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A Pedometer-based Intervention to Increase Physical Activity: Applying Frequent, Adaptive Goals and a Percentile Schedule of Reinforcement

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 Marc Anthony Adams is approved, and it is acceptable

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DEDICATION

I dedicate this dissertation to several influential people in my life. To my father, Jacob Khoshaba Adams, you encouraged me to do good work and value education. I will always remember that. To my mother, Christine Adams, I enjoyed our talks about the program. I was lucky to have your support and patience during this process. To my instructors and mentors throughout my education, you planted an early seed that lead me here today.

EPIGRAPH

A journey of a thousand miles begins with one small step.

Lao Tzu

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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ABSTRACT OF THE DISSERTATION

A Pedometer-based Intervention to Increase Physical Activity: Applying Frequent, Adaptive Goals and a Percentile Schedule of Reinforcement

by

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Doctor of Philosophy in Public Health (Health Behavior)

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The majority of U.S. adults perform insufficient amounts of physical activity to prevent disease and maintain fitness. National recommendations prescribe fixed physical activity goals (e.g. 10,000 steps per day) that may fall outside of an individual's current physical activity repertoire. Prescribing smaller, more adaptive goals based on participant past behavior may be more efficacious at increasing physical activity to the target level. This study tested a pedometer-based intervention that prescribed adaptive goals and rewarded behavior using a percentile schedule of reinforcement. Five individuals enrolled into the intervention and were evaluated with a single-case withdrawal (ABA) design over 10 weeks. The six-week intervention consisted of one-time educational materials, daily adaptive goals, and contingent financial rewards administered on a percentile schedule. Daily goals were determined by ranking a participant's prior 9 days of physical activity (i.e. step counts) and selecting the 40th

percentile of the distribution on a moving basis. A Lifecorder Plus, combined accelerometer and pedometer, measured moderate-to-vigorous physical activity (MVPA) minutes per day and steps per day simultaneously. Visual analyses and multilevel statistical models for longitudinal data tested for change across phases. Based on visual analysis, four of the five women increased their median number of steps/day, and all five increased their median MVPA minutes/day. Participants increased their activity by 851 steps/day (range -829 to 2,450 steps) or approximately 5,957 steps per week, and 3.34 MVPA minutes/day (range 1.93 to 17.27 minutes) or approximately 23.38 MVPA minutes per week from baseline to the intervention phase. After controlling for covariates, the multilevel model detected a significant increase of 551.21 steps/day (SE = 258.26, p = .03) and 2.65 MVPA minutes/day (SE =1.09, p = .02) during the intervention phase compared to the baseline phase, after adjusting for wear time and day of the week. This study provides a formal test of percentile schedules for physical activity research and provided intervention efficacy (i.e., ‘proof of concept’). The findings may be used as a preliminary study to inform future work in this line of research.

INTRODUCTION

Regular physical activity is associated with prevention of morbidity and mortality. Yet, the majority of the U.S. adults do not meet recommended physical activity guidelines. Theory-based interventions have had limited success explaining and changing physical activity. This may be partially due to a lack of theoretical fidelity. Public health recommendations tend to prescribe absolute or fixed goals for all individuals. As such, they are not personalized and may be outside of an individual's current abilities. The current study tested a novel approach to increase physical activity behavior of adults through an intervention that used personalized, adaptive goal setting, and frequent contingent reinforcement. A high level of theoretical fidelity was planned by specifying a formal contingency shaping program and its elements a priori: daily goals, and the magnitude, schedule, and latency of reinforcement for physical activity. Percentile schedules of reinforcement are an untested type of reinforcement schedule for physical activity that requires repeated measures.

This study aimed:

1) To determine whether an intervention based on percentiles of reinforcement from Operant Theory increased the number of steps/day, measured by pedometer, over baseline levels.
2) To determine whether the intervention can be attributed causally to changes in physical activity.
3) To determine whether the percentile intervention increased the amount of moderate-to-vigorous physical activity (MVPA), measured by accelerometer, over baseline levels.
4) To determine participants' satisfaction with the overall program and potential side effects.

BACKGROUND AND SIGNIFICANCE

Physical Activity and Health

The 1996 Surgeon General's report on Physical Activity and Health summarized the effect of physical activity (PA) on prevention of mortality and disease (U.S. Department of Health and Human Services, 1996). Low levels of physical activity are associated with an increased risk of cardiovascular mortality, and a substantially higher risk of stroke and coronary events. The protective effects of PA on cardiovascular disease start at moderate levels of regular activity (Arroll & Beaglehole, 1992; Kelley & McClellan, 1994). The greatest gain in prevention of all cause mortality occurs between inactivity and initiation of moderate intensity physical activity (Blair et al., 1989).

Type 2 diabetes, a risk factor for both heart disease and stroke, contributes to over 220,000 deaths a year and $132 billion dollars in total healthcare costs (Centers for Disease Control and Prevention, 2003; U.S. Department of Health and Human Services, 1996). Since 1991, the prevalence of diabetes has increased 61% (Centers for Disease Control and Prevention, 2003). Regular physical activity protects against development of non-insulin dependent diabetes through improved glucose removal and insulin sensitivity. Additionally, physical activity promotes lean muscle gain and fat loss thereby improving body composition.

The role of physical activity and overweight is even stronger. At least 112,000 premature deaths are attributable to inactivity or diet annually (Flegal, Graubard, Williamson, & Gail, 2005). Overweight-related health problems account for over 9% of health expenses in the United States and up to $147 billion in direct and indirect healthcare costs -- almost exclusively from treatment of obesity-related diseases (Pratt, Macera, & Wang, 2000; Finkelstein, Ruhm, & Kosa, 2005; Finkelstein, Trogdon, Cohen, & Dietz, 2009).

Overweight and obesity have become an epidemic in the United States. National surveys using representative samples of the U.S. population show the prevalence of overweight (BMI = 25.0-29.9 kg/m^2) and obesity (BMI $\geq$ 30 kg/m^2) increased dramatically among adults over the last half century -- from 44.8% in 1960 to 66.3% in 2004 -- with obesity rates doubling over the last 30 years (National Center for Health Statistics, 2004; Ogden et al., 2006). Sex and age-specific prevalence rates show that between 1960 and 2002 men and women from all age groups gained an average 24 pounds (Ogden, Fryar, Carrol, & Flegal, 2004). Other industrialized societies (e.g. Europe) and among urban areas in developing countries show similar prevalence rates (Puska, Nishida, & Porter, 2003; Hill et al., 2007).

A dose relationship exists between the frequency and duration of physical activity bouts, the duration of PA programs, and the rate of weight loss (U.S. Department of Health and Human Services, 1996). The addition of physical activity to a diet only weight loss program improves long-term weight maintenance (U.S. Department of Health and Human Services, 1996). These findings show that physical activity has protective effects for many diseases, even after controlling for dietary factors.

Overweight, Energy Expenditure, and Physical Activity

Because population-level changes in overweight and obesity resulting from environmental selection of genes would take many generations to occur, recent rapid and population specific increases in obesity are likely the result of greater energy intake and reduced physical activity. Hill et al. (2003) found that the rise in obesity rates could result from a net increase of only 100-150 calories (kcals) each day (Hill, Wyatt, Reed, & Peters, 2003). While a 150 kcal increase could be the result of increased energy consumption alone, the observed U.S. dietary trends do not support this conclusion (Levine, Vander Weg, Hill, & Klesges, 2006; Heini & Weinsier, 1997). A 150 kcal daily net increase is likely to result from a combination of energy balance behaviors, including stagnant or decreasing trends of physical activity. The national recommendations of moderate activity for adults is equivalent to expending about 150 kcal/day "over and above" energy expenditure from daily activities. (Tudor-Locke & Bassett, Jr., 2004)

Physical Activity Guidelines

National recommendations call for adults to perform 30 minutes of moderate-intensity physical activity 5 or more days per week, or 20 minutes of vigorous-intensity activity 3 or more days per week, or some combination of both (U.S. Department of Health and Human Services, 1996). Physical activity can be accumulated continuously or in short bouts of at least 10 minutes periodically throughout the day (Tudor-Locke & Bassett, Jr., 2004). Moderate-intensity activity is defined as activity between 3 and 5.9 metabolic equivalents of task (METs) or equivalently burns 3.5 to 7 calories per minute (kcal/min) (U.S. Department of Health and Human Services, 1996). Examples include brisk walking, bicycling, vacuuming, gardening, or other activities that cause small increases in breathing or heart rate. Vigorous-intensity activity is defined as activity equal to or greater than 6 METs or burns more than 7 kcal/min (U.S. Department of Health and Human Services, 1996). Examples include running, aerobics, heavy yard work, high-impact aerobic dancing, swimming continuous laps, bicycling uphill or any activities that cause large increases in breathing or heart rate where conversation is difficult or broken. Physical activity can be distinguished further by four broad categories: 1) leisure-time exercise preformed for health reasons (e.g. walking at a health club, running outdoors in the evening), 2) daily-living activities (e.g. cleaning the house), 3) transportation activities (e.g. walking to a store or bus stop), or 4) occupational activities (e.g. lifting boxes) (Craig, Marshall, Sjostrom, & the IPAQ Consensus Group and the IPAQ Reliability and Validity Study Group, 2003). These four categories include both moderate and vigorous activities.

Prevalence of Physical Activity

Based on self reports of physical activity, the prevalence of individuals performing no leisure-time physical activity declined from 29.8% in 1994 to 23.7% in 2004 (Centers for Disease Control and Prevention (CDC), 2005). The prevalence of people who met MVPA guidelines for leisure-time PA has remained static at about 25% (Centers for Disease Control and Prevention, 2004). Troiano et al. in the first ever national evaluation of physical activtiy using objective physical activtiy monitors (i.e. accelerometers) found only 3.5% of men and women between 20 and 59 years old attained the 30 minutes of recommendated moderate-to-vigorous activtiy (MVPA) on 5 or more days per week in 2004 (Troiano et al., 2004). Thus, the majority of the population likely overestimates their activity and likely does not meet national recommendations.

The most common type of leisure-time activity reported by both men and women is walking, with 44.1% of individuals walking for exercise in the past two weeks (U.S. Department of Health and Human Services, 1996). Individuals report gardening as the second most common activity (29.4%). Walking is a commonly accepted and highly prevalent activity that most subgroups (i.e. adults, seniors, overweight) can adopt. Unlike gardening, walking may be an ideal exercise behavior to target for public health interventions because it requires no additional training, equipment, or facilities, and can be accumulated through leisure-time, transportation, occupational, or daily activities (Siegel, Brackbill, & Heath, 1995). Walking can be objectively and reliably measured using motion sensors called pedometers (Freedson & Miller, 2000).

Pedometers. Pedometers are inexpensive motion sensors that measure steps taken. How many pedometer steps are needed to meet physical activity guidelines? Recommendations for 10,000 steps per day for adults became popular in Japan before support and evidence emerged that linked the amount to U.S. activity guidelines (Tudor-Locke, Hatano, Pangrazi, & Kang, 2008). However, one study found that 8,000 steps/day was quantitatively linked with the 30-minute MVPA recommendation, although the sample characteristics and size may limit generalizability (Tudor-Locke, Ainsworth, Thompson, & Matthews, 2002). Marshall et al. found that 3,000 steps performed at a rate of 100 steps per minute for 30 continuous minutes met the moderate intensity threshold and PA recommendation (Marshall et al., 2009). A review of pedometer-based studies found that 3,000 to 4,000 steps/day "over and above" daily activities (i.e. 6,000 – 7,000 steps) approximates the 30-minute MVPA recommendation and is in agreement with the 10,000 step/day recommendation (Tudor-Locke & Bassett, Jr., 2004).

Pedometer-based interventions. A recent systematic review of 26 pedometer-based interventions concluded that pedometers were associated with a 27% increase in physical activity (Bravata et al., 2007). The review found that randomized controlled trials showed greater improvements in step counts (i.e. 2,491 steps/day over control group) after weighting by sample size. Non-controlled trials in the review showed similar but slightly lower improvements (i.e. 2,183 steps/day). An improvement of 2,000 steps per day translates to about a one mile per day increase.

Bravata et al. also explored predictors associated with improvements in physical activity (Bravata et al., 2007). Individuals with a lower baseline of physical activity and younger individuals showed the greatest step/day improvements, although these characteristics were only marginally significant. The strongest predictor of improvement was having a step goal. Studies without a step goal failed to show statistically significant improvements. Participants in studies with either a fixed 10,000 step/day goal or a lower - more personalized - goal showed an average increase of 2,000 steps/day. A comparison of goal type (i.e. fixed versus personalized goals) by the number of participants who met their goals was not possible because only two studies reported the number of goals met. The authors concluded that the benefits of adjustable and personalized goals remained unclear. Pedometer type was not associated with differences between studies.

Review of Environment-Focused Theory Related to Physical Activity

Conceptual Views of Physical Inactivity

Ecological models of health behavior postulate that biological, intra-individual, inter-individual, structural, and cultural factors are important in reversing the trends for inactivity and obesity (Cohen, Scribner, & Farley, 2000; Sallis & Owen, 1996; Hovell, Wahlgren, & Gehrman, 2002). For physical activity behavior, ecological models have focused on built environments. Urban planning, transportation, and public health research has shown that structural factors such as land use mix (diversity of land uses and access to facilities), street connectivity (density of intersections), and residential density are related to moderate intensity walking for transportation (Sallis et al., 2006; Sallis & Kerr, 2006). Mixed-use neighborhoods offer a greater number of destinations and reduced effort for walking to, and between, destinations (Cerin, Leslie, du, Owen, & Frank, 2007). High street connectivity is associated with direct routes in all directions compared to low connectivity, which is associated with circuitous routes and longer distances. Residential density may provide more social destinations or behavioral models for physical activity. These structural and associated social factors can be changed by policy at local and state levels. However, structural variables are constrained by current laws, political lobbying, and the reality that the lack of specific policy suggestions makes changing structural variables -- while extremely important and necessary for the long term -- a slow process (Sallis & Kerr, 2006). Structural factors are unlikely to help inactive individuals become active in the short term. Nevertheless, current structural variables, such as supportive neighborhood designs, may help sustain and maintain physical activity once established for those living in such communities.

Ecological models and many individual-level behavioral theories in public health acknowledge, even if superficially, the contingent benefits and costs of health behaviors (Prochaska, Redding, & Evers, 1997; Sallis & Owen, 1996; Williams, Anderson, & Winett, 2005; Hovell et al., 2002; Glanz, Lewis, & Rimer, 1997) A number of studies have acknowledged the competing "economics" involved in energy balance behaviors (Epstein, Bulik, Perkins, Caggiula, & Rodefer, 1991; Epstein, Roemmich, Paluch, & Raynor, 2005; Epstein, Roemmich, Stein, Paluch, & Kilanowski, 2005; Epstein, Dearing, Handley, Roemmich, & Paluch, 2006; Estle, Green, Myerson, & Holt, 2007; Finkelstein et al., 2005; Lappalainen & Epstein, 1990). They emphasize a world where unhealthy behaviors have immediate benefits and delayed aversive consequences, and healthy behaviors have immediate aversive consequences and delayed benefits. Thus, current social and physical environment reward systems are unbalanced, and favor of unhealthy food intake and sedentary behaviors relative to healthful food intake and regular activity. For example, sedentary behavior in our culture is likely the result, at least partially, of powerful cultural products that promote sitting and inactivity. Products such as automobiles, televisions, dishwashers, computers, and escalators and elevators require inactivity and may decrease the total activity preformed during one's day (Finkelstein et al., 2005; U.S. Department of Health and Human Services, 1996). These powerful products have immediate utility and can draw in positive social attention further strengthening sedentary behaviors. Moreover, many social interactions can promote sedentary activity (e.g. meetings, email, etc). The negative consequences of sedentary behaviors, such as weight gain and its health consequences, are cumulative, hard to detect on a daily basis, and very delayed. Thus, these negative consequences are ineffective at causing people escape or avoid them.

People living sedentary lifestyles who initiate exercise may not experience immediate benefits or experience aversive bodily feedback (Ekkekakis & Lind, 2006; Ekkekakis, 2003; Hall, Ekkekakis, & Petruzzello, 2002). Biological rewards (e.g. endorphin release, weight loss, reduced disease risk), usually considered intrinsic to physical activity, are unlikely to occur because inactive individuals cannot sustain the frequency, duration, or intensity to produce them. These benefits can occur once exercise has become routine. Positive health benefits, outlined in previous sections, tend to occur months, years, and decades later. When all human ecological factors from multiple levels are accounted for, the low levels of physical activity can be conceptualized as an imbalance between the consequences (rewards versus aversive consequences) for activity versus sedentary behaviors and the temporal nature of these consequences (immediate versus delayed) (Hovell et al., 2002; Epstein, 1998; Adams, Norman, Hovell, Sallis, & Patrick, 2009).

Operant Theory and Behavior Change.

Interventions based on individual behavioral theories have only explained approximately 33% of the variance in physical activity (Baranowski, Anderson, & Carmack, 1998). Cohen noted that “as the behavioral scientist moves from his theoretical constructs, among which there are hypothetically strong relationships, to their operational realizations in measurement and subject manipulation, very much ‘noise’ (measurement unreliability, lack of fidelity to the construct) is likely to accompany the variables” (Cohen, 1988). One possible explanation for the limited variance explained by behavioral theories is researchers’ fidelity to their theoretical constructs and the “drift” operationalizing constructs (drift referring to a systematic change in an operational definition over time). Rovniak et al. coined the term "theoretical fidelity" to judge how well a study matches the ideals of theoretical constructs (Rovniak, Hovell, Wojcik, Winett, & Martinez-Donate, 2005). Contributions of future studies will be judged on how they test the assumptions of theories and identify modifiable predictors of behavior (Baranowski, Klesges, Cullen, & Himes, 2004).

Operant Theory emphasizes selection of behavior by consequences through experiential behavior-environment contingencies. Operant theory codified the effects of selective contingencies on behavior, including health-related behaviors. Briefly, operant theory has shown changes to stimuli contingent on a behavior -- contingent consequences -- define the types of functional relationships of learning (Chance, 2003). Five types of behavior-consequence are possible: positive reinforcement, negative reinforcement, positive punishment, negative punishment, and extinction. Operant theory postulates that tangible and social contingencies can function to increase deficit health behaviors, such as physical activity, or temporarily suppress or extinguish excess behaviors such as smoking (Skinner, 1953). Positive and negative reinforcement both refer to a mechanism of increasing behaviors. Positive reinforcement is the process of presenting stimuli contingent on a response that increases future probability of a response class. Negative reinforcement is the process of removing existing aversive stimuli contingent on a response that increases the future probability of a response class. Positive and negative punishment and extinction are methods to decrease excess behaviors. Substantial research has shown that latency and frequency of consequences are critical qualities (Chance, 2003; Estle et al., 2007; Lamb, Morral, Kirby, Iguchi, & Galbicka, 2004; Lamb et al., 2007; Lamb, Morral, Galbicka, Kirby, & Iguchi, 2005; Lamb, Kirby, Morral, Galbicka, & Iguchi, 2004; Skinner, 1953; Coleman et al., 1999; Coleman, Paluch, & Epstein, 1997; Collins, Jr. & Epstein, 1978; Epstein & Stein, 1974; Epstein, Paluch, Kilanowski, & Raynor, 2004; Epstein, Roemmich, Saad, & Handley, 2004; Epstein & Leddy, 2006; Epstein, Beecher, Graf, & Roemmich, 2007). Two axioms of behavior analytical principles are highly generalizable: immediate consequences change behavior better than delayed consequences, and richer schedules of consequences generally help develop behavior better than lean schedules (Skinner, 1953). Ecological models and behavioral economic theories with a foundation in Operant theory also postulate that alternative behaviors, such as physical activity versus sedentary behaviors, while not mutually exclusive, are different classes of behavior, each conceptualized to have their own rewarding and punishing consequences (Epstein, 1998; Hovell et al., 2002).

Operant, Social Learning and Social Cognitive Theories, and the Transtheoretical Model include three common behavior change constructs; goal setting, reinforcement, and shaping (Skinner, 1953; Bandura, Ross, & Ross, 1963; Prochaska et al., 1997). However, scientists using these theories vary in how they operationalize constructs when designing interventions. For example, *goals should be individualized and adaptive to participants' current behavioral repertoire* (Bandura, 1997). Most physical activity interventions adopt a target behavior that matches national recommendations (e.g. 30 minutes per day) for all participants and provide reinforcement only when the goal is met. A general fixed goal may lie outside of a participant's current repertoire, and therefore they may never attempt it or fail to reach it (Morral, Iguchi, Belding, & Lamb, 1997). Additionally, scientists may design reinforcement programs poorly by providing incentives or rewards that are not contingent on a specific behavior, too delayed, or infrequent relative to the behavior aimed to be changed. Shaping behavior requires differential reinforcement, which is defined as successively reinforcing greater approximations to a target behavior while systematically not reinforcing (extinguishing) approximations farther from the target behavior (Skinner, 1953). This is not a linear process. It requires researchers to collect repeated measures of behavior and pay attention to small improvements. Adherence to the ideals of reinforcement and shaping constructs is difficult and expensive to meet. Inadequate theoretical fidelity to goals, reinforcement, and shaping may partially explain the limited success of theory-based interventions.

Review of Magnitude of Reinforcement for Energy Balance

Popular belief is that the magnitude of the reward is the only important dimension for motivation. However, magnitude of a reward is but one aspect. The possibility of earning rewards frequently (schedule of reinforcement) and the immediacy of the reward to the incidence of the behavior (latency) are even more important qualities of consequences than magnitude (Chance, 2003; Herrnstein, 1990).

A recent systematic review of randomized controlled studies using financial rewards contingent on weight loss, dietary or physical activity behaviors among overweight adults found that reward amounts ranged from $21 to $300 (Paul-Ebhohimhen & Avenell, 2008). The amounts were standardized as a percent of personal disposable income (PDI) by country and year to adjust for currency changes over the years and between countries. Rewards ranged from 0.2% to 10.2% of PDI, with a median 1.2%. For comparison purposes, a 1.2% PDI in 1984 (the median year of articles reviewed) in the U.S. equaled $147 per year. Amounts equivalent to 1.2% PDI and above tended to be more effective than lower amounts or no financial reward. The review authors noted that the majority of articles did not justify their use of reinforcement schedule or address temporal discounting (the decreased efficacy of rewards resulting from delayed presentation), and subsequently, the review did not control for these aspects. However, the review found a weak but positive trend for rewarding behavior rather than for weight loss, and for rewards delivered by non-psychologists compared to psychologists.

A recent study by Finkelstein et al. was not included in the review, but found that participants who earned $7.00 for every 1% decrease in body fat lost an average of 3 pounds by the first opportunity to earn the reward at 3 months (Finkelstein, Linnan, Tate, & Birken, 2007). Participants could earn financial rewards for reducing BMI without limitation. A 1% decrease in body fat was equivalent to a reduction of 2 pounds for a 200 pound individual (i.e. the mean weight of their participants), or a net deficit of 7,000 calories. Finkelstein et al. concluded that larger amounts were more motivating, as the $14 reward group showed an average 4.7 pound loss. However, this study made reinforcement contingent on weight loss (not a behavior), and temporal discounting and schedules of reinforcement were not addressed.

Basic Schedules of Reinforcement for Behavior Change

Schedules of reinforcement have been defined as the "prescriptions for arranging reinforcement in time in relation to responses" or refer to "the specification(s) of the criteria by which responses become eligible to produce reinforcers" (Lattal & Neef, 1996). Ferster and Skinner conducted substantial formative research on schedules of reinforcement (Ferster & Skinner, 1957). Reinforcement can be based upon: a certain number of responses (ratio schedule), the first response after an interval of time as passed (interval schedule), the continuous performance of behavior over time (duration schedule), among others. The simplest schedule, and one the typically leads to rapid learning, is known as continuous reinforcement schedule; it is a special case of a ratio schedule where every response that met the criterion is reinforced. Reinforcement that occurs less than every instance of behavior is known as an intermittent schedule. Intermittent schedules can be fixed or variable. For fixed schedules, a behavior is reinforced after every *n*th number, interval, or duration of responses. Once the individual meets the criterion, it is repeated. For example, a trainee must lift a weight 10 times before a trainer will say “good job”; the requirement is then repeated. For variable schedules, instead of reinforcing a behavior after it has occurred a fixed number of times, the schedule specifies the number, interval, or duration of responses *on average*. For example, an individual gambling in a casino needs to pull the level of a slot machine an unknown, but programmed average, number of times to earn a win. Intermittent schedules decrease the impact of satiation of rewards, and produce resistance to extinction compared to continuous schedules. Basic schedules include fixed ratio, variable ratio, fixed interval, variable interval, fixed duration and variable duration schedules.

In addition to the frequency of reinforcement, different types of schedules produce unique steady state patterns of behavior (Ferster & Skinner, 1957). Figure 1 shows the steady state patterns produced with specific schedules (a notable omission are the fixed duration and variable duration schedules). It is important to note that basic research on schedules specified the type of schedule a priori with the goal of examining the steady state effects on behavior.

Basic Schedules and Physical Activity

Although schedules of reinforcement are used whenever rewards are, only a few studies have tested how schedules of reinforcement may increase physical activity. All targeted stationary cycling (De Luca & Holborn, 1992; Cohen, Paradis, & LeMura, 2007; Cohen, Chelland, Ball, & LeMura, 2002).

Cohen et al. tested the effects of fixed ratio schedules to increase cycling responses (revolutions of pedal) with three college women (Cohen et al., 2002). Twenty-five second video clips of cycling movies were used as the reinforcer. Three experimental conditions were compared to a no movie baseline: video for entire session, or 25 seconds of video on a fixed ratio 40 (FR40) schedule, or on a FR80 schedule. In a second experiment, the authors tested the effects of monetary reinforcement (i.e. 5 cents) contingent on cycling using a FR20 or

FR40 schedule. In the first experiment, participants cycled more in each of the video phases than baseline. However, no practical differences were found between the continuous video, FR40, and FR80 schedules. For the monetary phase, one of two participants showed an increase in pedaling rate on the FR40 and FR20 schedules relative to baseline, respectively. The authors concluded that reinforcement schedules can increase pedaling on a stationary cycle.

A study by Cohen et al. also tested the effects of fixed ratio schedules using monetary reinforcers to increase stationary cycling time and revolutions among 25 college students (Cohen et al., 2007). Three interventions were tested: contingent money (i.e. 15 cents) presented on a FR40 schedule, continuous presentation of music during entire session, or combination of contingent money plus music. Compared to the ‘no music/no money baseline phase’, only the ‘money only’ and ‘money plus music’ conditions significantly increased cycling time relative to baseline. The rate of cycling was also examined. Compared to baseline, cycling rate increased for the all three intervention conditions. Interestingly, the authors reported that the number of FR40 schedules completed increased during the ‘money plus music’ condition only. The authors concluded that ‘money only’ and ‘money plus music’ significantly increased the average amount of time on the cycle and cycling rate, while music alone significantly increased the cycling rate only.

De Luca and coauthors tested a variable ratio (VR) schedule to increase pedaling among overweight and normal-weight 11-year old boys over 12 weeks (De Luca & Holborn, 1992). For the first VR schedule, participants were exposed to a 15% increase over their personal mean responses during baseline. That is, a participant with a baseline mean of 60 revolutions per minute was given a VR 69 schedule. Two subsequent VR phases included increasing the VR schedule by an additional 15% over their last performance (changing criterion design). Participants earned one point per reinforcement, and could trade accumulated points for backup reinforcers, such as games, comic books, model cars, or planes. For both obese and non-obese boys, the authors found an increased rate of pedaling for each subsequent phase. Additionally, the program produced an increased duration of exercising compared to baseline for all participants.

The application of schedules of reinforcement to physical activity is limited, and more research is needed for different types of physical activity. No studies to date have examined schedule effects on ambulatory activities. The lack of research on reinforcement schedules for physical activity may have occurred because of the difficulty of measuring physical activity objectively, and applying schedules outside of a laboratory setting. The last decade has seen an improvement in the measurement of physical activity with objective measures such as pedometers and accelerometers, which may make this research more feasible in the field. A new class of schedules has also been advanced: dynamic schedules of reinforcement (Lattal & Neef, 1996).

Dynamic Schedules of Reinforcement. Dynamic schedules of reinforcement are not a specific type of schedule, such as a fixed ratio schedule, but rather a class of schedules. Dynamic schedules are defined by a change in the requirement for reinforcement after the delivery of each reinforcer as a function of: 1) some a priori algorithm independent of the individual's behavior, or 2) some aspect of an individual's prior responses on the schedule (Lattal & Neef, 1996). Common algorithm-based schedules specify a constant value added to the requirements for reinforcement. One algorithm-based schedule that may help shape physical activity is the percentile schedule.

Percentile Schedules of Reinforcement. The percentile schedule of reinforcement is an adaptive type of dynamic schedule. Percentile schedules use repeated measures of behavior to determine the range and distribution of an individual's ability. Then, the sample of behavior is ranked ordinally on one or more behavioral dimensions (e.g. frequency), and a percentile of the distribution is selected a priori for differential reinforcement. This guarantees that the criterion (or goal) is within the participant's repertoire, and he or she will have a high probability of meeting the initial criterion and earning reinforcement. In contrast, public health recommendations tend to use absolute or fixed goals for all individuals (e.g. 10,000 steps). As such, they may be outside of an individual's current abilities.

Applied Percentile Schedules of Reinforcement. Although contingency management interventions are often effective, they sometimes fail at both the group and individual levels. The failure may be because participants never perform the level of behavior required and therefore never interact with the programmed rewards. Morral et al. found that 88% of people who failed treatment never experienced or earned the programmed rewards for smoking cessation (Morral, Iguchi, Belding, & Lamb, 1997) Percentile schedules attempt to improve contingency management by setting the criterion for success consistently within a participants' repertoire, while slowly improving that repertoire. There are currently four studies of percentile schedules of reinforcement of human health behavior in the literature. All targeted tobacco use.

In their first pilot study, Lamb et al. (2004) tested the magnitude (amount) of financial reinforcement and differing criterion levels (Lamb et al., 2004) to reduce tobacco consumption. One group had to reduce their breath carbon monoxide (BCO) levels to less than or equal to 4 parts per million (ppm) to earn a reward. The 4 ppm criterion corresponds to a stringent cessation level, and represents a fixed target. In the second group, each participant had to reduce their BCO level to at least half of their baseline BCO level (a criterion known to be within their repertoire). Smokers earned $1 each day they met criterion and could earn a bonus reward (either $0, $1, $3, $10 or $30 each day) for continuous achievement over 6 weeks. Lamb found that increasing the magnitude of the reward increased the number of times participants met their criterion. Lamb et al. also found that easing the criterion to 50% of baseline created behavior change where the more stringent fixed criterion was ineffective.

In their second study, Lamb et al. (2004) examined the effects of a 50th percentile schedule aimed at reducing BCO levels between two small samples of women; one group "interested" and another "uninterested" in quitting smoking (Lamb et al., 2004). The authors used a moving window of repeated BCO measures to adjust the 50th percentile schedule. Among those individuals uninterested in quitting, participants met the criterion for reduced BCO levels about 50% of the time, as programmed. Among participants who wanted to quit smoking, Lamb et al. found that the 50% schedule helped 3 out of 5 participants decrease BCO levels immediately, and each ultimately showed sustained cessation for the final 40 days of the study. The remaining two participants reduced their BCO levels by more than half of their baseline BCO levels.

In a third study, Lamb et al. (2004) tested the differential effects of a 10th, 30th 50th, or 70th percentile schedule contingency on reducing BCO levels among a sample of men and women seeking to quit smoking (Lamb et al., 2004). This study attempted to identify the ideal percentile schedule for shaping smoking cessation. The 10th percentile schedule (a stringent criterion for targeting cessation of behavior) ensures that only the best 10% of a participants responses earn the reinforcer, while the 70th percentile schedule (a more generous criterion) ensures that 70% of a participants BCO levels meet criterion and are rewarded. The last 9 days of BCO levels was the sample window that each schedule was based upon. Participants could earn $2.50 for meeting the criterion and a $.50 bonus up to $10.00 for each sequential sample that met criterion.

All four types of percentile schedules were associated with reduced BCO levels immediately following presentation of the contingency incentives, and BCO levels continued to fall until reaching very low levels by the end of the study. There was an increasing trend on effectiveness across schedules indicating superior performance for the 70^{th} percentile schedule compared with the other schedules. However, the 50^{th} percentile schedule also produced immediate and favorable reductions in BCO levels. The 10^{th} percentile schedule preformed least favorable compared to the other conditions. In the 10^{th} percentile group, 16% of the participants never earned incentives, which may explain why all of them dropped out of the study. The 30^{th}, 50^{th} and 70^{th} percentile schedules showed similar effectiveness in promoting cessation by the end of the study. However, the 70^{th} percentile group showed the quickest shaping of cessation followed by the 50^{th}, 30^{th} and 10^{th} percentile groups. Interestingly, the more generous percentile schedule (defined as greater % of behavior rewarded), the more effective the contingency was at producing change among those who were identified as hard-to-treat (defined as not achieving CO levels ≤ 4 ppm during a ny baseline day). Lamb et al. also found that each schedule could be implemented effectively and adherence was very good.

In a fourth study, Lamb et al. tested whether a shorter, more responsive four-day window of past behavior was more effective than a nine-day window using only a 60^{th} percentile schedule of reinforcement among men and women smokers without plans to quit in the next 6 months (Lamb et al., 2005). The shorter sample window allows the value of the BCO criterion to adjust quicker should a participant relapse after cessation. Each subsequent day the new BCO measure was incorporated into the moving window to produce a new criterion. A 10-visit baseline was used to establish the four- or nine- day window. Lamb et al.

also tested whether participants' self-efficacy, stage of change, and readiness to quit increased or decreased during the study. The study included 70 visits where reinforcement could be earned. Participants in both groups earned $2.50 each day their BCO level met the percentile criterion, and they could earn a $.50 bonus for each sequential sample that met criterion up an additional $10.00. Participants could also earn the reinforcement payment for BCO levels of ≤4ppm (i.e. an indicator of cessation).

The study found that the four- and nine-sample window groups median percentage of earning rewards was 78.2% and 91.7%, respectively. Both groups were well above the programmed 60%. The results showed that the 4-sample window group had consistently lower BCO levels than the 9-sample window group (not statistically significant), and both groups decreased their BCO levels over time by more than half. Participants in the 4-sample window achieved the target goal of BCO of ≤4ppm more rapidly than the 9-sample window. The lower BCO levels were directly associated with a reduction in the number of cigarettes smoked. Both conditions showed increased readiness for quitting smoking, improvements in the action and maintenance stages of change, and self-efficacy.

As a whole, these studies suggest that higher magnitude rewards are more effective than lower magnitude rewards for promoting reduced BCO levels and tobacco cessation. They also suggest that 50th and 70th percentile schedules for decreasing a behavior produced the quickest reductions in BCO levels and longest cessation durations. While the 4-day window produced lower BCO levels compared to the 9-day window, these results were not statistically significant and cannot be considered different. Because these studies were applied to tobacco use behavior, the parameters identified in these studies may not generalize to physical activity behaviors.

The Promise of eHealth.

Technology-based interventions promise to make individual interventions more individualized and easier to disseminate. e-Health can be defined as any interactive technology (e.g., e-mail, Internet, CD-ROM program, handheld computer, kiosk, etc.) used to change behavior (Norman et al., 2007). Interventions that incorporate technology may be able to operationalize theory-based behavior change components better than other types of intervention strategies. eHealth interventions may have the ability to maximize a number of theoretically important qualities common to behavior change theories. One possibility of technology is to improve goal setting by assessing smaller milestones more frequently through daily communication, and then, automatically produce new, slightly more challenging goals. For example, Croteau used email to adjust step count goals biweekly by 5% or 10% to slowly increase daily physical activity to the desired levels, and found large and significant effects over time (Croteau, 2004). Technology also allows for delivery of specific and timely feedback (Rovniak et al., 2005). Two recent systematic reviews have been published on eHealth interventions related to dietary behaviors and physical activity. Kroeze et al. reviewed studies of computer-tailored materials delivered to participants without person-to-person contact (i.e., by mail, computer, or other media device) (Kroeze, Werkman, & Brug, 2006). They found little evidence for effective computer-based PA interventions. Norman et al. identified studies for physical activity, dietary behaviors, and the combination of both behaviors (Norman et al., 2007). Norman and colleagues concluded that results were mixed for activity and better research was needed to determine how technology could enhance behavioral outcomes. In particular, the lack of consistency in eHealth intervention outcomes could be explained by a lack of theoretical fidelity or poor study designs (Norman et al., 2007).

Summary

Regular physical activity is associated with prevention of morbidity and mortality. Yet, a large proportion of the population does not meet the recommended physical activity guidelines. This may be a result of an imbalance between behavioral consequences for sedentary behavior compared to physical activity behaviors. Walking is a highly accepted physical activity behavior to promote. Macro-environmental built environment modifications, while necessary for sustained behavior change of the population, are unlikely to be specific enough to individuals' needs to change their activity in the short-term. Alternatively, individual-level behavioral interventions have had limited success explaining PA variance and changing PA behaviors. This limited effect may be partially due to a lack of theoretical fidelity. Percentile schedules of reinforcement are an untested type of reinforcement schedule that require repeated measures of physical activity. Objective measures of physical activity and computer technologies may allow behavioral scientists to improve theoretical fidelity resulting in increased PA among inactive individuals.

The current study tested a novel approach to increase physical activity behavior of inactive adults through an intervention using personalized, adaptive goal setting, and frequent, contingent reinforcement. The primary aims were to increase the number of steps taken per day and to increase the frequency, duration, and intensity of moderate-to-vigorous physical activity to recommended guidelines. A high level of theoretical fidelity was planned by specifying a formal contingency shaping program and its elements a priori: daily goals, and the magnitude, schedule, and latency of reinforcement for physical activity. Contingent reinforcement was specified by a *percentile schedule* of reinforcement.

METHODS

Research Design. The intervention was evaluated with a single-case ABA design (withdrawal design) using repeated (daily) measures of physical activity over 10 weeks. The three phase design consisted of a no-intervention baseline phase (A), an intervention phase (B), and a no-intervention withdrawal phase (A) (Shadish, Cook, & Campbell, 2002). Five individuals who qualified for the study enrolled in the percentile schedule (PS) intervention. Pedometers measured baseline (A) physical activity for up to 20 days. The intervention phase (B) started once the following conditions were met: 1) the initial measurement reactivity had decreased, 2) at least 10 days of physical activity had been measured, and 3) baseline measures showed a flat or declining physical activity step counts, or 4) at least 20 days had elapsed. The six-week intervention consisted of brief, one-time educational materials, daily adaptive goals, and contingent financial rewards administered on a percentile schedule. At approximately week 9, the intervention was withdrawn (A_w) while participants continued to report their step counts for two weeks. The main outcome was change in pedometer steps over 10 weeks. A combined pedometer and accelerometer allowed for evaluation of change in steps per day and the duration and intensity of physical activity across phases over 10 weeks. The institutional review boards from the University of California, San Diego and San Diego State University approved this study.

Setting. The study occurred in San Diego County, California. San Diego County is geographically the 2nd largest county in California and the 4th largest in the U.S., and is located on the California/Baja Mexico, Mexico border (U.S.Bureau of the Census, 2000). San Diego County has a population of 2.9 million people in 2006 consisting of a racial/ethnic distribution of: 69.5% White, 5.2% African American, 10.6% Asian American/Pacific Islander, 10.3% Other, 0.7% American Indian or Alaska Native, and 29.9% Hispanic/Latino (U.S.Bureau of the Census, 2007). According to the 2005 California Health Interview Survey, the proportion of San Diego County adults overweight and obese was 36.3% and 18.4%, respectively (California Health Interview Survey, 2007). Over 24.4% of all San Diego residents perform no moderate or vigorous activity, with rates higher for obese individuals (42.1%), Asians (32.6%), Hispanic/Latinos (31.7%), and African Americans (26.2%) (California Health Interview Survey, 2007).

Recruitment, Inclusion, and exclusion criteria. The study identified 5 individuals who wanted to increase their physical activity and who met the criteria to test the efficacy of the intervention. Because this study is an efficacy test of percentile schedules, the author recruited individuals that had a high probability of being able to participate and complete the 10-week study. Inclusion and exclusion criteria consisted of: 1) men and women between 18 and 55 years old, 2) inactive (defined as frequency, duration, and intensity of activity less than current CDC guidelines for adults), 3) body mass index less than 35 kg/m^2, 4) free from injury or medical conditions that would limit physical activity, 5) not pregnant, 6) not currently using legal or illegal mood altering pharmaceuticals, and 7) daily access to a computer with internet connection. The following inclusion criteria refinements were adopted after problems were noticed: 1) participants could not leave San Diego County for more than 10 days over the next 4 months, 2) participants could not plan to move away from San Diego County in the next 4 months, and 3) inactivity was further defined as less than 1,000 MET-minutes per week. These changes were made after problems arose during recruitment that led to dropouts and inclusion of overactive participants.

The Physical Activity Readiness Questionnaire (PAR-Q), a physical activity health screener, determined candidates' health status for the adoption of an exercise intervention (Thomas, Reading, & Shephard, 1992), and the International Physical Activity Questionnaire (short form) determined inactivity status (Craig et al., 2003). Adults older than 55 years of age were excluded because of the increased probability that other known and unknown variables could affect the efficacy test of the intervention. Such variables can include a higher incidence of cardiovascular diseases, cancers, bone fractures, medication use, death, or other life events. Participants were recruited using email and print announcements approved by institutional review boards at the University of California, San Diego and San Diego State University. Print materials were posted at local coffee shops, and email announcements were posted on the University of California, San Diego listserve and Craigslist.com (http://sandiego.craigslist.org). Interested individuals called a telephone number shown on the recruitment materials at which time the author described the study in more detail and screened individuals for inclusion. Eligible candidates were invited to participate in the study.

Theoretical Perspective. Operant Theory, or more specifically Applied Behavior Analysis, guided the development of the intervention (Cooper, Heron, & Heward, 2006). Operant Theory proposes that a target behavior currently outside an individual's repertoire can be taught by shaping. Shaping is the process of identifying a target behavior and moving participants towards that behavior through differential reinforcement of successive approximations of the target behavior. Successive approximations refer to responses that are more similar to the target behavior relative to other responses. The concept of shaping behavior is prevalent in many theoretical models and preventive sciences (Biglan, 2003). However, the application of shaping by investigators and clinicians can vary between and within studies. At worst, reinforcement is applied non-contingently, non-successively, or with long delays relative to the incidence of the desired responses. Reinforcers can also be applied too infrequently. At best, shaping tends to be considered an art without formalized rules. The art of shaping is in knowing exactly when and how to use the principles; a skill believed learned only by doing (Galbicka, 1994). Percentile schedules attempt to formalize the rules of shaping (Galbicka, 1994). Formalized rules of shaping allow researchers or interventionists to design interventions that are more systematic and even automated.

Target Behavior. This study used 10,000 steps/day five or more days per week as the ultimate target behavior. Ten-thousand steps per day is equivalent roughly to 5 miles per day (i.e. 2,000 steps per mile). Evidence suggests that taking 3,000 to 4,000 steps/day “over and above” daily activities (i.e. 7,000 - 6,000 steps) approximates the current 30-minutes/day moderate-to-vigorous physical activity (MVPA) recommendation for adults (Tudor-Locke & Bassett, Jr., 2004; Le Masurier, Sidman, & Corbin, 2003). Thus, the well-known criterion of 10,000 steps per day has been shown to be indicative of an active adult lifestyle (Tudor-Locke & Bassett, Jr., 2004). Sedentary and inactive individuals likely do not reach that level of step counts often, if ever. Therefore, it is important to know the range of their activity and reinforce attempts that approach the target behavior.

Baseline Phase.

Pedometer. Participants received a Kenz Lifecorder Plus combined pedometer and accelerometer, and wore the device on their waistline at the midline of their right thigh. The author instructed participants to wear the device every day starting when they woke up until bedtime, or for at least 10 hours, except when swimming or in the shower. The pedometer measured the number of step taken each day beginning on the first full baseline day.

The unsealed pedometer displayed the date and time, the number of steps accumulated for that day, cumulative steps over the last 7 days, and the daily target goal of 10,000 steps. Additional physical activity data were stored in the internal memory, but inaccessible to the participant (see Outcome Measurement Section). At midnight, the pedometer reset to zero steps and started counting steps for the new day.

At the baseline office visit, participants were provided written instructions to follow. Instructions included: how to wear device correctly, reminders to wear the device for the required number of days and hours, and tips for not losing the device. To increase compliance, at the baseline meeting the author demonstrated how to wear the device properly and asked participants to demonstrate their ability to do so. The author provided corrective feedback if necessary. Participants were instructed to continue with their normal routine for the duration of the baseline phase. Participants earned $10 for providing up to 20 valid days of baseline data.

Email Communication. After the baseline visit, the primary mode of communication between participants and author was email. Participants reported their daily-accumulated steps by sending an email to the author by midnight or early the next morning. Participants reported their ID number, number of steps taken, and the date in the subject line of the email (e.g. #102 – 3500 steps on 1/2/09). Participants were not required to write a message in the email body. This simple approach reduced participant response burden and approximated mobile phone text messages. During the baseline phase, the author's response was a simple "Received" appended to the beginning of the subject header (e.g. Received: #102 – 3500 steps on 1/2/09) for every email received. The author responded within 1 hour on most occasions.

Intervention Phase and Components.

All participants received the same physical activity measurement and intervention components with the same percentile schedule criteria, but with varying absolute goals determined by their reported physical activity over the last 9 days.

Email Communication. On the first day of the intervention phase, the author sent participants an email to welcome them to the intervention and instruct them on how to earn reward points (Appendix A). During the intervention phase, the author responded to participants' emails by including the goal for the next day in the email (e.g. Goal for 1/3/09: 3,300 steps). The author also responded to participants' step reports differently depending on whether a participant accomplished that day's goal. Participants who met the day's goal received a response with one of the following exclamations in the subject header "Well done", "Met", "Success", "Accomplished", "Achieved", "Attained" and an increment on their reward points (e.g. Accomplished! Reward Points = 4). Participants could include any comments or concerns for the author in the email body.

Physical Activity Education Component. On the first intervention day, participants were provided two brochures on physical activity. One was entitled, "Be Active Your Way: A Guide for Adults" published by the U.S. Health and Human Services and available at the Centers for Disease Control and Prevention website (www.cdc.gov) (Department of Health and Human Services, 2008). The publication defined physical activity and covered the national recommendations for adults. It also included a number of sections tailored to individuals' current activity status. These sections included, "Getting Started with Physical Activity", "Making Physical Activity Part of Your Life", "Keeping It Up, Stepping It Up" and "Being Active for Life". The second brochure was entitled, "100 Ways to Add 2000 Steps" available at the America on the Move website (www.americaonthemove.org) (America On the Move, 2008). This brochure suggested 100 ways to increase steps throughout the day with the caveat that following only one tip would not provide 2000 additional steps. Tips included "Take your dog for a walk", "Take an aerobics step class", "Walk around the outside aisle of the grocery store before shopping", etc. America on the Move provides these materials free of charge to health professionals and researchers. No further educational materials were provided to participants.

Daily Physical Activity Goal Component. Participants were prescribed personalized, adaptive goals based on a 9-day moving window of their past physical activity measured by pedometer. As noted earlier, once a participant emailed their pedometer steps, the author sent the next day's step goal via email. Each step goal was only good for that day. The percentile algorithm determined new steps goals.

Percentile Schedule Shaping Component. Percentile schedules of reinforcement are concerned with relative values of behavior rather than absolute values. For example, a fixed ratio schedule would specify an absolute step count, such as 5,000 steps, and provide reinforcement each time the goal is met (continuous) or occasionally (intermittent). Percentile schedules consider the variance in the participant's repertoire of behavior to determine the criterion while specifying continuous or intermittent schedule independently. By specifying a percent of the participant's personal distribution, researchers can standardize the cut-point across participants and still have varying absolute values that lead to personalization.

Figure 2 shows the hypothetical distribution of step counts for an inactive individual over 6 months. Figure 2 Panel A shows the distribution of step counts is slightly positively skewed, with higher step counts less likely than lower step counts. Figure 2 Panel B shows the same distribution with the vertical dotted line representing the 10,000 step goal. It is evident from the figure that the proportion of the hypothetical participant's responses that meet or exceed the 10,000-step level is small. Thus, specifying reinforcement contingent upon this criterion level would likely be ineffective since a participant would infrequently interact with the reinforcement contingency (Lamb et al., 2007). Figure 2 Panel C shows that by moving the criterion cut-point to a lower value a larger proportion of the distribution met the criterion for reinforcement, and thus the individual is exposed to the reinforcement contingency more often. Greater interaction with the contingency should produce changes in the individual's behavior over time. Adjusting the criterion level lower (e.g. from 10,000 to 5,000 steps) corrects the problem of interaction with the reinforcement contingency, but it does not address how to capture and reinforce greater approximations to the target behavior (10,000 steps) in an efficient way.

An ideal shaping program is adaptive. It should be able to capture day-to-day variation in steps that are closer approximations to the target behavior while not rewarding relatively weaker responses. This requires continuous measurement, ranking of relative responses, and differential reinforcement.

Figure 3 is a two-by-two table that conceptualizes the parameters involved in shaping with percentile schedules (Galbicka, 1994). An experimenter makes two independent decisions while shaping: 1) whether a response meets the criterion level or not (shown by W and $\overline{W}$), and 2) whether the response will be reinforced or not (shown by Z or $\overline{Z}$). Responses in cell *a* meet the criterion and are reinforced. Responses in cell *b* meet the criterion and are not reinforced (similar to a false negative). Responses in cell *c* do not meet the criterion and are reinforced (similar to a false positive), while responses in cell *d* do not meet the criterion and are not reinforced.

The parameters *u* and *v* are the conditional probabilities of reinforcement for criterion and non-criterion responses (i.e., $\Pr(S^R|W)$ and $\Pr(S^R|\overline{W})$), respectively. These parameters specify the probability that once a criterion response occurs or does not occur that the consequence will occur. Thus, by increasing *u*, one increases the proportion of criterion responses that fall into cell *a* without changing the total number of responses in the top row (i.e. by increasing *u* one shifts the responses that fall in cell *b* into cell *a*). By increasing v, one shifts the proportion of responses from cell d into cell c. Increasing the proportion of responses in cell *c* is undesirable for learning, and increasing the number of responses in cell *a* is desirable for initiation of new behavior. For the current study, the author set these parameters to u = 1.0 and v = 0. By specifying v = 0, the author decided a priori that any response that did not meet criterion would not be reinforced (e.g. by withholding the reward points). By setting the parameter u = 1.0, the author specified that *all* responses that met criterion would be reinforced (i.e. continuous reinforcement).

Figure 4 shows the hypothetical movement of the distribution over time (panel A, B, and C) by reinforcing responses (shown by the grey area) and extinguishing responses (shown by the white area) while keeping the percentile cut-point constant. This figure shows how reinforcement can change a participant's behavior over time and thereby shift the distribution. Figure 5 is similar to Figure 4 and shows an example of an individual's actual step counts and reinforced steps (in red) and non-reinforced steps (in blue) over time on a percentile schedule intervention. Notice the improvement in steps/day and the number of times this participant meets the 10,000 step/day recommendation over time. The black line projects the linear trend and not the percentile criterion. Thus, percentile schedules can produce an individualized and highly systematic shaping method.

The current study used a 40% criterion with a moving 9-day window. For example, for one participant, the step count each day for the last 9 days (ranked from lowest to highest) was 500, 1000, 1500, 2600, 4500, 5000, 6300, 7000, and 15,000. This identifies the distribution of step counts. On the 10th day, any step count equal to or greater than 2600 steps would earn a reward point. Each new day's step count was used to re-rank the distribution and provide a new goal. This allowed the author to progressively shape participant's activity behavior over time to higher counts by always rewarding the best part of the distribution of behavior. The algorithm was adaptive, meaning that as PA behavior vacillates, the algorithm always kept the criterion of reinforcement to 40% of the last 9 days.

The author did not know the specific percentile value that would produce optimal change for physical activity behavior. Leaner schedules (e.g. 90th percentile) risked the possibility that a participant may never encounter the reward since only the top 10% of *n* samples would be rewarded. As noted by contingency management studies aimed at decreasing substance use, this lean schedule could cause participants to not earn incentives, experience frustration at the difficulty of the goals, and eventually lead participants to drop out of the study early (Morral et al., 1997). A 10th percentile schedule would produce consistent physical activity at some level, but would not result in differential reinforcement of longer bouts of physical activity in any meaningful way.

There were only three studies to date with human populations to help guide the percentile value to select (Lamb et al., 2005; Lamb et al., 2004; Lamb et al., 2004). Lamb et al. were interested in decreasing behavior for smoking cessation and tested a range of percentiles (i.e. 10th, 30th, 50th, and 70th) and generally found richer schedules worked better (note that when decreasing behavior, the distribution is reversed and the 70th percentile is a richer schedule). They also found that the 50th and 70th percentile schedules produced the quickest trajectory to decreasing CO levels and cessation compared with the more difficult 30th and 10th percentiles. For increasing physical activity, the author of the current study selected the 40th percentile schedule (equivalent to the 60th for decreasing behavior). This decision was informed Lamb and colleagues' studies and by simple computer simulations conducted by the author.

Reward Vouchers and Magnitude. The Premack principle (Premack, 1959) proposes, and applied research to increase physical activity has shown, that higher-rate behaviors (sedentary behavior) can be used as reinforcers to increase lower-rate behaviors (physical activity) if provided contingently (Goldfield, Kalakanis, Ernst, & Epstein, 2000; Chance, 2003; Coleman et al., 1997). Among sedentary individuals, behaviors such as watching movies, listening to music, reading books, etc. were considered higher rate than physical activity behavior. Moreover, music can be listened to while being inactive or active, making it a unique reinforcer.

Participants earned 1 reward point each time they met or exceeded their prescribed step goal. Each point was worth $1.00. This token economy was similar to a credit card reward system where individuals exchange points for various items and services. Once a participant accumulated 5 points, the author sent her a $5.00 voucher via email. Participants did not earn or lose vouchers for failing to meet a daily goal or reporting step counts. Participants had the option to receive vouchers from either Amazon.com or Apple's iTunes online stores, and could change their choice anytime. The voucher system aimed to increase the immediate reinforcement available for physical activity while simultaneously increasing response cost for sedentary behaviors.

As reviewed earlier, Finkelstein et al. found that participants who earned $7.00 for every 1% decrease in body fat lost an average 1.5% of their body weight (or 3 pounds for their 200 pound average participant) by the first opportunity earn the reward at 3 months (Finkelstein et al., 2007). In comparison, the current study offered $1.00 for each instance that participants meet their daily personalized goal which was usually less than 10,000 steps. As noted earlier, 10,000 steps/day is equivalent to 5 miles of walking. A 200 pound individual walking five miles at a moderate intensity (i.e. MET = 3.0) would take about 100 minutes and expend about 455 calories, and would earn $1.00. After matching on calorie expenditure, the current study offered an incentive about 119% more (Finkelstein et al.: 10,500 kcal = $10.50; current study: 10,500 kcal =$23.00) for the same calories expended (assuming a fixed caloric intake). However, the current study did not usually prescribe goals that difficult, so this difference could be greater. Nevertheless, compared to Finkelstein et al., the current study maximized theoretical fidelity by: 1) provided opportunities to earn smaller rewards more frequently (i.e. a $1 reward each day versus $7 every 3 months), 2) used a direct contingency of reinforcement for physical activity - instead of weight loss, which can include a number of desired and undesired behaviors, and 3) had a shorter latency between the occurrence of physical activity bouts and the presentation of the reward (i.e. the same day versus 3 months later for the Finkelstein et al. study).

Potential Problems. The study was intensive. It included objective measurement, goals, and communication daily. The author expected that participants would forget to report their step counts occasionally. The author planned for this possibility by using a pedometer with a 7-day memory display so that participants could still email their steps. The author informed participants at baseline that daily communication was required, and that they may be dropped from the study for failing to report their steps. If participants did not report their steps, they were prompted to report during their next expected communication. Since rewards were provided once the participant reported their counts, it was expected that reinforcement for reporting behavior would also occur. That is, the planned reinforcement contingencies should increase both physical activity and email reports.

Primary and Secondary Outcome Measures.

Objective Physical Activity Measures. This study used the Kenz Lifecorder Plus accelerometer and pedometer. The Lifecorder Plus is a small (2 3/4" x 1 1/2" x 3/4"), lightweight (less than 2 ounces) device with a 60-day memory. Participants wore the device on their waistband or belt. The Lifecorder Plus uses a piezo-electronic mechanism instead of spring-levered arm to measure steps. The piezo-mechanism was reliable and accurate for overweight and obese individuals (Crouter, Schneider, & Bassett, Jr., 2005). It preformed better than spring-levered pedometers for measuring slow walking, when both were compared to direct observation of steps (Crouter et al., 2005). The piezo-mechanism is less sensitive to error caused by pedometer tilt, which can result from excessive midsection adipose tissue. Both conditions were likely with inactive and overweight populations.

The Lifecorder Plus is one of the best performing pedometers with excellent intra-model reliability (95%-98%) and estimates of steps within 3% of actual steps taken when compared to direct observation (McClain, Craig, Sisson, & Tudor-Locke, 2007; Saito, Yamamoto, Sugiura, Shimizu, & Shimizu, 2004). Participants were provided a Lifecorder device at baseline. The primary outcome was pedometer-derived steps per day.

A secondary outcome was accelerometer-derived physical activity counts. Accelerometers measure the force of human body movement. No evidence to date supports the superiority of one accelerometer device over another (Trost, McIver, & Pate, 2005). The Lifecorder Plus uses a piezo-electronic mechanism (similar to Actigraph accelerometers) that records the force of human body movement on a uniaxial plane every 4 seconds (4-second epochs) and categorizes intensity of movement into one of 11 category levels. Epoch duration is the period over which accelerometer data are integrated and stored. The most common epoch duration for physical activity is 1 minute (Trost et al., 2005), although shorter durations can be more desirable. The effect of epoch duration on intensity estimates is lacking for adults. For children, moderate intensity activity estimates have not been sensitive to epoch duration, although evidence suggests that shorter epochs are related to greater vigorous activity counts (Trost et al., 2005). Participants could not access the stored activity count or pedometer data because those data are accessible only by specialized software available to the researcher.

The eleven Lifecorder intensity categories include 0, 0.5, and 1 to 9. Category level zero corresponds to no detectable acceleration signal (i.e. <0.06g). Category 0.5, or micro-activity, corresponds to detected accelerations, but ones not of significant intensity to be recognized as locomotor activity. When the device was validated against indirect calorimetery and an Actigraph accelerometer (model 7164) using the Freedson equation, Lifecorder categories 1 through 3 were shown to correspond to light intensity activity (<3.6 METs), and categories 4 to 9 with moderate-to-vigorous intensity activity (3.6 to 12 METs) (Kumahara et al., 2004; McClain, Craig, Sisson, & Tudor-Locke, 2007). Prior research has demonstrated that at least 3 to 5 days of monitoring is required to reliably estimate habitual moderate-to-vigorous free-living activity for adults (Trost et al., 2005; Matthews, Ainsworth, Thompson, & Bassett, Jr., 2002).

Accelerometer data reduction. Accelerometer data are often extensive and require data reduction strategies such identifying spurious data or days that do not meet the minimal wear time (Masse et al., 2005). However, studies vary considerably in their reduction strategies and parameters and these are often not documented (Masse et al., 2005). For the current study, Lifecorder category counts were recalculated as minutes of moderate-to-vigorous activity (i.e. number of 4 second intervals * 4 / 60 seconds) for each day using the cut-point of category 4 or higher. This study used all available data without imputing missing values or excluding participant's data for a day that did not meet wear time standards.

Demographic and Socioeconomic (SES) Variables. Demographic variables including sex, ethnicity/race, age, highest educational achievement, household income, were collected from participants at baseline.

Anthropometric measures. A research assistant (RA) objectively measured height and weight by stadiometer and digital scale (in light clothing and no shoes), respectively. RAs measured each participant twice and compute an average at baseline and 10 weeks. Body mass index was computed using the following formula: weight (kg) divided by height squared (m^2).

Follow-up Questionnaire. At the 10-week office visit, participants rated how motivating or burdensome specific study components were to them, and their overall satisfaction with the study. Participants were also asked about their personal experience with the intervention, any side effects or injuries, and their recommendations for improvement. This consumer satisfaction may be helpful for understanding how participants experienced the study, and for improving the intervention (Winett, Moore, & Anderson, 1991).

Statistical Analysis Decisions and Data Analysis Strategy.

Hypotheses and Sample Size. The null hypothesis is that the percentile intervention phase will not differ on the number of steps/day or minutes of MVPA per day compared to the baseline phase. The alternative hypothesis is that the participants will show improvements over the baseline phase in their steps/day and MVPA minutes/day during the intervention phase. Specifically, improvements of 2,000 steps/day above the median baseline level will be considered clinically significant. This effect is consistent with a recent systematic review of pedometer-based interventions that found a mean change of 2000 steps/day by 6 months (Bravata et al., 2007). Because this study was designed as a pilot to test the feasibility of using percentile schedules for promoting exercise, five participants were recruited into the study. Studies using single case designs with only one participant, or replicated across a small number of participants, to demonstrate control of causal variables have been part of sport psychology over the last 30 years (Martin, Thompson, & Regehr, 2004). A sample of five individuals was also determined to be financially and logistically feasible.

Study Aims. The primary aims of this proposal are to 1) To determine whether the percentile intervention increases the number of steps/day, measured by pedometer, over baseline levels and whether the intervention shows a functional effect on physical activity; 2) To determine whether the percentile intervention increases the amount of moderate and vigorous activity, measured by accelerometer, over baseline levels; 3) To examine participants satisfaction with the overall program and side effects.

Aim 1 was analyzed using two methods; visual or graphical inspection and statistically by exploring the use of a multi-level random effects regression for time-series data. Physical activity data were plotted to assess the mean level, slope, and variability for baseline, intervention, and withdrawal phases for each of the five participants.

Visual inspection. Participant's data were independently plotted to a time-series graph with lines to delineate changes in study phases. The mean level, ordinary least squares (OLS) slope, and variance for each phase was computed to contrast changes across the three phases for each respondent. Graphs were inspected for expected changes in the rate of steps/day and MVPA-minutes/day by phase.

Pooled statistical analyses. Because at least 10 weeks of daily pedometer and accelerometer data were available, a random-effects analysis explored the effects of the percentile schedule intervention across all participants over the entire study (at least 70 data points). The independence of observations assumption of many statistical tests are violated with single case designs because repeated measures of behavior show serial dependence (Kinugasa, Cerin, & Hooper, 2004). The multi-level random-effects analysis accounts for autocorrelation and did not require imputation of missing data (Ward & Leigh, 1993).

Two dependent variables, steps per day and MVPA minutes per day, were examined independently. First, graphs developed from the visual analyses for each dependent variable were examined. Following the modeling building procedures outlined by Singer and Willett (Singer & Willett, 2003) a number of statistical models were specified and tested. The first two models were unconditional means and unconditional growth models. The unconditional means models provided intraclass correlation estimates. The unconditional growth models considered the within-subject factor of time on physical activity. These first two models served as basic comparison models for more complex model building. Next, time-varying within-subject predictors were added to the model systematically. These predictors included 1) wear time (number of hours/day the device was worn centered to the grand mean) and 2) day of the week (0 = weekend, 1 = weekday). Discontinuous change in elevation for each phase was examined by adding a time-varying variable indicating the start of the intervention and withdrawal phases (0 = baseline, 1 = intervention, 0 = withdrawal). Discontinuity in the slopes for each phase was examined by adding a variable indicating the difference in slope observed during the intervention and withdrawal phases. Discontinuous change in slope was examined independently of the change in the elevation, followed by examining both discontinuities simultaneously using an interaction term. Inter-subject variables were not examined because of limited variance at level 2 and low statistical power resulting from the small sample size. Full maximum likelihood estimation determined population parameter estimates for the fixed effects and variance components. Three estimates of model fit helped identify the final model: 1) the Deviance statistic for nested models, and for non-nested models, the 2) the Akaike Information Criterion (AIC), and 3) the Bayesian Information Criterion (BIC). Except the unconditional growth models, all models were fitted using a heterogeneous autoregressive error covariance structure. SPSS version 12 was used for all analyses. All analyses were conducted in 2009.

Finally, participants' reactions to intervention and side effects were presented to determine the social validity and consumer satisfaction for the intervention.

RESULTS

Participants. Participants were recruited between November 2008 and February 2009. Sixty-five individuals (11 men and 54 women) responded to recruitment advertisements and expressed an interest in the study. Of the 65 individuals, 35 individuals could not be contacted and screened for various reasons, and 30 were screened for inclusion. Of the 30 screened, 13 did not meet inclusion criteria, 6 met inclusion criteria but refused to participate, 4 met inclusion criteria but failed to show to the baseline visit, and 7 eligible participants started the study (5 women and 2 men). The two male participants did not complete the baseline phase. Participant 104 dropped out after 10 days because he planned to spend a month in New York and felt that reporting his activity would take too much time. The author dropped participant 105 from the study after he reported eight consecutive days of over 10,000 steps (range 10,600 to 15,000 steps/day) during the baseline phase. This participant demonstrated by his high daily step counts that no intervention was needed. Appendix B presents demographic and personal characteristics of all the participants.

Table 1 shows demographic information for the sample that received the intervention. The sample consisted of five women (mean age = 36.6 years (SD = 14.12), mean weight = 62.95 kilograms (SD = 8.8), mean BMI = 24.16 kg/m^2 (SD = 4.06), 60% reported Non-White race and/or ethnicity. Four women (80%) were single and one was divorced. Three participants (60%) were current university-level students (undergraduate to doctoral level). The sample's median income was 25,999 to 49,999. Only one woman (20%) had children, and three women (60%) owned a dog. Participants reported an average of 886.6 MET-minutes (SD = 1067.23) of physical activity in the week prior to baseline.

Analyses of Steps Per Day.

Visual analysis.

Table 2 and Figures 7 to 11 reveal that four of the five participants showed evidence of increased number of steps/day associated with the intervention phase. Each participant's profile of step counts was evaluated for causality and categorized as either 'strong', 'mixed' or 'no' evidence of the intervention effect based on visual inspection of the level, slope, and variance characteristics across baseline, intervention and reversal phases. None of the participants showed the ideal relationship between the intervention and the hypothesized change in level, slope, or variance for steps per day.

Strong evidence of intervention effect for steps per day. Two participants showed strong evidence of increased steps/day over the course of the study. Participant 102 showed evidence consistent with the hypotheses in level and slope over the three phases. During baseline phase, Participant 102 had a median 4,917 steps/day (mean = 4,992, SD = 1,982) with a decelerating trend (slope = -269 steps/day) in activity. During the intervention phase, Participant 102's median steps improved to 5,978 steps/day (mean = 6,241, SD = 1,505) with an accelerating trend (slope = 25 steps/day). Figure 7 shows that the intervention effect appears to be delayed, with greater improvements occurring during the latter part of the intervention phase. An improvement of 22% or 1,061 steps between baseline and intervention phases was observed. Once the intervention was withdrawn, the participant's activity decreased to a median of 5,761 steps/day (mean = 5,775, SD = 1,325) and a decelerating trend was observed (slope = -22 steps/day). Variance in activity was not consistent with the study hypotheses. Variance decreased during the intervention phase as predicted by theory, but unexpectedly decreased once the intervention was withdrawn.

Participant 108 showed similar evidence for level and slope of activity (Figure 8). During the baseline phase, Participant 108 had a median of 5,724 steps/day (mean = 5,118, SD=3,101) with a decelerating trend (slope = -167 steps/day). During the intervention phase, the participant increased her activity to a median 6,575 steps/day (mean = 7,096, SD = 3,690) with an accelerating trend (slope = 55 steps/day). An improvement of 15% or 851 steps/day between baseline and intervention phases was observed. Once the intervention was withdrawn, the participant's activity decreased to 5,174 steps/day (mean = 5,910, SD = 2944) with a decelerating trend (slope = -84 steps/day). Changes in the amount of variance across phases was unexpected; increasing during the intervention phase and then decreasing during the withdrawal phase.

Mixed evidence of intervention effect for steps per day. Two participants showed mixed evidence of increase over the course of the study. Participant 103 showed expected movement in level, slope, and variance during the intervention phase only, but her behavior during the withdrawal phase was inconsistent with the author's hypotheses (Figure 9). Participant 103 increased from a median of 2,058 steps/day (mean = 3,551, SD = 3,185) during the baseline phase to 2,835 steps/day during the intervention phase (mean = 3,845, SD = 3,039) – an improvement of 38% or 777 steps/day over baseline. However, Participant 103 had a median of 3,564 steps/day (mean = 4,070, SD = 2,544) during the withdrawal phase – an unexpected improvement.

As expected, Participant 103's activity decelerated during the baseline phase (slope = -345 steps/day), and improved during the intervention phase (slope = -47 steps/day) but remained negative. However, once the intervention was removed, Participant 103 unexpectedly accelerated her activity (slope = 157 steps/day).

This pattern in level and trend may be explained by a third variable. Figure 9 shows that early in the intervention phase the participant improved, but then during the latter part of the phase the participant's activity quickly decreased. Indeed, the participant noted that she left town to visit family for the holidays on day 35 (during the intervention phase) and returned to San Diego on day 62 (during the withdrawal phase). Therefore, she was only in the same environmental context for part of the intervention and withdrawal phases. This move in context closely coincides with the observed changes in trend and level. The move to a new environment during the intervention can be considered a change in conditions that appears to have interacted with the intervention. If only the first 21 days of the intervention phase that the participant was living in San Diego are considered, then Participant 103 would have a median of 3,076 steps/day (mean=4,152, SD = 2872) – an improvement of 49% or 1,018 steps - with a positive trend (slope = 74 steps/day). If only the 20 days of the withdrawal phase that the participant was present in San Diego are considered, the participant had a median of 4,904 steps/day (mean = 4,516, SD = 2,523) with a positive trend (slope = 137 steps/day).

Participant 107 shows a very different pattern in level, trend, and variance, but one that also suggests mixed intervention effectiveness. Participant 107's activity improved from a median of 4,124 steps/day (mean = 4,356, SD = 1,785) during the baseline phase to 6,574 steps/day (mean = 6,662, SD = 815) during the intervention phase – an improvement of 59% or 2,450 steps/day. However, Participant 107's activity also increased during the withdrawal phase to a median of 8,474 steps/day (mean = 8,047, SD = 1,484).

Although this participant had an accelerating trend during the baseline phase (slope = 74), the intervention was started because the participant reached 20 baseline observation days. During the intervention phase, the participant continued a positive trend (slope = 49 steps/day). During the withdrawal phase, the participant showed a decelerating trend (slope =

-75 steps/day). Notice, however, that throughout most of the withdrawal phase the participant had a positive trend. The last 2 days of withdrawal phase show two days were her PA approximated values observed during the baseline phase, suggesting the start of a reversal. Because these two observations deviated farther from the others, they weighted heavier on the ordinary least squares regression line, which caused the trend to turn negative.

Figure 10 clearly shows that participant 107's variability decreased substantially during intervention phase when compared to the baseline phase. Variability then increased during the withdrawal phase. The reduction in variance matches the beginning of the intervention phase, and the increase in variance matches the withdrawal phase. This pattern in variability was consistent with the author's hypothesis.

No evidence of intervention effect for steps/day. Data for Participant 101 suggests that the intervention was not strong enough to increase the level or slope of physical activity. During the baseline phase, the participant had a median of 8,947 steps/day (mean = 8,602, SD = 3,649) and her activity decreased to 8,118 steps/day (mean = 7,876, SD = 2,789) during the intervention phase – a decrease of 9% or 829 steps/day. During the withdrawal phase, her activity further decreased to a median of 6,229 (mean = 6,697, SD = 3,476). Figure 11 shows an accelerating trend during the baseline phase (slope = 45 steps/day), that decelerates during the intervention phase (slope = -25 steps/day), and further decelerates the withdrawal phase (slope = -219 steps/day). However, the pattern in variability between phases was as predicted.

Pooled multilevel analysis for steps/day.

A series of models were systematically fitted to the data. First, an unconditional means model was fitted (not shown) and revealed an autocorrelation of 0.18 for steps/day. Table 3 shows four models; the unconditional growth model, discontinuous slope model, discontinuous elevation model and discontinuous intercept and slope model. Additional models explored differences in fixed and random effects, which were omitted for simplicity. Figure 12 shows the 4 models for steps/day graphically after substituting values for a prototypical individual.

The unconditional growth model provided a comparison for the subsequent models. The unconditional growth model showed that the number of steps/day on the first study day was significantly greater than zero and time (day of study) was not significantly related to steps per day. The variance components of the model show significant amounts of residual variance at level 1 (within person), suggesting that additional time-varying within-person variables would be useful.

All subsequent models include time-varying covariates (wear time, day of the week) and test for different discontinuities. The discontinuous slope model tested for discontinuity in the slopes only (baseline slope versus intervention slope, intervention slope versus withdrawal slope) for the intervention and withdrawal phases. After controlling for wear time and day of the week, an unexpected but significant deceleration was observed once the intervention started relative to the baseline phase (-55.51, $p=0.03$). A significant change in withdrawal phase slope was not observed relative to the intervention phase. The discontinuous slope model was a better fit than the unconditional growth model ($\Delta D = 61.74$, d.f. = 4, $p<.0001$; $\Delta AIC = 53.74$; $\Delta BIC = 37.73$). However, after plotting this model, the author observed that the large positive slope during the baseline phase and the negative slope during the intervention phase appeared to be an artifact of the modeling procedures, and did not represent the observed data well.

Next, the discontinuous elevation model tested for discontinuity in the average change during the intervention phase relative to the baseline and withdrawal phase. In this model, the slope was assumed static throughout the study, but once the intervention phase begun a shift in the level of activity occurred. After controlling for wear time, day of the week, and baseline trend, a significant increase in the average number of steps/day was observed during the intervention phase (551.21 steps/day, $p = 0.03$). The discontinuous elevation model fit better than the unconditional growth model ($\Delta D = 59.29$, d.f. = 3, $p<.0001$; $\Delta AIC = 53.29$; $\Delta BIC = 41.29$) and may be slightly improved relative to the discontinuous slope model ($\Delta AIC = -0.45$; $\Delta BIC = 3.56$). This model appears to approximate roughly the observed patterns in the data.

Finally, an interaction model tested for discontinuous elevation and slope, using an interaction term, during the intervention phase relative to the baseline and withdrawal phase. In this model, the magnitude of the elevation and slope change is a function of the interaction between phase and time. Once the intervention phase began, a discontinuous shift in the level of activity is modeled, and the slope during the intervention phase is allowed to vary. After controlling for wear time, day of the week, baseline trend, and time in the baseline phase, a significant increase in elevation for steps/day was observed during the intervention phase ((1328.70 + -17.59(Phase * Time)), $p=0.03$), but the slope during the intervention phase did not change significantly (-17.59, $p = .16$). The discontinuous elevation and slope model better fit the data than the unconditional growth model ($\Delta D = 61.28$, d.f. = 4, $p<.0001$; $\Delta AIC = 53.28$; $\Delta BIC = 37.27$), but did not fit better than the discontinuous slope model ($\Delta AIC = -0.46$; $\Delta BIC = -0.46$) or the discontinuous elevation model ($\Delta AIC = -.01$; $\Delta BIC = -4.02$).

In summary, of the five models derived from the pooled sample, the discontinuous elevation model appeared to fit the data best both quantitatively and graphically. The final steps/day multilevel regression model is represented by the following equation:

$$Y_{ij} = 5585.69_{i} + (361.90 * \text{wear time}_{ij}) + (-406.08 * \text{day of the week}_{ij}) + (4.26 * \text{time}_{ij}) + (551.21 * \text{Phase}_{ij}) + \varepsilon_{ij}$$

Analysis of Moderate-to-Vigorous Physical Activity (MVPA) Minutes Per Day.

Visual Analysis.

Table 4 and Figures 13 to 17 were evaluated for the pattern of change that provides the best evidence of causation attributable to the intervention. All participants showed increased time spent performing moderate-to-vigorous activity during the interventions phase. All five participants showed mixed, but encouraging evidence for attributing the changes to the intervention.

Mixed evidence of intervention effect for MVPA minutes/day. Participants 102, 101, and 108 showed the strongest evidence of improvement over the course of the study. All three participants showed the expected pattern of behavior for level across phases, but patterns for slope and variance were unique to the participant.

Participant 102 had a median of 14.57 MPVA minutes/day (mean = 16.53, SD = 13.61) during baseline phase. Her activity increased to 21.27 minutes/day (mean = 22.02, SD = 8.08) during the intervention phase – an improvement of 46% or 6.7 minutes/day. Participant 102’s activity decreased to a median of 19.83 minutes/day (mean = 18.43, SD = 5.21) once the intervention was withdrawn.

Figure 13 shows a decelerating trend for MVPA minutes/day during the baseline phase (slope = -1.12 minutes/day) that turns positive but flat during the intervention phase (slope = 0.07 minutes/day), and increases slightly during the withdrawal phase (slope = 0.30 minutes/day). The improvement from baseline to intervention was expected, but the subsequent improvement in the withdrawal phase was not. As hypothesized, the variability in activity decreased during the intervention phase. However, variance did not increase once the intervention was removed.

Participant 108 had similar pattern for level of activity (Figure 14). During baseline phase, Participant 108 had a median of 8.23 MVPA minutes/day (mean = 12.29, SD = 11.60). During the intervention phase her activity increased to a median of 11.57 minutes/day (mean = 16.20, SD = 14.85) – an improvement of 41% or 3.34 minutes/day. She maintained her activity level during the withdrawal phase with a median 11.27 minutes/day (mean = 12.73, SD = 8.17).

Trend also showed improvements across phases. A decelerating trend (slope = -1.09 minutes/day) in activity was observed during baseline phase, and a slightly positive trend (slope = 0.08 minutes/day) was observed during the intervention phase. However, an unexpected positive trend was also observed during the withdrawal phase (slope = 0.20 minutes/day). Participant 108's variance in activity increased substantially during the intervention phase, but then decreased during the withdrawal phase. This pattern for variance was not predicted across phases.

Participant 101 also showed some evidence of an intervention effect (Figure 15). Participant 101 had a median of 24.60 MVPA minutes/day (mean = 26.10, SD = 13.61) that increased to 27.13 minutes/day (mean = 27.09, SD = 10.53) during the intervention phase – an improvement of 10% or 2.53 minutes/day. During the withdrawal phase, her activity decreased to a median of 19.60 minutes/day (mean = 20.70, SD = 9.55).

Changes in trend were not as expected. During baseline, she had a positive trend (slope = 0.13 minutes/day) which deteriorated and turned negative during the intervention phase (slope = -0.05 minutes/day). The trend further deteriorated during the withdrawal phase (slope = -0.33 minutes/day). Variance in activity decreased during the intervention phase, but decreased further during the withdrawal phase.

Participant 107 showed mixed evidence of improvements in level and variance of activity across phases (Figure 16). During the baseline phase, Participant 107 was active a median 9.13 MVPA minutes/day (mean = 11.13, SD = 8.13). Activity increased to 26.40 minutes/day (mean = 26.24, SD = 7.46) during the intervention phase – an improvement of 189% or 17.27 minutes. As seen on Figure 16, this change in activity was immediate once the intervention phase started. During the withdrawal phase, the median again increased to 36.00 minutes/day (mean = 33.59, SD = 11.50).

Participant 107 did not show improvement for trend. She started the intervention with an existing positive trend in her activity behavior (slope = 0.16 minutes/day). This trend was stable and did not change once the intervention started (slope = 0.18 minutes/day). During the withdrawal phase, the trend turned negative (slope = -0.68 minutes/day). However, this observation was most likely due to the last two study days. If these last two days are not considered, the trend during the withdrawal phase remained positive, but lower than the intervention phase (slope = 0.12 minutes/day). Participant 107's variance in activity decreased substantially during intervention phase and increased during the withdrawal phase, as hypothesized.

Participant 103 also showed mixed evidence of an intervention effect with improvements primarily in level and variance (Figure 17). Participant 103 was active a median of 2.80 minutes/day (mean = 8.90, SD = 12.39) during the baseline phase and her activity increased to 4.73 minutes/day (mean = 8.21, SD = 10.10) during the intervention phase -- an improvement of 69% or 1.93 minutes/day. Unexpectedly, once the intervention was removed, her activity increased to a median of 6.67 minutes/day (mean = 10.30, SD = 10.88).

Trend in activity also improved over the course of the study. Participant 103 had a negative trend during baseline (slope = -1.35 minutes/day), which improved but was still negative during the intervention phase (slope = -0.30 minutes/day). Again, the trend during the first part of the intervention phase was positive, but once the participant left town, her activity level and trend deteriorated. During the withdrawal phase, once the participant returned to San Diego, the trend turned unexpectedly positive (slope = 0.59 minutes/day), which may have been a result of leaving the family environment. Change in variance across phases was as hypothesized; an improvement (decrease) was observed during the intervention phase and variance increased during the withdrawal phase.

Pooled multilevel analysis for MVPA minutes/day.

Similar systematic modeling procedures for steps/day were used for MVPA minutes/day. The unconditional means model (model not shown) revealed an autocorrelation of 0.23. Table 5 shows four models; the unconditional growth model, discontinuous slope model, discontinuous elevation model, and discontinuous elevation and slope model. Additional models that explored other fixed and random factors are omitted. Figure 18 shows the 4 models for MVPA minutes/day graphically after substituting values for a prototypical individual.

The unconditional growth model provided a comparison for the subsequent models. The unconditional growth model showed that MVPA minutes/day on the first study day was significantly greater than zero, and time did not significantly change MVPA minutes over the course of the study. The variance components of the model show that the majority of remaining variance occurred at level 1 (within-person), suggesting that additional time-varying within-person variables could be added to the model.

All subsequent models included time-varying covariates (wear time, day of the week) and tested for different discontinuities. The discontinuous slope model tested for discontinuity in the slopes only for the intervention and withdrawal phases. After controlling for wear time and day of the week, an unexpected but significant deceleration in MVPA minutes/day was observed once the intervention started relative to the baseline phase (-0.29 minutes/day, $p=0.03$). A significant change in slope resulting from the withdrawal phase was not observed. The discontinuous slope model fit the data better than the unconditional growth model (ΔD = 21.04, d.f. = 4, p = .0003; ΔAIC = 13.04; ΔBIC = -2.97).

The discontinuous elevation model tested for discontinuity in the average change during the intervention phase relative to the baseline and withdrawal phase. After controlling for wear time, day of the week and baseline trend, a significant increase in the average MVPA minutes/day was observed during the intervention phase (2.65 minutes/day, p = 0.02). The discontinuous elevation model fit better than the unconditional growth model (ΔD = 20.83, d.f. = 3, p = .0001; ΔAIC = 14.83; ΔBIC = 2.83) and fit may be slightly improved compared to the discontinuous slope model (ΔAIC = 1.79; ΔBIC = 5.80). This model appeared to approximate the observed patterns in the data.

Finally, an interaction model tested for discontinuous elevation and slope. After controlling for wear time, day of the week, baseline trend, and time in the baseline phase, an expected marginally significant increase in MVPA minutes (p = 0.056) was observed, but the phase by time interaction (slope) during the intervention phase did not change significantly during the intervention phase (p = .34). The discontinuous elevation and slope model appears to fit the data better than the unconditional growth model (ΔD = 21.74, d.f. = 4, p = .0002; ΔAIC = 13.74; ΔBIC = -2.27), but did not fit better relative to the discontinuous slope model

(ΔAIC = 0.70; ΔBIC = 0.70) or the discontinuous elevation model (ΔAIC = -1.09; ΔBIC = -5.10).

In summary, of the five models derived from the pooled sample, the discontinuous elevation model appeared to fit the observed data best both quantitatively and graphically. The final MVPA minutes/day multilevel regression model is represented by the following equation:

$$Y_{ij} = 14.07_i + (0.69 * \text{wear time}_{ij}) + (1.85 * \text{day of the week}_{ij}) + (0.05 * \text{time}_{ij}) + (2.65 * \text{Phase}_{ij}) + \varepsilon_{ij}$$

Follow-up Questionnaire.

The use of the 40th percentile during the intervention ensured that participants always contacted the reinforcement contingency. This programming also ensured that participants met an average of 60% of their goals over time. Table 6 shows the percent of goals participants believed they accomplished compared to the actual percent they achieved during the intervention phase. These data reveal that almost all participants estimated the number of goals they met under conditions of daily self-monitoring and explicit feedback.

None of the participants reported physical or psychological side effects from the intervention. All participants reported that the author responded to their email messages “on the same day, within 1 hour,” and that goals adapted to them “just right.” Two participants (102, 103) thought the incentives “maybe” helped them improve their activity, and 3 reported that the incentives “definitely” helped (101, 107, 108). Two participants (101, 103) said that wearing the pedometer was “sometimes burdensome”; the remaining said it was “not burdensome at all”. Only one participant (103) sometimes avoided looking at the pedometer; the others reported never avoiding it. Four of 5 participants (101, 102, 103, 108) would “definitely recommend” the intervention to their friends and family. Participant 107 would “maybe recommend” it. Participants were asked if the intervention was made available for a longer period how much longer would they continue to use it. Two participants expressed fatigue (101, 107) and noted “less than 1 month.” The other three participants reported “6 months to 1 year.”

DISCUSSION

National recommendations call for adults to accumulate 150 minutes of moderate-to-vigorous activity per week. Ten-thousand steps per day roughly equal the national guideline when steps accumulated from leisure, transportation, occupational, and daily living activities are measured. This study found that an intervention based primarily upon the use of frequently adapting goals and a small amount of financial reinforcement using a percentile schedule was modestly efficacious at increasing steps per day among a sample of adult women. Four of the five women increased their median number of steps per day, and all five increased their median MVPA minutes per day. In the context of extensive competing events and confounding factors, the observed changes in behavior among this small sample are encouraging evidence of the efficacy of the intervention.

Recent studies using a nationally representative sample show that adult women average about 5,756 steps/day and 19.9 to 23.6 moderate-to-vigorous physical activity minutes per day (Tudor-Locke, Johnson, & Katzmarzyk, 2009; Troiano et al., 2008). Participants in the current study had a median of 4,917 steps/day and 9.13 MVPA minutes/day at baseline. Participants increased their activity by 851 steps/day (range -829 to 2,450 steps) and 3.34 MVPA minutes/day (range 1.93 to 17.27 minutes) from baseline to the intervention phase, or an improvement of about 17% for steps/day and 37% for MVPA minutes/day. The modest improvements in this study occurred under non-optimal conditions. Participants 101, 102, and 103 were recruited in November, and started their interventions during the holiday season in December. Many competing obligations promote inactive or sedentary behaviors during the holidays. Participant 103 left San Diego half way through the intervention phase to live with her parents in Ventura County, California for 1 month. Participant 101 began moonlighting as a waitress during the baseline phase, which increased the time she spent walking for occupational reasons, and then took fewer shifts during the intervention phase, which decreased her walking. Despite these conditions, the minimal intervention was potent enough to produce changes in physical activity.

The steps per day increase, however, was less than the 2,000 steps/day or 27% improvement over baseline found in a recent review of pedometer-based interventions (Bravata et al., 2007). The smaller effects found in the current study may have occurred for several reasons (in addition to the events noted above). First, studies included in the review had an average duration of 18 weeks (±24 week standard deviation) with some studies lasting as long as 104 weeks (Bravata et al., 2007). This average duration is 8 weeks longer than the current study. Second, the review included studies that reported findings from study completers (e.g. Schneider, Bassett, Jr., Thompson, Pronk, & Bielak, 2006; Chan, Ryan, & Tudor-Locke, 2004), which may have inflated effect sizes. Third, 46% of the studies included in the review used sealed pedometers during the baseline phase and unsealed pedometers during the intervention phase, thus inflating the effects. Fourth, the 40th percentile schedule prescribed easier to attain goals than a fixed goal of 10,000 steps, which may have resulted in a smaller magnitude of change given the period of time. Finally, the percentile schedule produced delayed effects during the intervention phase by design, and therefore may require longer studies than ones that prescribe a fixed target.

The intervention phase produced modest improvements in physical activity. Although not foreseen by the author, the reason for modest effects became obvious. The percentile schedule prescribed goals within the participant's repertoire. A 40% percentile schedule always prescribed goals that were lower than the median observed over the last 9 days. Therefore, changes were not programmed to be large or immediate. The slowly changing requirements over time have a number of benefits for the participant, such as deterring attrition by prescribing goals that participants could accomplish, providing immediate feedback on the first intervention day, and providing tangible rewards soon after the intervention started. Other pedometer interventions have reported attrition rates of 30% to 40% (Schneider et al., 2006; Chan et al., 2004). It is possible that adaptive goals result in slower change than larger fixed goals (e.g. 10,000 steps), but may produce more sustainable behavior change.

The percentile schedule also resulted in delayed change. At the start of the intervention phase, some participants earned reward points each day for the first week (e.g. participant 102 and 103). Not until participants experienced differential reinforcement for their physical activity (reinforced behavior that met criterion and withheld reinforcement for behavior that did not meet criterion) did participants begin to modify their behavior. Importantly, each participant differed on how quickly differential reinforcement was experienced. This was seen clearest for participants 102 and 108. Participant 102 did not begin to experience differential reinforcement until days 22 through 29, while participant 108 experienced it almost immediately once the intervention started. Participants did not met every goal, and the percentile adjusted the absolute value of the goal. As the study progressed, the 40^{th} percentile schedule algorithm adjusted the goals (criterion for reinforcement) depending on the last 9-day window. This shaping can be seen over time as higher highs and higher lows for both steps/day and MVPA minutes/day that occurred during the second half of the intervention. Participant 102 had a median 6,155 steps/day during the last half compared to 5,748 steps/day during the first half of the intervention phase, and Participant 108 had a median 7,579 steps/day during the last half compared to 6,612 steps/day during the first half of the intervention phase. Interestingly, Participant 107 met every goal and did not experience differential reinforcement. However, it is possible that she found failing to meet the daily goal an aversive experience, maybe because of some past experience with goals, and likely avoided this outcome by being physically active. Just the possibility that an aversive experience could occur may have been enough to promote her change.

These observations also suggested that the author's a priori hypotheses about the magnitude and immediacy of change might have been naïve. The author based his expectations on pedagogical examples of single case designs and the limited literature on percentile schedules. The expectation of instantaneous, large, and stable changes, usually seen in pedagogical examples and well-designed single case withdrawal studies, may be unrealistic with percentile schedules. Higher percentiles (e.g. 80%) may produce larger and immediate changes, but should not be expected to produce instantaneous change that is outside the repertoire observed during baseline.

The author would use the current findings to design the next study with a different a priori understanding. The current study used a 40% percentile schedule, and unlike the tobacco consumption studies by Lamb et al. (Lamb et al., 2004; Lamb et al., 2007; Lamb et al., 2005; Lamb et al., 2004), the 40^{th} percentile appeared too easy for participants. In future studies, the author would test more difficult percentiles ranging from 50% to 90%. Moreover, the author would begin to adjust upward the percentile to speed the "automatic shaping" process. For example, one could move to a 50%, 60%, or 70% incrementally during the intervention phase. This might speed up the change, and even make it more resistant to extinction. Also, the author would not expect immediate changes to result, but rather would plan for a longer intervention phase. The author might also expect that the potency of a $1 reward for meeting each goal is adequate for some individuals, but limited by the dynamic competing events that occur in real life.

Functional effects. Although four participants increased their steps per day during the intervention phase, only participants 102 and 108 showed the pattern that provides the strongest evidence of causality. The patterns of change in level and slope for physical activity coincide with the presentation and removal of the intervention. This pattern provides strong evidence that the intervention components were responsible for the observed change in physical activity for both participants. Activity that decreases during baseline phase, increases during the intervention phase, and decreases once the intervention is removed provides the strongest evidence of a causal effect (Shadish et al., 2002). This ‘off-on-off’ intervention testing is analogous to presenting and removing a drug while observing its effect on a physiological process.

Support for causality is based in probability logic (M.F. Hovell, personal communication, July 7, 2009). Repeated measures of physical activity that show a decelerating rate during the baseline phase establishes a trend counterfactual to that expected by the intervention. Once the intervention starts, physical activity behavior is expected to increase because of the intervention procedures. The likelihood that a confounding variable would change behavior in a similar direction to that expected by the intervention, and importantly, occur at the same time the intervention started is likely low (precise estimates of probability may be made). Once the intervention is removed, it is expected that physical activity would no longer continue to improve, and the participants’ environments would exert influence on activity back towards baseline level. The probability that the confounding variable would also cease once the intervention ends and result in a decrease in activity over time is also likely low (again, unknown but can be estimated). The probability of both of those events occurring is assumed to be independent, and, therefore, is the product of the two. This product results in a low probability that extraneous factors account for the observed physical activity changes. Moreover, when replicated across individuals, the probability that a confounder caused the associated changes in behavior that matched the phases is even lower. Therefore, withdrawal designs control for alternative explanations that can occur in time.

Consider plausible examples. An alterative explanation for the observed findings is that a community-based media intervention to promote 10,000 steps per day occurred during the study period. If true, the community intervention would have had to start on the same day as the current study's intervention, and cease at on the same day as the withdrawal phase. The community program is unlikely to have such a temporal match. Moreover, since participants started and ended the intervention on different dates, this alternative explanation is implausible. Another possibility is that holiday or seasonal variation may account for changes in walking. Again, the presentation and withdrawal of the intervention occurred on different dates for each participant. Thus, this explanation is also unlikely. Any potential confounding event would have to match the temporal pattern of the observed temporal phase changes and changes in behavior patterns.

Two participants showed increased steps per day, but did not show the pattern needed to attribute change solely to the intervention. Evidence for Participant 107 was mixed. Participant 107 showed an accelerating trend during the baseline phase with high variability in physical activity behavior. Once the intervention started, she maintained the positive trend, but the variability in her activity decreased substantially (Figure 10). Indeed, Participant 107 was the only participant to meet every one of the prescribed goals. Once the intervention was withdrawn, her activity maintained for about a week, and then increased variability was observed with a significant drop in steps on the last two days. This reduced variability during the intervention phase is remarkable and could be partially, if not fully, attributed to the intervention. When the author asked about her activity during the last two study days, the participant noted that, during the intervention, she exercised 7 days a week, but once intervention phase was over, she took a break on the weekend. Because this participant continued to improve once the intervention was withdrawn, it is difficult to attribute the changes solely to the intervention. However, the observed patterns for variance matched the phase changes and met the criteria for causality.

The other participant (103) increased steps/day, but did not show the ideal pattern for attributing causality. She had a strong negative trend during the baseline phase as required. During the intervention phase, her activity increased in elevation (median steps/day), but did not accelerate. Figure 9 shows that her steps increased substantially during the first part of the intervention phase, but decelerated during the last part suggesting that the intervention worked initially. When the author inquired during the posttest interview about the last part of the intervention, the participant reported that she left San Diego for approximately 1 month to visit her family in Ventura County, California. According to the participant, once arriving home she was "spoiled" by her grandmother, dad and mom. She reports, "I had no responsibilities such as work or school. This caused me to become a human vegetable where I just ate, slept, and watched TV. I gained 15 pounds during this period." Participant 103 returned to San Diego during the withdrawal phase, and her activity accelerated. This extraneous event resulted in a pattern that does not allow for attributing causality. Moving to a different environment during the study for an extended period can be considered a change in conditions in addition to the intervention conditions. This interaction between the family environment and the intervention appears to have attenuated the effects of the intervention on physical activity. The family environment likely overwhelmed the intervention effect. This observation may define the limits of generalizability for the current intervention procedures (i.e. \$1.00 reinforcement on a 40^{th} percentile schedule), but more potent interventions may not be affected as strongly.

Participant 101 showed no increase for steps per day during the intervention phase, and as a result, no evidence for the causal effect of the intervention. During the baseline phase, Participant 101 unexpectedly accelerated and met the 10,000 step recommendation on many occasions. The author noticed this pattern during the baseline phase and inquired about it before the intervention started. The participant reported that her new job as a restaurant server required walking. She predicted that over the following holiday weeks she would be working more shifts. Based on this unexpected event, the author asked the participant to continue with the baseline phase for several more weeks to establish a new baseline of activity that included the new job. The participant agreed. However, the she insisted that the intervention start on a specific day. Once the intervention phase started, the participant reported that she would be working fewer shifts for the remaining month and would be going on vacation from her new position during the last part of the intervention phase. These events resulted in a negative level and slope during the intervention phase for steps per day. However, it is interesting that her MVPA increased by 2.5 minutes/day during the intervention phase and decreased by 7.5 minutes/day during the withdrawal phase. This suggests that the intervention may not have increased the total volume of her activity, but may have increased the amount of time spent performing moderate-to-vigorous intensity activities such as leisure-time exercise.

Some participants showed higher variability during the intervention phase relative to the baseline for steps per day (e.g. Participant 108), and some showed less variability during the withdrawal phases relative to the intervention phase (e.g. Participant 108, Participant 103). This was counter to the author's hypothesis that reinforcement decreases variability in behavior. However, the author may have been naïve again and not considered complex topics. The concepts of transition and steady states may be important in considering change and level of variance (Sidman, 1966; Ferster & Skinner, 1957). Steady states are defined as ones were the behavior of interest does not change its characteristics over a period of time; the behavior is stable (Sidman, 1966). The baseline phase of an experiment attempts to describe the steady state of each participant's behavior under "usual conditions." Transition states refer to the process of change from one steady state to another. If a participant started an intervention, and is in the process of accelerating or decelerating, variance is likely to be relatively higher, partly due to definition. Once a stable state is reached, variance may be limited, again partly by definition. Thus, during periods of transition, variance is expected to be relatively high. It is possible that some participants were still "in transition" throughout the intervention phase. Longer studies using percentile schedules are needed to account for delayed effects and transition periods relative to steady states.

Visual analyses. Two types of analytical methods were used to evaluate change: visual analysis and pooled multilevel statistical analyses. Visual analyses combined with the experimental control of the phases allowed for the detection of elevation, slope, and variance change, identification of extraordinary high and low days of physical activity, and for other patterns that would not have been detected by summaries of central tendency. For example, Participants 101, 102, 103 and 108 had several days of over 10,000 steps, and participant 107 showed an impressive reduction in variation for her activity during the intervention phase. These exceptional days and patterns are important to explore further. The author asked all participants during the posttest follow-up interviews about their activity, and specific events were noted. Participant 101 reported waitressing, walking the dog, or going to the gym on exceptional days. Also, the visual analysis highlighted her accelerated physical activity pattern observed during the baseline phase. Participant 102 had a more stable activity pattern, but reported longer walks with her dog on extraordinary days. For participant 103, the visual analysis allowed the author to detect a deceleration during the second part of the intervention phase, and notice that some days exceeded the 10,000 step target. On days she exceeded the target, she walked with a friend. Participant 108 reported walking the dog, walking with her children, or taking public transportation to work on exceptional days. These "other reasons" or “other contingencies” are powerful influences in individuals’ ecologies that should be explored (Hovell, Wahlgren, & Adams, 2009). Indeed, studies have shown that dogs (Coleman et al., 2008; Yabroff, Troiano, & Berrigan, 2008) and social interactions (Adams et al., 2006; Sallis & Owen, 1999) are associated with increased activity.

Pooled multilevel models. Five multilevel models were derived for both steps/day and MVPA minutes/day. The discontinuous elevation model showed an effect that appears to represent the data best for both dependent variables. The discontinuous elevation model revealed an average increase of 551 steps/day and 2.65 MVPA minutes/day during the intervention relative to the baseline phase. This is lower but similar to the amounts found by the visual analyses. Indeed, when standard errors are accounted for, both steps/day and MVPA minutes/day values overlap with values derived from the visual analysis. However, as the prototypical figures show, the predicted trajectories derived from the multilevel model did not capture the complexity of the repeated observations for individuals. Moreover, the author fitted the models using each participant’s actual data (not shown) and noticed substantial differences between the observed and predicted values each day and trends over time. This may have been due to the small sample size or limited number of variables. Additional time-varying and time-invariant predictors are needed to explain the remaining residual variance. These figures, however, were consistent with the variance components of the final multilevel model for steps/day and MVPA minutes/day that show large level-1 (within person) residual variance remaining in the model. If measured systematically, time-varying variables such as workdays, dog walking, and use of public transportation may explain portions of the residual variance.

It should be noted that the amount of time participants wore the Lifecorder accelerometer each day varied over the course of the study and was an important time-varying predictor of activity. The average wear time across all participants and all days was 10.44 hours, but ranged from 1.5 to 22.1 hours. Wear time was associated with about 360 steps per hour and 0.70 MVPA minutes per hour. Participant's daily wear time was estimated by summing sedentary, light, moderate, and vigorous activity minutes for the day and subtracting by the devices total recorded minutes (sum of these intensities plus non-wear time for the day). This estimate was conservative because all non-wear time minutes were included regardless of whether accumulated in bouts. The standard method of calculating non-wear time minutes is to sum non-wear minutes that occur in bouts lasting at least 30 continuous minutes each. Bouts are used instead of summing all minutes because the device will register non-wear time minutes intermittently when participants are wearing the device but are motionless (Masse et al., 2005). It was not possible to calculate bouts of non-wear time with the Lifecorder without substantial computer programming. Therefore, the method used to calculate non-wear minutes may have resulted in an underestimate of wear time per day.

Participants could accumulate more steps/day and MVPA minutes/day by wearing the Lifecorder for longer periods. This might have lead to participants wearing the device longer on days where they were more inactive, and removing the device earlier on days when they met their goal. Indeed, this pattern was noticed (data not shown), and 42.1% of all data fell below 10 hours of wear. Participants were instructed at baseline and reminded several times throughout the study to wear the device the same duration each day: from the moment they awoke to bedtime, or for 10 hours each day. The physical activity measurement literature suggests a 10-hour standard to determine a "valid day" (Tudor-Locke, Johnson, & Katzmarzyk, 2009). Ten hours approximates 80% of a normal individual's daily awake time. The standard method of reducing accelerometer data is to limit analyses to only days when wear time exceeded the 10-hour threshold (Masse et al., 2005). However, this duration is based on epidemiological or pre/post test experiments where 4 to 7 days of observations were obtained. These studies are unlike the current one where participants wore the device for 70 days minimum. No long-term lab or free-living accelerometer studies of longer duration could be found that addressed wear time. And traditional pedometers can not measure duration of wear. Therefore, this standard was not adopted in the current study. Instead, wear time was included as a time-varying covariate in the analysis. This method adjusted for wear time and allowed days to be included in the analyses regardless of the wear time duration.

Generalization to the population. This study tested a theory-based approach to changing physical activity that is scalable to large populations. The potential to scale the intervention using technology is especially attractive. eHealth interventions for physical activity, diet, and weight loss have incorporated ubiquitous technologies including mobile phones, video games, web sites, expert systems, electronic kiosks, etc. (Norman et al., 2007; Patrick et al., 2009; Patrick, Intille, & Zabinski, 2005). Many of these technologies use incentives or rewards to persuade people to change behavior (Fogg, 2003). Any intervention or persuasive technology programmed to use rewards to change behavior has an implicit reinforcement schedule. Percentile schedules are a “behavior change technology” that could be incorporated into new and existing electronic technologies. Moreover, the current intervention may be integrated with other methods of behavior change (e.g. text-message prompting) to increase physical activity or other behaviors, potentially increasing the potency of an intervention.

This intervention was grounded in conceptual views of individual distributions, which is analogous to population-level distributions. Rose (1992) noted that population distributions can be normal or skewed. Distributions skewed in the direction of disease can signal abnormality. Population distributions can be shifted in the desired direction by identifying community factors, and modifying them to evoke small to large changes that become magnified over the population over time (Rose, 1992). Similarly, individuals' distributions skewed in the direction of unhealthy behavior can be shifted towards healthful behavior by modifying external factors (or stimuli) through shaping over time (Cooper et al., 2006). The effects of the current study could be extended to whole populations by exposing a large number of people to the current intervention by incorporating it into existing technologies. For example, mobile phones are used by 3 billion people worldwide and 89% of the U.S. population (Gorin, 2009; "USA Annual Subscriber Growth", 2009). Indeed, if large populations were exposed, the current study could promote approximately 5,957 steps per week or approximately 23.38 MVPA minutes per week. This activity could accumulate over a year's time to 310,000 steps or 1,200 MVPA minutes. For comparison purposes, communities that differ on walkability status (low versus high) differ by 34 to 47 MVPA minutes (measured by accelerometer) per week for low- and high-income groups, respectively (Sallis et al., 2009).

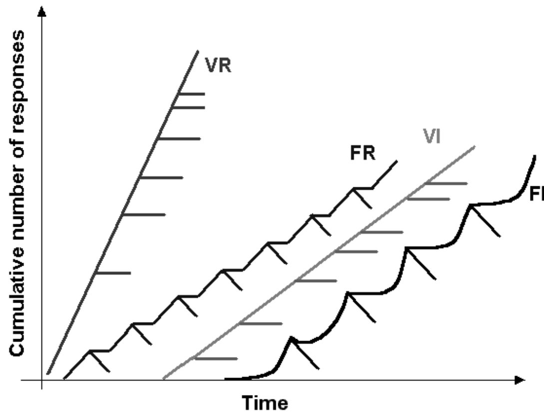
Strengths of study. Several strengths of this study should be noted. This study operationalized an intervention grounded in a strong and precise theory of overt behavior change. The study used repeated measures of behavior over 70 days with an experimental design that can provide causal evidence. This study measured behavior objectively, and was not limited by self-reported activity (Sallis & Saelens, 2000). A combined pedometer and accelerometer allowed for two objective measures of physical activity behavior. Outcomes included steps, intensity, and duration, which provided confidence in the changes observed. Accelerometer guidelines for adults suggested at least 3 to 4 days of monitoring for a stable estimate (Trost et al., 2005; Matthews et al., 2002). A review found that writing down steps taken each day was predictive of increased steps per day (Bravata et al., 2007). A recent study of pedometer reactivity found that 7 or more days of monitoring are needed to overcome reactivity among adults when participants wore an unsealed pedometer and self-recorded their steps counts (Clemes & Parker, 2009). The 10- to 20-day baseline phase in the current study allowed significant time for reactivity from measurement to subside and for a stable baseline to form. Nevertheless, even with a long baseline phase, two participants showed an existing positive trend.

There were few missing data for the intensive nature of this experiment. This observation may be attributed to the device and participants. The Lifecorder had a 60-day internal memory that captured almost all of the 70 study days. Participants were also compliant wearing the device and reporting their activity each day. Only 14 (3%) of the 418 total observations were missing. Reasons for the missing data included 1) device failure, 2) a personal emergency, and 3) lost data because the device memory was full. The author made every effort to meet with the participants and download the data from the device before the memory filled, but it was not always possible due to conflicting schedules. The author predicted that earning frequent reinforcement vouchers would reinforce participants' 'reporting behavior'. Lamb et al. found that participants' adherence was very good in their percentile schedule intervention (Lamb et al., 2004). The high compliance for such an intensive intervention in the current study appears to support Lamb et al.'s findings and the author's prediction. In addition to these strengths, two methods of analyses, visual and statistical, were employed. Multilevel models controlled for autocorrelation present in the repeated measures data.

Study limitations. Several limitations were present in this pilot study. Potential participants over-reported their MVPA, which made screening of participants more difficult than planned. It was difficult to establish cut-point that captured inactive individuals early in the recruitment process. Additionally, one participant left town for an extended period, and one began a job that required physical activity. Inclusion criteria were modified once these events occurred. Although participants wore the device every day, they did not always meet the 10-hour wear time standard. Longer durations of wear on inactive days may have overestimated light activity minutes, but probably not MVPA minutes. There was also more variability in physical activity than was expected. This variability may have advantages and limitations. High variability at baseline suggests more independence between observations and lower autocorrelation. However, high variability makes it more difficult for visual analysis to detect an effect. Group designs may be needed to detect a smaller effect when 'noise' is high.

The intervention resulted in change for four of five participants for steps per day. As Dremer (1999) stated, "failures to replicate the relationship between the independent and dependent variable indicates that the relation is not fully understood, and systematic examination, such by experimentation to examine internal validity and further tests of generalization to establish limits of external validity are needed" (Dermer & Hoch, 1999). Because the behavior change did not reverse for some participants once the intervention was withdrawn, it may be unrealistic to try to reverse this behavior change. Perhaps a different design should have been undertaken, such as a multiple baseline design, a group design, or some hybrid. A hybrid group design that includes aspects of single case designs, such as repeated measures and multiple phases, with a larger sample would be able to control for the substantial variability in physical activity. Moreover, a significant and practically important amount of residual variance remained when the observed data were compared to predicted multilevel models. The remaining residual variance could be reduced by adding time-varying variables to a model with sufficient power and sample size to accommodate those variables. Finally, the small sample size of only women limits generalizability. Future studies must include men and a more heterogonous sample of other characteristics (e.g. adolescents, seniors, overweight and obese, married, unhealthy, walkable neighborhoods) to define the limits of generalizability.

The current study modestly increased physical activity among a small group of women. Four of five women showed increases in steps/day and all five showed increases in MVPA minutes/day. Two women showed the pattern of evidence needed to attribute improvements in activity to the intervention alone. Almost all participants would recommend the intervention to their friends and family. This study provides the first formal test of percentile schedules for physical activity research, and provided intervention efficacy (i.e., ‘proof of concept’). The findings may be used as a preliminary study to inform future work in this line of research.



VR=variable ratio; FR=fixed ratio; VI=variable interval; FI=fixed interval. Diagonal ticks indicate the occurrence of reinforcement

Figure 1. Types of basic reinforcement schedules and steady state patterns produced.

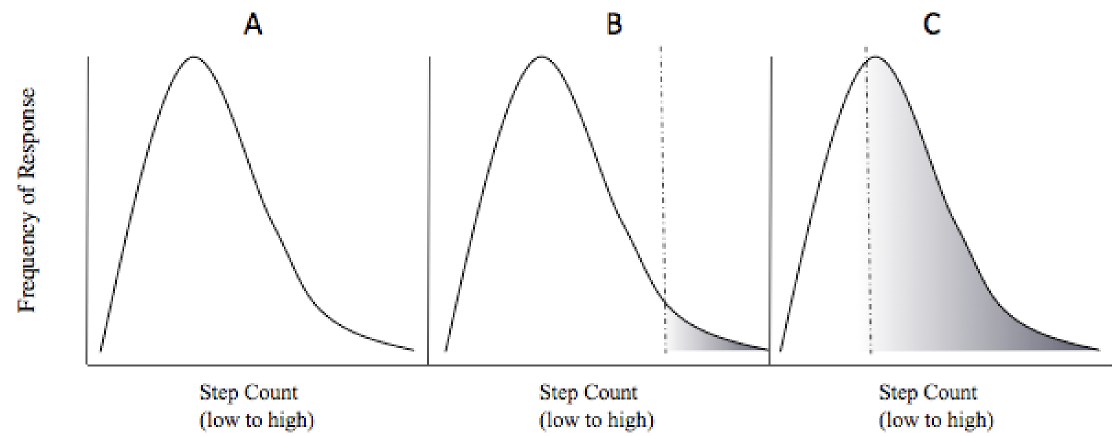


Figure 2. Hypothetical distribution of pedometer step counts over six months.

		Consequence		
Criterional Response		Z	$\bar{Z}$	
	W	**a**	**b**	$u = \Pr(S^R \mid W) = a/(a+b)$
	$\bar{W}$	**c**	**d**	$v = \Pr(S^R \mid \bar{W}) = c/(c+d)$

$$w = \Pr(W) = (a + b) / (a + b + c + d)$$

Figure 3. Criterion response by consequences (adopted from Galbika, 1994).

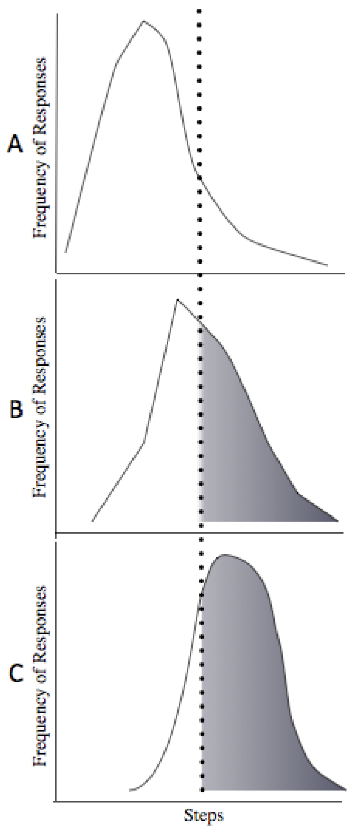


Figure 4. Effects of shaping on an individual's distribution of behavior over time.

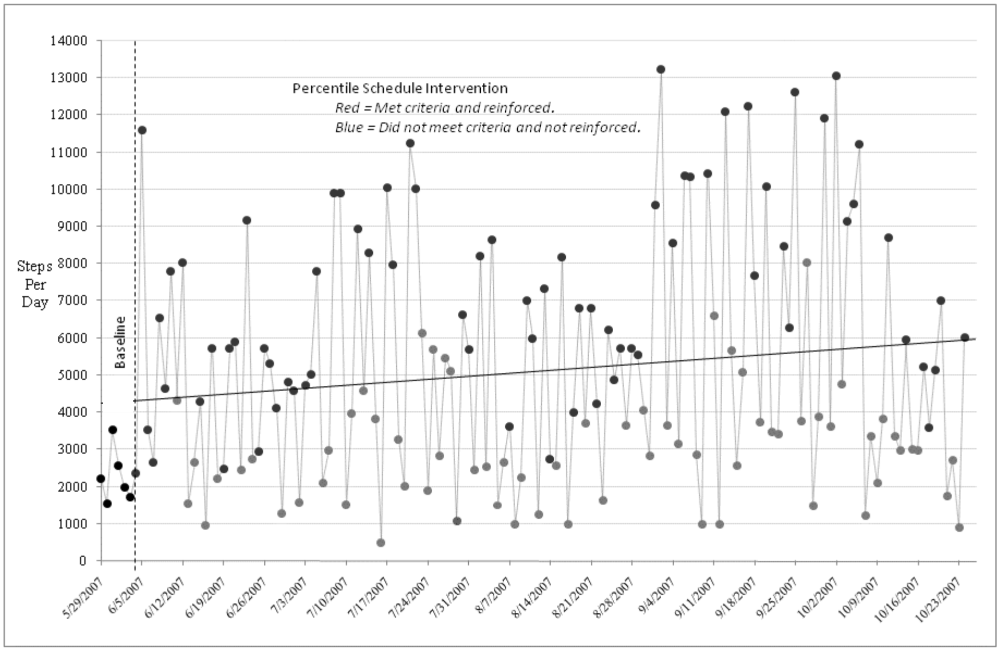


Figure 5. Shaping step/day using a percentile schedule of reinforcement over 5 months.

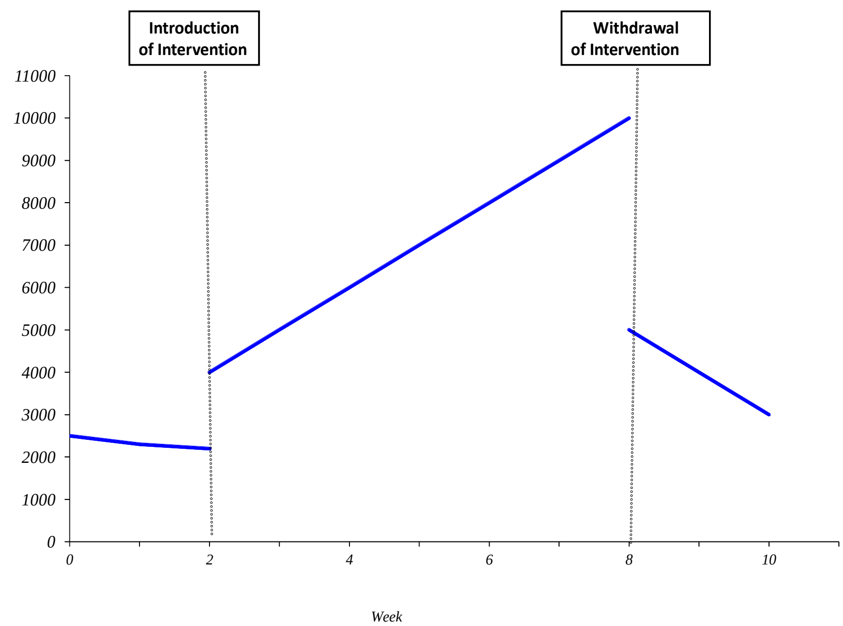


Figure 6. Ideal physical activity pattern for attributing causality to the intervention.

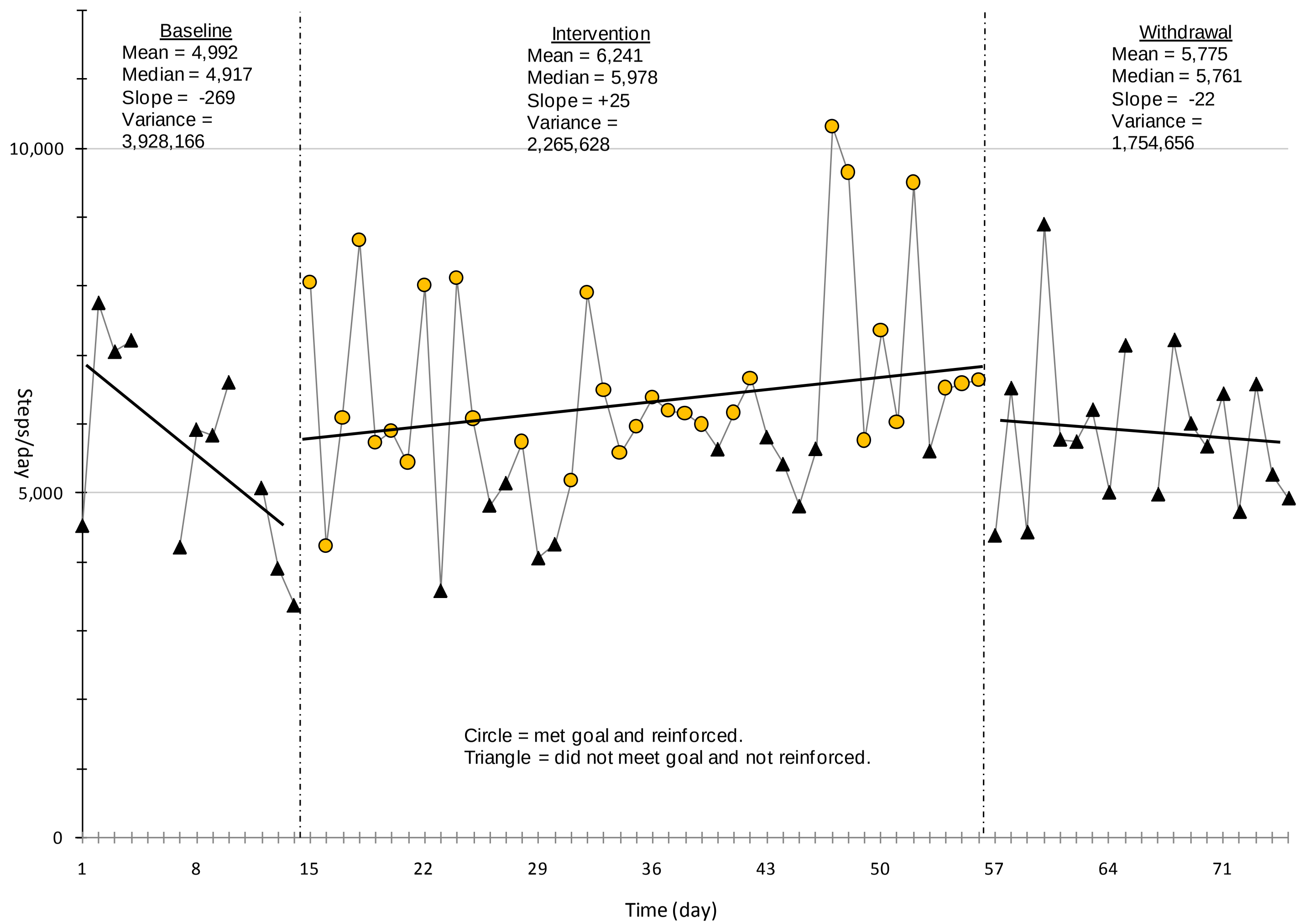


Figure 7. Participant 102's steps per day over the course of the study.

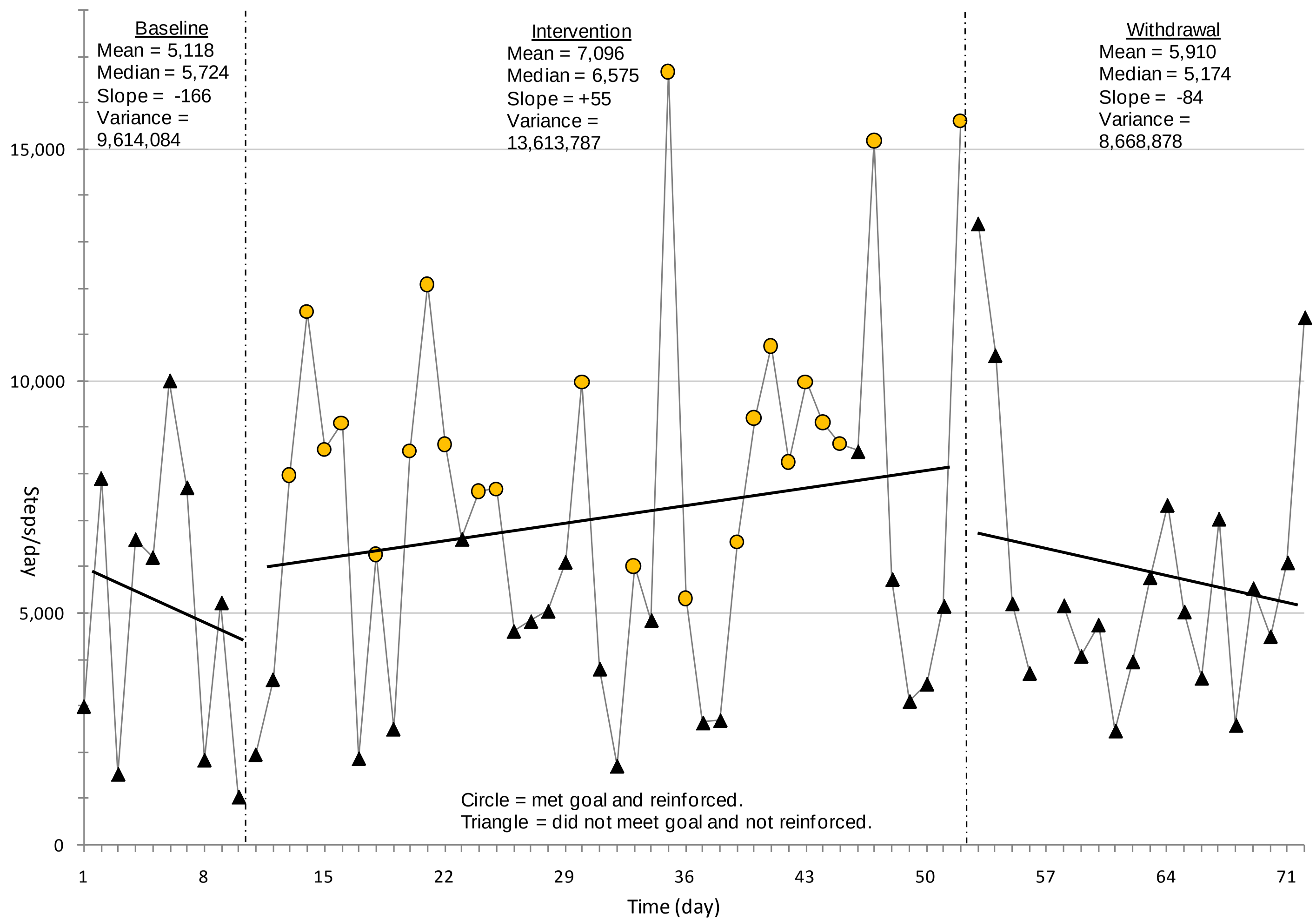


Figure 8. Participant 108's steps per day over the course of the study.

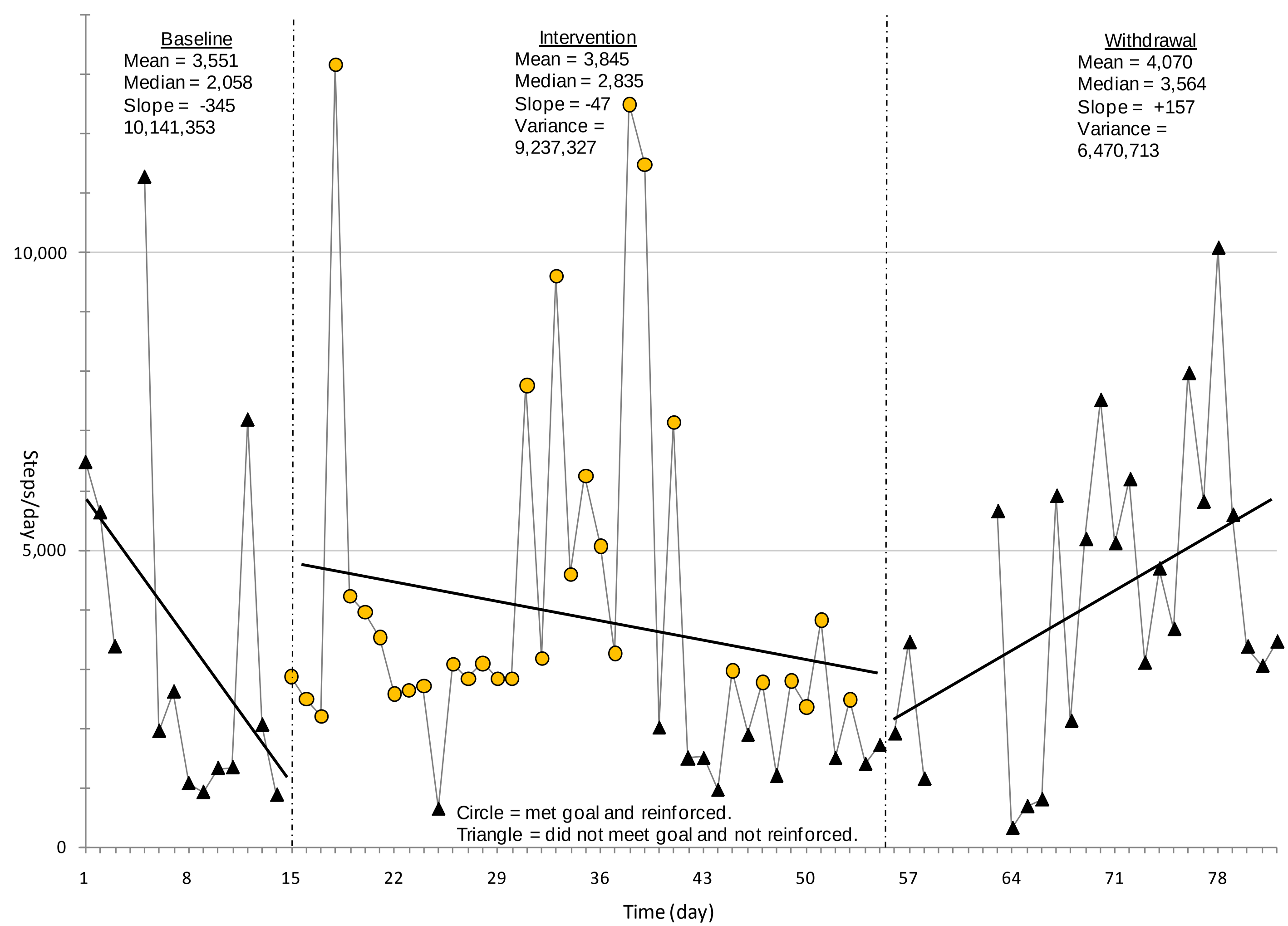


Figure 9. Participant 103's steps per day over the course of the study.

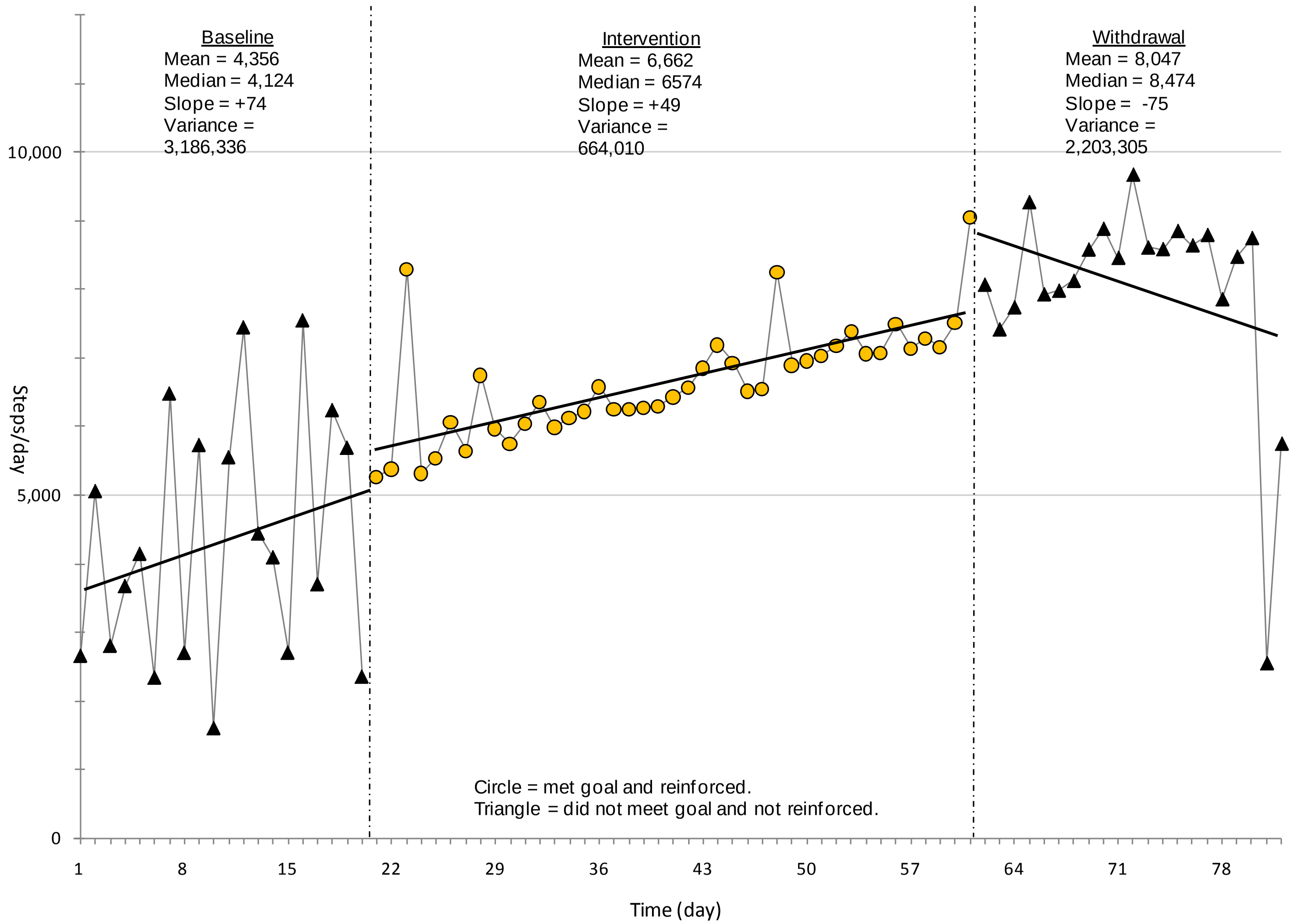


Figure 10. Participant 107's steps per day over the course of the study.

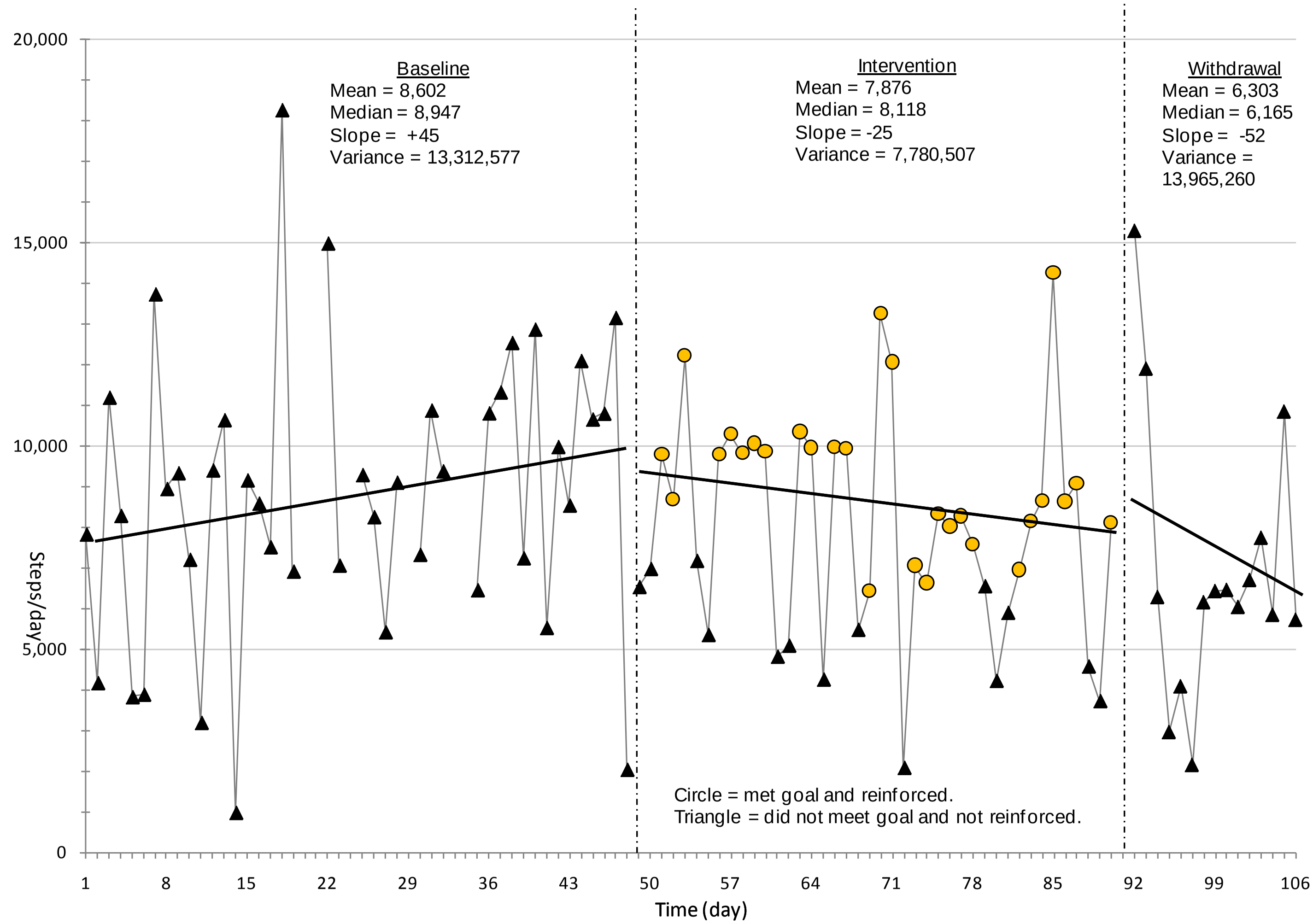


Figure 11. Participant 101's steps per day over the course of the study.

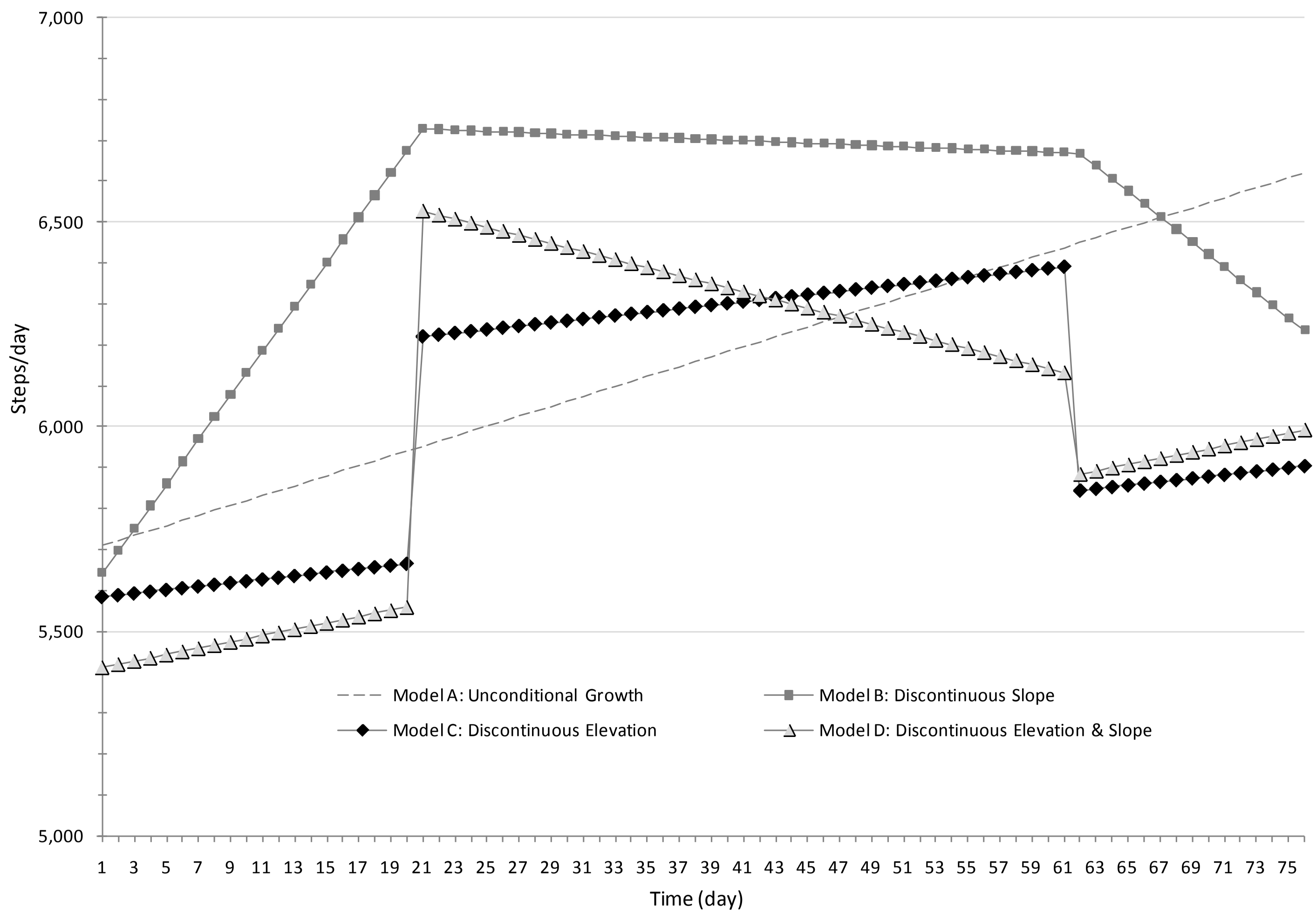


Figure 12. Four multilevel models displaying prototypical trajectories for steps per day.

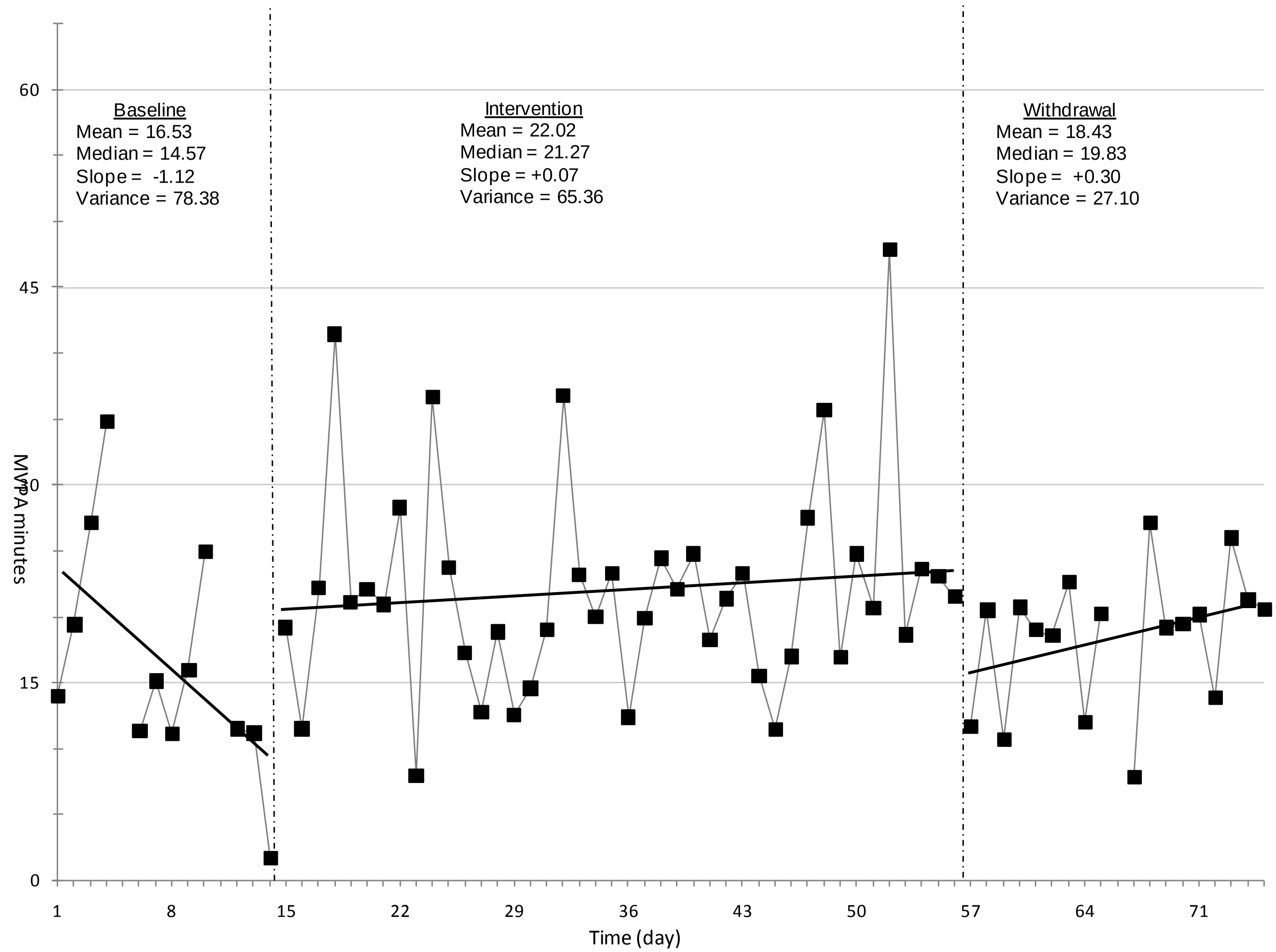


Figure 13. Participant 102's moderate-to-vigorous physical activity minutes per day over course of the study.

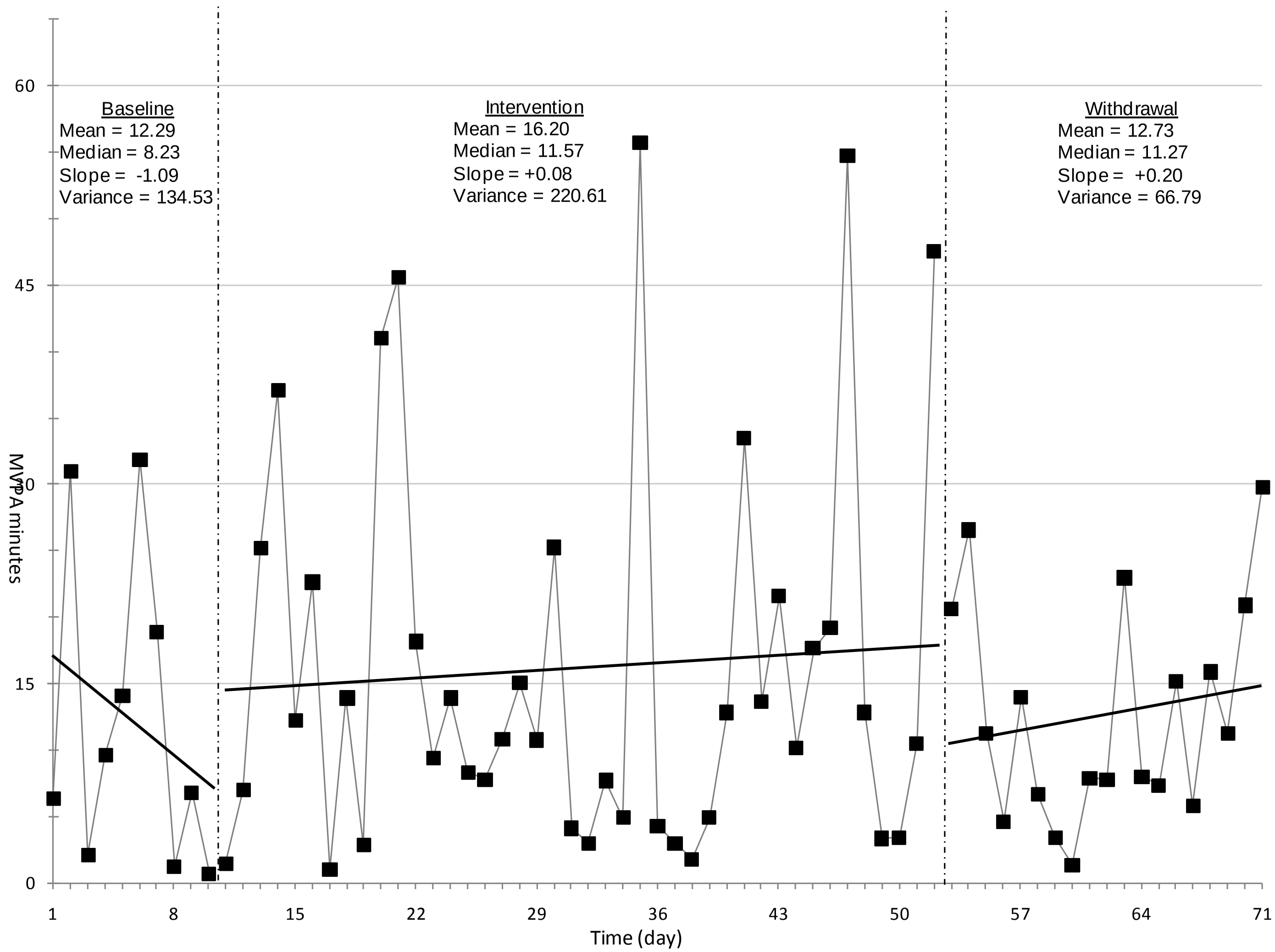


Figure 14. Participant 108's moderate-to-vigorous physical activity minutes per day over course of the study.

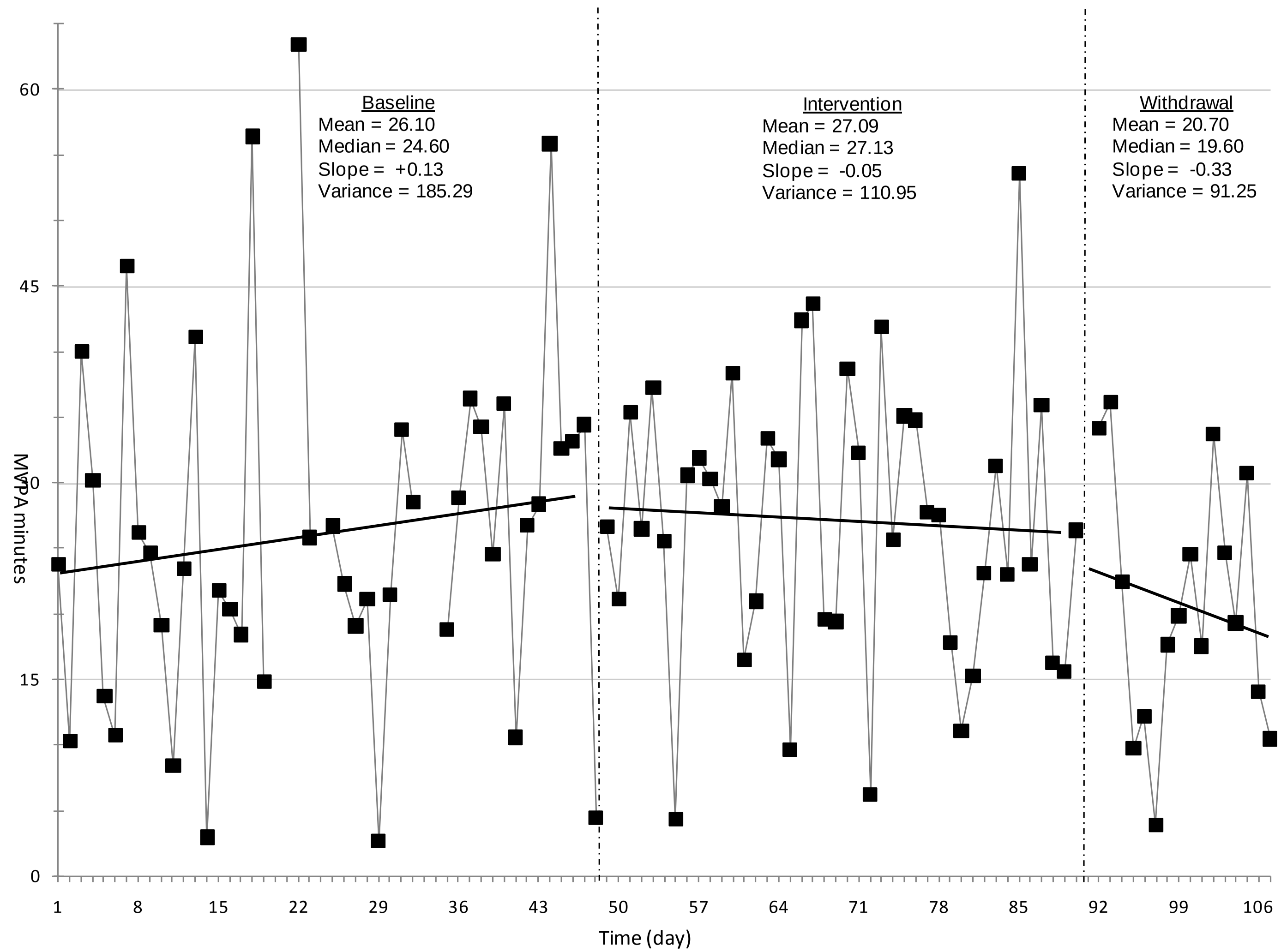


Figure 15. Participant 101's moderate-to-vigorous physical activity minutes per day over course of the study.

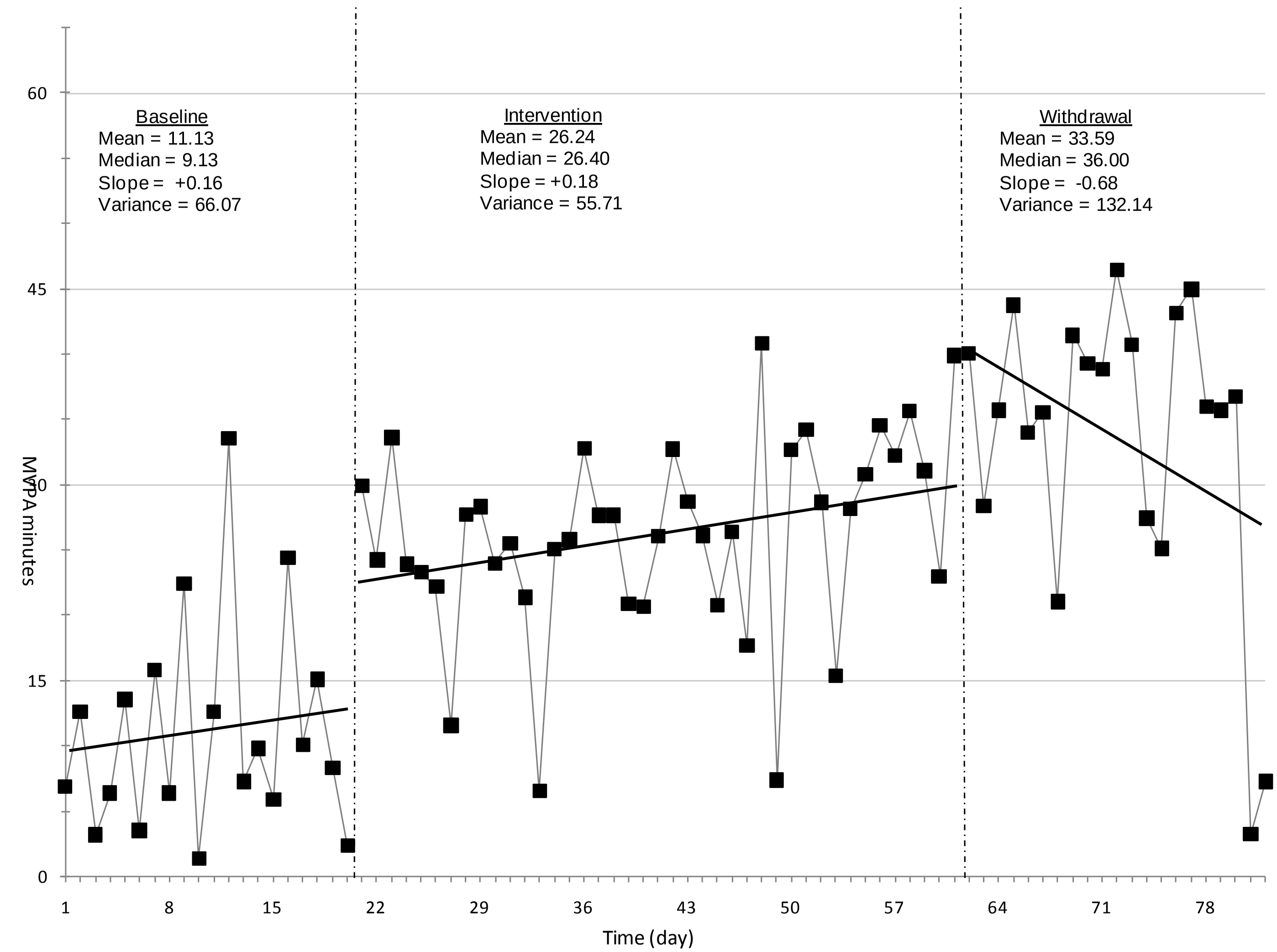


Figure 16. Participant 107's moderate-to-vigorous physical activity minutes per day over course of the study.

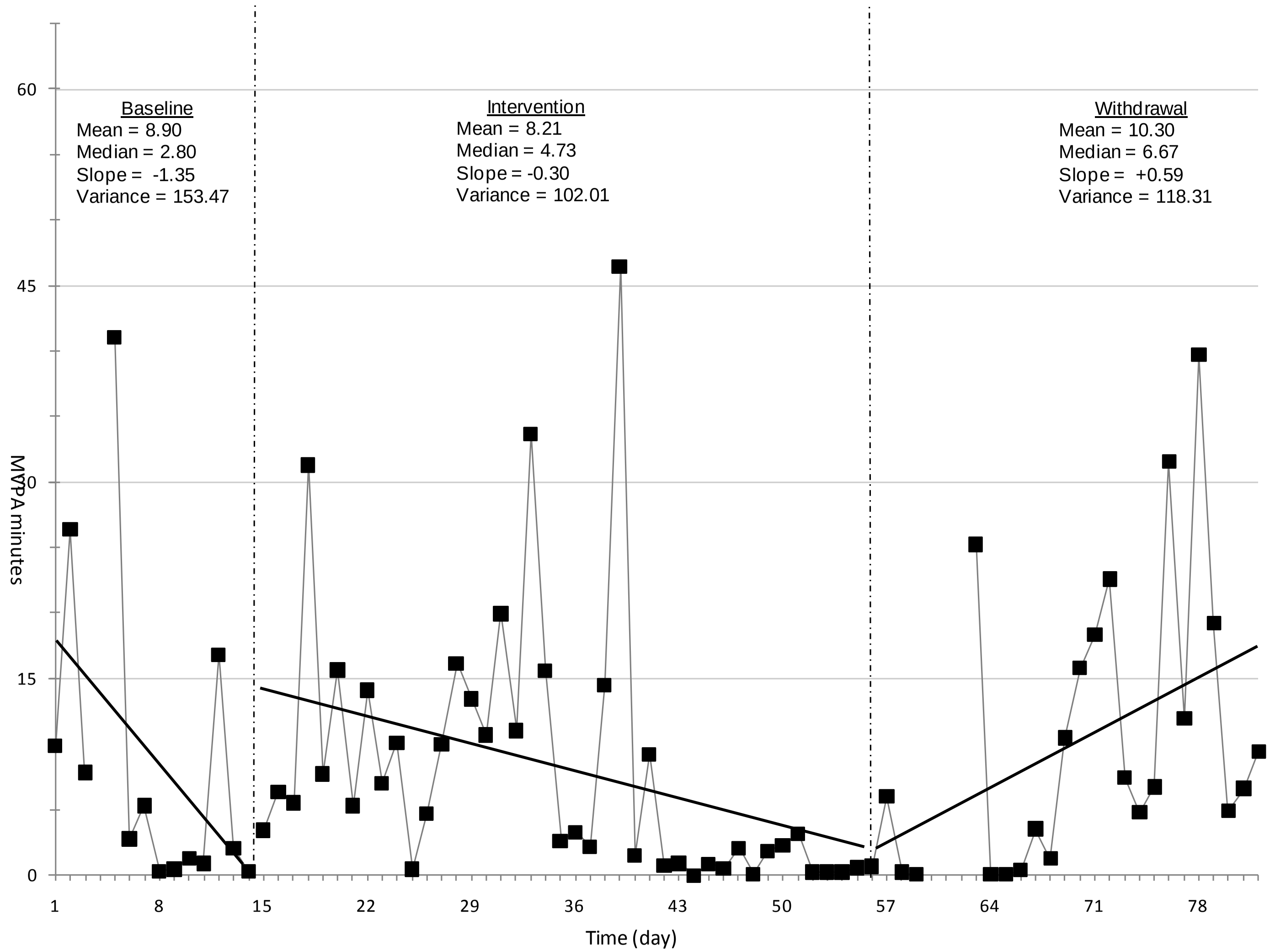


Figure 17. Participant 103's moderate-to-vigorous physical activity minutes per day over course of the study.

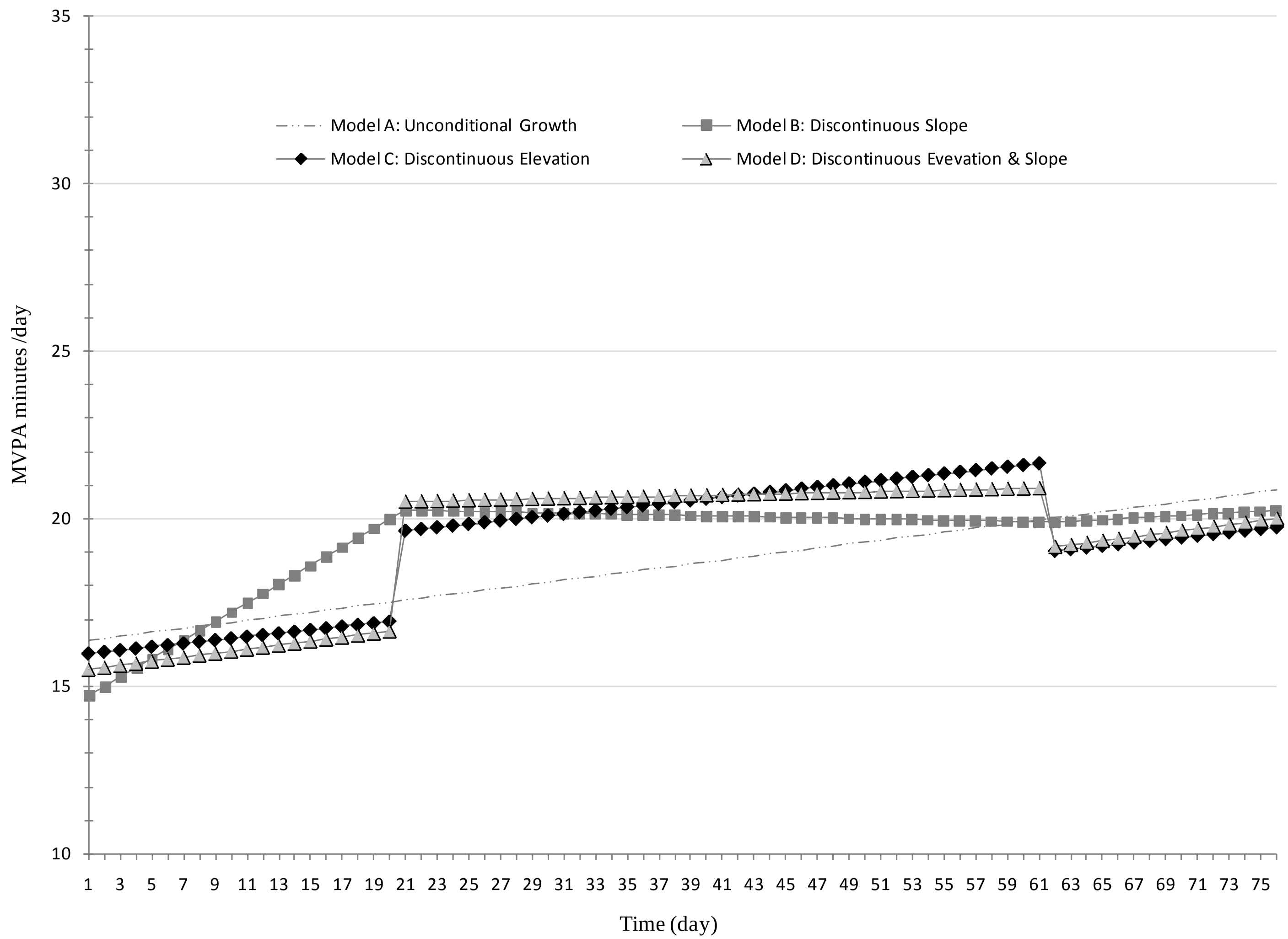


Figure 18. Four multilevel models displaying prototypical trajectories for moderate-to-vigorous physical activity minutes/day.

Table 1. Participants' demographics and personal characteristics.

ID	Sex	Age	Ethnicity	BMI	Marital Status	Children	Occupation	Income ($)
101	F	49	White	22.6	Single	No	Real Estate Sales / Waitress	25,999 - $49,999
102	F	54	White	22.1	Single	No	Professional or administrative	50,000 - $74,999
103	F	23	Asian	23.5	Single	No	Graduate Student	<25,000
107	F	25	Asian/White	21.4	Single, w/partner	No	Undergraduate Student	25,000 - 49,999
108	F	32	Hispanic	33.4	Divorced	Yes	Graduate Student	<25,000

Table 2. Participants' level, slope and variance across study phases for steps/day.

			Steps per day						
Phase	ID	n	Median	Mean	SD	Min	Max	Slope	Variance
Baseline	101	43	8,947	8,602	3,649	974	18,273	45.16	13,312,577
	102	12	4,917	4,992	1,982	1,537	7,766	-268.83	3,928,166
	103	13	2,058	3,551	3,185	879	11,285	-344.61	10,141,353
	107	20	4,124	4,356	1,785	1,612	7,553	73.78	3,186,336
	108	10	5,724	5,118	3,101	1,054	10,013	-166.50	9,614,084
	Total	98	6,226	6,268	3,671	879	18,273	114.56	13,476,892
Intervention	101	42	8,118	7,876	2,789	1,603	14,243	-24.76	7,780,507
	102	42	5,978	6,241	1,505	3,595	10,324	24.89	2,265,628
	103	41	2,835	3,845	3,039	648	13,169	-46.77	9,237,328
	107	41	6,574	6,662	815	5,273	9,055	48.75	664,009
	108	42	6,575	7,096	3,690	1,708	16,667	55.03	13,613,787
	Total	208	6,252	6,354	2,907	648	16,667	35.95	8,450,059
Withdrawal	101	16	6,229	6,697	3,476	2,169	15,285	-219.6	12,082,277
	102	18	5,761	5,775	1,325	2,981	8,899	-21.81	1,754,657
	103	24	3,564	4,070	2,544	317	10,085	156.53	6,470,713
	107	21	8,474	8,047	1,484	2,558	9,673	-75.83	2,203,305
	108	19	5,174	5,910	2,944	2,478	13,400	-84.12	8,668,878
	Total	98	5,833	6,021	2,774	317	15,285	25.494	7,692,999

Table 3. Four multilevel models for steps per day (N = 5).

		Model A: Unconditional Growth			Model B: Discontinuous Slope		
Fixed Effects	Parameter	Coefficient	SE	p-value	Coefficient	SE	p-value
Intercept	γ_{00}	5,700.63	840.06	<0.001	5,590.23	778.24	<0.001
Wear time (centered hours/day)	γ_{02}				363.13	47.12	<.0001
Day of week (weekday)					-424.31	273.08	0.12
Time	γ_{10}	12.09	11.13	0.32	54.26	23.53	0.03
Intervention Slope	γ_{11}				-55.71	26.44	0.04
Withdrawal Slope	γ_{13}				-29.54	35.43	0.41
Variance Components							
Level 1. Within-person	σ^2_e	7,262,762.34	517,311.00	<.0001	6,219,020.70	442,965.38	<.0001
Level 2. Initial status	σ^2_o	3,157,773.66	2,203,844.35	.08	2,186,804.55	1,574,619.58	.08
In rate of change	σ^2_1	453.35	371.14	.11	592.85	456.20	.10
Covariance/ARH1 Rho	σ_{01}	-25,309.74	24,016.01	.15	-0.63	0.31	.02
Deviance		7,550.92			7,489.18		
AIC		7,562.92			7,509.18		
BIC		7,586.93			7,549.20		

Table 3. Four multilevel models for steps per day (N = 5), Continued.

		Model C: Discontinuous Elevation			Model D: Discontinuous Elevation & Slope		
Fixed Effects	Parameter	Coefficient	SE	p-value	Coefficient	SE	p-value
Intercept	γ_{00}	5985.69	811.89	<0.001	5798.16	844.95	<0.001
Wear time (centered hours/day)	γ_{02}	361.90	47.23	<.0001	368.63	47.32	<.0001
Day of week (weekday)		-406.08	273.22	.14	-392.52	272.62	.15
Time	γ_{10}	4.26	10.99	.71	7.73	10.99	.51
Phase	γ_{11}	551.21	258.26	.03	1328.70	603.35	.03
Phase * Time	γ_{12}				-17.59	12.37	.16
Variance Components							
Level 1. Within-person	σ^2_e	6,233,233.06	443,996.38	<.0001	6,198,449.35	441,517.48	<.0001
Level 2. Initial status	σ^2_o	2,670,582.18	1,879,497.10	.08	2,861,402.28	2,004,056.88	.08
In rate of change	σ^2_1	453.17	367.85	.11	424.62	349.84	.11
Covariance/ARH1 Rho	σ_{01}	-0.40	0.43	.18	-0.37	0.44	.20
Deviance		7491.63			7489.64		
AIC		7509.63			7509.64		
BIC		7545.64			7549.66		

Table 4. Participants' level, slope, and variance across study phases for moderate-to-vigorous physical activity minutes/day.

			Moderate-to-Vigorous Activity Minutes Per Day							
Phase	ID	n	Median	Mean	SD	Min	Max	Variance	Slope	Variance
Baseline	101	43	24.60	26.10	13.61	2.67	63.40	185.29	0.13	185.29
	102	12	14.57	16.53	8.85	1.73	34.80	78.38	-1.12	78.38
	103	13	2.80	8.90	12.39	0.33	41.07	153.47	-1.35	153.47
	107	20	9.13	11.13	8.13	1.47	33.53	66.07	0.16	66.07
	108	10	8.23	12.29	11.60	0.73	31.87	134.53	-1.09	134.53
	Total	98	15.50	18.18	13.67	0.33	63.40	187.00	0.36	187.00
Intervention	101	42	27.13	27.09	10.53	4.40	53.60	110.95	-0.05	110.95
	102	42	21.27	22.02	8.08	8.00	47.80	65.36	0.07	65.36
	103	41	4.73	8.21	10.10	0.00	46.47	102.01	-0.30	102.01
	107	41	26.40	26.24	7.46	6.60	40.80	55.71	0.18	55.71
	108	42	11.57	16.20	14.85	1.07	55.67	220.61	0.08	220.61
	Total	208	20.67	19.98	12.58	0.00	55.67	158.31	0.18	158.31
Withdrawal	101	16	19.60	20.70	9.55	3.93	36.13	91.25	-0.33	91.25
	102	18	19.83	18.43	5.21	7.87	27.13	27.10	0.30	27.10
	103	24	6.67	10.30	10.88	0.07	39.73	118.31	0.59	118.31
	107	21	36.00	33.59	11.50	3.27	46.47	132.14	-0.68	132.14
	108	19	11.27	12.73	8.17	1.40	29.80	66.79	0.20	66.79
	Total	98	19.10	18.95	12.63	0.07	46.47	159.59	0.16	159.59

Table 5. Four multilevel models for moderate-to-vigorous physical activity minutes per day (N = 5).

		Model A: Unconditional Growth			Model B: Discontinuous Slope Model		
Fixed Effects	Parameter	Coefficient	SE	p-value	Coefficient	SE	p-value
Intercept	γ_{00}	16.30	2.93	0.002	12.64	2.87	.002
Wear time (centered hours/day)	γ_{02}				0.70	0.20	<0.001
Day of week (weekday)					1.80	1.15	0.12
Time	γ_{10}	0.06	0.06	0.34	0.28	0.11	0.02
Intervention Slope	γ_{11}				-0.29	0.12	0.01
Withdrawal Slope	γ_{13}				0.03	0.15	0.82
Variance Components							
Level 1. Within-person	σ^2_e	116.01	8.26	<.0001	110.46	7.87	<.0001
Level 2. Initial status	σ^2_o	37.03	26.79	.08	25.46	19.65	.10
In rate of change	σ^2_1	0.01	0.01	.16	0.02	0.01	.02
Covariance/ARH1 Rho	σ_{01}	-0.29	0.41	.24	-0.54	0.37	.07
Deviance		3092.28			3,071.24		
AIC		3104.28			3,091.24		
BIC		3128.29			3,131.26		

Table 5. Four multilevel models for moderate-to-vigorous physical activity minutes per day (N = 5), Continued.

		Model C: Discontinuous Elevation Model			Model D: Discontinuous Elevation & Slope Model		
Fixed Effects	Parameter	Coefficient	SE	p-value	Coefficient	SE	p-value
Intercept	γ_{00}	14.07	3.11	.003	13.53	3.23	.005
Wear time (centered hours/day)	γ_{02}	.69	.20	<.001	.71	.20	<.001
Day of week (weekday)		1.85	1.15	.11	1.89	1.15	.10
Time	γ_{10}	.05	.06	.44	.06	.06	.36
Phase	γ_{11}	2.65	1.09	.02	4.86	2.53	.056
Phase * Time	γ_{13}				-.05	.05	.34
Variance Components							
Level 1. Within-person	σ^2_e	109.89	7.83	<.0001	109.58	7.81	<.0001
Level 2. Initial status	σ^2_o	37.36	27.07	.08	39.52	28.52	.08
In rate of change	σ^2_1	0.02	0.01	.02	.01	.01	.16
Covariance/ARH1 Rho	σ_{01}	-0.32	0.44	.23	-.30	.45	.25
Deviance		3071.45			3070.54		
AIC		3089.45			3090.54		
BIC		3125.46			3130.56		

Table 6. Comparison of reported versus actual physical activity goals met during the intervention phase.

Participant	Reported (%)	Actual (%)
101	70	64
102	78	74
103	75	74
107	100	100
108	30	55

Appendix A.

[Participant's Name], You've made it this far, now things get interesting!

We've been entering your data into our system. It has designed customized program for you, and for each day forward it will continue to use the information you provide to create new goals. The ultimate target is to help you move your physical activity habits closer to the national recommendation of 10,000 steps/day 5 days a week. The target of 10,000 steps in a day is a rough equivalent to the Surgeon General's recommendation to accumulate 30 minutes of moderate activity most days, preferably every day, of the week. It should be enough to reduce your risk for disease and help you lead a longer, healthier life.

This target, however, is tough to accomplish. Breaking down this ultimate target into smaller steps is the best approach. We don't expect you to make it there in 6 weeks, but we will help you slowly move in the right direction.

First, you will need to review the attached pamphlet on regular physical activity (PDF attachment). This pamphlet is includes important health information for adults from the CDC. Stop for moment and open this attachment.

Second, the ActiveRewards Program...

Starting today, you will receive a step goal to try to meet. A new goal will arrive each day for the next 6 weeks. The goal is good only for that day. Your job is to figure out ways to increase your physical activities throughout the day to try to meet this goal. The prescribed amount is the minimum for that day. Feel free to do more and go beyond!

We want to help. A second email will arrive shortly. It includes 100 tips on how to increase your steps. We know people dislike a lot of homework. This is all the educational material we will send. The rest is up to you!

Email us your step count for the day between 10 and 11 PM each night. This is exactly what you have been doing over the last 2 weeks. Please email us even if you forget to wear the pedometer or do not meet your goal. We will need to know your step count before we can provide the next goal.

Each day you exceed a prescribed step goal you will earn one reward voucher point. Each point is worth $1.00.

Once you've accumulated 5 points, you will receive a gift code via email that can be exchanged for music at your preferred music store. You can redeem this alphanumeric code for music or other items.

Meet more goals to accumulate more points. You'll have daily opportunities for the next 6 weeks.

Some things to keep in mind: The goals adjust. They can get harder, easier, or stay the same. Please be aware that you will not meet every goal. And we don't expect you to meet every goal. If you don't meet a goal, don't worry. You'll have another opportunity tomorrow to improve.

Remember: The study is designed to test how well this approach can work. Never fake, add, or subtract steps when reporting (yes, we can tell at the end). This will cause your personalized goals to be mismatched to your abilities and slow down your progress. And make sure to wear you pedometer for at least 10 hours per day.

I've been emailing my steps. Any idea how far have I been walking? Yes. 1 Mile of Walking = 2,000 Steps. This is a good rough estimate. Actual step counts vary based on how tall you are and how fast you walk.

YOUR FIRST GOAL IS: 6225 steps for 2/28/09. Good luck!

Appendix B.

Participant 101 was a 49-year-old Caucasian woman, college graduate, employed as a full time realtor, and moonlighted as a part-time waitress. She reported a household income of $25,000 to $49,000 per year, single without children, but has a dog. On the PAR-Q, she indicated a heart murmur and minor arthritis in her leg, but met inclusion criteria after she provided a physician's medical waiver for both conditions. She had a BMI of 22.6 and reported 2,613 MET-minutes of physical activity in the week prior to baseline week. This level of activity was higher than the phone screening, but because the author noticed substantial over-reporting during phone screening and he had no experience with the IPAQ as a screening tool, the author made a decision to accept her as a participant.

Participant 102 was a 54-year-old Caucasian woman who reported no medical issues. She is college graduate, employed full time as an administrator at a local university, with a household income between $50,000 and $74,999 per year. She is single without children and had a dog. She has a BMI of 22.1 and reported 944 MET-minutes of physical activity in the week prior to baseline.

Participant 103 was a 23-year-old Asian woman with no medical issues. She is a part-time graduate student and is employed part-time as a teacher. She is single without children, and reported a household income of less than $25,000 per year. She has a BMI of 23.5 and reported 876 MET-minutes of physical activity in the week prior to baseline.

Participant 104 was a 19-year-old Caucasian man with no medical issues. He was a full-time undergraduate student, employed part time as a laboratory assistant with a household income of less than $25,000 per year. He was single and had no children. He had a BMI of 24.6 and reported 2,586 MET-minutes of physical activity in the week prior to baseline.

Participant 105 was a 52-year-old Caucasian man with no medial issues. He was single without children, a college graduate, and was employed in the engineering field with a household income of $25,000 to $49,999 per year. He had a BMI of 26.2 and reported 219 MET-minutes of physical activity in the week prior to baseline.

Participant 107 is a 25-year-old Asian and Caucasian woman with no medical problems. She is a part-time undergraduate student, unemployed, with a household income of $25,000 to $49,999 per year. She is single with no children and lives with a significant partner. She has a BMI of 21.4 and self-reported 0 MET-minutes of physical activity in the week prior to baseline.

Participant 108 is a 32-year-old Hispanic woman with no medical problems. She is a full time doctoral student, unemployed, with a household income of less than $25,000. She is divorced and has two children ages 10 and 12 years old, and owns a dog. She has a BMI of 33.4 and self-reported 0 MET-minutes of physical activity in the week prior to baseline.

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