J Behav Med (2018) 41:74–86
DOI 10.1007/s10865-017-9878-3

Adaptive step goals and rewards: a longitudinal growth model of daily steps for a smartphone-based walking intervention

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Received: December 7, 2016 / Accepted: July 22, 2017 / Published online: September 16, 2017

Abstract Adaptive interventions are an emerging class of behavioral interventions that allow for individualized tailoring of intervention components over time to a person's evolving needs. The purpose of this study was to evaluate an adaptive step goal + reward intervention, grounded in Social Cognitive Theory delivered via a smartphone application (Just Walk), using a mixed modeling approach. Participants (N = 20) were overweight (mean BMI = 33.8 ± 6.82 kg/m^2), sedentary adults (90% female) interested in participating in a 14-week walking intervention. All participants received a Fitbit Zip that automatically synced with Just Walk to track daily steps. Step goals and expected points were delivered through the app every morning and were designed using a pseudo-random multisine algorithm that was a function of each participant's median baseline steps. Self-report measures were also collected each morning and evening via daily surveys administered through the app. The linear mixed effects model showed that, on average, participants significantly increased their daily steps by 2650 (t = 8.25, $p < 0.01$) from baseline to intervention completion. A non-linear model with a quadratic time variable indicated an inflection point for increasing steps near the midpoint of the intervention and this effect was significant ($t^2 = -247$, $t = -5.01$, $p < 0.001$). An adaptive step goal + rewards intervention using a smartphone app appears to be a feasible approach for increasing walking behavior in overweight adults. App satisfaction was high and participants enjoyed receiving variable goals each day. Future mHealth studies should consider the use of adaptive step goals + rewards in conjunction with other intervention components for increasing physical activity.

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Keywords Adaptive goals · Walking behavior · mHealth · Personalized behavior change

Introduction

Recent advances in the collection and assessment of real-time health behaviors via mobile technologies and wearable devices invite behavioral scientists to consider new ways to use these data for behavior change (Patrick et al., 2016). Adaptive interventions represent a new class of behavior change research in which the intervention is designed to adjust for both baseline information (e.g. person's walking behavior prior to the intervention), and additional information that is gathered throughout the intervention process (e.g. changes in weekly steps during the intervention) (Collins et al., 2004; Rivera et al., 2007).

Although mHealth interventions are being designed and evaluated for a variety of health outcomes (e.g. diabetes, obesity, depression treatment, stress management) (Direito et al., 2016; Kazemi et al., 2017) intervention scientists have only just begun to implement and evaluate adaptive interventions for behavior change (e.g. physical inactivity, smoking cessation). Adaptive interventions offer an individualized approach to chronic disease prevention in which the treatment is adapted and re-adapted over time in response to the individual's changing needs (Almirall et al., 2014). Adaptive interventions are also referred to as "dynamic treatment regimes" (Almirall et al., 2014) and specify if, how, and when the researcher should alter the intensity, dose, or type of treatment.

Adaptive goals are one type of adaptive interventions that have been implemented to promote increases in physical activity (PA) behavior. Traditionally, goal-setting approaches for PA are fixed over time and the same across all participants in the study. For example, one type of goal would be to recommend that all individuals engage in 10,000 steps per day (Schneider et al., 2006). A second common approach is to use a person's baseline level of steps as a starting point and then to specify a linear stepped increase (e.g., +500 steps per day this week more than last week's goals) that do not take into account whether a person is meeting their goals or not (Lin et al., 2006). The use of static goals is conceptually limited as a tool for supporting behavior change because static goals fail to account for previous goal achievement, day-to-day changes in context (e.g. illness, work, weather, daily hassles), or changes in cognitive constructs that may have a direct effect on the targeted behavior (e.g. self-efficacy, motivation, commitment). In addition, static goals generally do not account for inter-individual differences in response rate (e.g. one person in a weight-loss intervention may lose a large amount of weight in the first 2 weeks, while another may have a "slower" response rate). Beyond conceptual reasons, prior work indicates the potential advantage of adaptive goals relative to static goals for fostering behavior change (Adams et al., 2013, 2017). In sum, an intervention that both adapts to the individual's performance and accounts for changes in context may increase the likelihood of producing the targeted health behavior outcome based on theory and prior work.

Purpose

The purpose of this paper is to describe the methods and design of the adaptive intervention (Just Walk v1), results of feasibility tests (i.e., acceptability, demand, and implementation) (Bowen et al., 2009) and results of the within-person efficacy of the intervention for influencing steps over the 14-week trial. It was hypothesized that the intervention would result in significant increases in steps taken per day compared to a baseline period and that the walking levels would be maintained across five consecutive, identical "cycles" (defined below but, in brief, identical interventions that are repeated within an individual as a single case design of ABBBBB).

Related work

A small number of mHealth researchers have begun to test adaptive intervention approaches for behavior change. Adams et al. (2013) tested an adaptive goal-setting, feedback, and reward algorithm to evaluate the effects of a 60th percentile-rank daily step goal on walking behavior. In this study, participants in the adaptive intervention group received a daily step goal that was based on the previous nine days of achieved steps. After the 10-day baseline phase, this became a sliding nine-day window in which the oldest step count would drop off. This was compared to participants in a static intervention (SI) group who were instructed to meet the goal of at least 10,000 steps each day on at least five days per week. For both groups, meeting the daily step goal translated to receiving a point, which, when sufficient points were earned, translated to an online gift card. Results indicated that the SI group improved their daily step count by 18% (984 steps/day) over the intervention, while the adaptive intervention group improved by 48% (2205 steps/day); on average, participants in the SI group met 22.6% of their goals (10,000 steps/day), while those in the adaptive intervention achieved 58.2% of their daily goals.

Building on this study (Hurley et al., 2015), Adams et al. (2017) conducted a 2 × 2 factorial designed RCT with the primary aim of evaluating whether adaptive goals and immediate reinforcement resulted in a greater change in objectively measured PA compared to the SI and delayed reinforcement groups. Results of this trial indicated that those participants receiving individualized and adaptive goals saw a smaller initial increase in the number of steps walked per day than those randomized to receive static goals (i.e. 10,000 steps/day), but were able to maintain their walking behavior over the four months of intervention. Individuals in the SI group slowly declined in the number of steps they were walking per day over the intervention duration. In addition, immediate rewards resulted in increasing physical activity (~746 steps/day), and this effect was independent of the type of goal received. The authors concluded that adaptive goals contributed to a more sustainable behavior change process over the four months of intervention compared to static goals and that "smaller, but sooner" incentives out-performed "larger and later" rewards (Adams et al., 2017).

In line with this work, Poirier et al. (2016) developed Walkadoo, an adaptive internet-based walking intervention that used wireless activity trackers to automatically send data to the internet-based program (via Bluetooth). The system generated goals that were tailored to the participant based on their most recent activity level, also using the percentile-rank algorithm developed by Adams et al. (2013). However, participants in Walkadoo could also receive day-to-day variations in difficulty level of the step goal, introducing a game-like element. The intervention group significantly increased their steps by 970 steps/day over control ($p < 0.001$) and this effect was consistent across sedentary (<5000 steps/day) and non-sedentary (5000–9999 steps/day) participants. The results from the Walkadoo study suggest that introducing random variability into personalized step goals throughout the intervention duration may provide an additional benefit over and above the percentile-rank method.

One emerging and exciting approach for developing adaptive interventions comes from control systems engineering (Rivera et al., 2007). Control systems engineering is a discipline focused on supporting decision-making in dynamic and often complex contexts even with imperfect knowledge. System identification (system ID; Ljung, 1999), which includes strategies for designing experiments and the use of dynamical systems modeling as an analytic technique, is an approach used by control systems engineers to understand transient and time-varying responses within systems to plausible 'interventions" that could be made within the "system" (in the case of behavior change, the person is a "system") to produce the desired state over time. For example, system ID is often used in chemical plants to generate dynamical models that provide insights on how a system responds to various "intervention options" (e.g., inclusion of different chemical reagents, use of cooling mechanisms to reduce the reactions), ultimately to support a "controller" to use that information to make dynamic decisions. As such, system ID work is focused on understanding the dynamics of a phenomenon in the service of supporting evidence-based decisions within a complex and dynamic domain.

This exciting approach for supporting dynamic decision-making has recently been applied to health behavior (smoking cessation research, gestational weight gain, and PA) (Hekler et al., 2013; Martín et al., 2014; Rivera et al., 2005; Timms et al., 2014), and may offer a means to explore adaptive interventions even more rigorously. Specifically, system ID provides a robust approach for generating individualized (i.e. person-specific) dynamical systems models that can describe how important time-varying variables (e.g., contextual factors such as perceived stress, perceived busyness, as well as theoretical "mechanisms of action" that influence behavior, such as self-efficacy) interact across time to predict an individual's future behavior. In this context, behavior is represented as an inventory that increases and decreases in frequency and/or duration over time and is allowed to fluctuate both between and within individuals (Riley et al., 2015a, b; Martín et al., 2014). Martín et al. (2014) have operationalized a dynamical systems model of the Social Cognitive Theory (SCT) and compared this model to both PA simulations and data from an mHealth PA intervention. The relevance of these individualized computational models for adaptive interventions is that they can be used in conjunction with a tool called a "model-predictive controller" that can take into account the predictions from these models, and relevant time-varying individual and contextual factors in selecting intervention options.

Theoretical grounding of our work and targeted adaptive intervention

In the context of adaptive goals, it is common for clinicians and practitioners to try and find an "ambitious but doable" goal to strive for; one that is not too easy, to instill a sense of challenge and also one not too hard to minimize the risk of repeated failure. This idea is implicitly acknowledged within Social Cognitive Theory, particularly as it manifests towards the suggestion of graded goals to ensure individuals meet them and, by extension, progressively increase their self-efficacy to be active (Stajkovic & Luthans, 1979). This ambitious but doable daily step goal is a dynamical target that is particularly well-suited to be studied via system identification as goals can be randomly assigned from one day to the next within the individual's "ambitious but doable" range. With this randomization of goal-levels occurring within-person over time, the analytic techniques used within system ID can then examine how individual and contextual differences (e.g., daily stress, busyness, weather) might impact the right "ambitious but doable" range for a person on any given day (including analytic methods for examining the possibility of issues such as carry over effects). In other work (Freigoun et al., 2017), we have conducted these dynamical systems modeling analyses to generate individualized dynamical models for each person. The focus of this article is on the within-person evaluation of our intervention for producing increased steps over time using a variation of a single-case experimental design that fits within a system ID approach and to also provide insights related to feasibility.

Methods

Overview

Just Walk was developed as an mHealth adaptive, walking intervention app for sedentary, overweight adults. The intervention included a front-end Android app, "Just Walk" (see Fig. 1), a backend server, and physical activity tracker (Fitbit Zip) to objectively measure PA and to automatically sync with the smartphone application. As shown in Fig. 1, participants could track their progress towards their daily goal and previous history anytime the app was opened. The

Fig. 1 Just Walk app

Fitbit Zip tracker was chosen to measure daily steps because it is inexpensive, easy to wear, allows automatic syncing with the Android app via Bluetooth, has a long battery life, and has shown strong validity for measurement of steps in free living conditions (Evenson et al., 2015; Ferguson et al., 2015). Participants were recruited nationally to partake in a walking intervention in which they would receive a daily step goal via the Just Walk app, and points if goal was achieved. Points were exchanged for Amazon gift cards after a certain threshold was reached. Participants also completed a series of daily surveys (Shiffman et al., 2008) that measured a number of constructs (e.g. confidence in achieving goal, predicted busyness for that day, previous night's sleep quality, etc.) in the morning and evening of each day of the entire study.

The total study duration was 14-week, including an initial 2-week baseline period in which no step goals were delivered and no points were available. Each participant's step goals were based on his/her median daily step value calculated from the baseline period and were designed to establish a mechanism for individualizing the definition of an ambitious, but doable step range (described below). All PA data were collected from the Fitbit Zip in the form of steps per day (provided to participants as a part of the study). The Just Walk app relied on the Fitbit API to collect the user's step data. The password-protected encrypted system included a back-end database and a web service for monitoring participants' activity. The University Institutional Review Board approved the intervention trial and all the procedures used in data collection and all participants provided informed consent prior to participating in any part of the study.

Inclusion and exclusion criteria

Participants were generally healthy, insufficiently active, 40–65 years old, with a body mass index (BMI) of 25–45 kg/m^2, who owned and regularly used an Android phone capable of connecting to a Fitbit Zip via Bluetooth 4.0, and were willing to engage with the mHealth intervention for 14 weeks. Participants were considered insufficiently active and eligible for the study if they engaged in less than 1000 metabolic equivalent of task (MET)-minutes/week as measured by the International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003). Individuals were excluded if they did not speak English, were pregnant, had a BMI > 45 kg/m^2, indicated medical problems that preclude unsupervised PA based on the Physical Activity Readiness Questionnaire (PAR-Q), or were currently participating in a commercial or research-related diet or exercise program. Participants were recruited nationally through community advertising techniques (e.g., emails to student listservs,

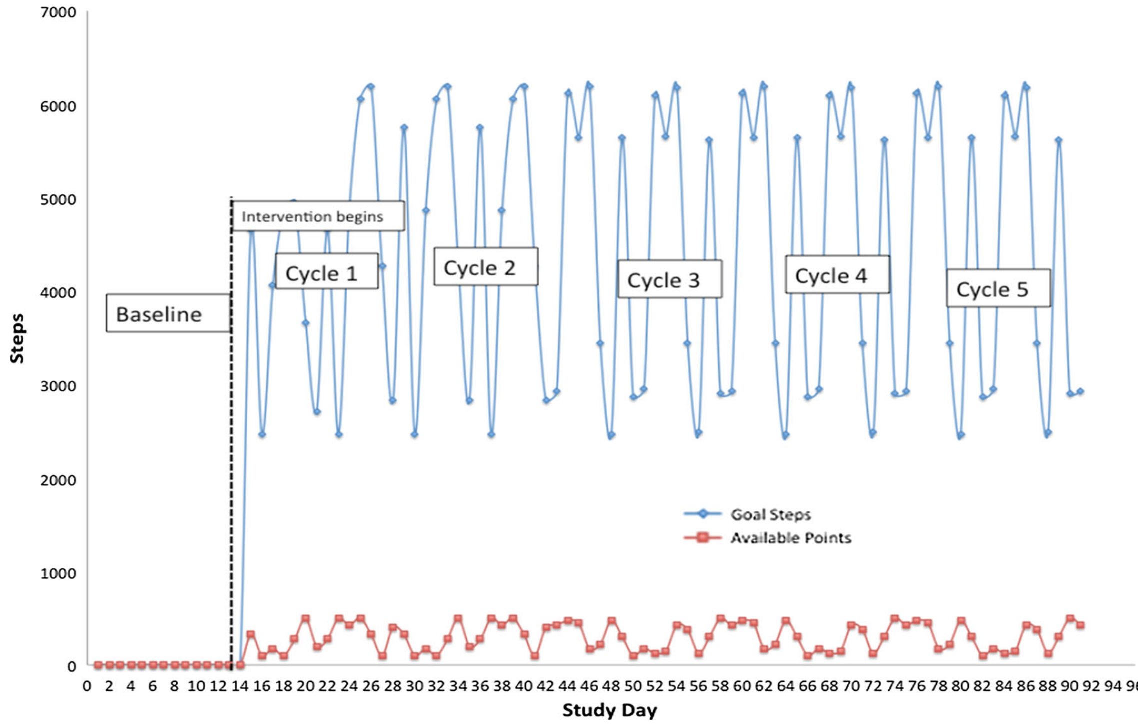

Fig. 2 Just Walk study design

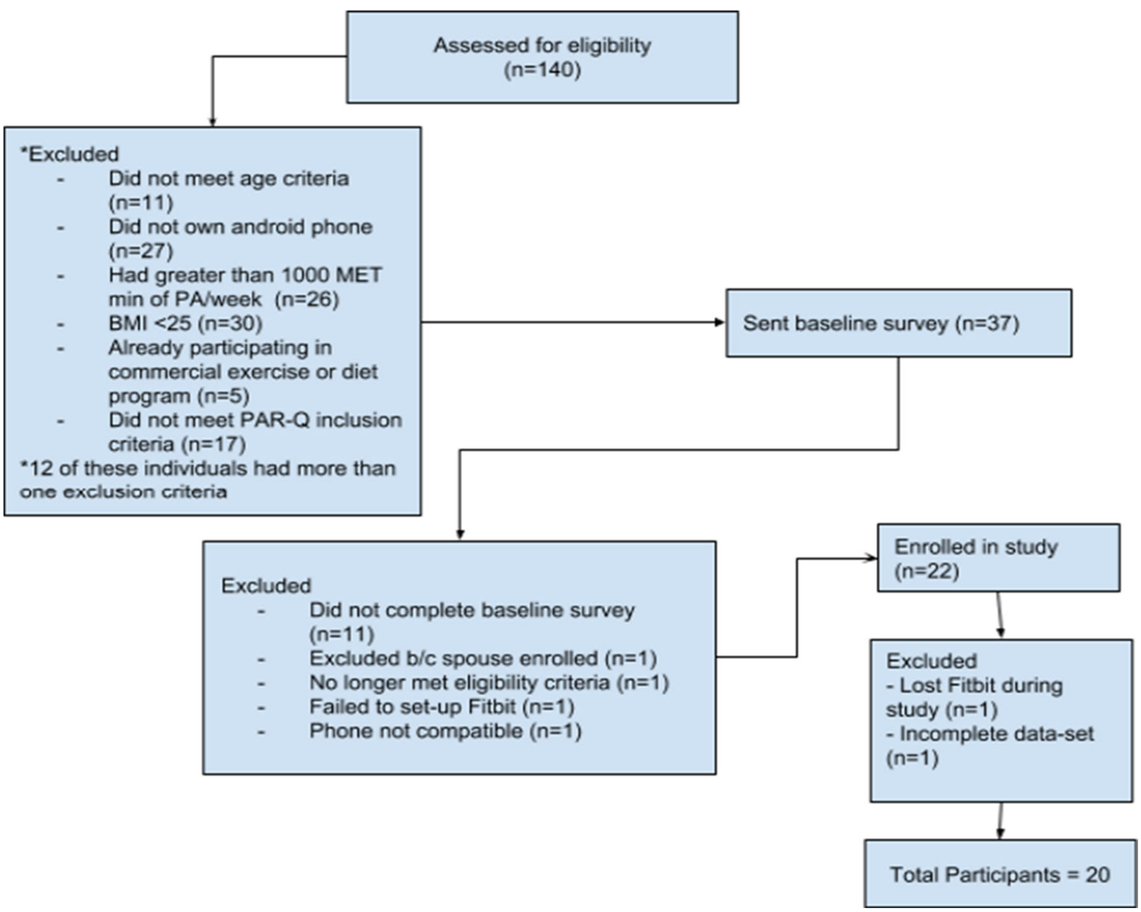

Fig. 3 Just Walk recruitment diagram

word-of-mouth, social media advertisements) and were provided a Fitbit Zip upon enrolling in the study.

Our recruitment strategy can be seen in Fig. 3. Participants were initially contacted using nationwide university listservs and through social media advertisements (Facebook). Through these efforts, 140 individuals were assessed for eligibility in the study using an online survey; of these, 103 were excluded and 37 were sent the online informed consent and the baseline survey. Of these 37, 11 people did not respond, four individuals were excluded for reasons listed in Fig. 3, and 22 people were enrolled in the Just Walk intervention. Two individuals were excluded from the final analyses—one of these lost their Fitbit during the study and one individual was excluded from analyses due to missing data.

Intervention design

System identification experimental design

Our experimental design was based on practices from system ID. As discussed earlier, system ID is a suite of experimental and analytic techniques that are used to quantify and describe dynamical systems using mathematical models. System ID allows the researcher to model variations and responses within temporal data, in a single "system" (defined as one individual, though it could feasibly be an aggregation of individuals) (Martín et al., 2015a, b). The manipulated variables in this system ID experiment were the daily step goals delivered via the Just Walk app and the points that were available each day for achieving the goal (Fig. 2); inputs consisted of time-varying covariates that were measured daily (e.g. perceived stress, perceived busyness, sleep quality, etc.) and the output were the actual steps taken each day.

Goal setting and rewards

Participants received their step goal through the Just Walk app every morning. The system ID open-loop experiment pseudo-randomly assigns step goals from doable (i.e., baseline median) to ambitious (i.e., up to 2.5 × baseline median) for each person (for full discussion on the logic of using a pseudo-random as opposed to purely random signal, see Martín et al., 2015a, b), using a multisine signal with a time period defined as a 16-day cycle (Table 1). This experimental design was created based on SCT and, in particular, the hypothesis that, on any given day, there could exist goals that would be ambitious on some days, doable on others, and ambitious but still doable on other days. Further, the measures used in this study were explicitly chosen based on SCT and this dynamic hypothesis, particularly variables such as self-efficacy, that would be theorized to influence, on any given day, if a suggested step goal were ambitious vs. doable, even with the same goal number. For example, if a person's perceived self-

Table 1 Sample goal factors and step goals for a single participant during one intervention cycle

Day	Participant median	Goal factor	Daily step goal	Available points
1	2475	1.18	2921	425
2	2475	2.47	6113	475
3	2475	2.28	5643	450
4	2475	2.50	6188	175
5	2475	1.39	3440	225
6	2475	1.00	2475	475
7	2475	2.28	5643	300
8	2475	1.16	2871	100
9	2475	1.19	2945	175
10	2475	2.46	6089	125
11	2475	2.29	5668	150
12	2475	2.50	6188	425
13	2475	1.39	3440	375
14	2475	1.01	2500	125
15	2475	2.27	5618	300
16	2475	1.17	2896	500

Goal factors ranged from 1 to 2.5 and were used to set the daily goal given to each participant by multiplying the goal factor (e.g. 1.18) by the participant median (e.g. 2475) efficacy for a given day is low, then a goal of 10,000 steps may be perceived as too ambitious. In contrast, if a person's self efficacy is high, 10,000 steps might be perceived as "doable." Our experimental design was explicitly formulated to explore this dynamic hypothesis implied by SCT. Table 1 is an example of the actual daily step goals and daily points that were delivered to one participant (baseline median = 2475 steps/day) in the Just Walk study. This goal-setting strategy was designed to "excite" variability into the step goals, to allow for modeling efforts about how individuals respond to different step goals in different contexts or states.

Participants were able to earn points if they achieved their daily step goal (Fig. 2; Table 1). Specifically, when participants were informed of their goal in the morning, they were also informed of the number of points (range 100–500 per day) available to them if they met said goal. Points, like the goals, were determined by a pseudo-random multisine approach over a 16-day cycle, with five identical cycles across the study. Each time participants accumulated 2500 points, they were automatically sent a $5 Amazon gift card via email. Progress towards this threshold amount could be viewed in the Just Walk app. The system ID design ensured that recommended goals and points provided were delivered orthogonally (Martín et al. 2015a, b).

A 16-day cycle for the multisine signal was used to minimize the risk of aliasing signals, particularly with day of the week and also to provide minimal excitation for dynamical models based on previous calculations (Martín et al. 2015a, b). Specifically, these calculations could conceptually be thought of as a "power" calculation but, in this context, the calculations examine how to reduce noise within a dynamical modeling effort to support generating and validating stable individualized dynamical models.

Each 16-day cycle was repeated within participants, representing the implementation of a rigorous single-case design—a family of methods in which each participant serves as his or her own control (Dallery et al., 2013). Because the intervention was systematically introduced across participants and not changed within participants (for each cycle, the 16-day sequence of goals was replicated), each cycle represents another test of the effect of the intervention. This design is especially advantageous given that the outcome (i.e., achieving "ambitious but doable" step goals) was something that was conceptualized as inherent to the individual (rather than a property of a group of individuals). Another advantage of single case research is that "it demonstrates preliminary efficacy, which can be defined as clinically significant patient improvement over the course of treatment," (Dallery et al., 2013). In this context, our goal was to see if our adaptive intervention strategy, as defined via system ID, could produce clinically similar, on average increases in steps to those observed by Adams et al. (2013).

Specifically, longitudinal walking step data were subjected to a linear growth model with "cycle" as the time metric. After baseline (time 0), each participant went through a total of five cycles (time 1, 2, 3, 4, and 5). To stabilize the measurements (particularly because our goal-setting component was systematically prescribing variable steps each day), we aggregated steps taken across the baseline period and then across each cycle to treat the study as a single group design with repeated measures, as described above (Dallery et al., 2013).

Five cycles were chosen as the minimal number of cycles needed based on a variety of plausible noise characteristics (e.g. white noise and autoregressive Gaussian forms) and also based on a desire to create both estimation cycles and validation cycles. From a single case design perspective, the use of these cycles is an ABBBBB single-case design (A = baseline, B = intervention cycle). As stated previously, it is important to note that our recommended step goals never increased between cycles. As such, the "on average" step goal suggestions from one cycle to the next were exactly the same (i.e., the goals provided during cycle one were identical to cycle five). Based on this point, it was hypothesized that there would be a significant increase in daily steps from baseline to cycle one but no major increases from cycles one to five. This point is empirically tested with our modeling efforts below (see results).

Daily survey measures

Participants were prompted by the Just Walk app to fill out a short survey each morning and evening during the 14-week study. Participants were sent a prompt to take the survey at self-selected times and could change their preferred time as desired throughout the study within the app. Table 2 presents a sample of the survey items that were developed based on constructs from the SCT. In addition, it was hypothesized that the effect of these variables may be different for each individual (e.g. some individual's PA might be affected by predicted daily stress while another's by whether it is a weekday or weekend), which was examined via separate analyses using idiographic modeling techniques (Freigoun et al., 2017). There were thirteen daily items, six weekly items, and four monthly items. Weekly and monthly questions were administered on a random day that week, meaning participants received the weekly question on a different day every week. Participants were also contacted through email within one month following the completion of the Just Walk intervention to

Table 2 Example daily survey items

Variable	Question	Scale	Frequency
Predicted busyness	How busy is today going to be for you?	1–5 scale (not at all to extremely)	Daily
Predicted stress	How stressful do you expect your day to be?	1–5 scale (not at all to very)	Daily
Self-efficacy	How confident are you that you can walk [your baseline median] steps five days a week?	1–4 scale (not at all to extremely)	Weekly
Outcome expectancy	I expect improvements in the following areas of my life from being physically active/walking	Checkbox	Weekly
Identity	I see myself as a physically active person	1–5 scale (strongly disagree to strongly agree)	Monthly
Habit	I take long walks/walk throughout the day without having to think about it	1–4 scale (not true to very true)	Monthly

Table 3 Descriptive statistics of just walk participants (N = **20)**

Mean age (SD)	47.25 (6.16)
Mean daily steps at baseline (SD)	4863.3 (2097)
% Female	90%
% White	95%
Mean BMI (kg/m^2) (SD)	33.79 (6.82)
*Daily survey adherence (%)	>90%
Expressed interest in continued app use	88%
Total study days (mean)	89–95 days (93.05)
Baseline period	14 days
Cycle length	16 days
Number of intervention cycles	5

* Based on answering any of the daily survey questions at a given assessment time (morning and evening)

participate in an exit interview. The semi-structured Interviews were conducted by one of two research members via a phone call and were 30 minutes long in duration and were audio-recorded. Sample interview questions include: "How often, if ever, did you perceive the goals to be too hard for you to achieve?", "A core part of this research study was to try and figure out what your "ambitious but doable" sweet spot range is for step goals each day, what do you think this is for you?", "What did "confident" in meeting a goal mean to you each day?" On average, each participant was asked approximately 20 questions relating to their overall experience of the intervention.

Feasibility

Feasibility was assessed by the overall adherence to the intervention, including the number of wear days of the Fitbit Zip by each participant, missing step data, completion of the daily surveys delivered via the Just Walk app, and participant reported satisfaction.

Analysis

The purpose of this paper is to present the preliminary efficacy results of the intervention using mixed effects and longitudinal growth modeling, particularly to test the within-person effects of the intervention. Specifically, we sought to test if the intervention condition resulted in significant increases in steps over the course of the intervention relative to baseline levels.

The NLME package in R (Pinheiro et al., 2016) was used for all analyses, with time nested within participants as the random effect, intervention (baseline vs. treatment phase) as the fixed effect, and full maximum likelihood estimation. Polynomial time functions were also tested to determine if the step data demonstrated any non-linear patterns across time. If non-linear patterns appeared evident, then other patterns (e.g., quadratic, cubic, non-linear) were examined via improved model fit.

Results

Key descriptive statistics are summarized in Table 3. Participants (N = 20) were primarily overweight (mean BMI = 33.79 kg/m^2), female (90%) adults (Mean age = 47 years) who were walking <5000 steps per day before the intervention on average (M = 4863 steps/day).

Feasibility

There was high adherence to the intervention overall. Out of all participants, only 10 had days with missing step data. Overall, there were 40 (M = 4 ± 4.39) non-wear days, defined as days with fewer than 500 steps. Non-wear days typically occurred during days 40–70 of the intervention. In addition, there was high adherence for the daily surveys (90% of all morning and evening surveys were completed during the intervention duration).

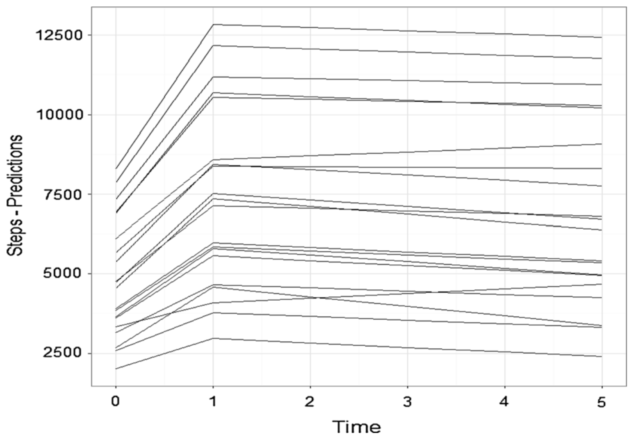

Fig. 4 Linear step trajectories over cycles of Just Walk intervention

Exit interviews/surveys (n = 9) indicated participants liked receiving different daily goals (100%), perceived the app as easy-to-use (85%) and expressed interest in continued app use (88%). The most common problem was sync lag with Fitbit.

Model 1: linear mixed- effects model fit by maximum likelihood to test main effect of the intervention

The research team first employed a mixed effects model with time and an intervention variable (0 = baseline, intervention cycle = 1) entered in the model to test the main effect of the Just Walk intervention, controlling for time/cycles. The results of this model are reported in Table 4. The mean intercept had a value of 4863.3 steps and was significant (t = 8.51, $p < 0.01$), indicating that, on average, before the start of the Just Walk intervention, a person was typically walking just under 5000 steps per day and that there was significant variation in baseline steps (Table 4). The fixed effect, intervention, had a mean value of 2650.9 steps (t = 8.25, $p < 0.01$), indicating that, on average, participants increased their daily steps by ~2500 steps per day as a result of the Just Walk intervention. The random factor, time (as defined by each cycle), had a mean value of −109.1 steps per day and was not significant (t = −1.35, $p = 0.18$), indicating there may have been some loss of the effect of daily step goals over the course of 12 weeks of intervention; however this decrease was modest at best, and not significant. Individual predicted linear models are shown in Fig. 4 and demonstrates that almost all participants experienced a large increase in steps from baseline to cycle 1 of Just Walk. This increase remained fairly stable or slightly decreased over the duration of the study. A plot of the residuals was constructed and inspection of these residuals indicated that the error terms may be exhibiting a parabolic structure and therefore a second model that included a time–squared variable in the equation was estimated. It appeared that our hypothesized increase from baseline to cycle 1 and no major changes between cycles 1-5 was possible, thus requiring nonlinear models. In summary, the results from the linear mixed effects model indicated an on-average increase in steps from baseline to intervention of 2650.9 steps per day and a non-significant decrease in steps from cycle 1 to cycle 5.

Model 2: mixed-effects model with quadratic term fit by maximum likelihood

The results of this model are reported in Table 5. The mean intercept was 5301 steps (t = 11.29, $p < 0.001$), indicating that, on average, at baseline, participants were walking approximately 5000 steps per day. The random factor, time, had a mean value of 1505 steps (t = 5.52, $p < 0.001$), indicating that, on average, a person increased his/her steps by over 1500 steps from baseline to cycle 1. The time

Table 4 Linear mixed effects model for Just Walk

Parameter	Value	SE	Degrees of freedom	t value	*p* value
beta_1	4863.3	463.30	98	10.49	<0.001
beta_2	−109.1	76.57	98	−1.42	0.157
beta_3	2650.9	405.03	98	6.54	<0.001

Parameter	Standard deviation
d_1i	1838.42
d_2i	183.70
d_3i	1227.36

Model: steps ~ (beta_1 + d_1i) + (beta_2 + d_2i)* (Time) + (beta_3 + d_3i)* (Intervention)

* Beta_1 represents the intercept in the model (average daily steps before Just Walk). Beta_2 represents the impact of time on daily steps over the intervention duration. Beta_3 represents the on –average increase in daily steps over Just Walk

Table 5 Non-linear mixed effects model for Just Walk

Parameter	Value	SE	Degrees of freedom	t value	*p* value
beta_1	5301.5	469.22	98	11.29	<0.001
beta_2	1505.8	272.62	98	5.52	<0.001
beta_3	−247.3	49.38	98	−5.01	<0.001

Parameter	Standard deviation
d_1i	1862.04
d_2i	847.52
d_3i	143.60

Model: Steps ~ (beta_1 + d_1i) + (beta_2 + d_2i)* (Time) + (beta_3 + d_3i)* (TimeSquared)

*Beta_1 represents the intercept in the model (daily steps before Just Walk). Beta_2 represents the impact of the intervention over time. Beta_3 is the coefficient for the quadratic term in the model (indicates quadratic trajectory, concave in shape)

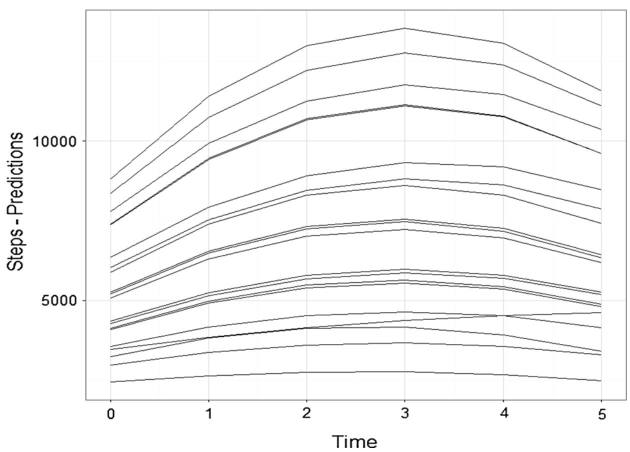

Fig. 5 Quadratic step trajectories over cycles of Just Walk intervention

squared coefficient, beta 3, is negative and had a raw value of −247 steps per day ($t = -5.01$, $p < 0.001$). This indicates a quadratic trajectory that is concave in shape, and that the average participant hits a ceiling for increasing steps near cycle 3 of the intervention (Fig. 5). The AIC for this model was 2099.961, lower than that of the corresponding linear model with only time entered (AIC = 2136.323) indicating that a model including a time squared variable is a better fit for these data. In summary, when a quadratic term is included, results indicate that individuals increased their steps from baseline to intervention and this increase continued until cycle 3, whereby there was an inflection after which steps began to exhibit a decline. (Fig. 5).

Discussion

This study demonstrated that adaptive step goals delivered via a smartphone app might be a feasible approach for increasing walking behavior in a sample of overweight and previously sedentary adults relative to baseline levels, and that participants were willing to engage with our system during the three-month duration of this intervention. On average, participants increased their daily steps by over 2600 steps per day during the intervention period compared to the baseline period. These results are in line with previous work by Adams et al. (2013), who reported an increase of 2728 steps/day for participants enrolled in the adaptive intervention step goal group. In the current study, the step goals delivered during each 16-day intervention cycle were a function of the participant's daily step median obtained from the 2-week baseline phase in which no step goals were delivered (see Table 1 for example 16-day cycle). Adams and colleagues based their adaptive goals on a sliding nine-day window that took into account the participant's previous walking behavior during that window. Both methods appear to produce similar results and provide evidence for the value of personalized and adaptive step goals in achieving the desired behavior change.

The results of the quadratic model suggest that, on average, participants tended to hit a local daily step maximum around cycle three of the Just Walk intervention (Fig. 5). This could have been a result of the study design, decreasing novelty of the application or due to changes in user context (e.g. weather, stress, schedule). By design, goals were not made more challenging from one cycle to the next nor were more points available earlier or later in the intervention. As such, while there was variability in the daily goals within a cycle, the goals were not designed to produce increases in steps from cycle one to five. With that said, this model was a better fit than our more simplified model, which only tested for changes from baseline to intervention, thus suggesting the presence of other dynamics. For example, one participant commented that, "I couldn't meet the goals because I was sick, and the last 3 weeks of the study I was super busy at work with like auditors and everything, so I couldn't take the 15-minute walks during the day, so it kind of just depends on what else is going on in my life, as to whether I can [meet the goals].” It is plausible that individuals were initially influenced by the daily step goals in the first two cycles but reduced/plateaued by cycle three, possibly through reduced commitment/decreased novelty of the daily goals along with other contextual factors that affect PA behavior. Therefore, in order to sustain perpetual increases in PA over time, it may be important for step goal algorithms to account for changes in user-context, which is the eventual target of the broader research efforts and thus indicative of the potential of the approach.

This work is the starting point for the systematic application of control systems engineering practices for the development of behavioral interventions. As discussed elsewhere, control systems engineering is a discipline focused on supporting dynamic decision-making in complex “systems” often with imperfect prior knowledge (Rivera, 2012). Control systems engineering is ubiquitous with far-reaching applications from aerospace and robotics, to pacemakers and artificial pancreases. At present though, these methods have only been minimally applied to behavioral interventions (Spruijt-Metz et al., 2015a, b). An important pre-condition for using control systems engineering approaches is to determine if the sort of experiments required, particularly system ID “open loop” experiments such as the one we conducted, can result in fostering behavior change and are feasible in terms of acceptability by the participants. To the best of our knowledge, this is the first time a system ID open loop experiment has been conducted with a “human” as the system. As such, the results presented in this work provide empirical justification for continuing to explore the use of control systems engineering practices within a behavioral context as our results indicate that a system ID open loop experiment can, indeed, be conducted with humans.

Beyond the implications for further advancing the use of control systems engineering in a behavioral context, this study adds support to the current literature on adaptive interventions for increasing PA using personalized step goals and rewards delivered via a smartphone application every day. On average, participants were walking nearly one mile more per day by the end of the intervention and 30% of participants had achieved a cycle median of over 9000 steps/day. Nine-thousand steps per day is recognized as an accepted threshold for realizing health benefits (Tudor-Locke et al., 2008). Overall satisfaction with the app was high; participants tended to enjoy getting different goals each day, suggesting that variability may be important for maintaining long-term increases in PA and engagement with behavior change techniques, such as goal-setting. One participant commented, “I actually did like the [variability of the goals], I was wondering if you guys kept track and then said “let’s see these days she seems to get more, so let’s keep the goals up on these days…like on Tuesday or Wednesday.” When asked for “gut reactions” to the app, another participant commented, “It was really good, I liked it, I looked forward to the challenge, it made me walk more than I typically walked for sure. I was very aware of how little I was walking before hand. I thought it might start asking me to walk more and more, I probably would have…[preferred] if I could fit it in; the hardest part was fitting it into my daily routine.”

Finally, another contribution of this research is to inform future adaptive and personalized health behavior interventions using other methods. For example, Hotchberg and colleagues (Hochberg et al., 2016) used an automatic Reinforcement Learning algorithm to optimize messages aimed at improving diabetes participants’ compliance with a physical activity regimen. Patients who received the tailored messages increased the amount of exercise they were doing and saw greater improvements in A1c levels than those who did not receive personalized messages. Future studies need to investigate under what contexts and for whom personalized and adaptive interventions can be used to optimize behavior change.

Limitations

The strengths of this study included objectively measured steps, high adherence to our study protocol for the vast majority of participants, the use of a system ID-inspired single case experimental design, and national recruitment of mid-life adults who are at risk of developing a variety of chronic diseases in the near future. The primary limitation of the study is the lack of a between-group control condition. As such, no conclusions can be drawn on the value of our adaptive intervention relative to other interventions strategies, such as the use of static goals. That said, similar step goal increases observed in Adams et al. (2013) and this study increase confidence in the utility of our approach. Further, participants acted as their own control, and the baseline phase provided a counterfactual comparison for the intervention phase and each subsequent cycle acted as a replication of the intervention strategy compared to the previous cycle, thus further increasing confidence in our estimated effect.

Another limitation is our small and relatively homogeneous sample, which limits generalizability. However, participants were recruited nationally and represent middle class Americans who are likely to use wearable devices, health/fitness apps, and should be targeted for behavior change interventions as they are at increased risk of a variety of chronic disease conditions (Troiano et al., 2008).

Finally, the 12-week intervention period is relatively short, and longer trials are needed to examine if this intervention strategy can be used over a longer time period to support behavior change. Results from our exit interviews indicated plausible acceptability for use of this in a person's current life, demand for continued use and the feasibility of implementing the intervention. Based on these points, the investment in longer trials in likely warranted.

Conclusions

This study employed a theory-driven adaptive step goal and reward intervention to increase walking behavior via a smartphone application in sedentary, overweight mid-life adults at risk for a variety of chronic diseases. Results provided evidence for the effectiveness of personalized and varying step goals and rewards to help individuals increase and sustain changes in physical activity. Participants enjoyed receiving different step goals each day, had few difficulties engaging with the app and using the Fitbit tracker, and commented that they would continue to use the app after the end of the study if available. In addition, to the best of our knowledge, this study is the first to attempt to conduct a system ID open loop experiment with humans as the system. The results indicate that the experiment can be conducted with humans in a feasible way and produce meaningful behavior change. Future studies should continue to explore ways of using control systems engineering practices to evaluate behavioral interventions and to test the use of perpetually adaptive step goals in a larger and more diverse sample. In addition, researchers should consider ways to incorporate daily changes in psychosocial variables that may influence fluctuations in PA, and further study goal variability—which in itself, might be a useful strategy to support more sustained engagement.

Acknowledgements Funding was provided by National Science Foundation (Grant Number IIS-1449751).

Compliance with ethical standards

Conflict of interest Elizabeth V. Korinek, Sayali S. Phatak, Cesar A. Martin, Mohammad T. Freigoun, Daniel E. Rivera, Marc A. Adams, Pedja Klasnja, Matthew P. Buman, and Eric B. Hekler declare that they have no conflicts of interest.

Human and animal rights and Informed consent All procedures followed were in accordance with ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000. Informed consent was obtained from all patients for being included in the study.

References

Adams, M. A., Hurley, J. C., Todd, M., Bhuiyan, N., Jarrett, C. L., Tucker, W. J., et al. (2017). Adaptive goal setting and financial incentives: A 2 × 2 factorial randomized controlled trial to increase adults' physical activity. *BMC Public Health, 17,* 286.

Adams, M. A., Sallis, J. F., Norman, G. J., Hovell, M. F., Hekler, E. B., & Perata, E. (2013). An adaptive physical activity intervention for overweight adults: A randomized controlled trial. *PLoS ONE, 8,* e82901.

Almirall, D., Nahum-Shani, I., Sherwood, N. E., & Murphy, S. A. (2014). Introduction to SMART designs for the development of adaptive interventions: With application to weight loss research. *Translational Behavioral Medicine, 4,* 260–274.

Bowen, D. J., Kreuter, M., Spring, B., et al. (2009). How we design feasibility studies. *American Journal of Preventive Medicine, 36,* 452–457.

Collins, L. M., Murphy, S. A., & Bierman, K. L. (2004). A conceptual framework for adaptive preventive interventions. *Prevention Science, 5,* 185–196.

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., et al. (2003). International physical activity questionnaire: 12-country reliability and validity. *Medicine and Science in Sports and Exercise, 35,* 1381–1395.

Dallery, J., Cassidy, R. N., & Raiff, B. R. (2013). Single-case experimental designs to evaluate novel technology-based health interventions. *Journal of Medical Internet Research, 15,* e22.

Direito, A., Carraça, E., Rawstorn, J., Whittaker, R., & Maddison, R. (2017). mHealth technologies to influence physical activity and sedentary behaviors: Behavior change techniques, systematic review and meta-analysis of randomized controlled trials. *Annals of Behavioral Medicine, 51*(2), 226–239.

Evenson, K. R., Goto, M. M., & Furberg, R. D. (2015). Systematic review of the validity and reliability of consumer-wearable activity trackers. *International Journal of Behavioral Nutrition and Physical Activity, 12,* 159.

Ferguson, T., Rowlands, A. V., Olds, T., & Maher, C. (2015). The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity, 12,* 42.

Freigoun, M. T., Martín, C. A., Magann, A. B., Rivera, D. E., Phatak, S. S., Korinek, E. V., et al. (2017). System identification of just walk: A behavioral mhealth intervention for promoting physical activity. In *Proceedings of the 2017 American control conference, May 24–26, Seattle, WA* (in press).

Hekler, E. B., Buman, M. P., Poothakandiyil, N., Rivera, D. E., Dzierzewski, J. M., Morgan, A. A., et al. (2013). Exploring behavioral markers of long-term physical activity maintenance a case study of system identification modeling within a behavioral intervention. *Health Education and Behavior, 40,* 51S–62S.

Hochberg, I., Feraru, G., Kozdoba, M., Mannor, S., Tennenholtz, M., & Yom-Tov, E. (2016). A reinforcement learning system to encourage physical activity in diabetes patients. arXiv:1605.04070

Hurley, J. C., Hollingshead, K. E., Todd, M., Jarrett, C. L., Tucker, W. J., Angadi, S. S., et al. (2015). The walking interventions through texting (WalkIT) trial: Rationale, design, and protocol for a factorial randomized controlled trial of adaptive interventions for overweight and obese, inactive adults. *JMIR Research Protocols, 4,* e108.

Kazemi, D. M., Borsari, B., Levine, M. J., Li, S., Lamberson, K. A., & Matta, L. A. (2017). A systematic review of the mhealth interventions to prevent alcohol and substance abuse. *Journal of Health Communication, 22*(5), 413–432.

Lin, J. J., Mamykina, L., Lindtner, S., Delajoux, G., & Strub, H. B. (2006). Fish'n'Steps: Encouraging physical activity with an interactive computer game. In *International conference on ubiquitous computing* (pp. 261–278). Berlin: Springer.

Ljung, L. (1999). *System identification: Theory for the use* (2nd ed.). Upper Saddle River, NJ: Prentice Hall.

Martín, C. A., Deshpande, S., Hekler, E. B., & Rivera, D. E. (2015a). A system identification approach for improving behavioral interventions based on social cognitive theory. In *IEEE 2015 American control conference (ACC)* (pp. 5878–5883).

Martín, C. A., Rivera, D. E., & Hekler, E. B. (2015b). Design of informative identification experiments for behavioral interventions. In *Proceedings of the 17th IFAC Symposium on system identification, Beijing, China* (Vol. 48, pp. 1325–1330).

Martín, C. A., Rivera, D. E., Riley, W. T., Hekler, E. B., Buman, M. P., Adams, M. A., et al., (2014). A dynamical systems model of social cognitive theory. In *IEEE 2014 American control conference* (pp. 2407–2412).

Patrick, K., Hekler, E. B., Estrin, D., Mohr, D. C., Riper, H., Crane, D., et al. (2016). The pace of technologic change: Implications for digital health behavior intervention research. *American Journal of Preventive Medicine, 51,* 816–824.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team, (2016). *nlme: Linear and nonlinear mixed effects models*. R package version 3.1-128. http://CRAN.R-project.org/package=nlme

Poirier, J., Bennett, W. L., Jerome, G. J., Shah, N. G., Lazo, M., Yeh, H. C., et al. (2016). Effectiveness of an activity tracker-and internet-based adaptive walking program for adults: A randomized controlled trial. *Journal of medical Internet research, 18,* e34.

Riley, W. T., Martin, C. A., Rivera, D. E., et al. (2015a). *Behav. Med. Pract. Policy Res.*. doi:10.1007/s13142-015-0356-6

Riley, W. T., Serrano, K. J., Nilsen, W., & Atienza, A. A. (2015b). Mobile and wireless technologies in health behavior and the potential for intensively adaptive interventions. *Current Opinion in Psychology, 5,* 67–71.

Rivera, D. E. (2012). Optimized behavioral interventions: What does system identification and control engineering have to offer? *IFAC Proceedings Volumes, 45,* 882–893.

Rivera, D. E., Pew, M. D., & Collins, L. M. (2007). Using engineering control principles to inform the design of adaptive interventions: A conceptual introduction. *Drug and Alcohol Dependence, 88,* S31–S40.

Rivera, D. E., Pew, M. D., Collins, L. M., & Murphy, S. A. (2005). Engineering control approaches for the design and analysis of adaptive, time-varying interventions. *The Methodology Center Technical Report*, 05–73.

Schneider, P. L., Bassett, D. R., Jr., Thompson, D. L., Pronk, N. P., & Bielak, K. M. (2006). Effects of a 10,000 steps per day goal in overweight adults. *The American Journal of Health Promotion, 21,* 85–89.

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4,* 1–32.

Spruijt-Metz, D., Hekler, E., Saranummi, N., Intille, S., Korhonen, I., Nilsen, W., et al. (2015a). Building new computational models to support health behavior change and maintenance: New opportunities in behavioral research. *Translational Behavioral Medicine, 5,* 335–346.

Spruijt-Metz, D., Wen, C. K. F., O'Reilly, G., Li, M., Lee, S., Emken, B. A., et al. (2015b). Innovations in the use of interactive technology to support weight management. *Current Obesity Reports, 4,* 510–519.

Stajkovic, A. D., & Luthans, F. (1979). Social cognitive theory and self-efficacy: Implications for motivation theory and practice. In R. M. Steers, L. W. Porter, & G. A. Bigley (Eds.), *Motivation and Work Behavior* (pp. 126–140). Boston: MA. McGraw-Hill.

Timms, K. P., Rivera, D. E., Collins, L. M., & Piper, M. E. (2014). A dynamical systems approach to understanding self-regulation in smoking cessation behavior change. *Nicotine & Tobacco Research, 16,* S159–S168.

Troiano, R. P., Berrigan, D., Dodd, K. W., Masse, L. C., Tilert, T., & McDowell, M. (2008). Physical activity in the United States measured by accelerometer. *Medicine and Science in Sports and Exercise, 40,* 181.

Tudor-Locke, C., Hatano, Y., Pangrazi, R. P., & Kang, M. (2008). Revisiting "how many steps are enough?". *Medicine and Science in Sports and Exercise, 40,* S537.