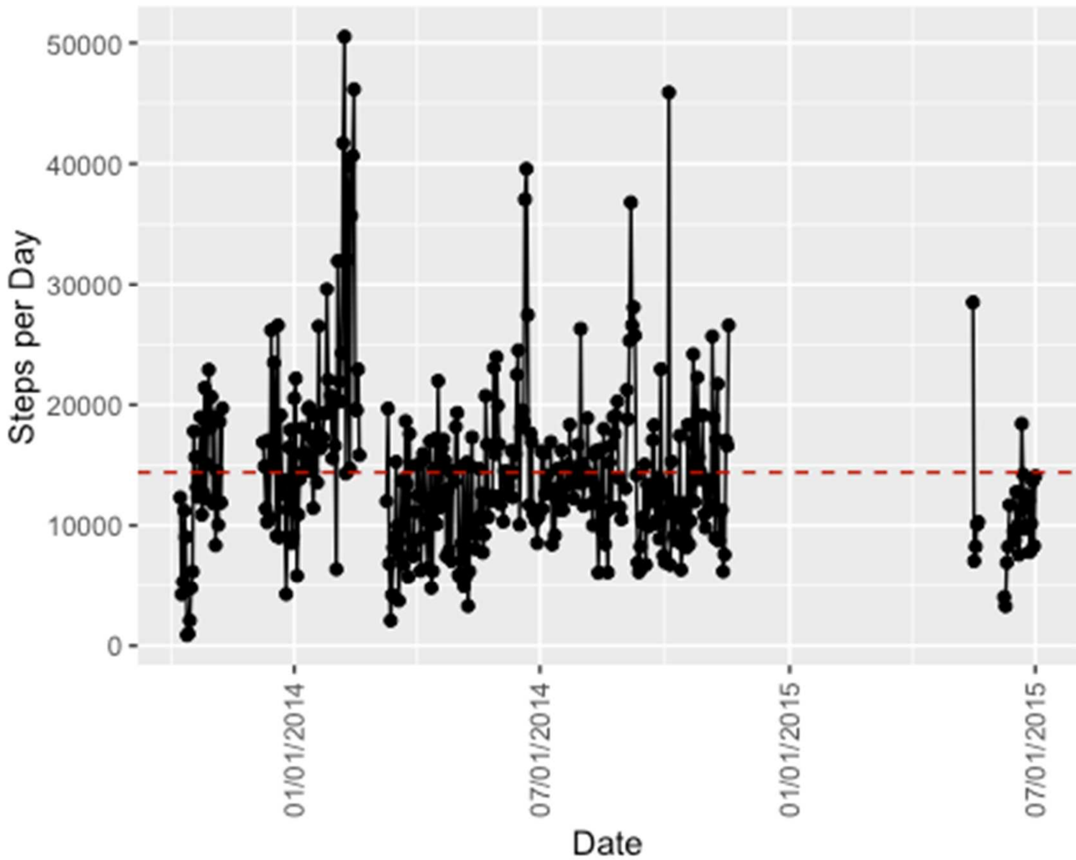

Figure A10. Steps per Valid Day: Participant 10

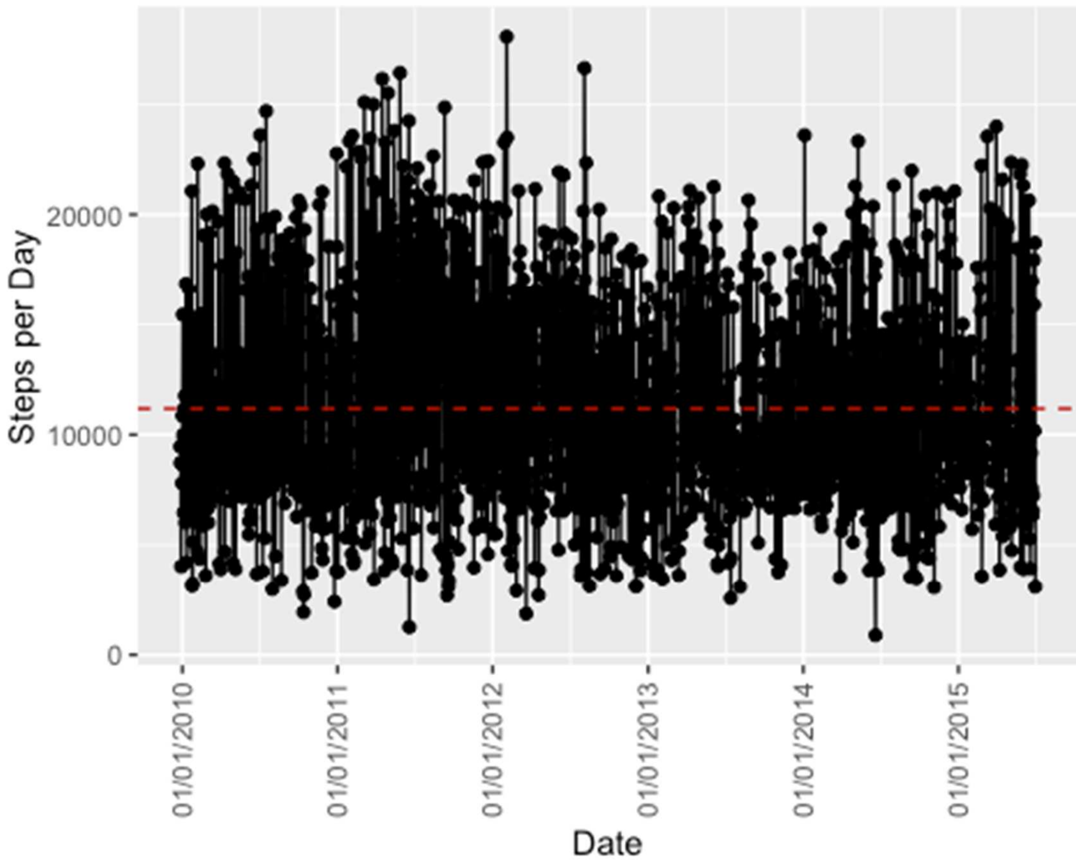

Figure A11. Steps per Valid Day: Participant 11

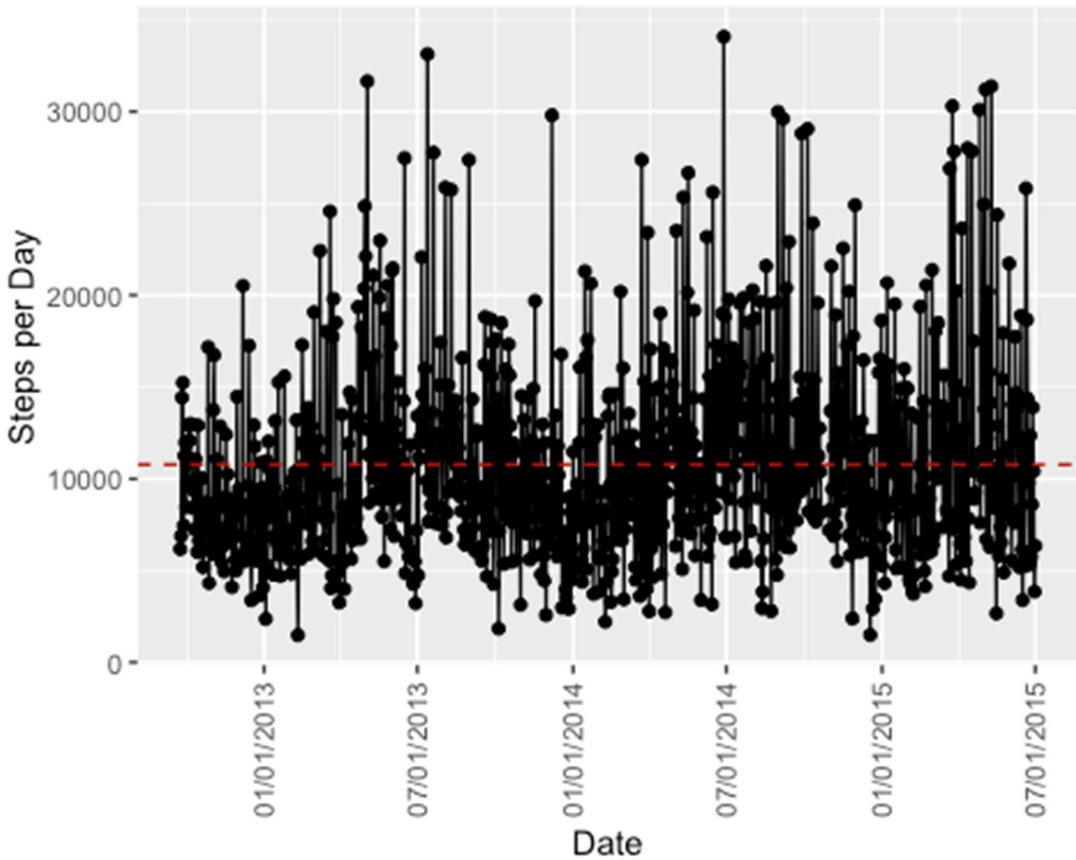

Figure A12. Steps per Valid Day: Participant 12

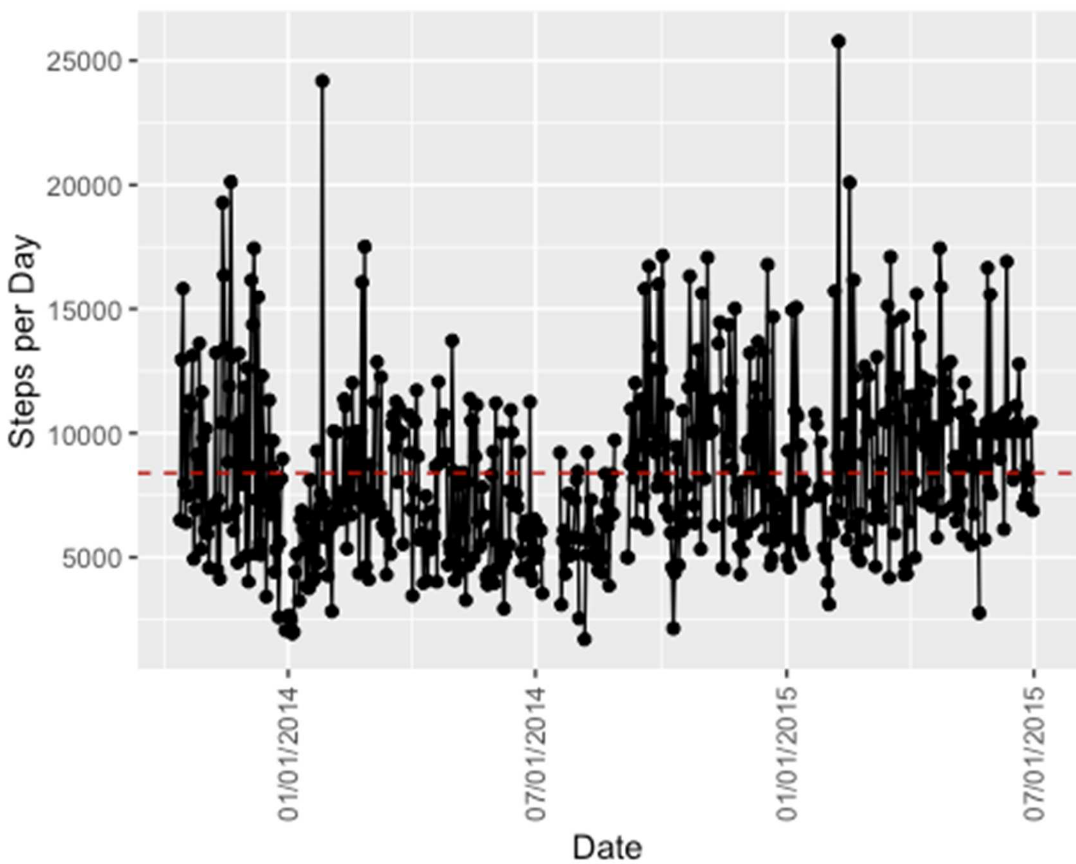

Figure A13. Steps per Valid Day: Participant 13

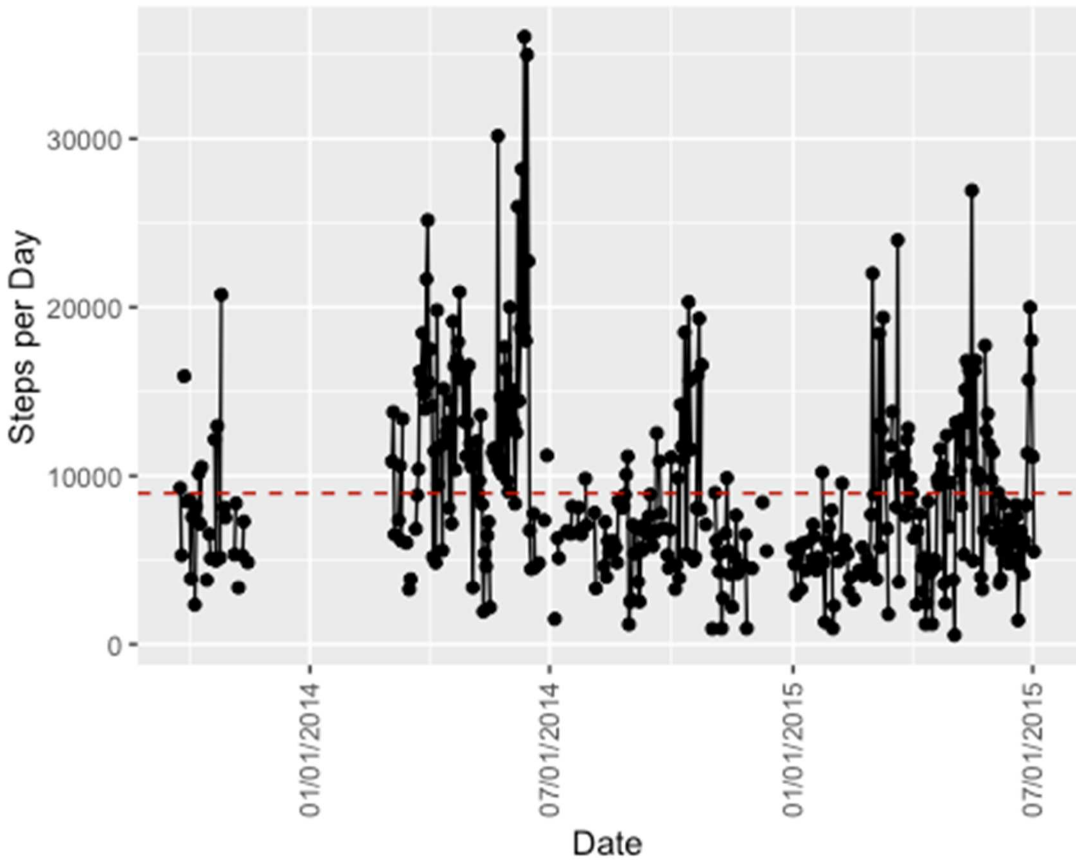

Figure A14. Steps per Valid Day: Participant 14

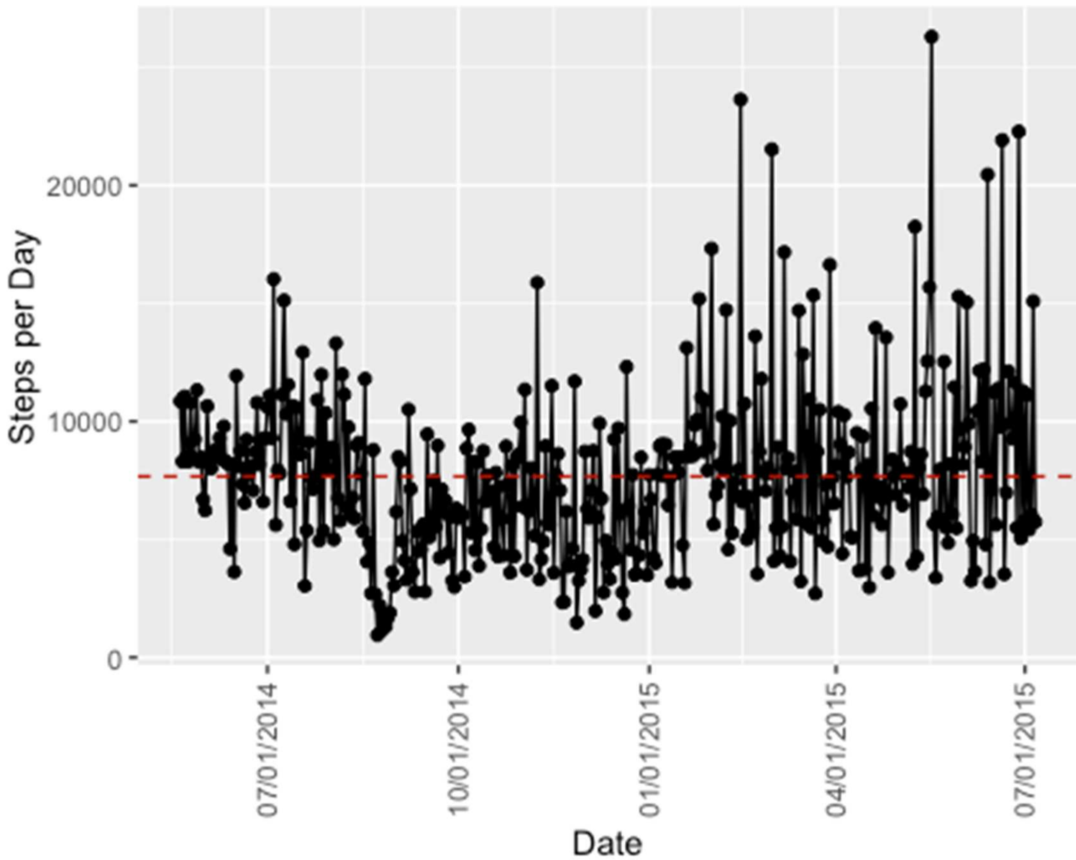

Figure A15. Steps per Valid Day: Participant 15

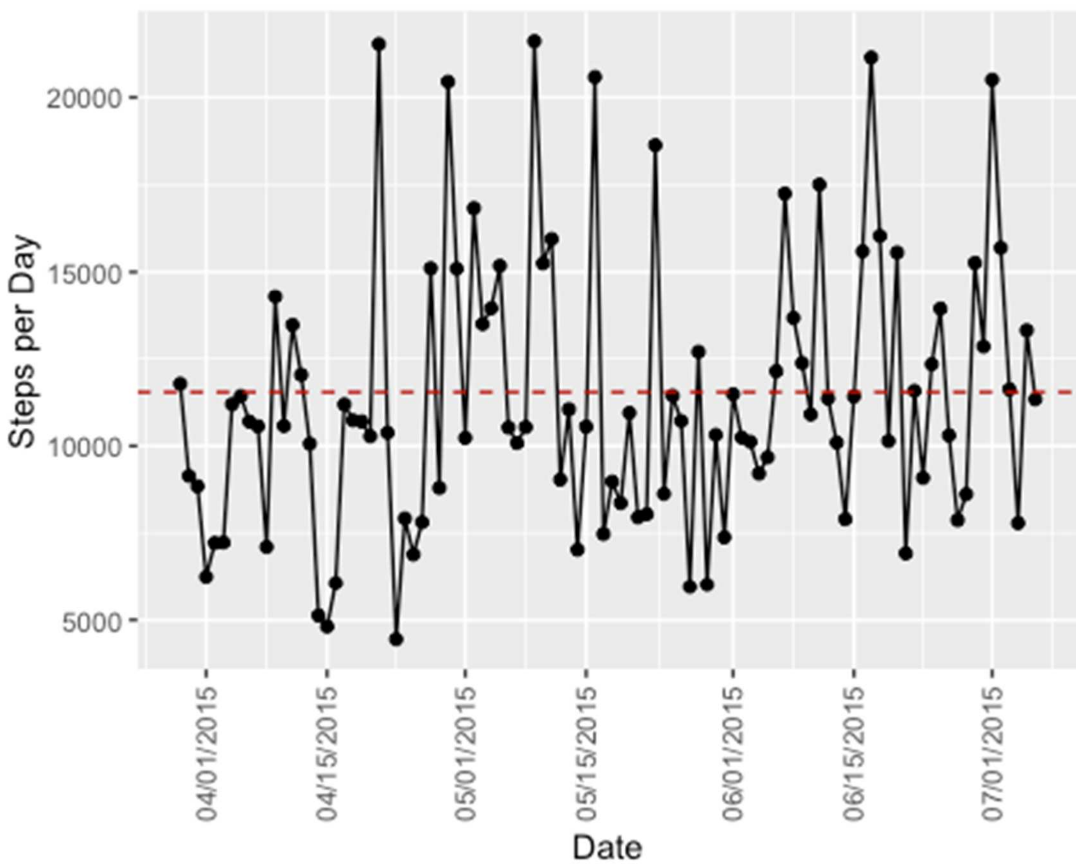

Figure A16. Steps per Valid Day: Participant 16

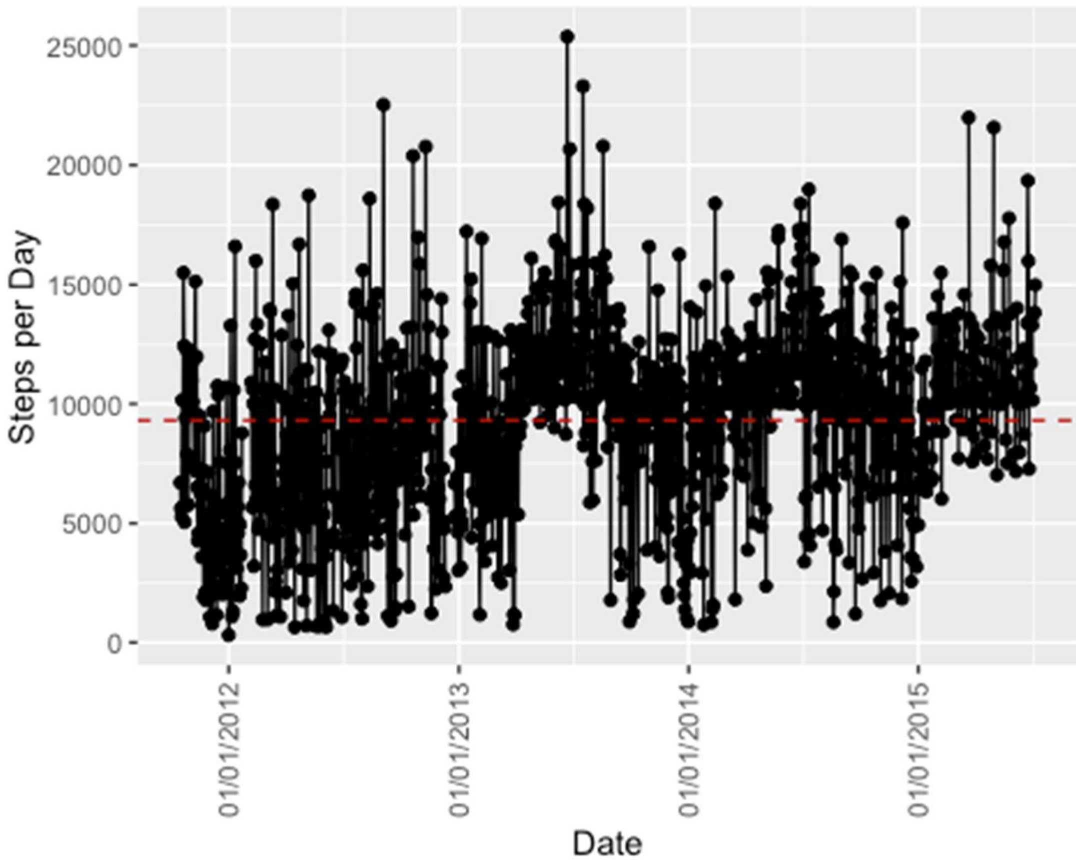

Figure A17. Steps per Valid Day: Participant 17

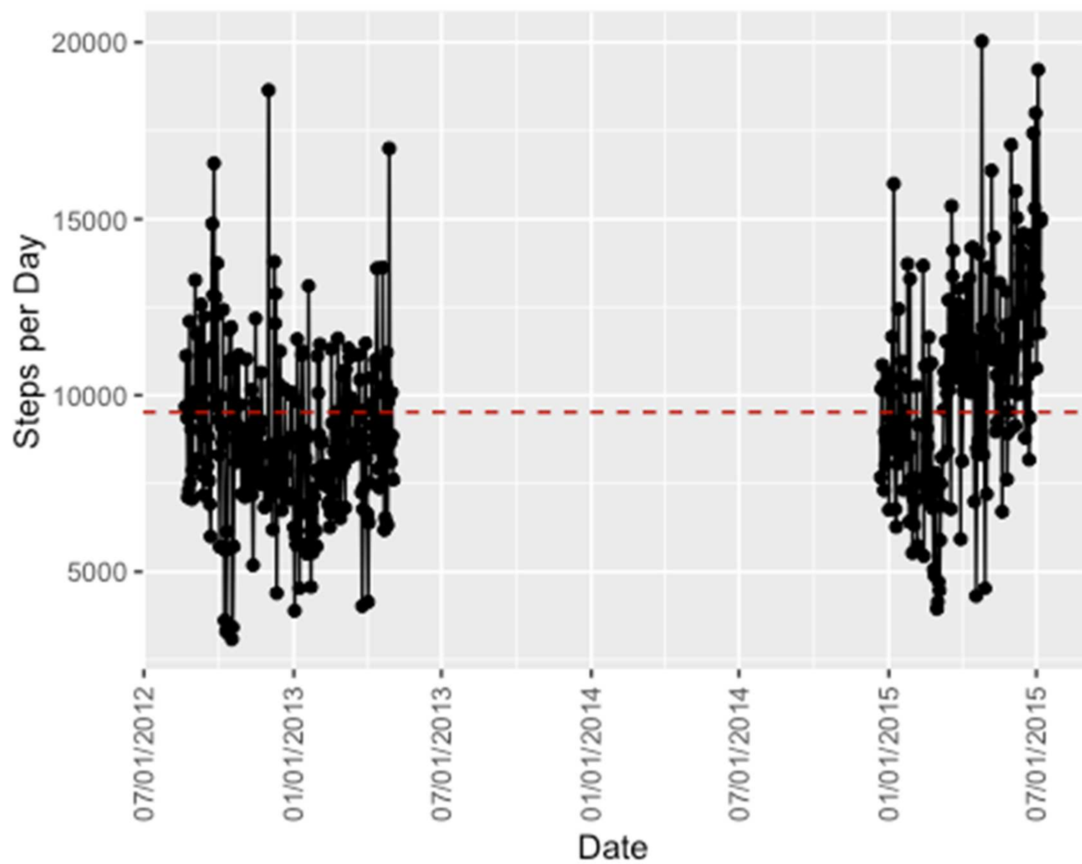

Figure A18. Steps per Valid Day: Participant 18

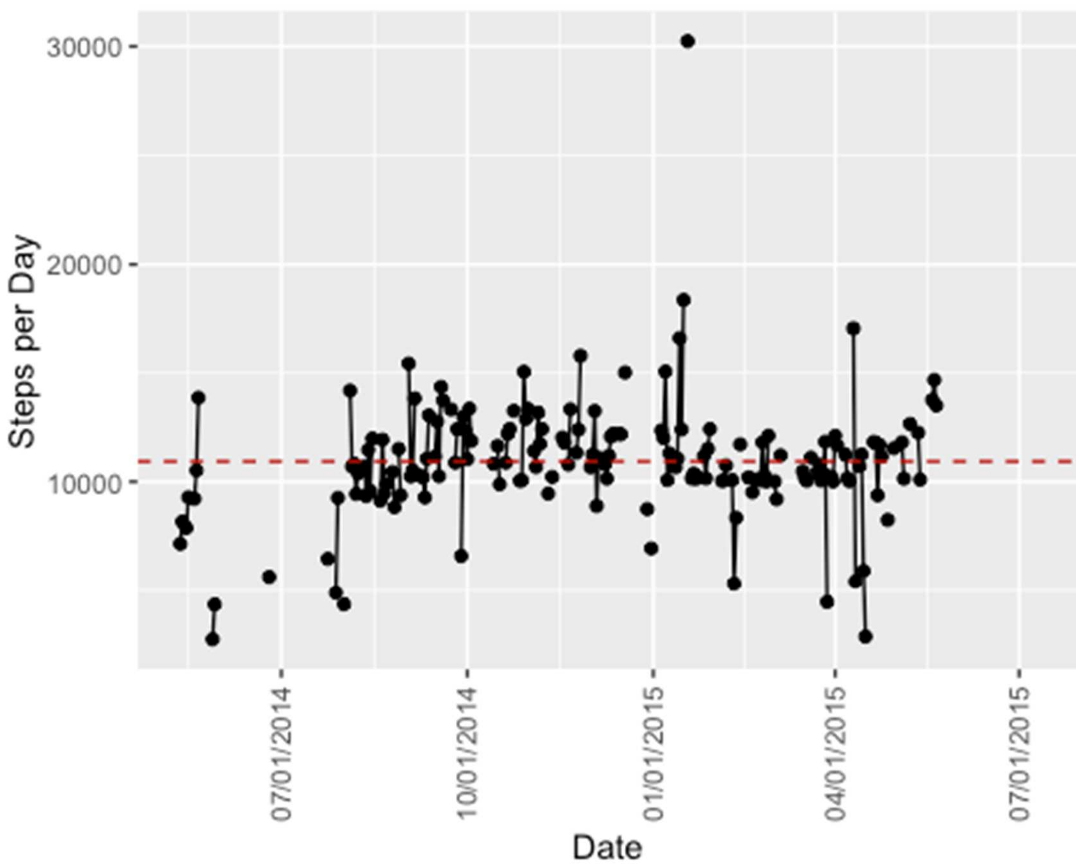

Figure A19. Steps per Valid Day: Participant 19

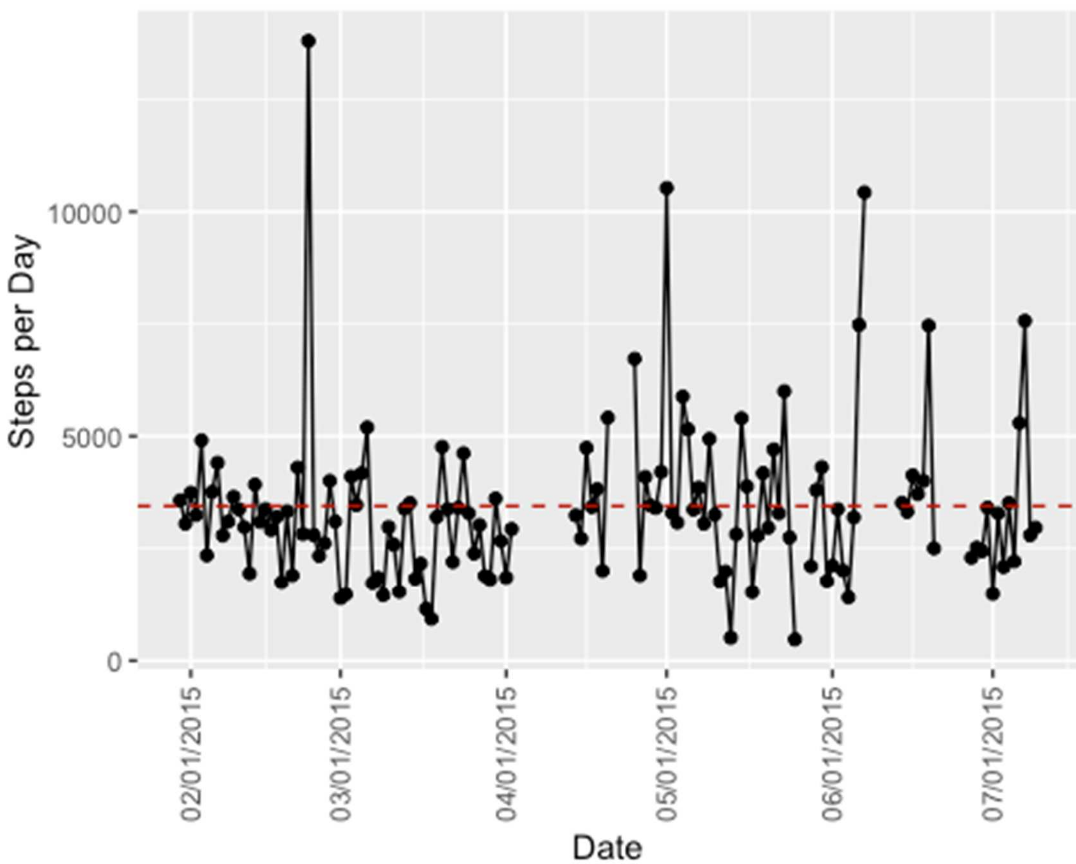

Figure A20. Steps per Valid Day: Participant 20

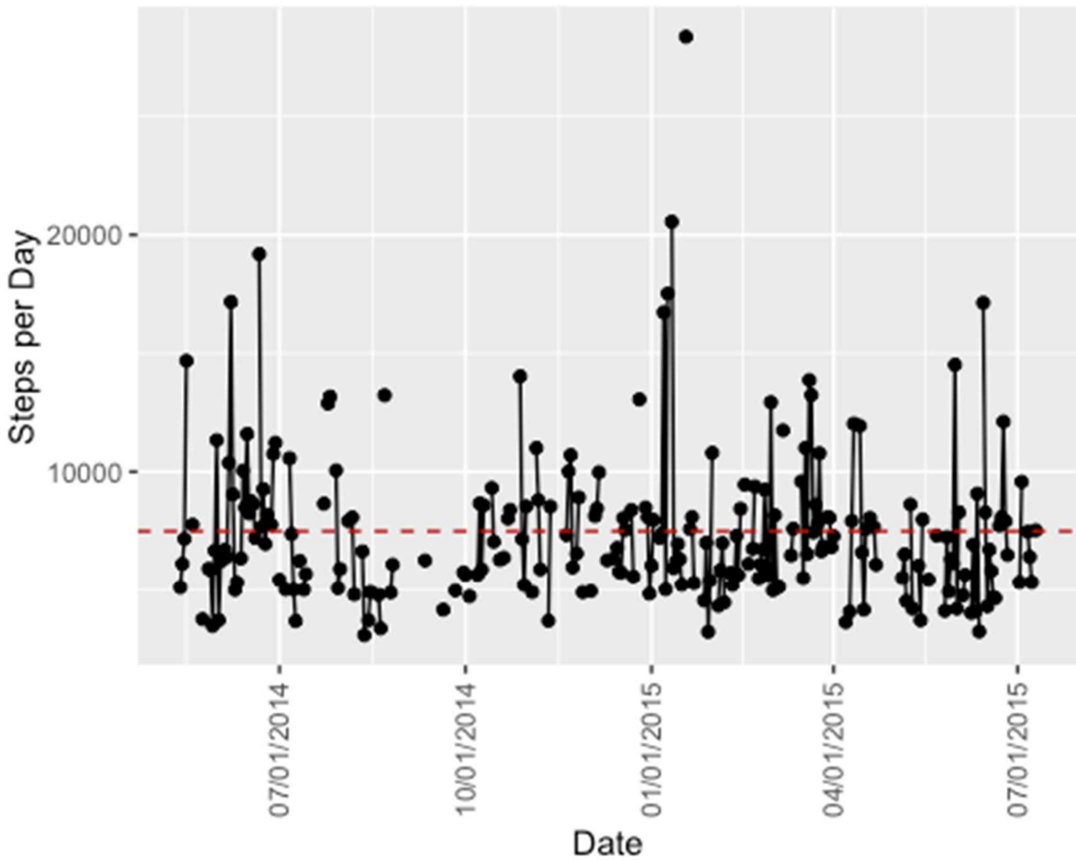

Figure A21. Steps per Valid Day: Participant 21

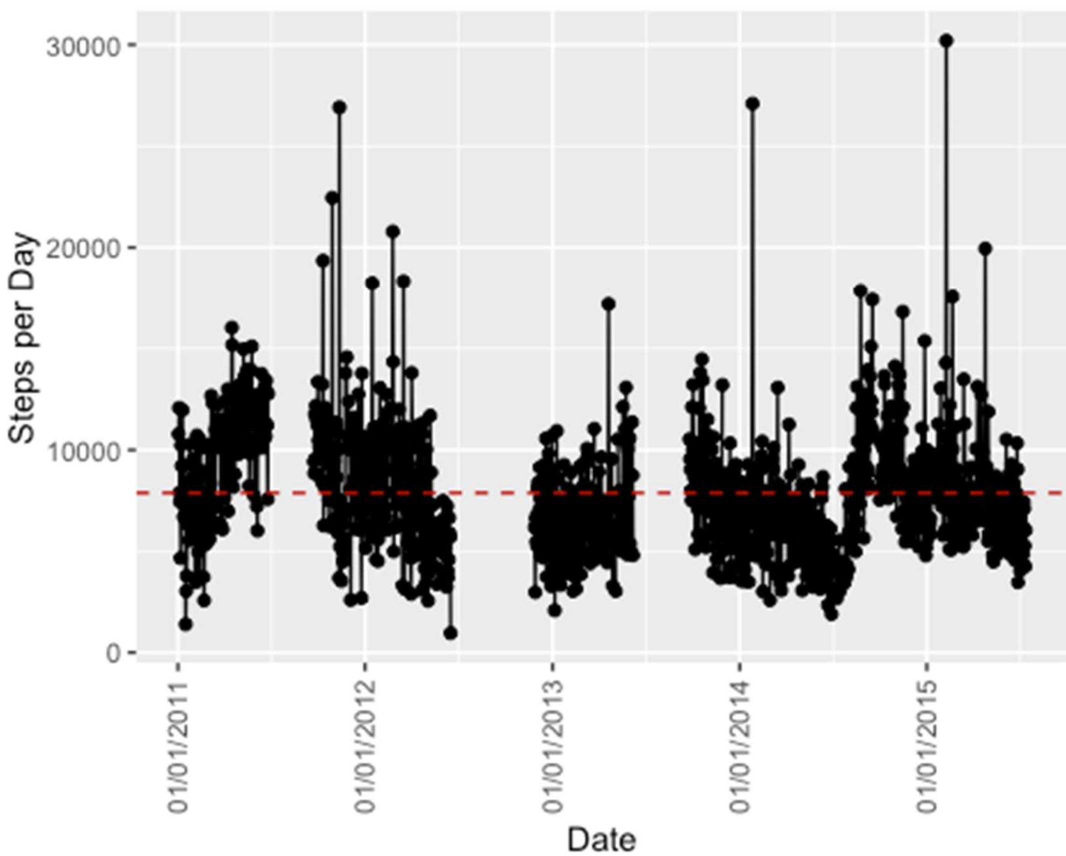

Figure A22. Steps per Valid Day: Participant 22

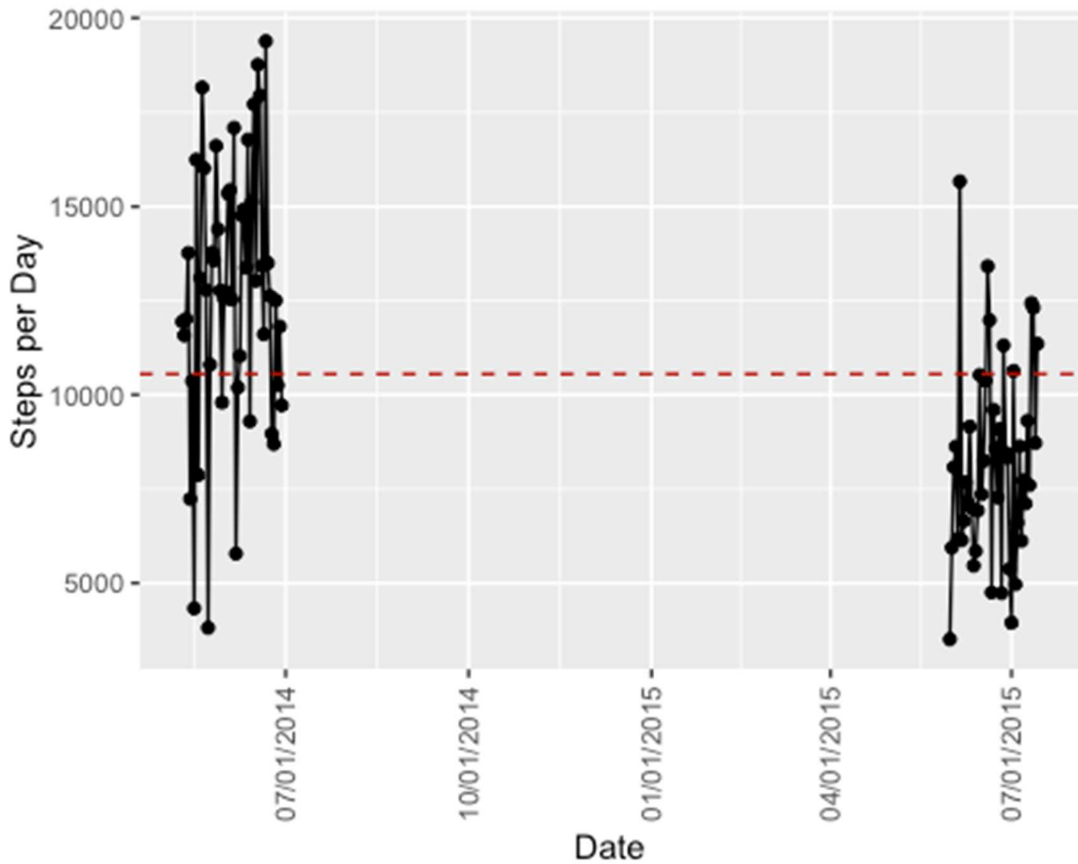

Figure A23. Steps per Valid Day: Participant 23

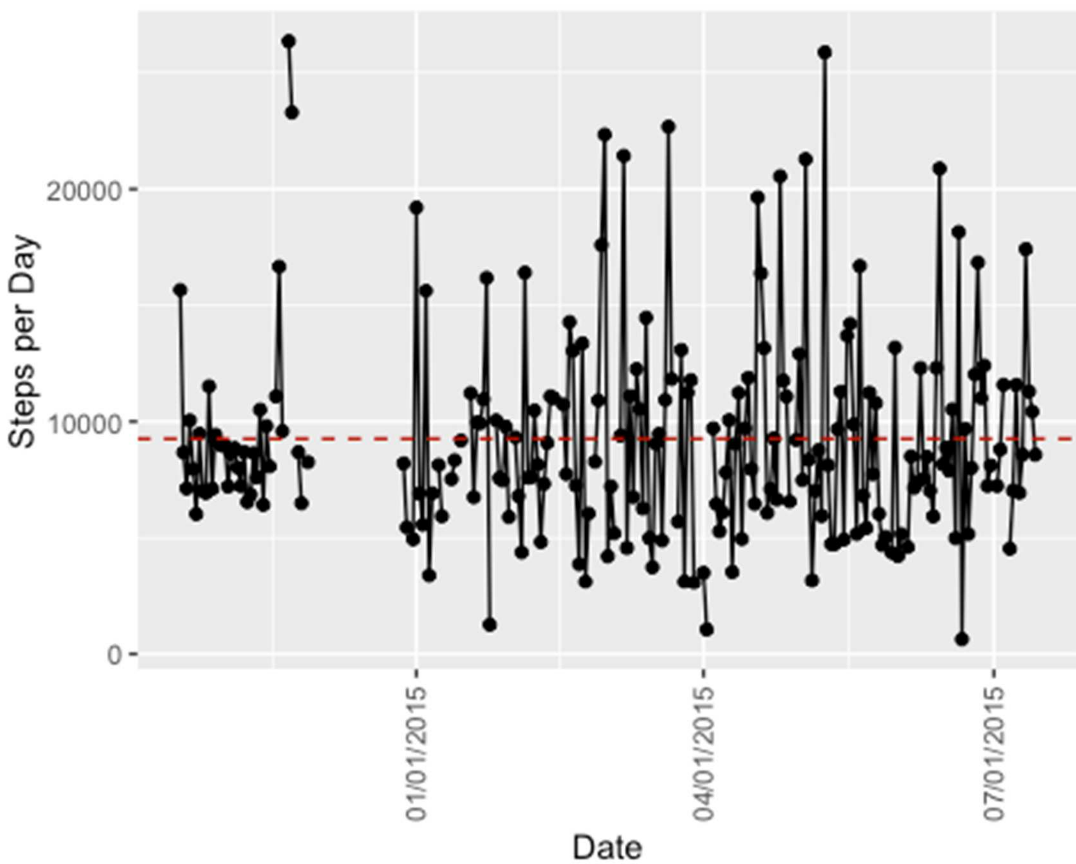

Figure A24. Steps per Valid Day: Participant 24

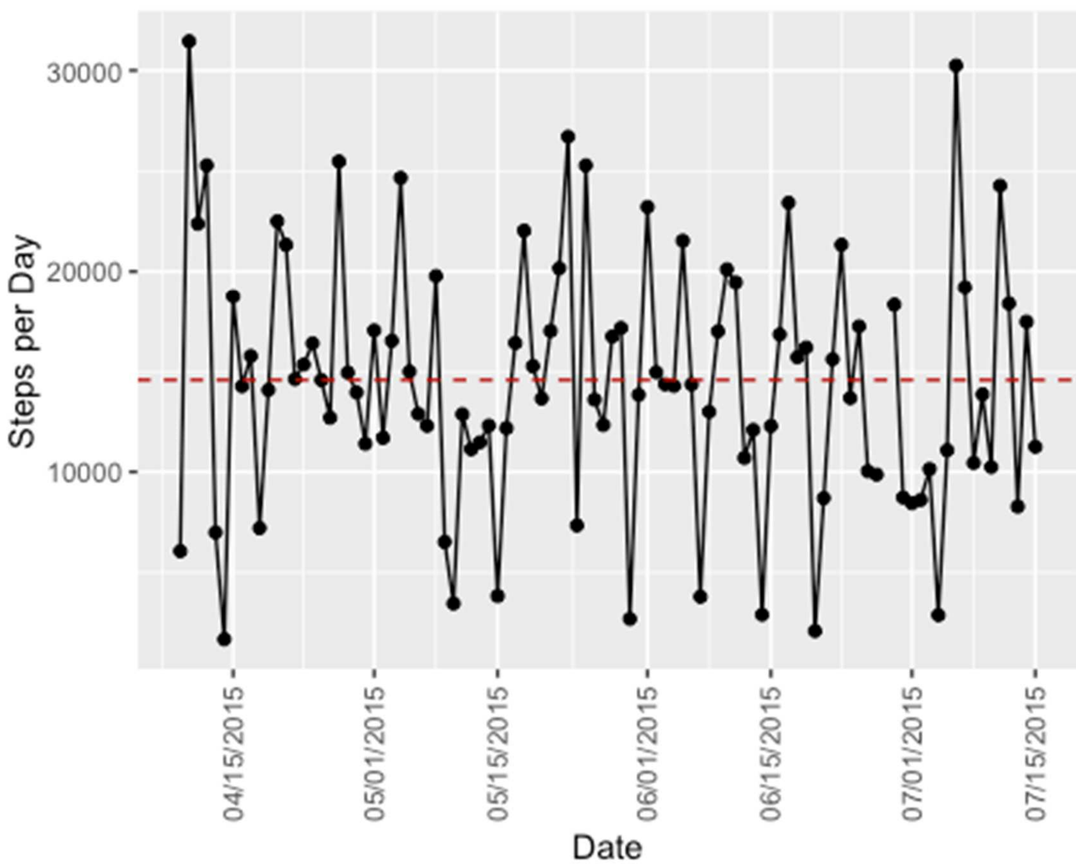

Figure A25. Steps per Valid Day: Participant 25

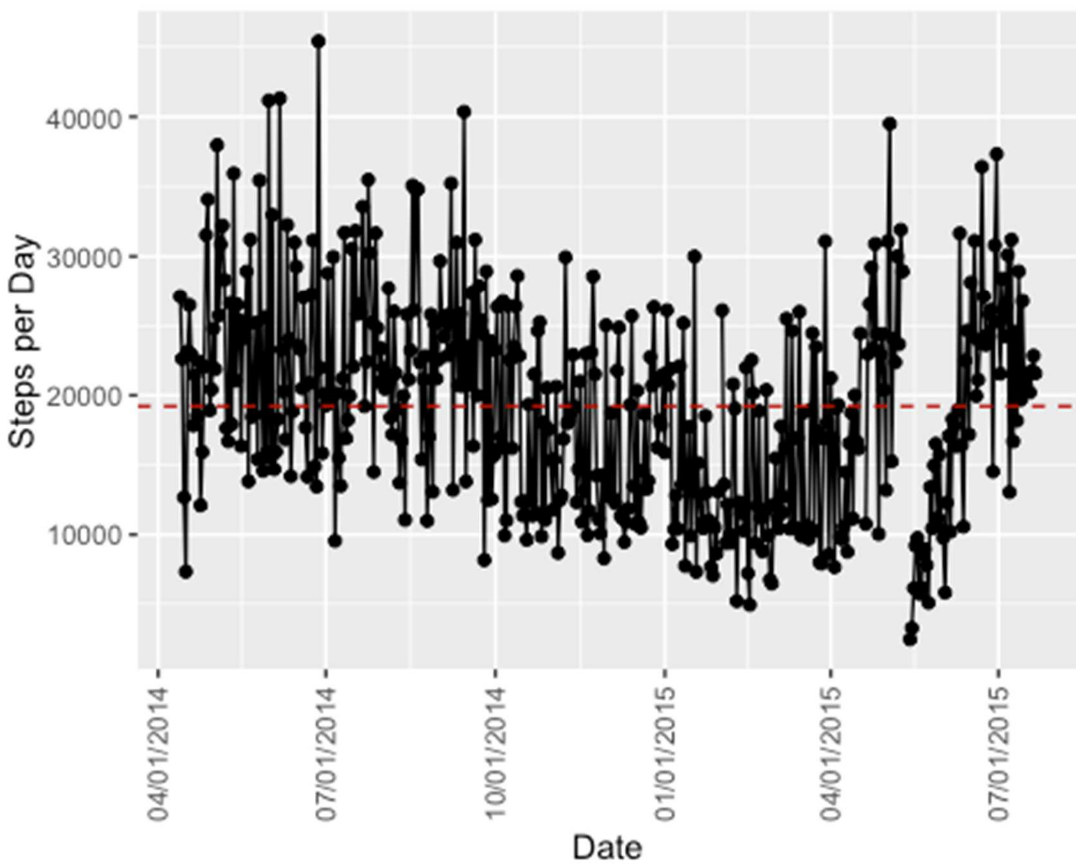

Figure A26. Steps per Valid Day: Participant 26

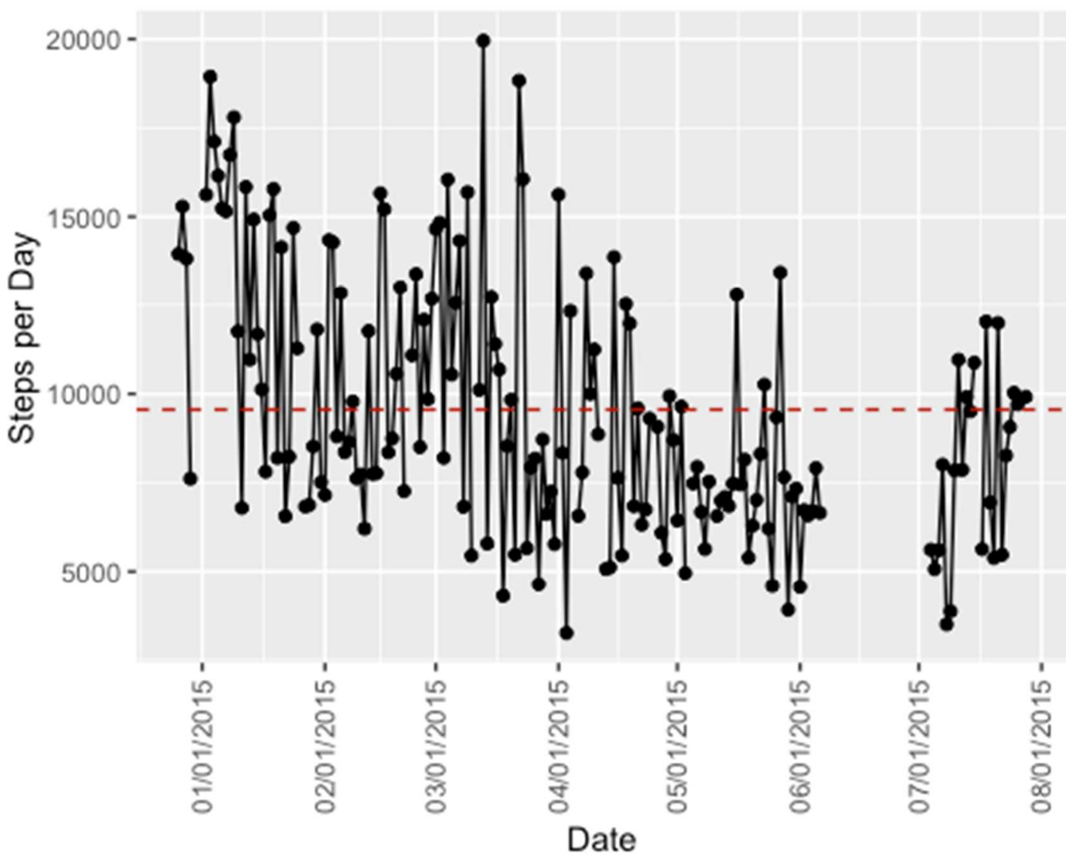

Figure A27. Steps per Valid Day: Participant 27

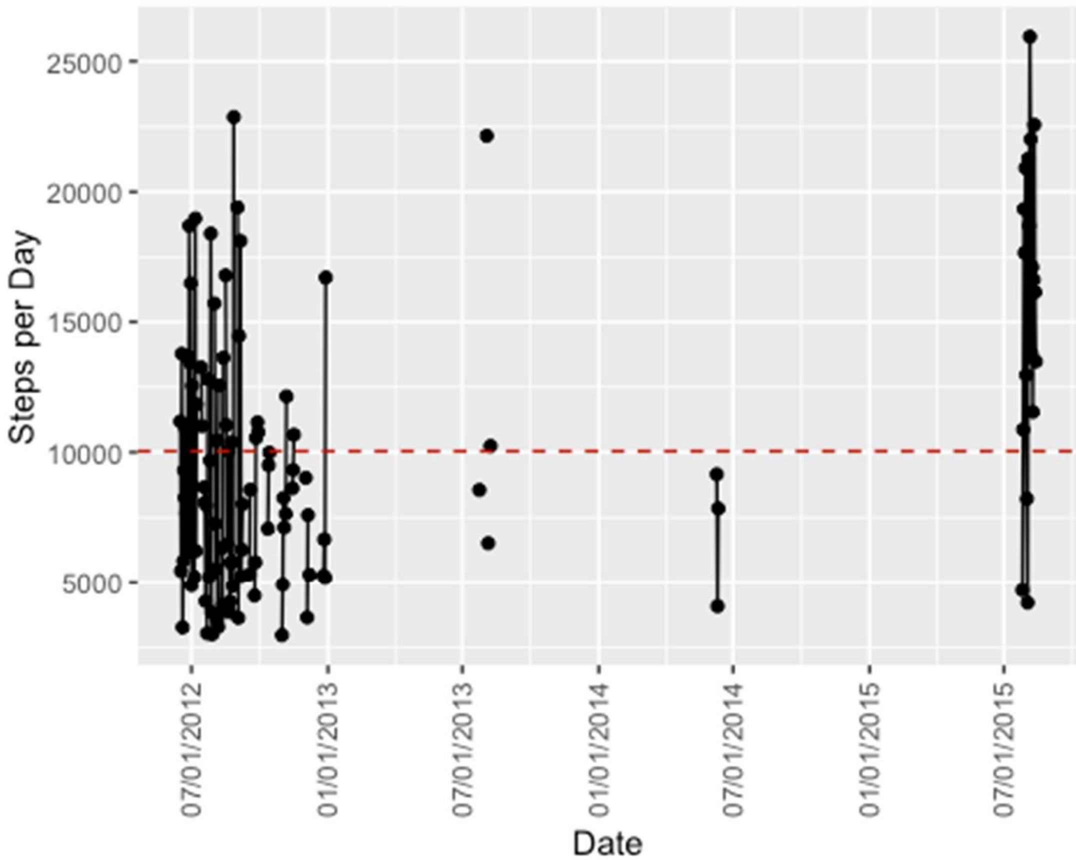

Figure A28. Steps per Valid Day: Participant 28

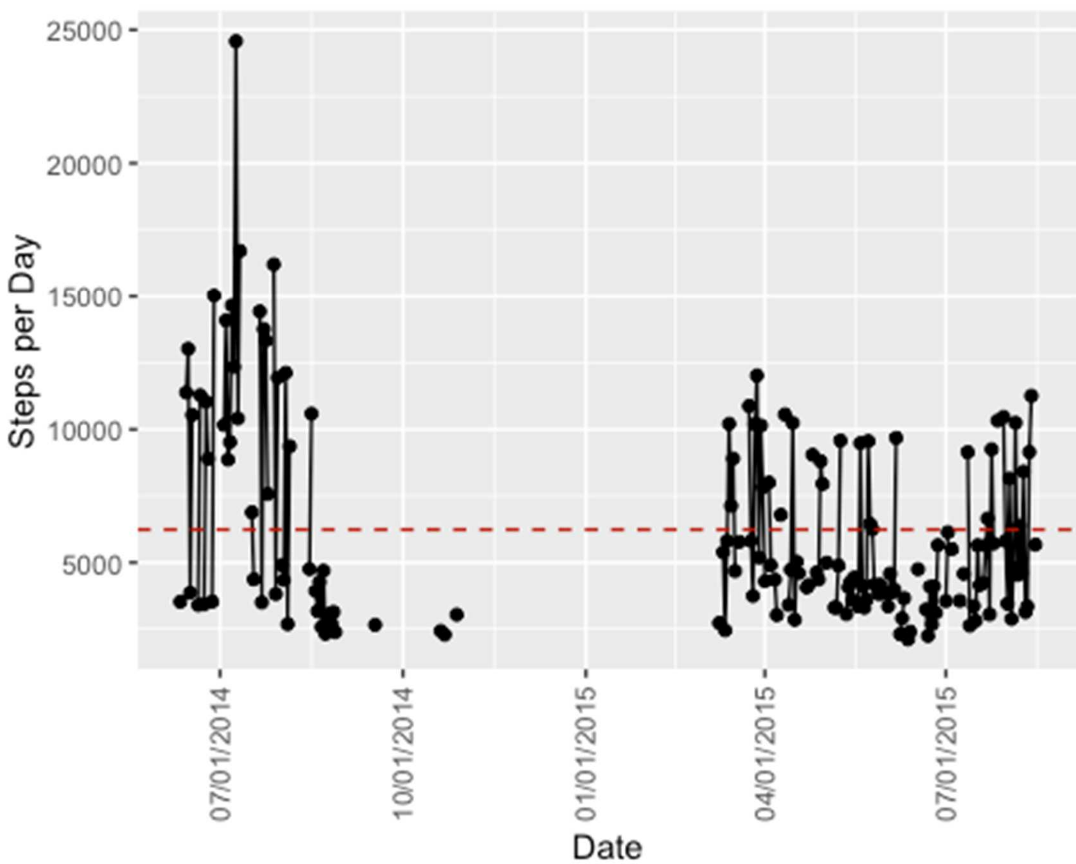

Figure A29. Steps per Valid Day: Participant 29

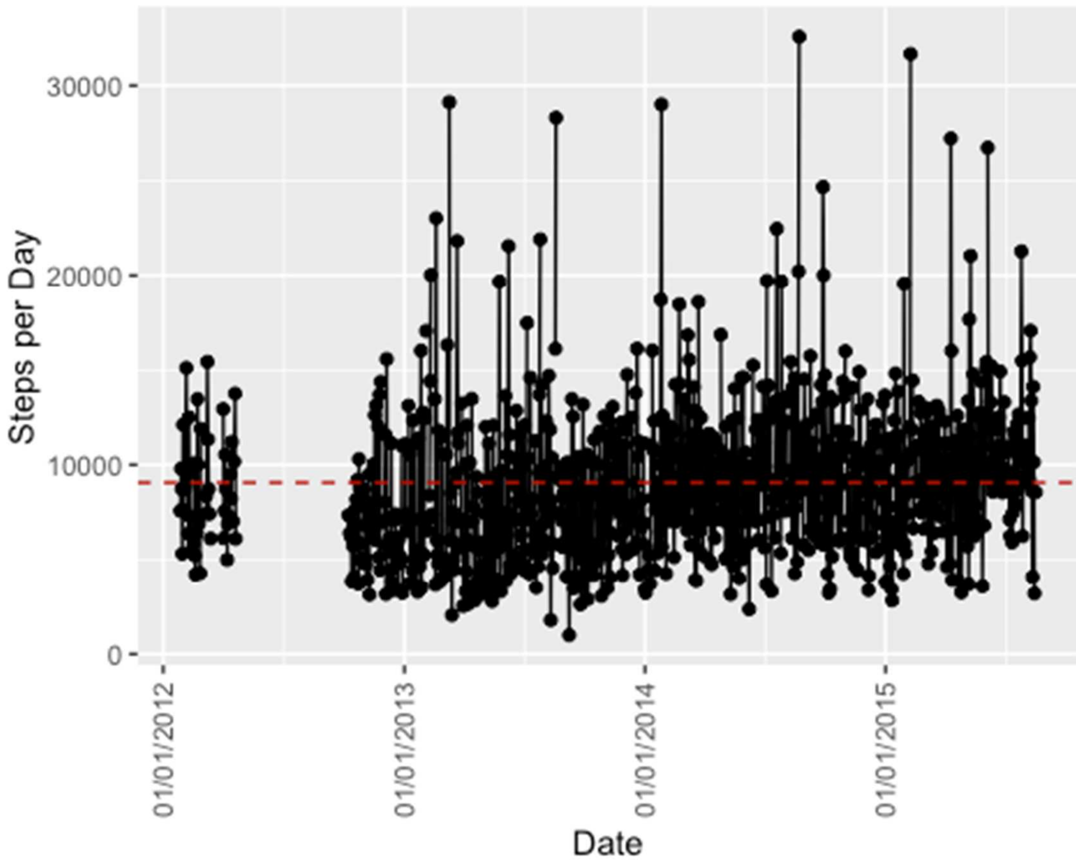

Figure A30. Steps per Valid Day: Participant 30

APPENDIX E

Minutes of MVPA (Bouts) per Day Figures

Note: For all figures included in Appendix B the red dashed line indicates the mean value for minutes of MVPA per day.

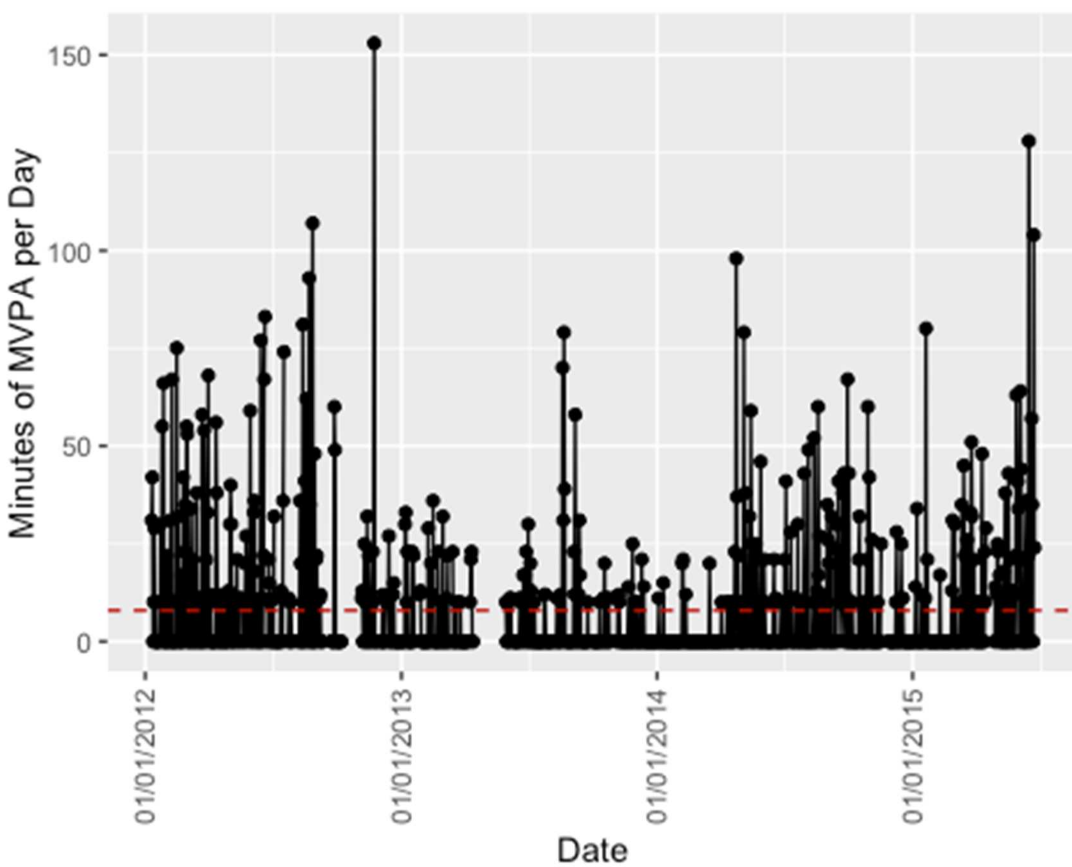

Figure B1. Minutes of MVPA (Bouts) per Valid Day: Participant 1

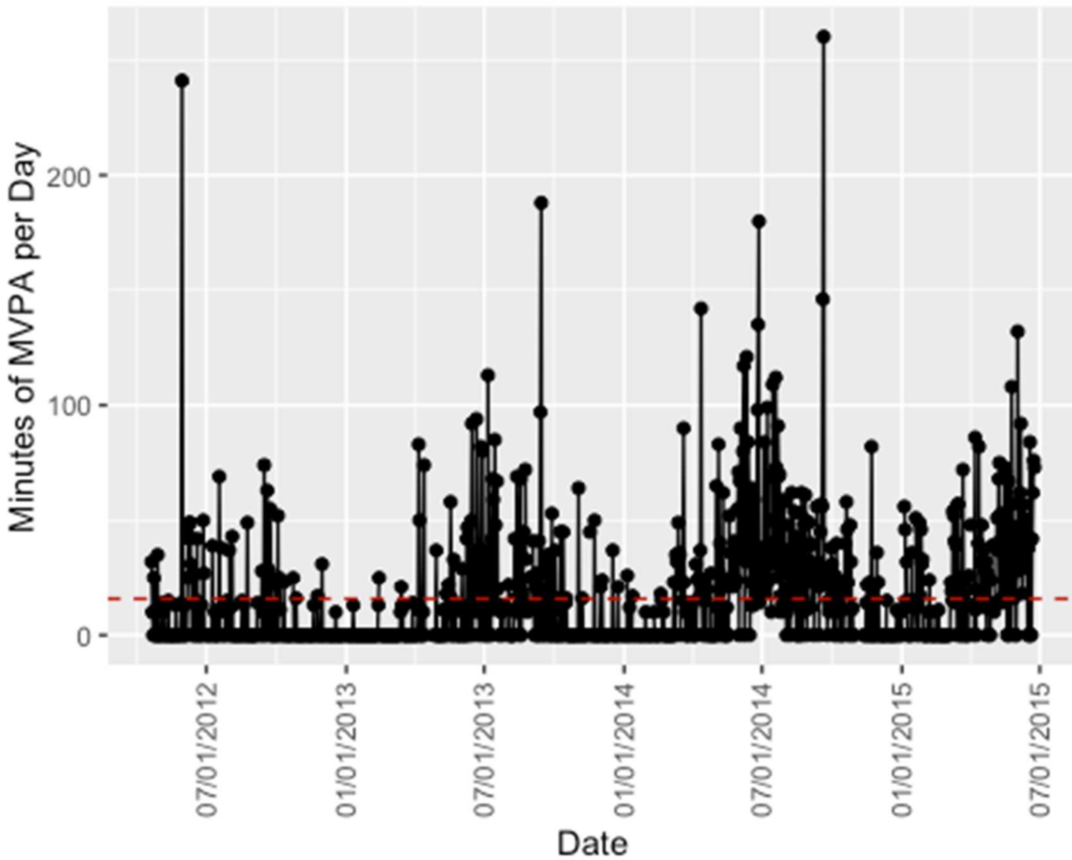

Figure B2. Minutes of MVPA (Bouts) per Valid Day: Participant 2

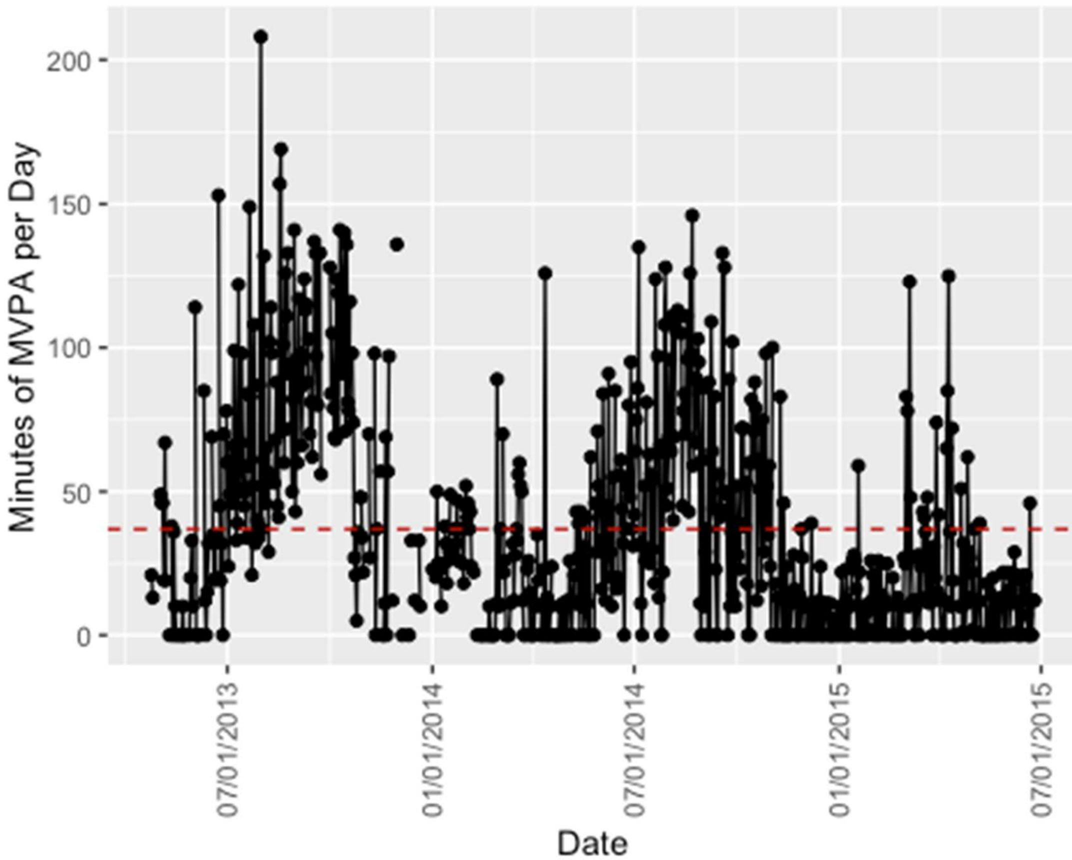

Figure B3. Minutes of MVPA (Bouts) per Valid Day: Participant 3

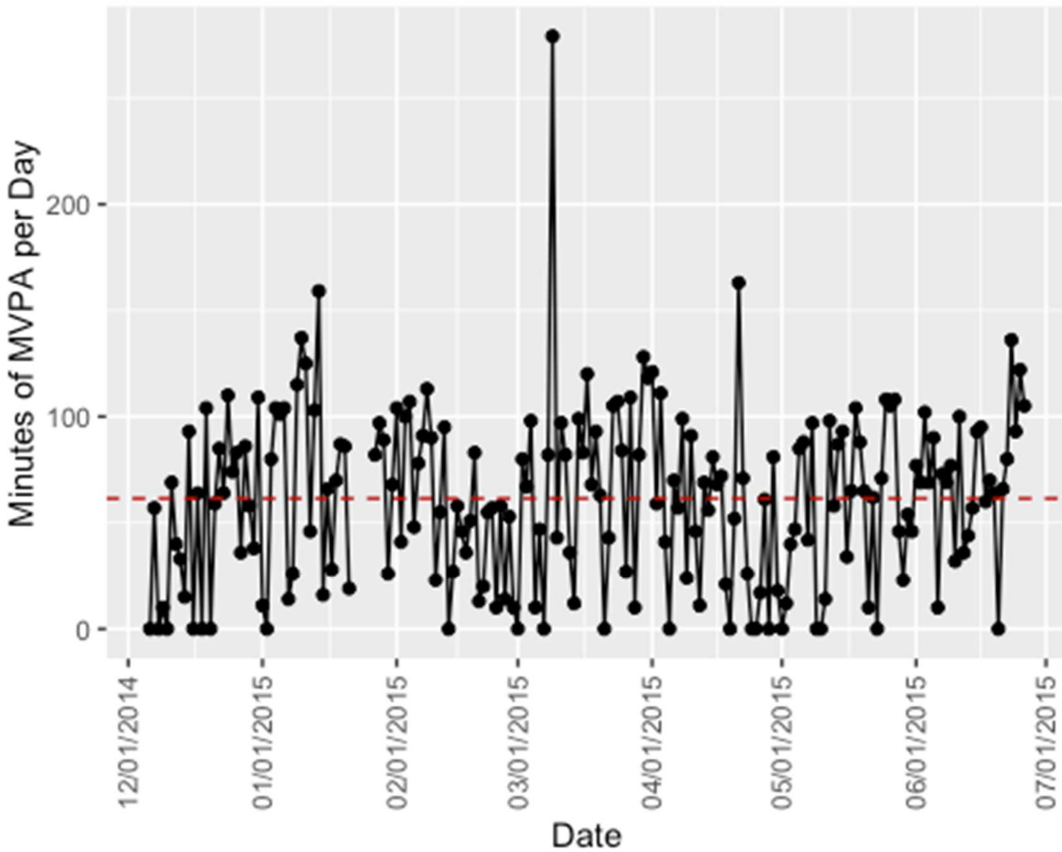

Figure B4. Minutes of MVPA (Bouts) per Valid Day: Participant 4

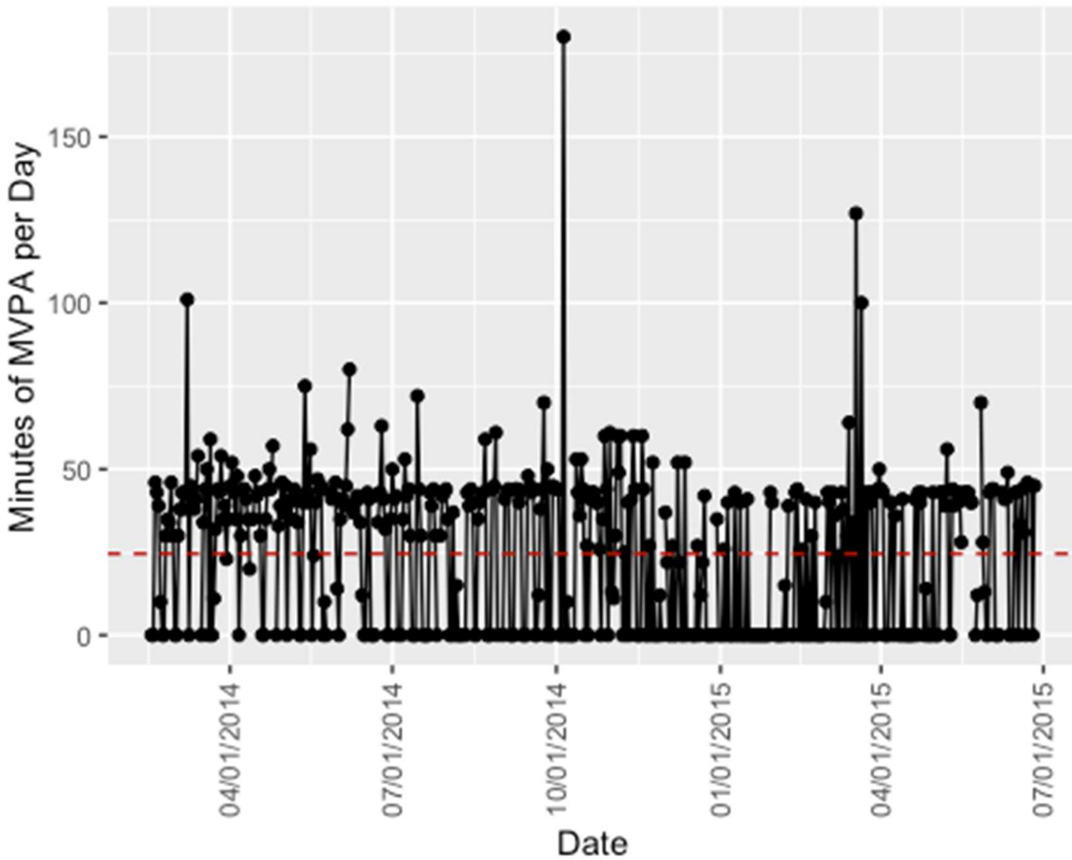

Figure B5. Minutes of MVPA (Bouts) per Valid Day: Participant 5

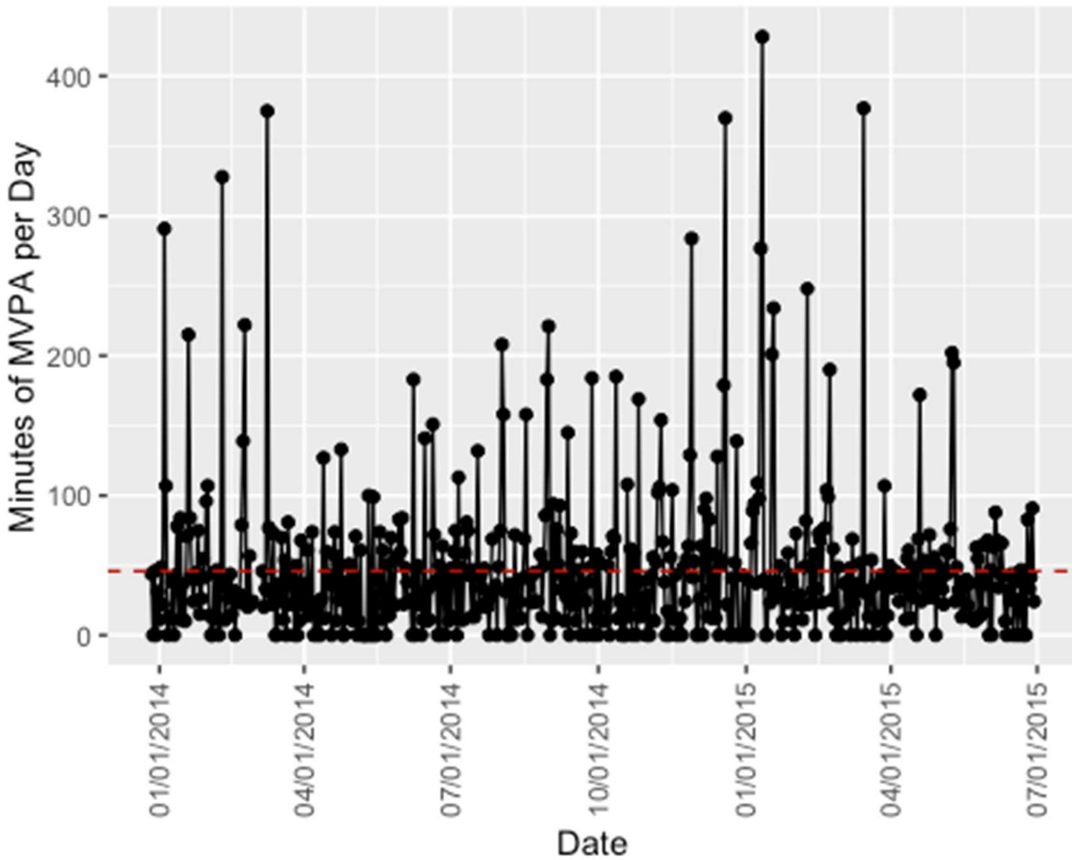

Figure B6. Minutes of MVPA (Bouts) per Valid Day: Participant 6

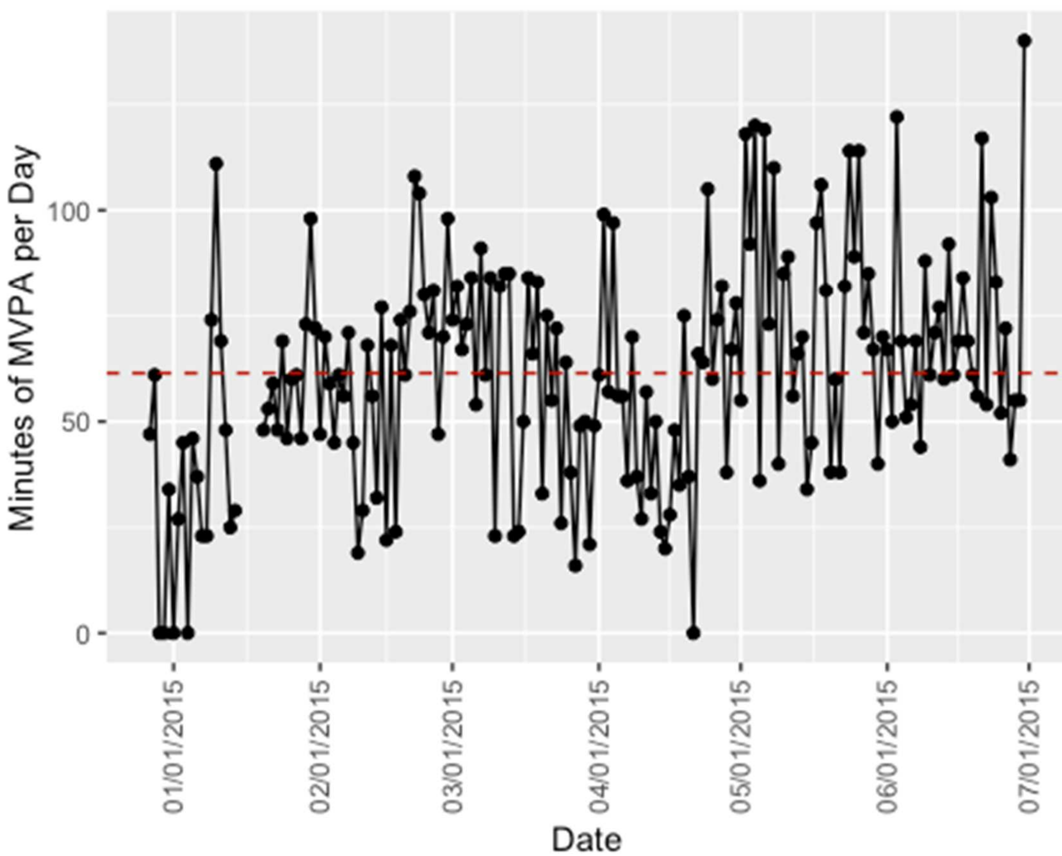

Figure B7. Minutes of MVPA (Bouts) per Valid Day: Participant 7

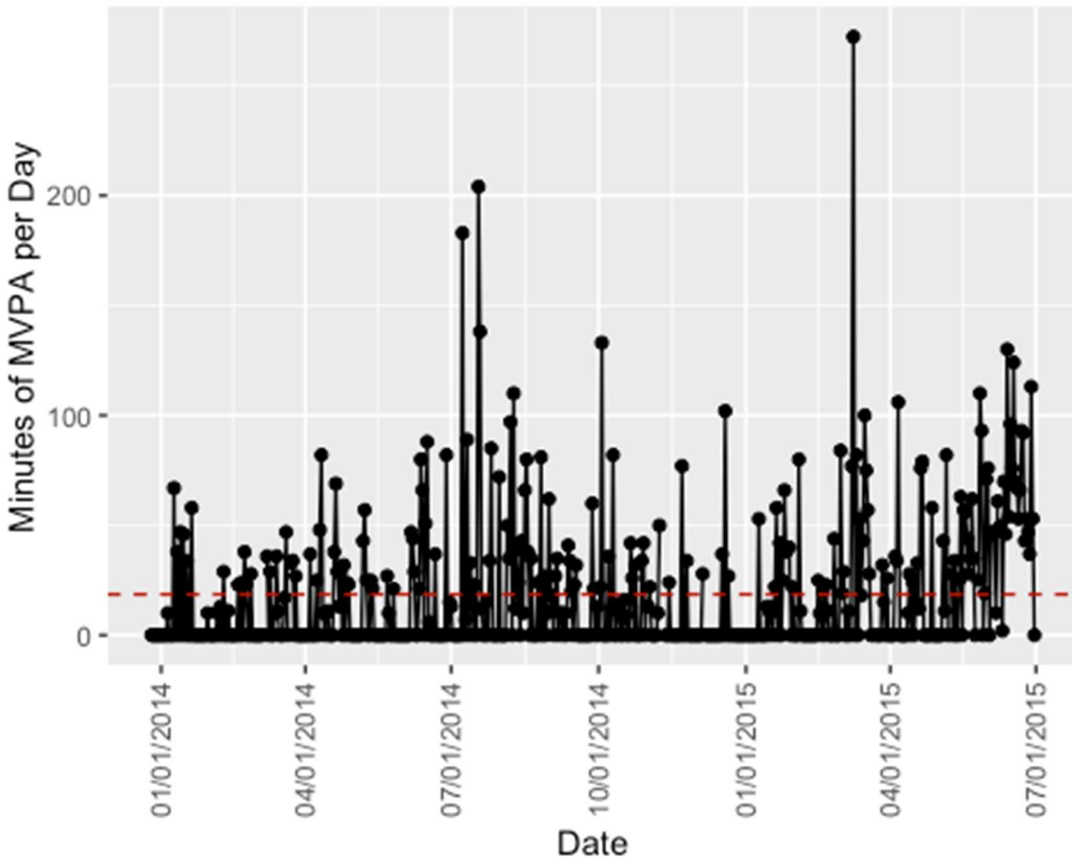

Figure B8. Minutes of MVPA (Bouts) per Valid Day: Participant 8

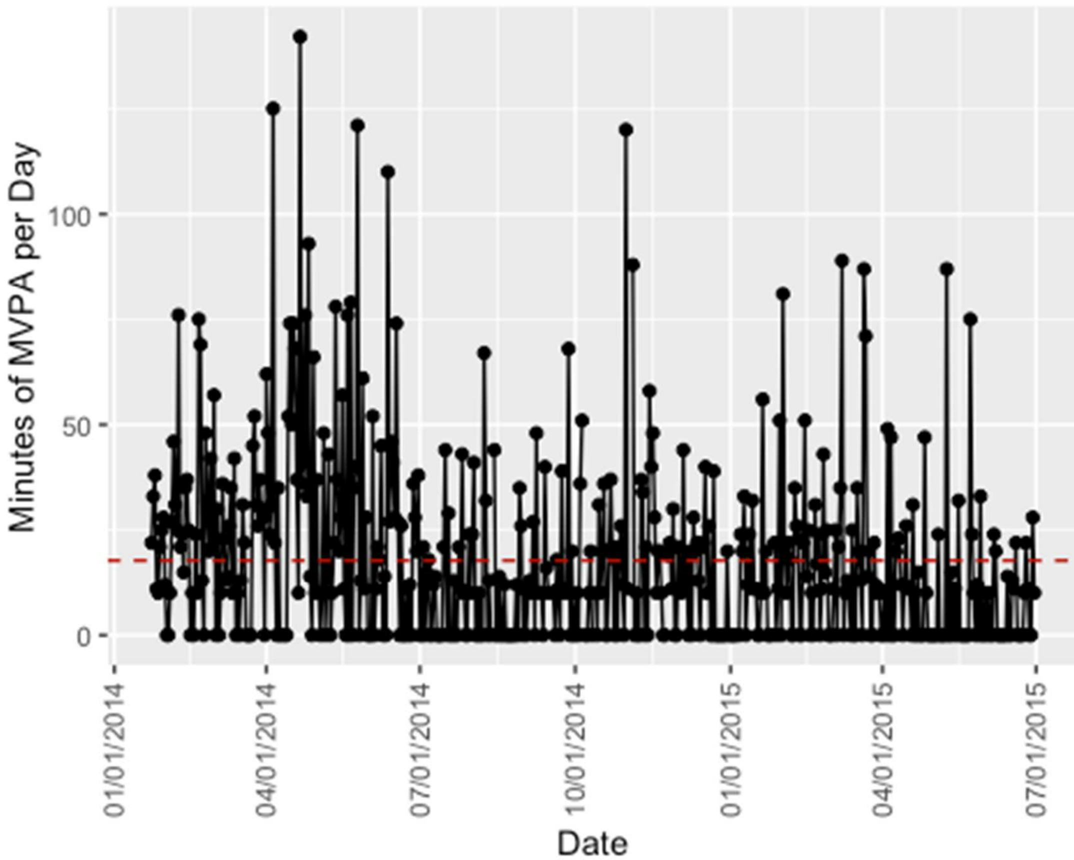

Figure B9. Minutes of MVPA (Bouts) per Valid Day: Participant 9

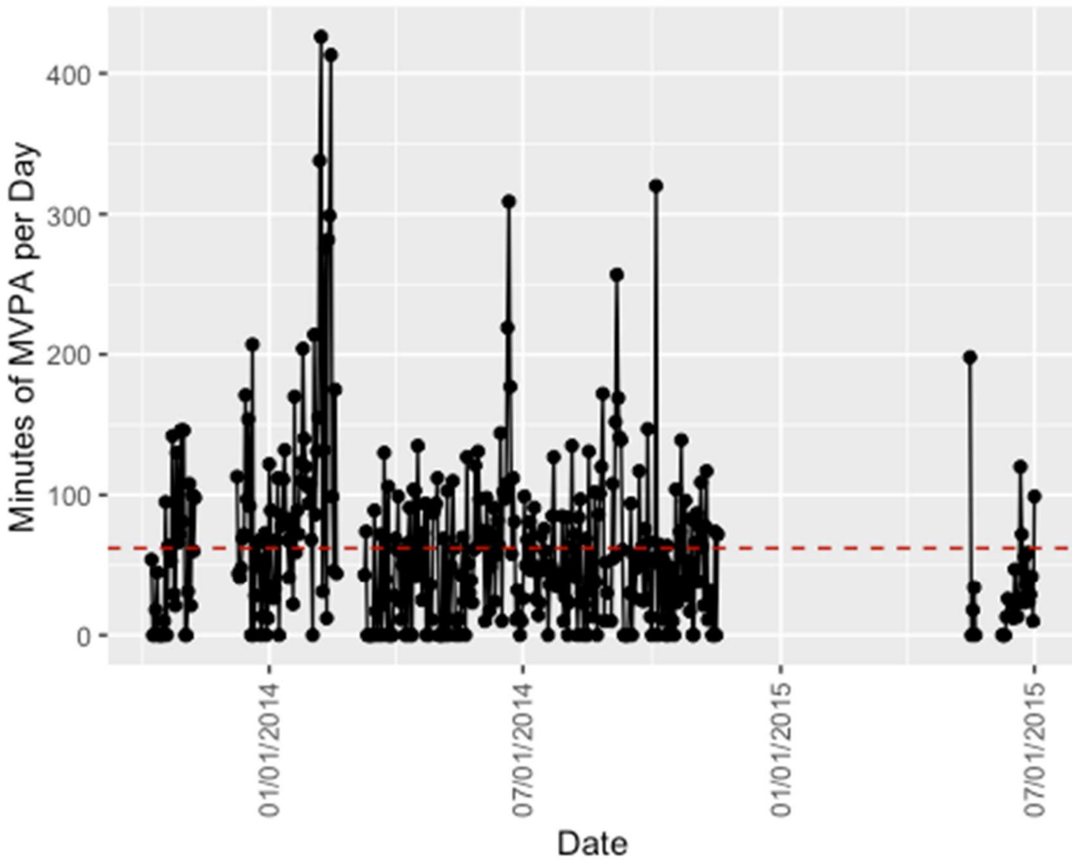

Figure B10. Minutes of MVPA (Bouts) per Valid Day: Participant 10

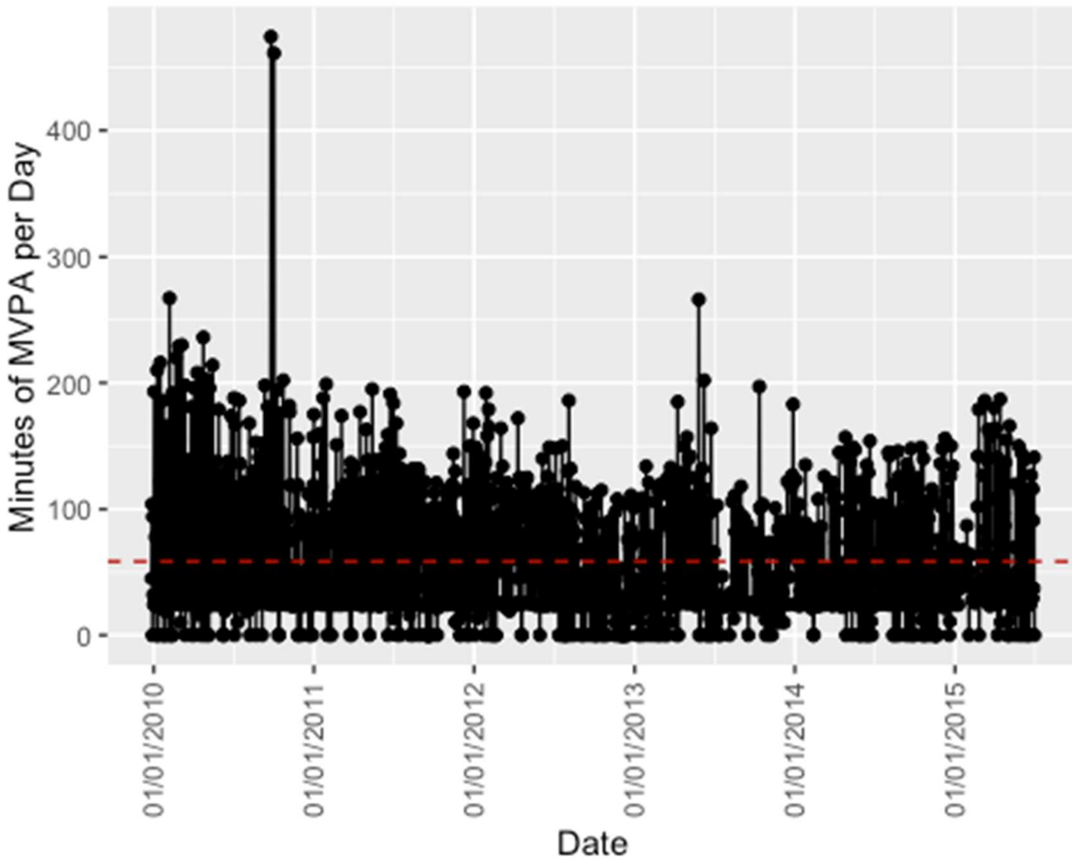

Figure B11. Minutes of MVPA (Bouts) per Valid Day: Participant 11

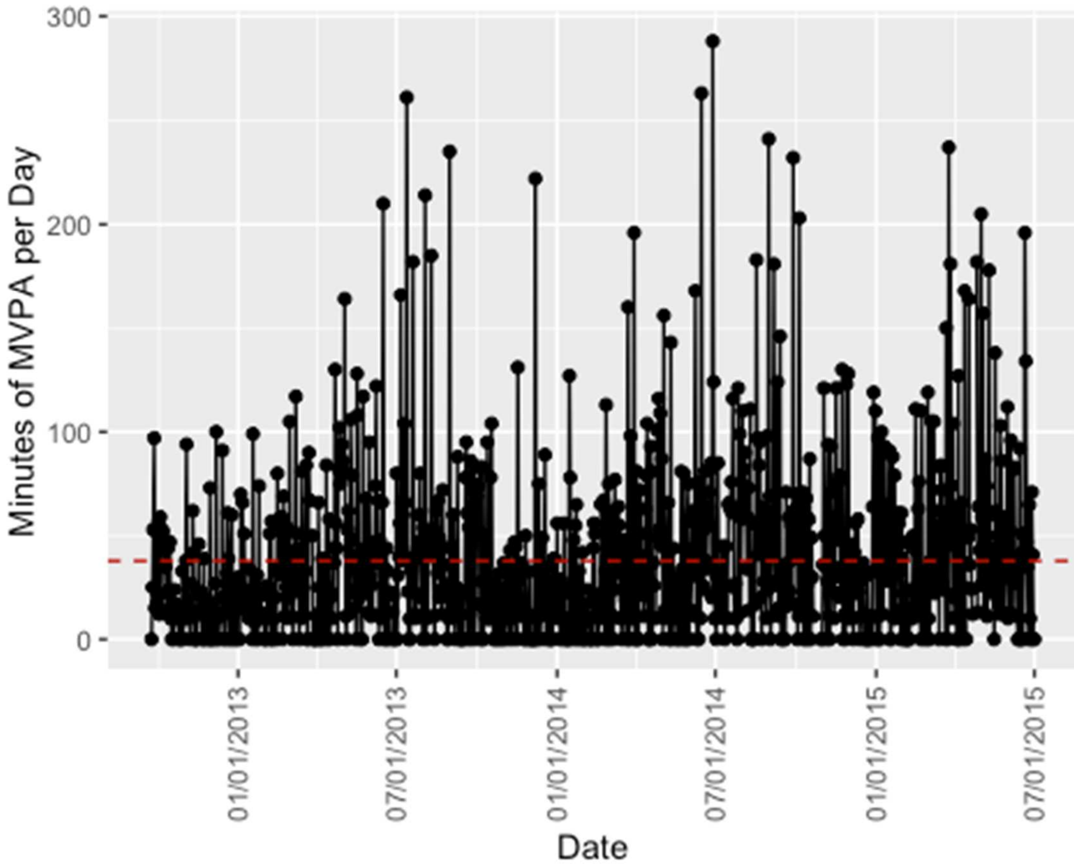

Figure B12. Minutes of MVPA (Bouts) per Valid Day: Participant 12

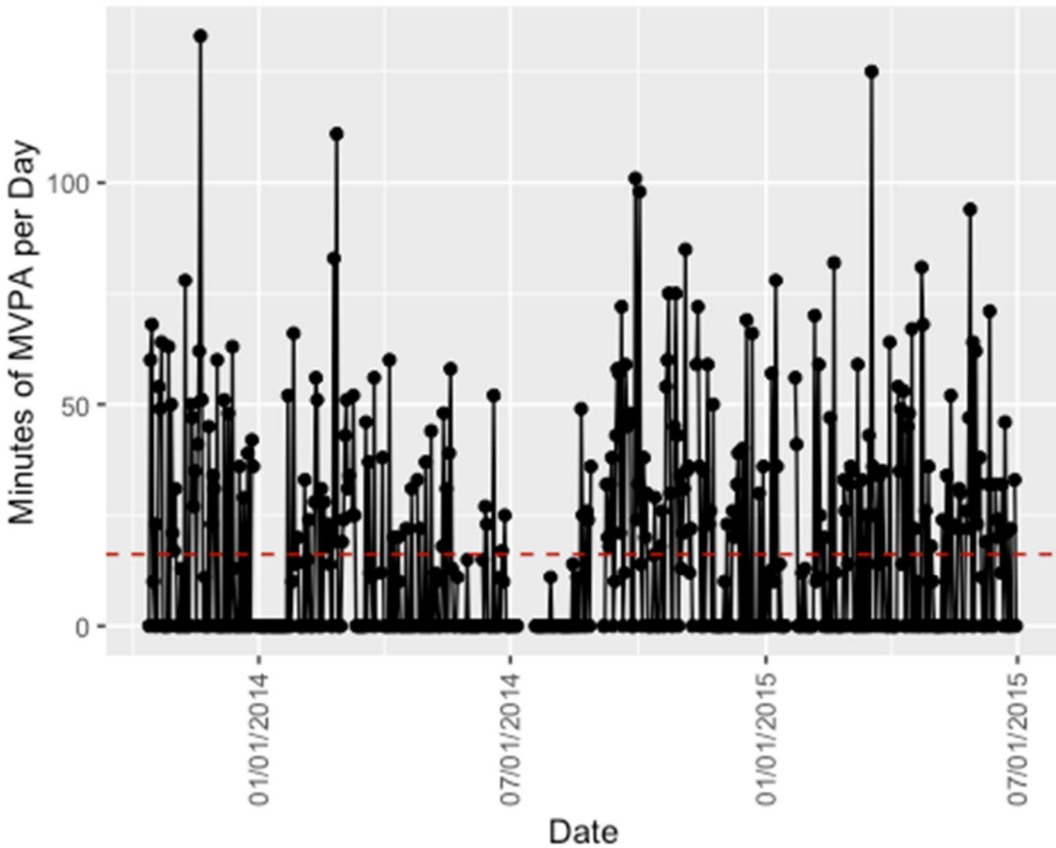

Figure B13. Minutes of MVPA (Bouts) per Valid Day: Participant 13

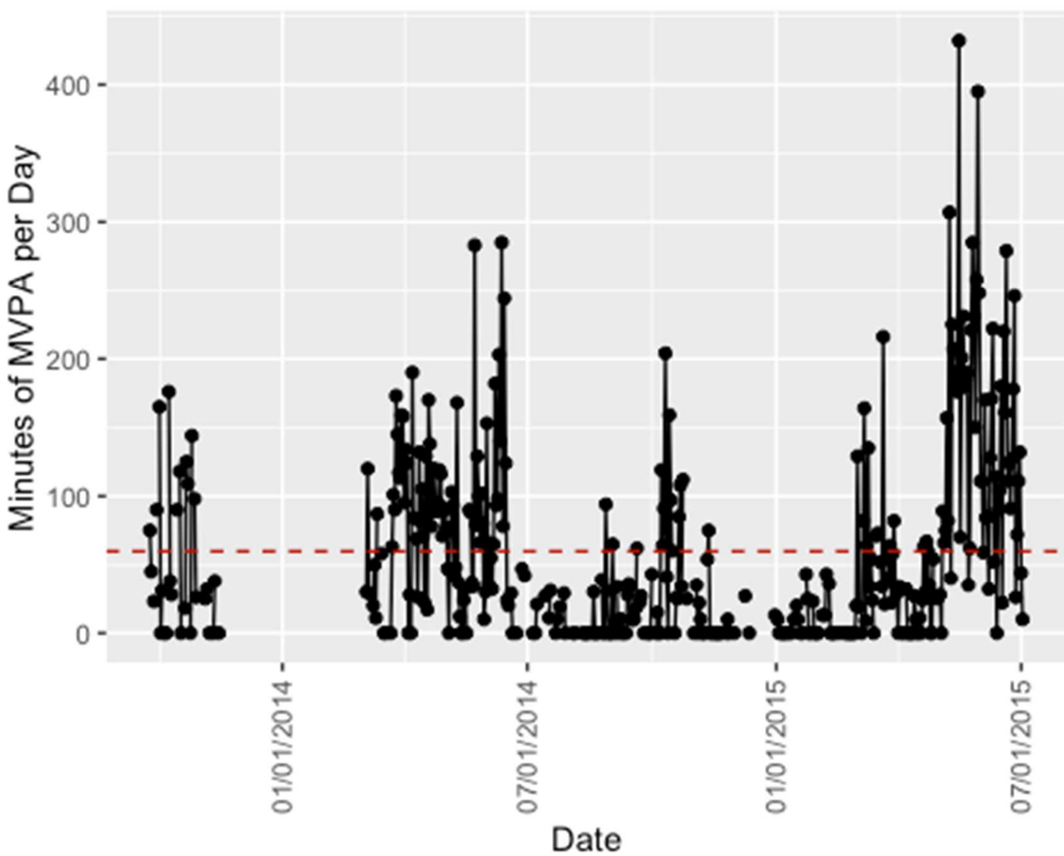

Figure B14. Minutes of MVPA (Bouts) per Valid Day: Participant 14

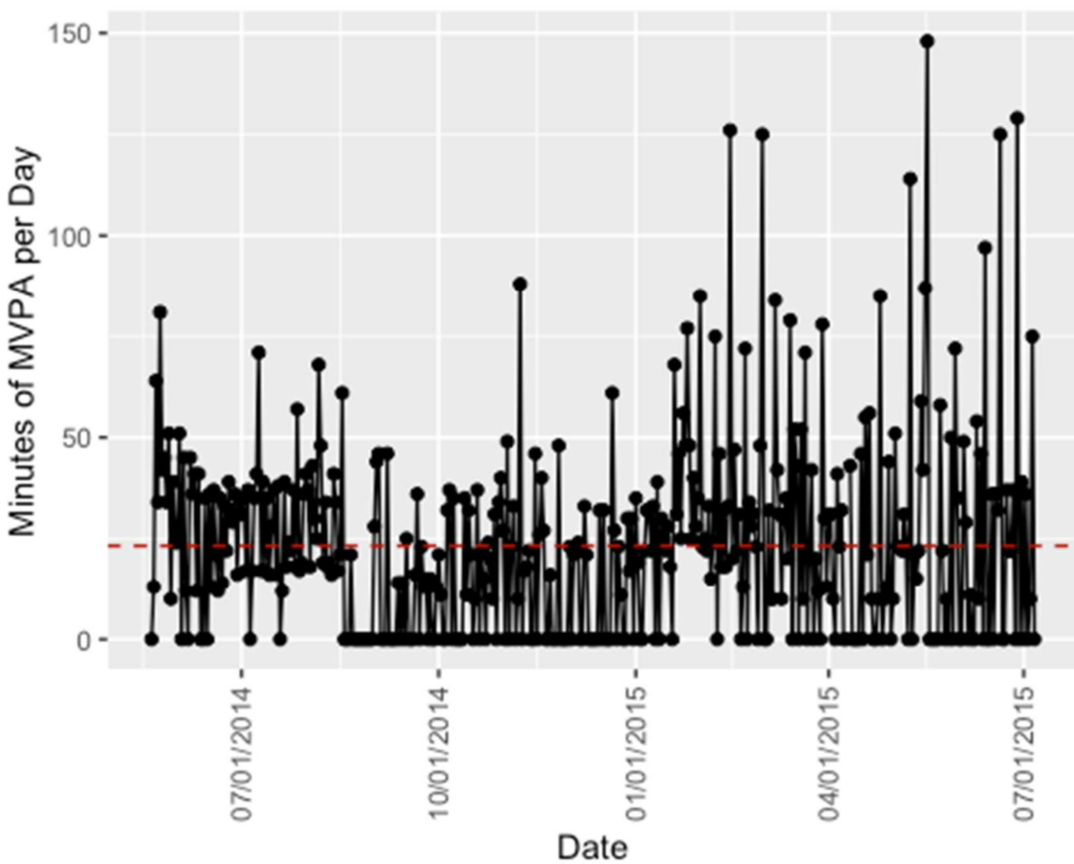

Figure B15. Minutes of MVPA (Bouts) per Valid Day: Participant 15

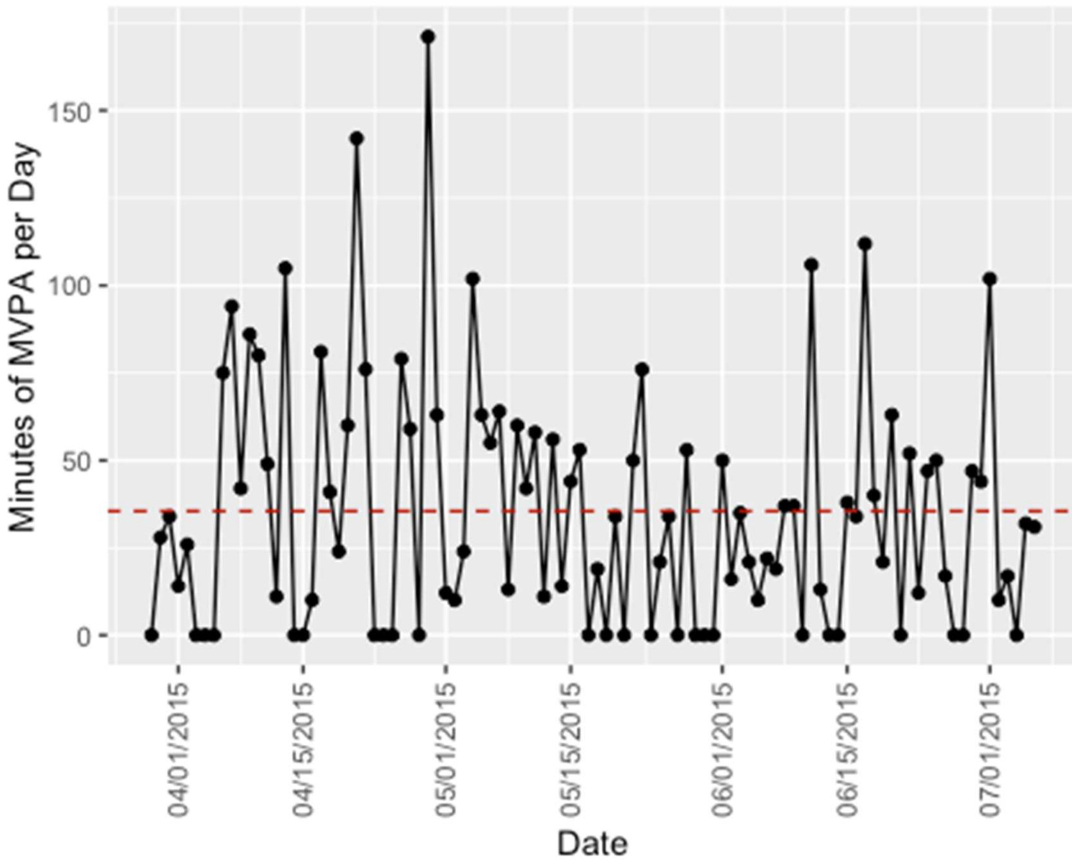

Figure B16. Minutes of MVPA (Bouts) per Valid Day: Participant 16

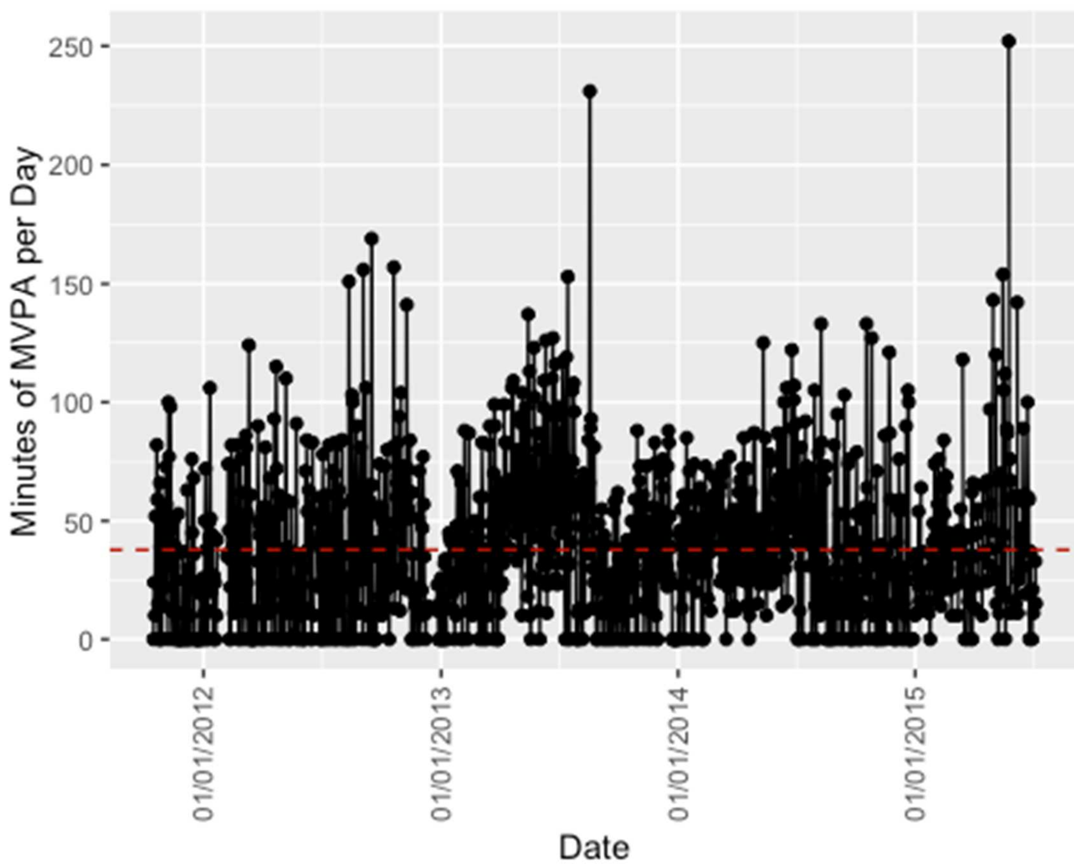

Figure B17. Minutes of MVPA (Bouts) per Valid Day: Participant 17

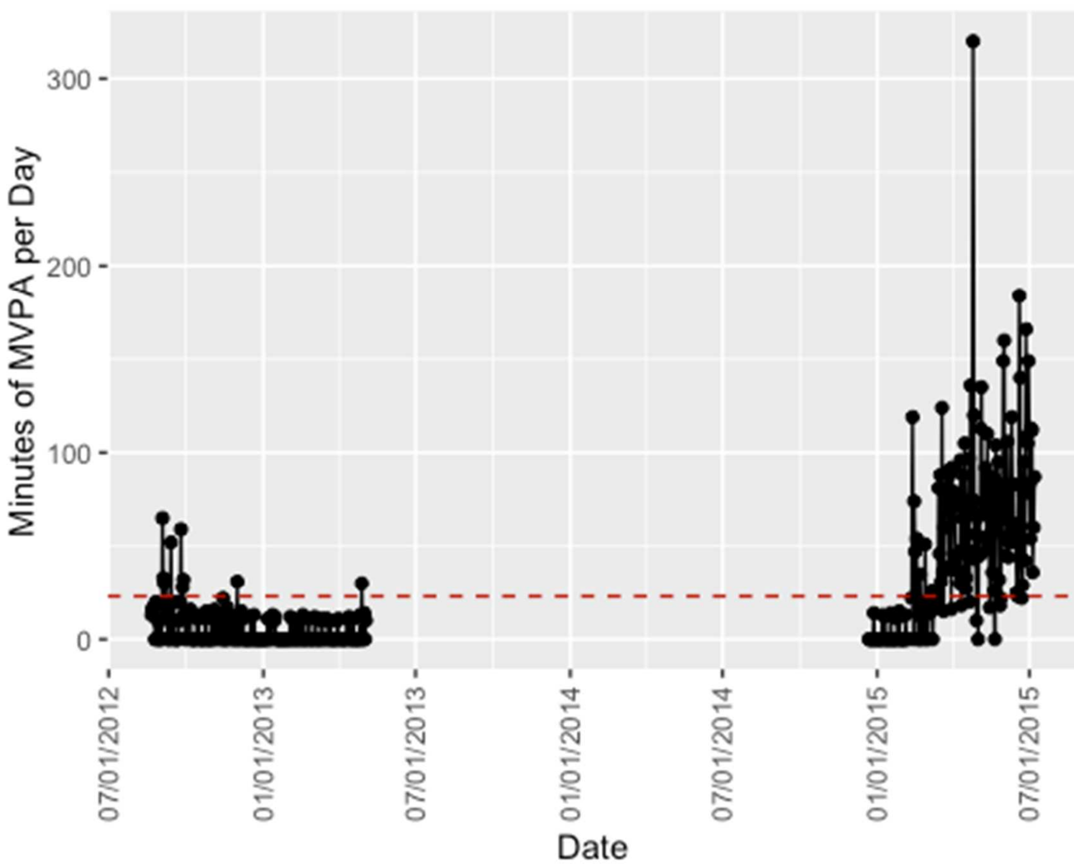

Figure B18. Minutes of MVPA (Bouts) per Valid Day: Participant 18

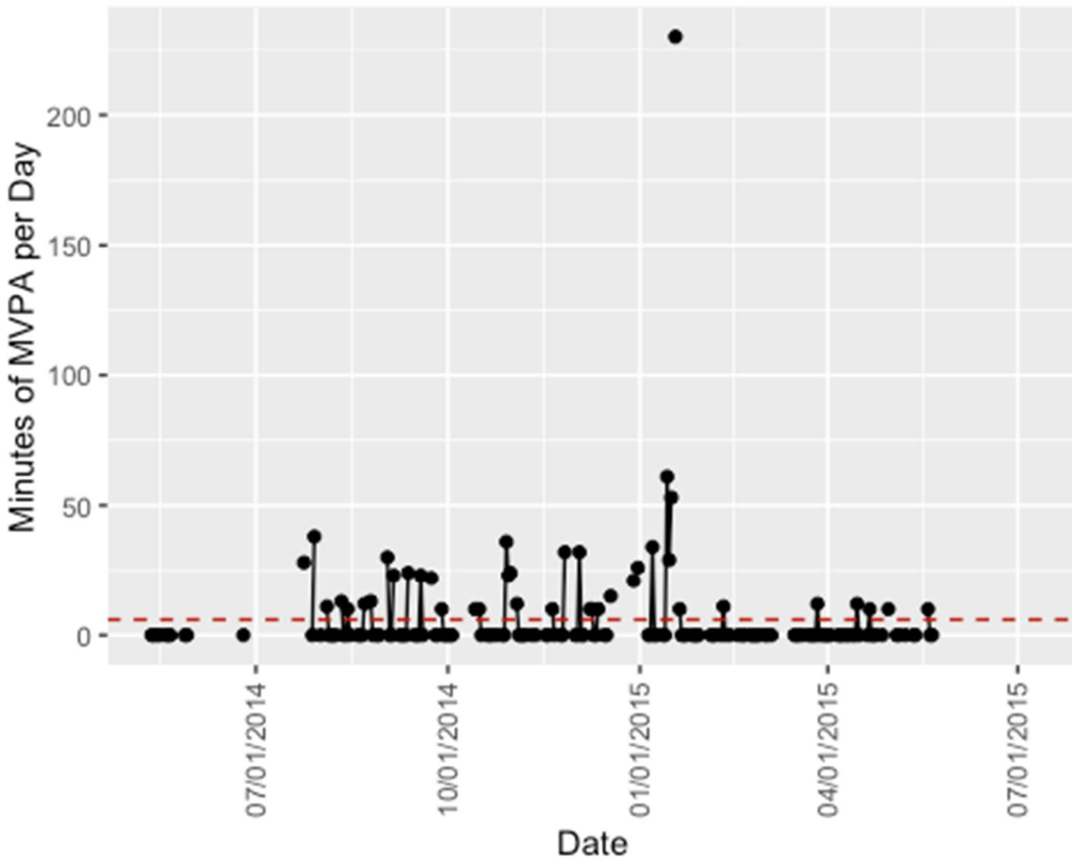

Figure B19. Minutes of MVPA (Bouts) per Valid Day: Participant 19

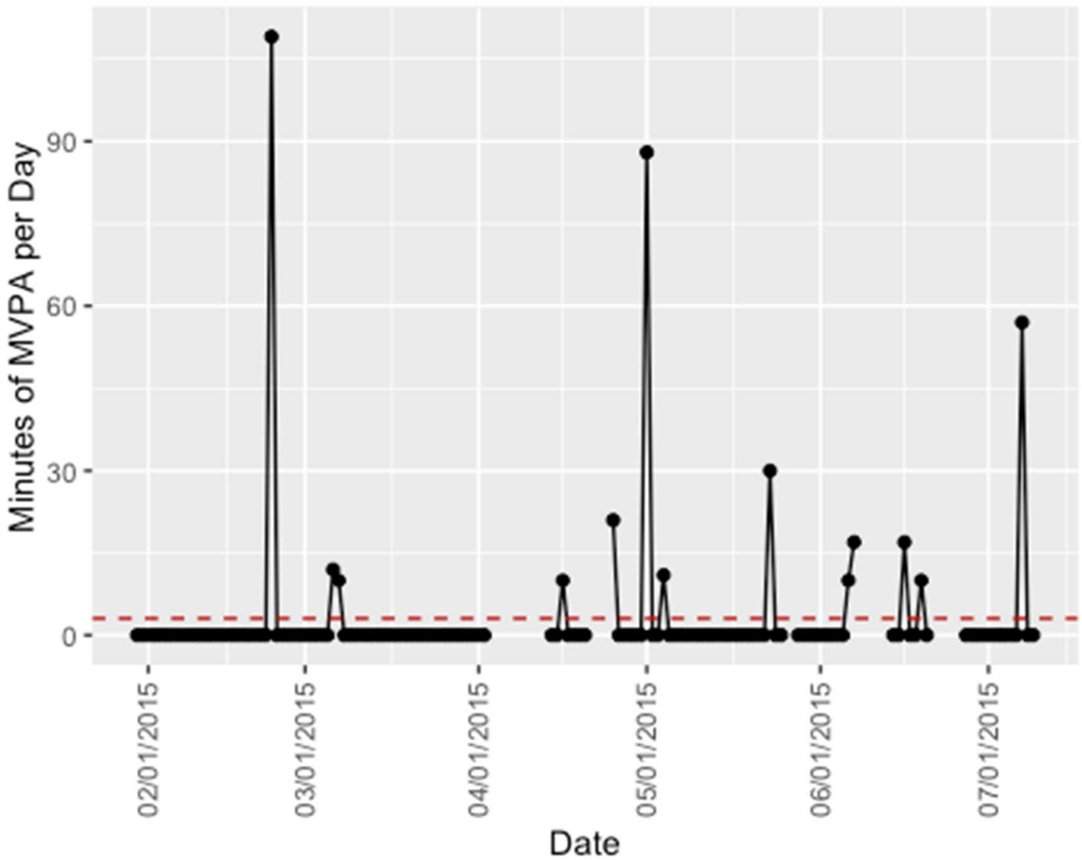

Figure B20. Minutes of MVPA (Bouts) per Valid Day: Participant 20

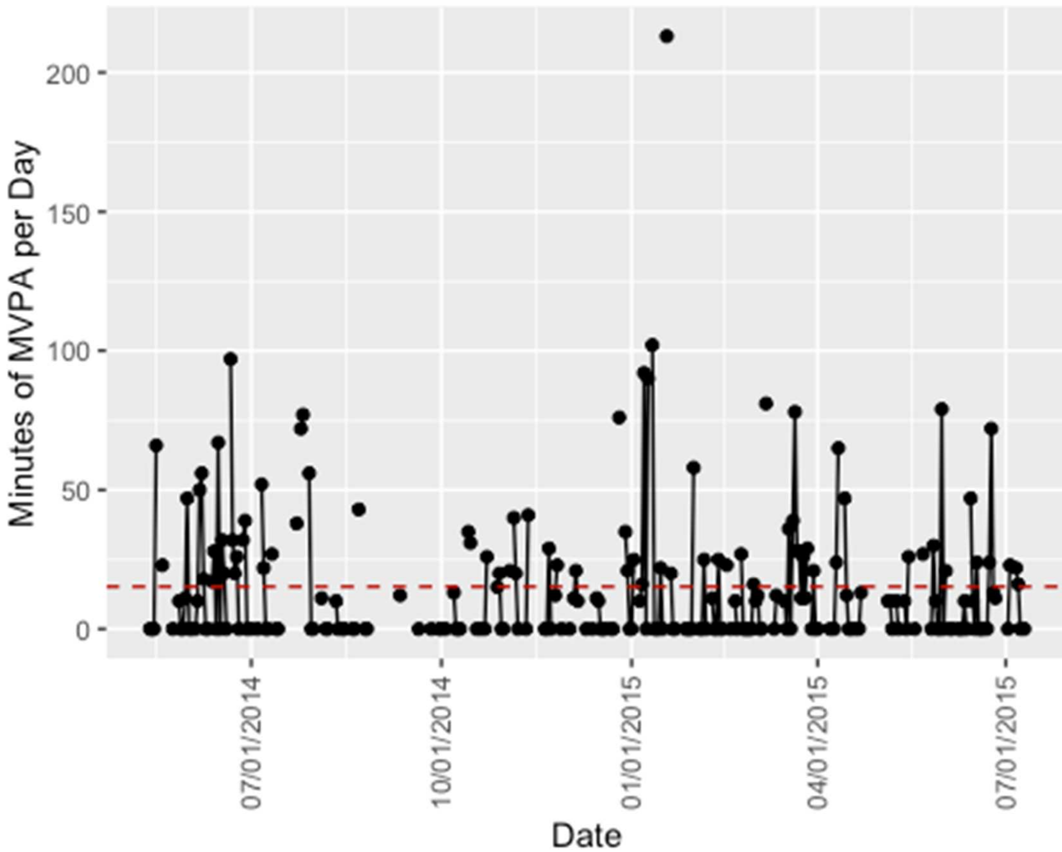

Figure B21. Minutes of MVPA (Bouts) per Valid Day: Participant 21

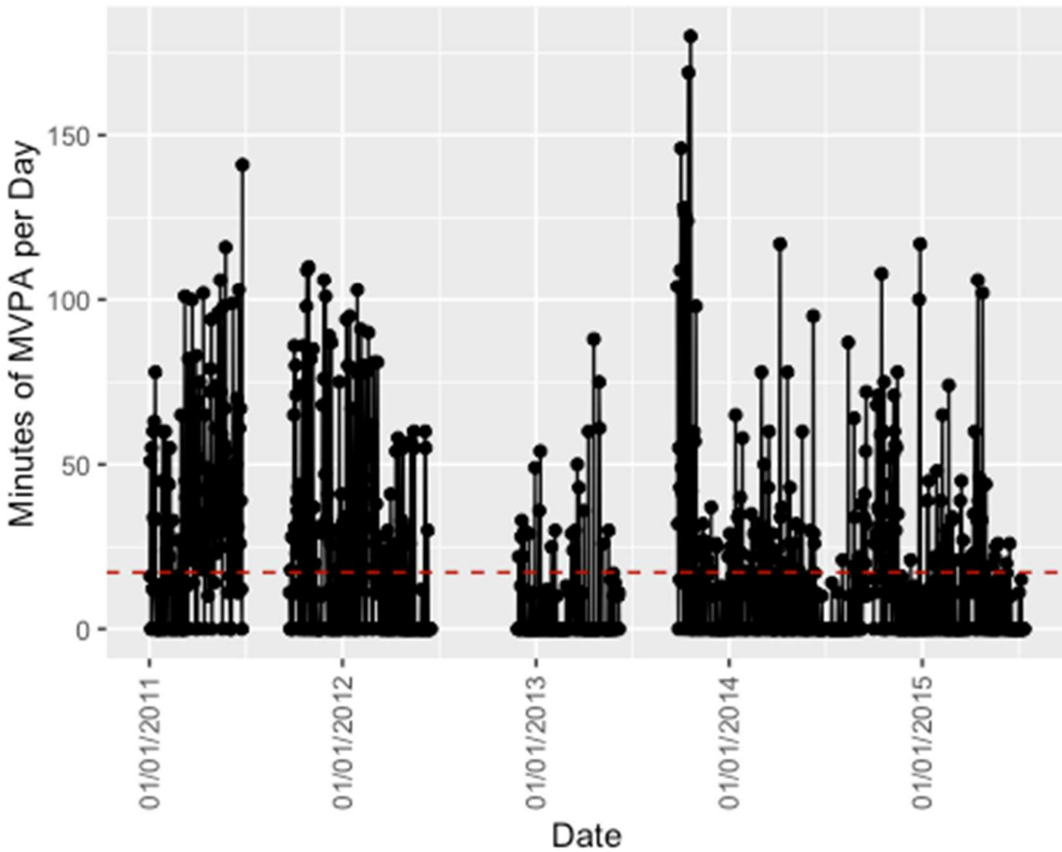

Figure B22. Minutes of MVPA (Bouts) per Valid Day: Participant 22

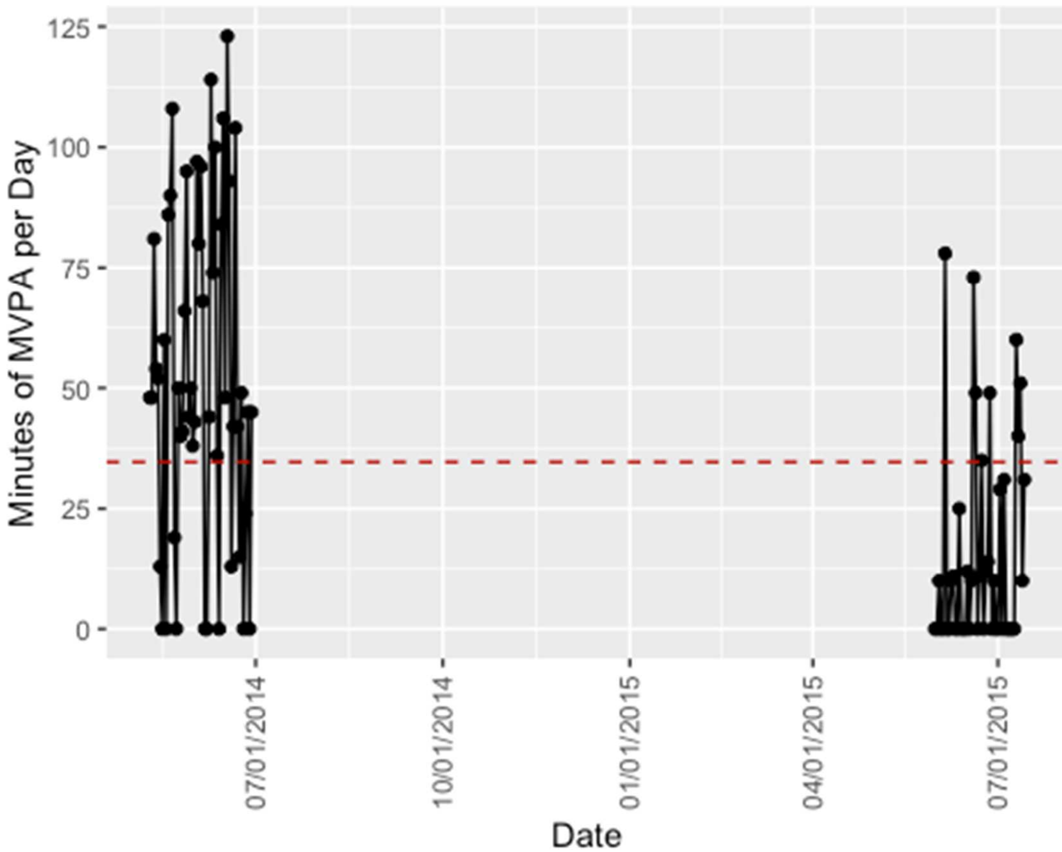

Figure B23. Minutes of MVPA (Bouts) per Valid Day: Participant 23

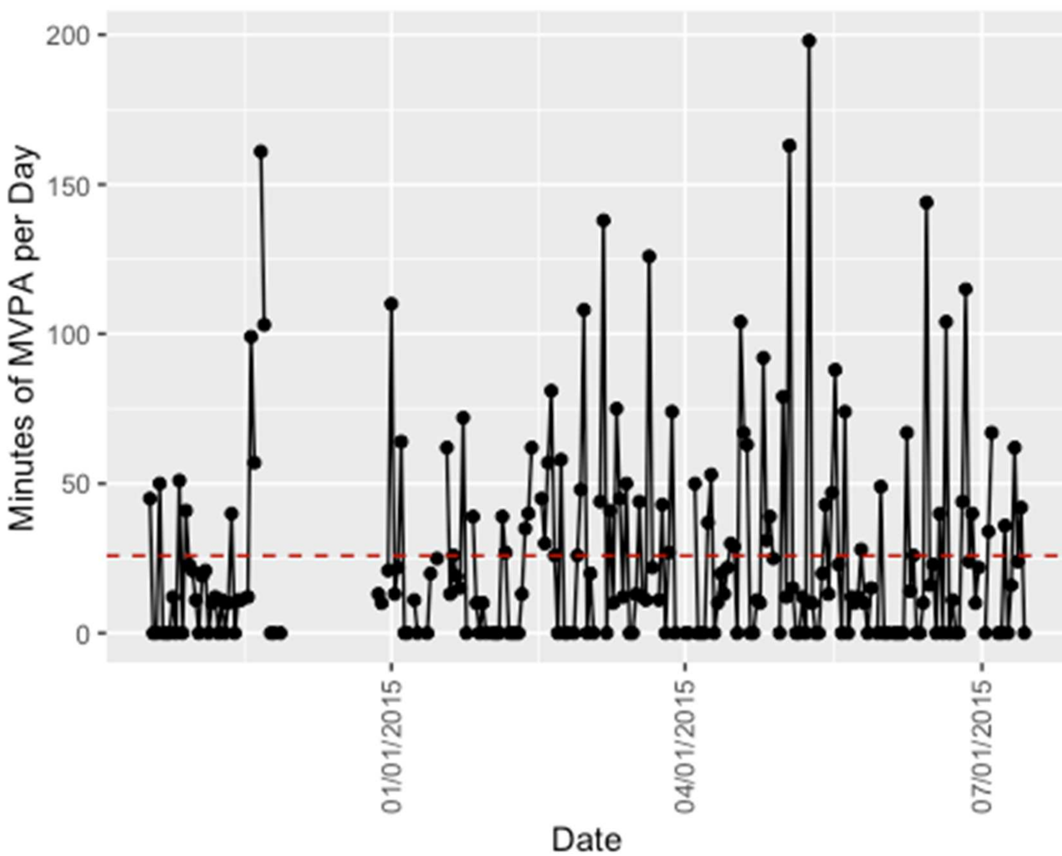

Figure B24. Minutes of MVPA (Bouts) per Valid Day: Participant 24

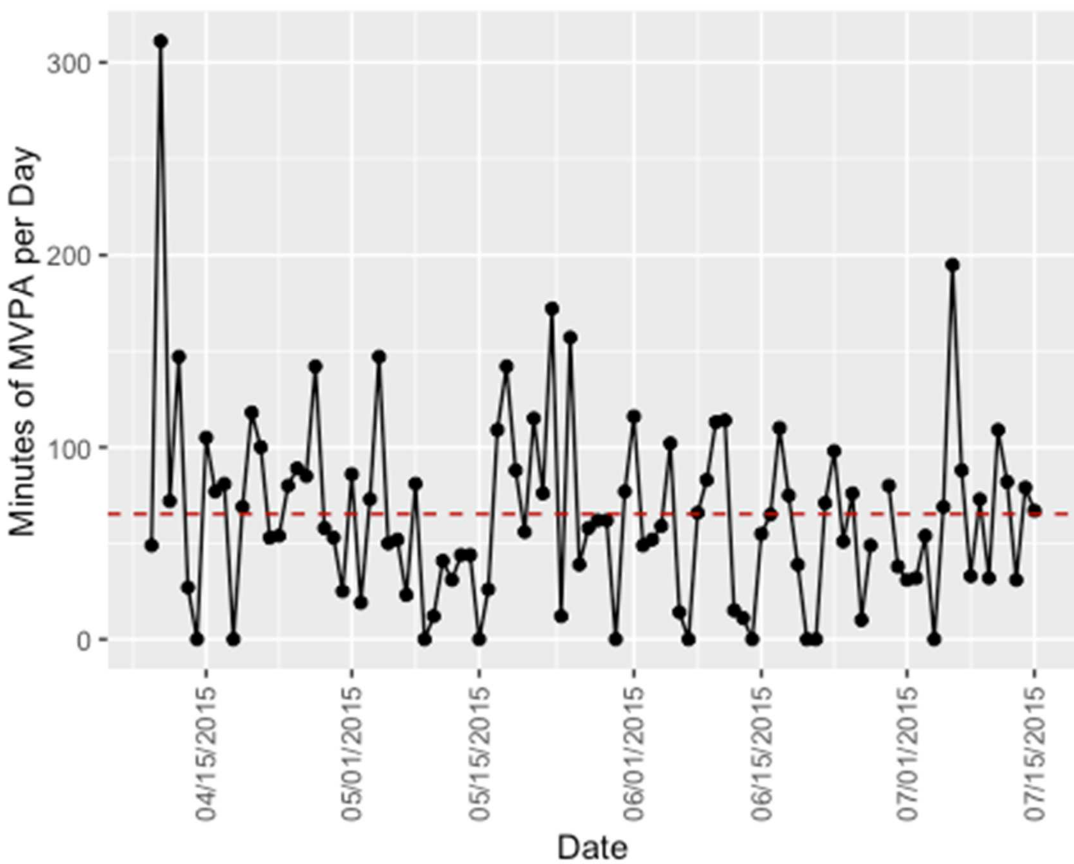

Figure B25. Minutes of MVPA (Bouts) per Valid Day: Participant 25

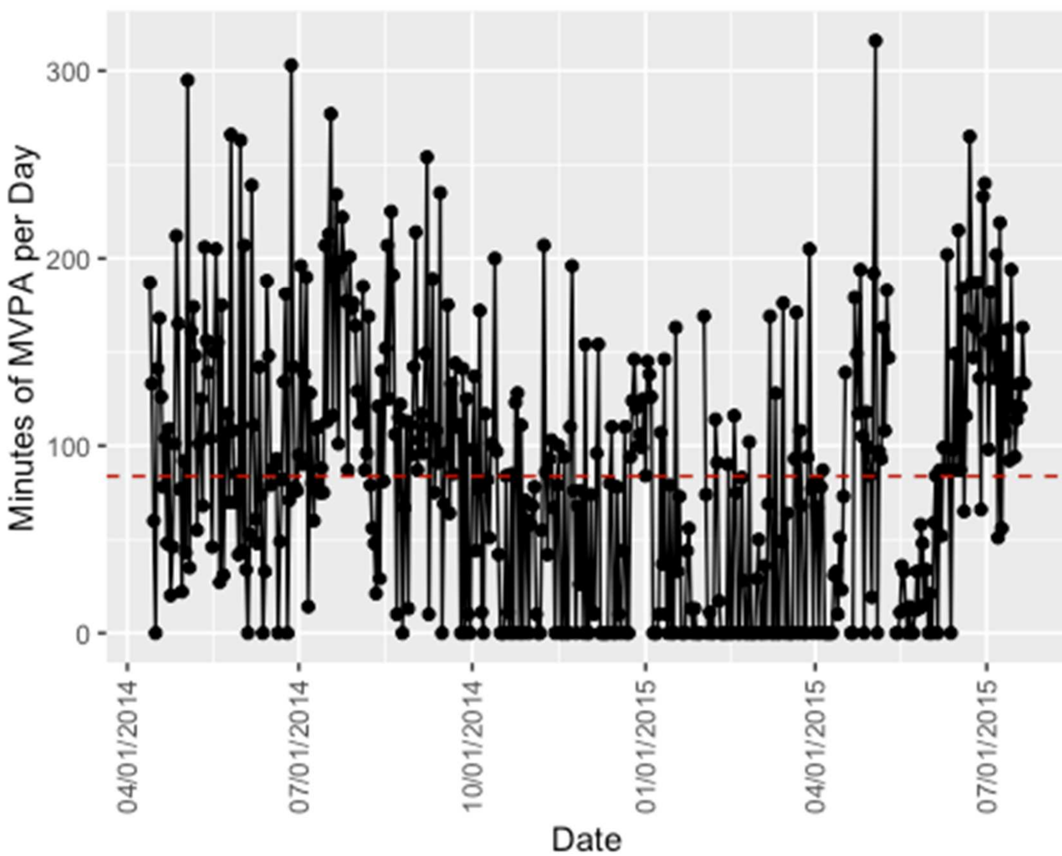

Figure B26. Minutes of MVPA (Bouts) per Valid Day: Participant 26

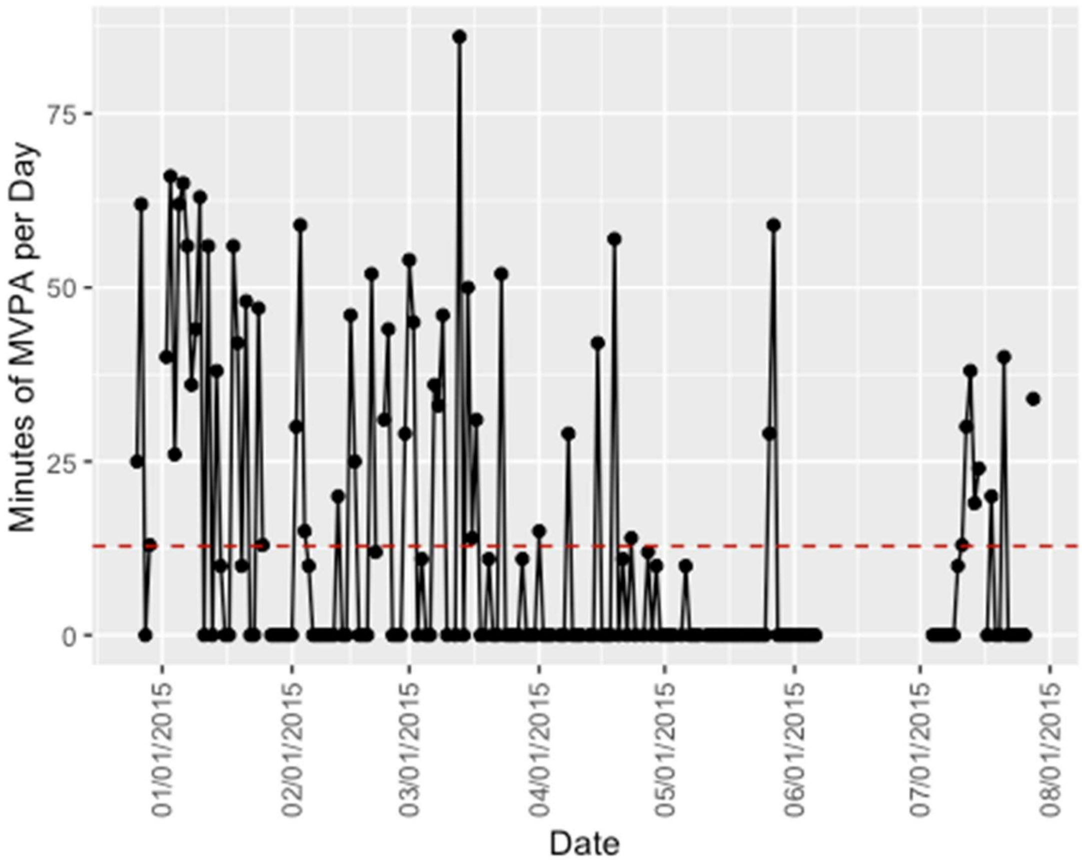

Figure B27. Minutes of MVPA (Bouts) per Valid Day: Participant 27

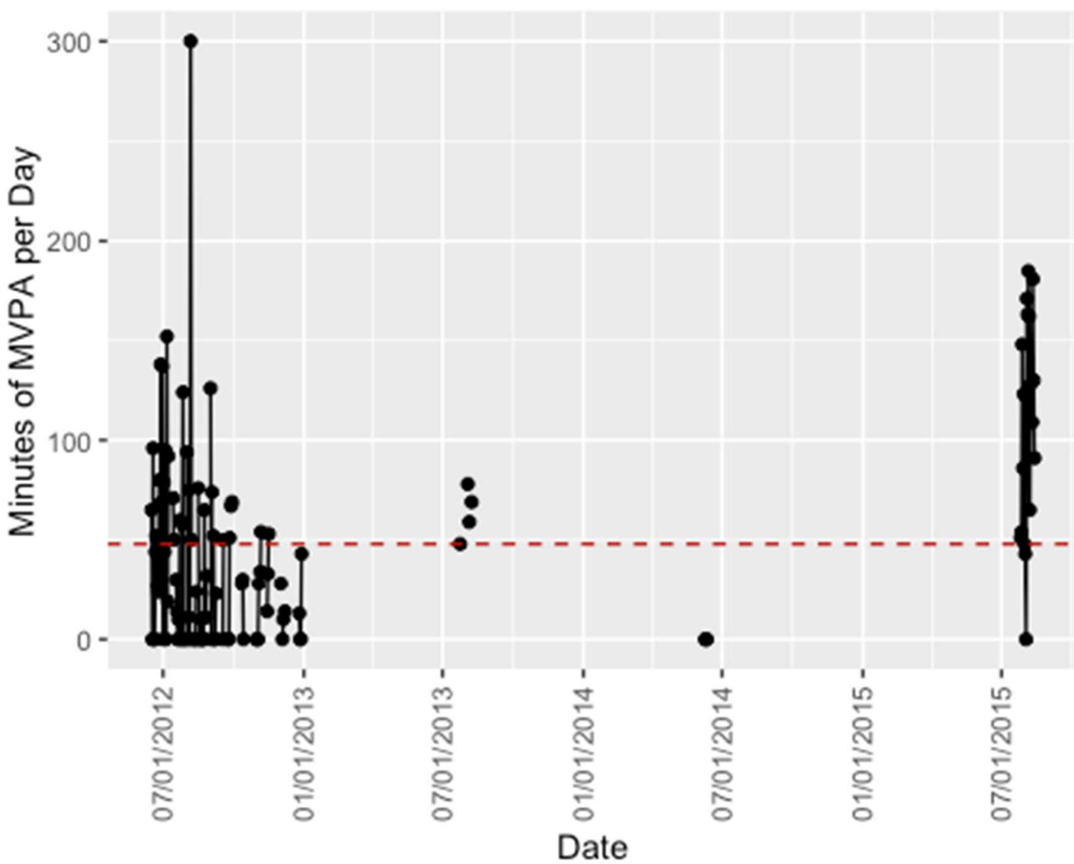

Figure B28. Minutes of MVPA (Bouts) per Valid Day: Participant 28

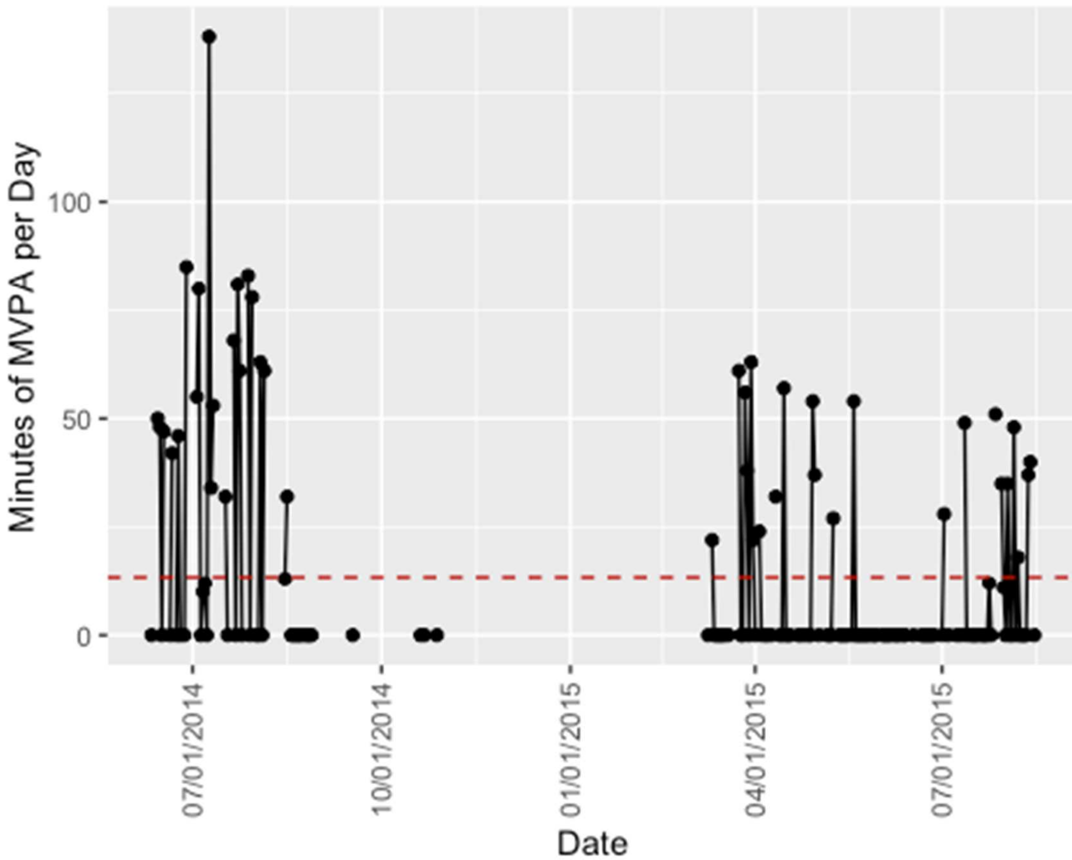

Figure B29. Minutes of MVPA (Bouts) per Valid Day: Participant 29

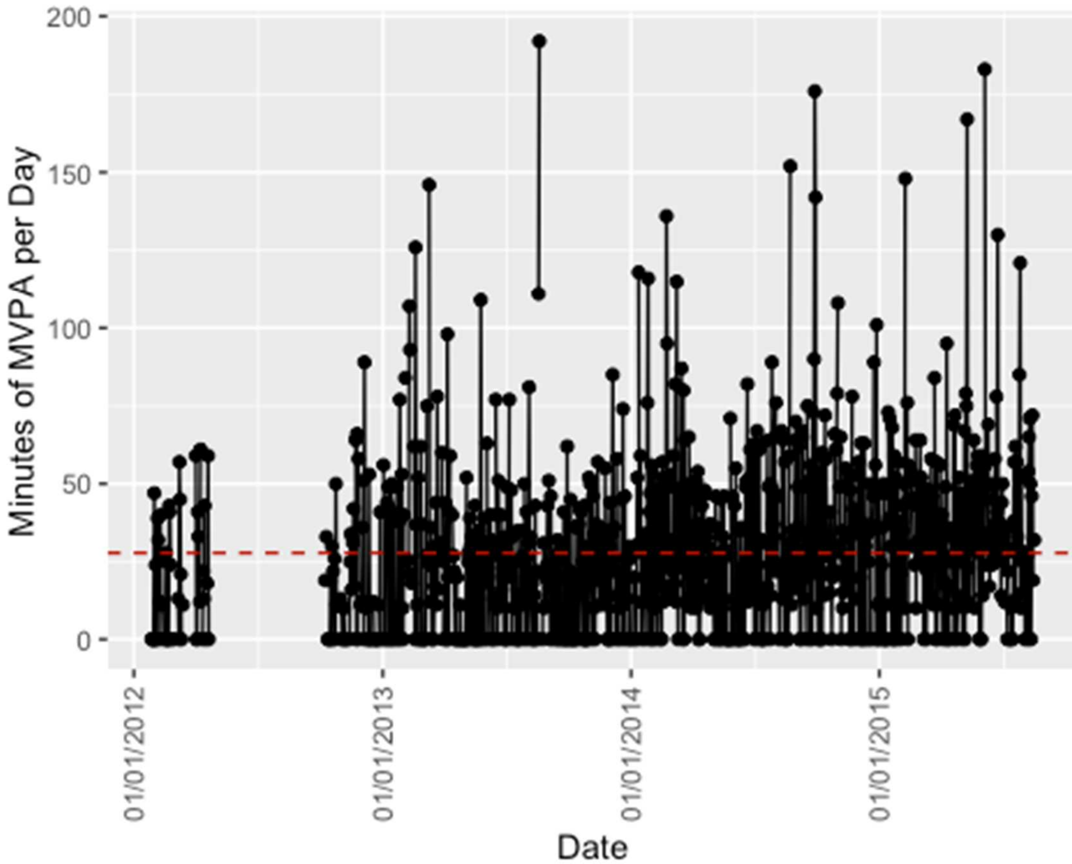

Figure B30. Minutes of MVPA (Bouts) per Valid Day: Participant 30

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